UNIVERSIDAD
POLITÉCNICA
DE MADRID

UNIVERSIDAD POLITÉCNICA DE MADRID

Escuela Técnica Superior de Ingeniería Agronómica

Alimentaria y de Biosistemas

**Designing an Index based insurance using NDVI
as an impact indicator of drought and flood risks
in rice cultivation:
An application to the region of Babahoyo
(Ecuador)**

TESIS DOCTORAL

Omar Roberto Valverde Arias

Ingeniero Agrónomo

Madrid 2018

UNIVERSIDAD
POLITÉCNICA
DE MADRID

UNIVERSIDAD POLITÉCNICA DE MADRID
Escuela Técnica Superior de Ingeniería Agronómica
Alimentaria y de Biosistemas

**Designing an Index based insurance using NDVI
as an impact indicator of drought and flood risks
in rice cultivation:
An application to the region of Babahoyo
(Ecuador)**

TESIS DOCTORAL

Omar Roberto Valverde Arias

Ingeniero Agrónomo

Directores

Alberto Garrido Colmenero

Dr. Ingeniero Agrónomo

Ana María Tarquis Alfonso

Dra. Ingeniera Agrónoma

Madrid 2018

Tribunal nombrado por el rector Magfco. De la Universidad Politécnica de Madrid, el díade201...

Presidente:.....

Vocal:.....

Vocal:.....

Vocal:.....

Secretario:.....

Suplente:.....

Suplente:.....

Realizado el acto de defensa y lectura de la Tesis el día dede 201... en
la E.T.S.I./Facultad.....

Calificación:.....

EL PRESIDENTE

LOS VOCALES

EL SECRETARIO

“Si tienes un gran sueño debes estar dispuesto a un gran esfuerzo para concretarlo porque solo lo grande alcanza a lo grande”

Facundo Cabral

Agradecimientos

Quiero expresar mis sinceros agradecimientos a los directores de esta tesis doctoral: Alberto Garrido y Ana Tarquis, quienes me han guiado sabiamente desde la formulación del proyecto de tesis, en todas sus fases hasta su finalización exitosa. Sin ellos no hubiera sido posible este trabajo.

Agradezco también al Gobierno de la República del Ecuador; el cual, por medio de la Secretaria Nacional de Educación Superior, Ciencia, Tecnología e Innovación (SENESCYT) han financiado mis estudios de máster y doctorado en la Universidad Politécnica de Madrid.

Agradezco al Centro de Estudios e Investigaciones para la Gestión de Riesgos Agrarios y Medioambientales (CEIGRAM) por acogerme durante estos años de estudios, principalmente a su directiva vigente: José María Sumpsi, Ana Tarquis y Margarita Ruíz. A su personal administrativo, Esperanza Luque y Katerina Kucerova; a Begoña Cadiñanos por el soporte técnico. Y a todos las compañeras y compañeros investigadores con los que compartí estos años, que hicieron mi permanencia en el Centro y en España más amena y de los que aprendí mucho en lo técnico y en lo personal.

Agradezco al Ministerio de Agricultura y Ganadería del Ecuador, el cual, por medio de la Coordinación General del Sistema de Información Nacional y Agroseguros, proporcionaron los datos necesarios y el asesoramiento técnico para la realización de esta tesis; así como, por abrirme sus puertas durante el proceso de investigación.

Y finalmente agradezco a toda mi familia, en especial a mis padres Franklin y Rosario, y a mis hermanos Frank, Gaby y Carlos, por su amor y apoyo incondicional.

Resumen

La agricultura es una actividad económica de riesgo que se enfrenta tanto amenazas biofísicas como económicas. Las biofísicas incluyen los eventos climáticos extremos, como sequías inundaciones, heladas, o granizos, además de plagas y enfermedades. Las amenazas económicas incluyen la variabilidad de los precios de venta y de los insumos, variación de mercados internos y externos, falta de crédito, entre otros.

Dentro de las amenazas biofísicas, las más importantes por su frecuencia e intensidad son los eventos climáticos extremos. La agricultura ha sido condicionada por el clima desde tiempos históricos, hasta que por medio de la tecnología se ha logrado adaptar la producción agrícola a medios crecientemente más adversos. A pesar de estas innovaciones, las variaciones e inestabilidad del clima siguen siendo difíciles de predecir y controlar y todavía constituye el riesgo más importante dentro de la producción agrícola, especialmente en los países en vías de desarrollo. Este riesgo se ve acentuado por las consecuencias del cambio climático.

Los seguros agrícolas han demostrado ser una herramienta eficiente de transferencia del riesgo desde los agricultores hacia entidades más capacitadas para gestionar el riesgo. Los seguros agrícolas incentivan o posibilitan el acceso al crédito y la inversión en mejoras tecnológicas que hacen a los agricultores más productivos y disminuyen la tasa de morosidad.

El seguro basado en índices (IBI siglas en inglés) es un tipo de seguro agrícola que no necesita verificación *in situ* de la ocurrencia de un siniestro, ni tampoco la peritación de daños. Es decir, no requiere de la visita de un perito especializado a la finca para verificar el siniestro, sino que lo hace por medio de un índice que está altamente correlacionado con el evento catastrófico y/o con las pérdidas ocasionadas por el mismo.

El objetivo de esta tesis es diseñar un seguro indexado que complemente al actual seguro agrícola convencional implementado en Ecuador desde el año 2010 (Agroseguro), y que utilice el Normalized Difference Vegetation Index (NDVI), como un indicador de sequías e inundaciones, en el cultivo de arroz en el cantón Babahoyo (Ecuador).

Esta investigación se inició con la determinación de áreas homogéneas a partir de un mapa agroecológico de la costa ecuatoriana a escala 1:250,000. Para lo cual se probaron tres

métodos de agregación, dos de ellos de criterio experto y uno estadístico. El primero agrupó las porciones de tierra con similares características de pendiente, textura y profundidad efectiva, se obtuvo 196 zonas agroecológicas homogéneas (AHZs, siglas en inglés). El segundo agrupó las áreas con similares precipitaciones y temperaturas, obteniéndose solo 11 AHZs, mientras que el tercero utilizó el análisis de componentes principales (PCA) para la generación de áreas homogéneas, obteniendo 26 AHZs. Se encontró que el tercer método es el que agrupa de mejor manera las características agroecológicas del área de estudio.

El principal inconveniente en los IBI es el riesgo de base o riesgo básico, el cual se produce cuando el índice seleccionado no está fuertemente correlacionado con las pérdidas que ocurren en el campo, quedando algunos asegurados afectados sin indemnización y otros que reciben compensación a pesar de no haber sido afectados.

Por esto es necesario evaluar con precisión la variabilidad en el área donde se quiere implementar el seguro indexado. Para esto hemos utilizado el mapa de AHZs generado en la primera etapa, sobre el caso particular del cantón Babahoyo. En Babahoyo las AHZ más representativas son *f7* y *f15*.

Posteriormente se verificó si las diferencias topográficas, de suelo y clima propias de cada zona *f7* y *f15* eran también visibles sobre el suelo desnudo (por medio de imágenes satelitales al inicio de la siembra de arroz cuando se puede observar suelo desnudo), y si estas diferencias influían también sobre el cultivo de arroz (por medio del NDVI promedio durante el ciclo de cultivo -NDVI_ave-). Los resultados nos muestran una diferencia significativa entre la reflectancia de las zonas *f7* y *f15* para las bandas roja, azul, infra-rojo cercano (NIR) e infra-rojo medio (MIR).

Para la tercera parte del diseño del IBI, se determinaron dos umbrales de impacto de la sequía e inundaciones sobre el cultivo de arroz en Babahoyo. El primero es un índice fisiológico, el cual nos indica la máxima afectación detectable sobre el cultivo de arroz, por nuestro índice seleccionado (NDVI_ave). El segundo es un umbral económico que nos indica cuál es el rendimiento mínimo necesario para que un agricultor pueda cubrir sus costos de producción, en dos escenarios económicos. El primer escenario asume que los costos de producción son diferentes entre las zonas *f7* y *f15*; y el segundo cuando utilizamos un mismo costo de producción promedio para ambas zonas *f7* y *f15*.

En una etapa posterior se ha calculado la probabilidad de ocurrencia de los eventos climáticos extremos en cada una de las AHZ (*f7* y *f15*) bajo cada uno de nuestros umbrales (fisiológico y económico) para los dos escenarios económicos.

Se calculó un precio de la prima de seguro diferenciado por cada zona *f7* y *f15*, dependiendo del riesgo particular que cada zona enfrenta. También considera si el agricultor ha llegado al umbral fisiológico, cuando el agricultor experimenta una pérdida que no le permite alcanza a cubrir sus costos de producción; o si llega al umbral económico, cuando el agricultor alcanza a cubrir sus costos de producción, pero ha experimentado una pérdida total de sus beneficios.

Al establecer un cálculo de prima de seguro diferenciado por AHZ se consigue mantener controlado el riesgo de base. Esto es así porque los agricultores pagan una prima en base al riesgo real al cual se enfrentan y no en base a un promedio regional que puede introducir distorsión en los cálculos.

Como un producto de gestión de riesgo agrícola adicional proponemos la generación de un mapa de riesgo de sequía en el cultivo de arroz. Para lo cual se ha utilizado información cartográfica muy detallada a escala 1:25,000. A partir de esta información se ha evaluado el riesgo confrontando la vulnerabilidad, en base a la capacidad de uso de la tierra para el cultivo de arroz y la disponibilidad de agua en la época lluviosa; y la amenaza que está determinada por la probabilidad de ocurrencia de sequía. Se ha validado el mapa de riesgo de sequía mediante la prueba Chi cuadrado y mediante reportes de casos de sequía del seguro convencional Agroseguro en el cantón Babahoyo.

Summary

Agriculture is a risky activity that faces both biophysical and economic hazards. Biophysical hazards include extreme weather events, such as droughts, floods, frosts, or hail, as well as pests and diseases. Economic threats include the variability of products and inputs prices, variation of internal and external markets, and lack of access to credit, among others.

Amongst the biophysical threats, the most important in terms of frequency and intensity are the extreme climatic events. Agriculture has been conditioned by climate since historical times; but improvements and technological innovations made possible agricultural production to adapt to and cope with adverse conditions. Despite these innovations, climate remains a difficult phenomenon to predict and control, and still constitutes the most important risk in agricultural production, especially in developing countries. This risk is accentuated by the consequences of climate change.

Agricultural insurance has been proven to be an efficient tool for transferring risk from farmers to more qualified entities to manage risk. Agricultural insurance facilitates farmers' access to credit and promotes investment in technological improvements that make farmers more productive. It also reduces the default rate of credit commitments and poor performing loans.

Index-based insurance (IBI) is a type of agricultural insurance that does not require *in situ* verification of the occurrence of a hazards. It does not require the visit of a loss adjuster to the farm to verify the losses. Instead it does so through an index that is strongly correlated with the extreme event and / or the losses caused by it.

The objective of this thesis is to design an index insurance that complements the current conventional agricultural insurance implemented in Ecuador since 2010 (Agroseguro), using the Normalized Difference Vegetation Index (NDVI), as an indicator of droughts and floods, in rice cultivation in the Babahoyo canton (Ecuador).

This investigation started with the determination of homogeneous areas from an agro-ecological map of the Ecuadorian Coastal region at a scale of 1:250,000. Three aggregation methods were tested, two of them generated through expert judgement criteria and one through a statistical method. The first one grouped portions of land with

similar slope, texture, effective depth, precipitations and temperature, resulting in 196 homogeneous agro-ecological zones (AHZs). The second aggregation method grouped the areas with similar precipitations and temperatures, obtaining only 11 AHZs; and the third method, based on the principal components analysis (PCA), generated 26 AHZs. This last grouping method yielded the best of grouping agro-ecological characteristics of the study area.

The main drawback with IBI is basis risk, which occurs when the selected index does not strongly correlate with actual losses that occur in the field, leaving some insured affected farmers without compensation while others receiving compensation despite not having been affected.

Because of that, it is necessary to evaluate carefully the variability in the area where IBI is implemented. Therefore, we have used the map of AHZs generated in the first stage, on the particular case of Babahoyo canton. In Babahoyo the most representative AHZs are *f7* and *f15*.

Then, we checked if the topographic, soil and climate differences of each AHZ *f7* and *f15* were also evident on the bare soil (through satellite images at the beginning of rice sowing, when bare soil can be observed), and if these differences also influenced rice cultivation (through the average NDVI during the rice crop cycle -NDVI_ave-). The results revealed a significant difference between the reflectance of the *f7* and *f15* zones for the red, blue, near infra-red (NIR) and medium infra-red (MIR) bands.

In the third stage of the IBI design, we determined two thresholds for the impact of drought and floods on rice cultivation in Babahoyo. The first is a physiological threshold, which indicates the maximum detectable impact on the rice crop, by our selected index (NDVI_ave). The second is an economic threshold that indicates what is the minimum yield required by a farmer to break-even, in two economic scenarios. The first scenario assumes that production costs are different between zones *f7* and *f15*; and the second uses the same average production cost for both zones *f7* and *f15*.

Afterwards, we have calculated the probability of occurrence of extreme weather events in each of the AHZs (*f7* and *f15*) under each of our thresholds (physiological and economic) for the two economic scenarios.

The price of the differentiated insurance premium for each zone *f7* and *f15* was calculated, regarding the risk that each area faces. It also considers if the farmer has reached the

physiological threshold, when a farmer experiences a loss that does not allow him to break even; or if it reaches the economic threshold, by which the farmer breaks-even, but has experienced a total loss of his profit.

By establishing an insurance premium calculation differentiated by AHZ, the basis risk is kept low. This is because farmers pay a premium based on the real risk they are facing and not based on a regional average that can introduce bias into the calculations.

As an additional agricultural risk management product, we proposed the generation of a drought risk map in rice cultivation. To this end, we have used high detailed cartographic information at 1:25,000 scale. The risk has been evaluated confronting vulnerability, based on land use capacity for rice cultivation and the availability of water in the rainy season, including the risk of the occurrence probability of drought. The drought risk map has been validated through the Chi-squared test and through claims of drought cases of the conventional insurance (Agroseguro) in Babahoyo canton.

Table of contents

1	GENERAL INTRODUCTION.....	1
1.1	Climatic risk in agriculture	1
1.2	Climatic risk in Ecuador	2
1.3	Agricultural insurance	3
1.4	Conventional insurance in Ecuador	5
1.5	Index-based insurance	5
1.6	Rice crop in Ecuador and Babahoyo canton.....	8
1.7	Research stages for designing an IBI	9
1.7.1	Determination of agro-ecological homogeneous zones (AHZs) for index based insurance design (IBI)	9
1.7.2	Evaluation of agro-ecological variability effects on an eventual index-based insurance design for extreme events.....	11
1.7.3	Design of an NDVI index-based insurance for covering economic impacts in rice cultivation.....	12
1.7.4	Generation of a drought risk map for rice cultivation using GIS: case study in Babahoyo canton (Ecuador)	14
1.8	Research gaps	16
1.9	General and specific Objectives	16
1.10	Research context and publications	17
2	MATERIALS AND METHODS.....	21
2.1	Determination of agro-ecological homogeneous zones (AHZs) for index based insurance design (IBI).....	21
2.1.1	Location of study area and data acquisition	21
2.1.2	Description of variables.....	22
2.1.3	Map generation.....	23
2.1.4	Control and climatic maps.....	24

2.1.5	Principal component analysis (Factorial map)	26
2.2	Evaluation of agro-ecological variability effects on an eventual index-based insurance design for extreme events	28
2.2.1	Location of study area	28
2.2.2	Cartographic Data.....	28
2.2.3	Bare soil and NDVI sampling methodology	31
2.2.4	Statistical analysis of bare soil and NDVI.....	33
2.2.5	Effect of Agro-ecological variability on failure probability in a rice crop	33
2.3	Design of an NDVI index-based insurance for covering economic impacts in rice cultivation	34
2.3.1	Location of study area	34
2.3.2	Cartographic data.....	34
2.3.3	Statistical analysis	34
2.3.4	Rice-yield estimation through NDVI_ave.....	35
2.3.5	Thresholds determination	36
2.3.6	Risk assessment in AHZ.....	38
2.3.7	Insurance contract design	39
2.4	Generation of a drought risk map for rice cultivation using GIS: case study in Babahoyo canton (Ecuador)	41
2.4.1	Location of the study area	41
2.4.2	Drought risk framework	42
2.4.3	Cartographic data.....	43
2.4.4	Drought vulnerability evaluation (DVE).....	45
2.4.5	Drought hazard evaluation (DHE).....	49
2.4.6	Drought risk analysis	49
2.4.7	Risk maps adjustment.....	50

2.4.8	Drought risk map novelty: approach and validation	50
2.4.9	Validation data.....	52
2.4.10	Adjusted DRM and DRcM validation	52
2.4.11	Comparison between DRM and DRcM	53
3	RESULTS AND DISCUSSION	57
3.1	Determination of agro-ecological homogeneous zones (AHZs) for index based insurance design (IBI).....	57
3.1.1	Spatial analysis of the resulting control map.....	57
3.1.2	Spatial analysis of the resulting climatic map	59
3.1.3	PCA results for the factorial map	60
3.1.4	Spatial analysis of the resulting factorial map.....	62
3.1.5	Comparison of maps.....	68
3.2	Evaluation of agro-ecological variability effects on an eventual index-based insurance design for extreme events	68
3.2.1	Representative agro-ecological homogeneous zones (AHZs).....	68
3.2.2	Statistical analysis of soil variability	69
3.2.3	Statistical analysis of NDVI	72
3.2.4	Effect of soil variability on failure probability in rice crops	73
3.2.5	Sampling density effect	74
3.3	Design of an NDVI index-based insurance for covering economic impacts in rice cultivation	75
3.3.1	Statistical analysis	75
3.3.2	Rice-yield estimation.....	77
3.3.3	Thresholds determination	77
3.3.4	Risk assessment of AHZ and Babahoyo canton.....	80
3.3.5	Insurance contract design	83

3.4	Generation of a drought risk map for rice cultivation using GIS: case study in Babahoyo canton (Ecuador)	87
3.4.1	Adapted land evaluation map for rice cropping	87
3.4.2	Rice crop location suitability categories.....	88
3.4.3	Availability water characterisation for rice cropping in irrigation requirement zones.....	88
3.4.4	Drought vulnerability map	89
3.4.5	Drought risk map (DRM)	90
3.4.6	Adjusted drought risk map	91
3.4.7	Validation of the resulting maps.....	92
4	CONCLUSIONS	97
4.1	General and specific conclusions	97
4.2	Limitations and further research.....	101
4.2.1	Limitations during research	101
4.2.2	Limitations in proposed IBI product	101
4.2.3	Further research	102
	REFERENCES	103
	APPENDICES	125

List of Tables

Table 1. Description of soil variables and the corresponding code for each range	23
Table 2. Technical characteristics of imagery set (MODIS MOD13Q1V6)	30
Table 3. Official production cost of different rice-production systems in Ecuador in 2017	37
Table 4. Variables included in soil map database, classified by characteristic, symbol, quantitative or qualitative type and the unit or number of ranges used respectively.	43
Table 5. Matrix for soil characteristic classification in rice cropping suitability categories	46
Table 6. Precipitation requirement to crop water consumption and for maintaining pool levels	48
Table 7. Qualification matrix for drought vulnerability analysis	48
Table 8. Qualification matrix for drought risk analysis	50
Table 9. Pattern matrix, correlation between transformed variables with retained factors	60
Table 10. Representative variables of each factor	61
Table 11. Ranges of soil and climatic characteristics found inside <i>f7</i> class	64
Table 12. Ranges of soil and climatic characteristics found inside <i>f15</i> class	66
Table 13. Soil and climatic characteristics of agro-ecological homogeneous zones (AHZs) in Babahoyo canton	69
Table 14. Descriptive statistics of bare soil reflectance bands (red, NIR, blue and MIR) and NDVI_ave of rice crop cycle	69
Table 15. ANOVA for agro-ecological homogeneous zones (AHZs) of bare soil reflectance bands (red, NIR, blue, and MIR)	70
Table 16. ANOVA of NDVI_ave for agro-ecological homogeneous zones (AHZs) <i>f7</i> and <i>f15</i>	72

Table 17. ANOVA for different NDVI sampling densities of agro-ecological homogeneous zones (AHZs) <i>f7</i> and <i>f15</i>	74
Table 18. Parameters of GEVmin distribution for each AHZ and cantonal and distribution adjustment statistic of maximum likelihood	76
Table 19. Fisher`s Least significant difference test for comparing means, and Bonferroni test for comparing medians, for years	76
Table 20. Different categories of impact thresholds for scenarios of differentiated and non-differentiated production costs	79
Table 21. Simulation of NDVI_ave by GEVmin distribution for AHZs and cantonal, and basis risk calculation between observed (O) and estimated (E) frequencies of NDVI_ave.....	80
Table 22. Z-test for probability of events susceptible of compensations (ESC) under physiological and economical and thresholds in AHZ (<i>f7</i> and <i>f15</i>) and cantonal	83
Table 23. Indemnity calculation for physiologic threshold in AHZ (<i>f7</i> and <i>f15</i>) and cantonal.....	84
Table 24. Calculation of net incomes (gross margin) for economic threshold, for each AHZ (<i>f7</i> and <i>f15</i>) and <i>cantonal</i> , both in scenario 1 and 2	85
Table 25. Calculation of commercial premium rate for physiologic and economic thresholds in scenarios 1 and 2 and for AHZ (<i>f7</i> and <i>f15</i>) and <i>cantonal</i>	87
Table 26. Proportion of each drought risk category in rural districts of Babahoyo canton	92
Table 27. Proportion of drought events occurred in 2001-2014 in risk categories of DRM and DRcM in Babahoyo canton	93
Table 28. Likelihood of a drought event occurring in drought risk categories	94
Table 29. Likelihood of a drought event occurs in drought risk categories	94

List of figures

Figure 1. Scheme of the research goals and stages of the thesis	9
Figure 2. A) Study area location in Ecuador and South America; B) spatial location of rice and hard maize crop inside the study area	21
Figure 3. A) Location of Ecuador in South America, B) location of Babahoyo canton in Ecuador, and C) Babahoyo canton with rice crop coverage.....	28
Figure 4. A) Agro-ecological homogeneous zones (AHZs) map from (Arias et al., 2018); B) AHZs in Babahoyo canton, C) rice crop coverage, and D) AHZs on rice cultivation area in Babahoyo canton	29
Figure 5. Very high spatial resolution images RapidEye of study area portion (represented by black rectangle in A) and sampling random points of: B) bare soil prepared for rice sowing at January 13th, 2014 and C) rice cultivation affected by flood at March 29 th , 2012 both inside of AHZs <i>f7</i> and <i>f15</i>	32
Figure 6. Agro-ecological homogeneous zones <i>f7</i> and <i>f15</i> over rice cultivation area with yield observations in Babahoyo canton	36
Figure 7. Location of Ecuador in South America and Babahoyo canton in Continental Ecuador	41
Figure 8. Schematic representation of risk evaluation that was run in a geographical information system	42
Figure 9. A) Isotherms in study area, B) zones of irrigation requirement.....	47
Figure 10. A) Study area with homogeneous classes of the control map; B) homogeneous classes of the control map intersected with rice and maize layer.....	58
Figure 11. A) Study area with homogeneous classes of the climatic map; B) homogeneous classes of the climatic map intersected with rice and maize layer	59
Figure 12. Statistics to determine the number of clusters: A) Concordance correlation coefficient index (CCC), B) Pseudo F index and C) Pseudo T-squared index	61
Figure 13. A) Study area with homogeneous classes of the factorial map; B) homogeneous classes of the factorial map intersected with rice and maize layer.....	62

Figure 14. Least significant difference test (LSD) for reflectance means of agro-ecological homogeneous zones <i>f7</i> and <i>f15</i> , by Fisher: A) for red band, B) for near infra-red band NIR, C) for blue band, and D) for medium infra-red MIR.....	71
Figure 15. A) Multiple rank test (LSD) for NDVI_ave means of agro-ecological homogeneous zones (AHZs) <i>f7</i> and <i>f15</i> ; B) NDVI average distribution along rice crop cycle for AHZs <i>f7</i> and <i>f15</i> zones; and C) histograms of NDVI_ave data in analysed period (2001-2017) in Babahoyo for <i>f7</i> and <i>f15</i> , (t) drought affectation threshold (0.4)	73
Figure 16. Multiple rank test (LSD) of NDVI_ave means for the interaction between agro-ecological homogeneous zones (<i>f7</i> and <i>f15</i>) and sampling densities.....	75
Figure 17. A) Scatter plot of observed rice-yield and NDVI_ave, curve of Equation [1] for estimating yield; and B) correlation of observed and estimated rice-yield	77
Figure 18. Positive anomalies of precipitation (flood) in A) year 2008, B) year 2012, E) year 2010, F) year 2017; negative anomalies of precipitation (drought) in C) year 2013 and D) year 2016, G) year 2014 and H) year 2015. Source: NOAA, (2018).....	78
Figure 19. Generalized-minimum extreme value (GEVmin) distribution of NDVI_ave for physiologic threshold for: A) <i>cantonal</i> , B) <i>f7</i> and C) <i>f15</i>	81
Figure 20. Generalized-minimum extreme value (GEVmin) distribution of NDVI_ave for differentiated production cost (scenario 1) for: A) <i>cantonal</i> , and agro-ecological homogeneous zones C) <i>f7</i> and E) <i>f15</i> ; and for non-differentiated production cost (scenario 2) for: B) <i>cantonal</i> , and agro-ecological homogeneous zones D) <i>f7</i> and F) <i>f15</i>	82
Figure 21. Monthly water precipitation in each irrigation requirement category and water requirement during growth stages of rice	89
Figure 22. Model that used soil and climate to generate drought risk map: A) drought vulnerability map, B) drought risk map DRM, C) adjusted DRM. Model that used only climate to generate drought risk map: D) drought hazard map, E) operative irrigation projects used to adjust DRM and DRcM, F) drought vulnerability map only based in water availability, G) drought risk map DRcM only based in climatic vulnerability and hazard, and H) adjusted DRcM	90

List of abbreviations

AHZ	Agro-ecological Homogeneous Zone
CA	Climatic Analysis
CCC	Concordance Correlation Coefficient
CEIGRAM	Centro de Estudios e Investigaciones para la Gestión de Riesgos Agrarios y Medioambientales
CGSIN	Coordinación General del Sistema de Información Nacional
CMI	Crop Moisture Index
DHE	Drought Hazard Evaluation
DIGDM	Dirección de Investigación y Generación de Datos Multisectoriales
DRcM	Drought Risk Climatic Map
DRM	Drought Risk Map
DVE	Drought Vulnerability Evaluation
ECE	Extreme Climatic Event
EGU	European Geosciences Union
ENSO	El Niño Southern Oscillation
ESC	Event Susceptible of Compensation
ESPAC	Encuesta de Superficie y Producción Agrícola Continua
FAO	Food and Agriculture Organization
GEV _{min}	Generalized-Minimum Extreme Value
GIS	Geographic Information System
HDF	Hierarchical Data Format
IBI	Index-based Insurance

IIA	Insurance Influence Area
INIAP	Instituto Nacional Autónomo de Investigaciones Agropecuarias
LEM	Land Evaluation Methodology
LSD	Least Significance Difference
LP DAAC	Land Processes Distributed Active Archive Center
MAG	Ministerio de Agricultura y Ganadería del Ecuador
MIR	Medium Infra-Red
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NDVI_ave	NDVI average of rice crop cycle
NIR	Near Infra-Red
OIP	Operative Irrigation Projects
PDSI	Palmer Drought Severity Index
RCL	Rice Crop Location
RPS	Random Points Shapefile
SD	Standard Deviation
SOC	Soil Organic Carbon
SPI	Standard Precipitation Index
UNISA	Unidad del Seguro Agrário
USDA	United States Department of Agriculture
UTM	Universal Transverse Mercator
VCI	Vegetation Condition Index
WGS84	World Geodetic System 1984

1 GENERAL INTRODUCTION

1.1 Climatic risk in agriculture

Weather is one of the most important factors that has conditioned human activities throughout the world history (Hu et al., 2018), allowing the development of some civilizations and the extinction of some others (Kgakatsi and Rautenbach, 2014). For example Hodell et al., (1995) suggested that the classic Maya civilization extinction could have been caused by an unusual long drought.

Over history, and even more in present times, scientists have been concerned about climatic variability (Fuhrer et al., 2006). Despite meteorologists' and climate experts' significant advances in this field, climate and weather forecasts still have a considerably degree of uncertainty that conditions our production activities (Wilke and Morton, 2015).

About 70% of the natural hazards in the world are related to weather, climate or water-related hazards (Shannon and Motha, 2015). Kgakatsi & Rautenbach, (2014) showed using global data that extreme natural phenomena have been more destructive and frequent in the last decade, and concluded that they will become even more damaging in the future. Isch (2011) and Cai et al., (2014) showed that, as consequence of climate change, extreme climatic events (ECE) as droughts, floods, and forest fires are more frequent, intense and unexpected than in the past. Morton (2007) and Piao et al., (2010) pointed out that it is expected that climate change will impact massively smallholder farmers in developing countries. Some models foresee that a moderate rise of temperature could harm the production of rice, maize and wheat which are the main crops for smallholder farmers and food security (Harvey et al., 2014).

Agriculture is one of the most affected economic activities by extreme climatic events (Sivakumar et al., 2005; Wilke and Morton, 2015). Harvests depend on weather, climate and water availability, and even a small variation of one of these factors can reduce them significantly. The effect of an extreme climate event (ECE) over a given agricultural production depends on the complex interaction between its frequency or probability, intensity and duration and the crop's resilience to this event (Bullock et al., 2017; Fuhrer et al., 2006).

Sivakumar et al., (2005) highlighted that flood and drought are the most important ECEs whose impact is greater in the world both in number of people affected and in economic

losses. Drought and flood are also the most important ECEs that affect agriculture (Sivakumar and Motha, 2008).

Hayes et al., (2011) and Maestro et al., (2016) divided the drought events in relation to agriculture into three types: a) meteorological drought, when there is a long period with a precipitation lower than the normal average during rainy season. b) Agricultural drought, when the soil moisture is not enough for an average crop production. Moreover, c) hydrologic drought, when the water level in storage reservoirs as aquifers, lakes, dams, etc., decreases under the statistical levels.

Nakanishi and Black, (2018) and Pantaleoni et al., (2007) defined agricultural flood as extreme events that occur when an unexpected flux of water covers agricultural lands. It is produced by the rise of a river's level, affecting commonly farms that are located on the riverside or close to it. Additionally, Sanyal and Lu (2004) mentioned that floods could be produced by an intense and prolonged rainfall that overcomes soil's drainage capacity, which is worsened by flat topography, resulting in crops partially or completely covered by water. This phenomenon could cause physical damage in the crops and affects the roots breathing, producing the plant's death or hitting the yield totally or partially (Sivakumar and Motha, 2008).

1.2 Climatic risk in Ecuador

Ecuador is one of the countries located on the Pacific fire belt and on the subduction zone of the Oceanic Nazca plate into South American plate (Bunge and Grand, 2000). This fact explains why Ecuador has a high and permanent volcanic and seismic activity (FAO and Un-Habitat, 2010). There are 84 volcanoes in Ecuador, 16 of them are potentially active, five are currently active, and three are in eruption (Instituto Geofísico, 2015).

Cardona, (2007) pointed out that Ecuador is located inside of a low-pressure region in the inter-tropical convergence zone. In addition, the influence of Andes Mountain, the Amazon, and the currents of Humboldt and El Niño, which are cold and warm respectively, are other important factors. Because of these characteristics, Ecuador is liable to suffer constantly hydro-meteorological phenomena as flood, drought, and frost (Espinoza Villar et al., 2008; Vuille et al., 2000).

An increase of ECEs in Ecuador has already been identified by some authors (e.g. Blöschl et al., 2007 and Gergis and Fowler 2009), with visible exacerbating trends. Cai et al.,

(2014) suggested that extreme El Niño phenomenon events could be exacerbated during 21st century.

The climate of the Coastal region of Ecuador is highly influenced by El Niño Southern Oscillation (ENSO) (Trenberth, 1997; Moy et al., 2002). El Niño phenomenon has impacted Ecuador drastically many times in the last century, causing hundred thousands of affected people and millions of dollars in economic losses (Gergis and Fowler, 2009). These extreme event affect mainly the Ecuadorian Coastal region with strong rainfalls that causes overflows of rivers, floods, and landslides (Bendix et al., 2011). Although, the majority of extreme climatic events caused by ENSO are related to extreme precipitations, also drought events in Ecuador and Peru have been associated with this phenomenon (Kripalani and Kulkarni, 1997; Howden et al., 2007).

FAO & Un-Habitat, (2010) and Centre for Research on the Epidemiology of Disasters (2015) have reported that in the last twenty years, Ecuador has suffered 29 important natural disasters, out of which 59% have been climatic events. The extreme events that have affected more people in the last 115 years were flood and drought with 700,000 and 600,000 affected people, respectively. The largest event was the extreme flood of 2008, with economic losses of 1 billion USD.

In Ecuador, drought and flood are the ECEs that have hardest impact in agriculture both in affected area and in economic losses. For instance, the farm census of 2012-winter impact showed that out of 140,000 cultivated hectares that were analysed, 56,562 ha were completely damaged by flood and 24,103 ha were partially damaged by the same event (MAGAP, 2012a).

1.3 Agricultural insurance

Agriculture is one of the riskiest economic activities (Ullah et al., 2015). Farmers have to deal with many production factors that are beyond their control, including, input and output price instability, pests, climatic and markets variability, among others (OECD, 2009). This has caused that many farmers abandon their agricultural productions looking for new economic alternatives, or decide to keep their farms but marginally, which accentuate even more their risk exposure (Wauters et al., 2014; Akter, 2012). Mahul and Stutley (2010) suggested this phenomenon happen mainly in developing countries, where farms lack government aid, modernization and technology transfer, among other obstacles.

In this context, it is very important for farmers to have an option that helps them to cope with the agricultural production risk (OECD, 2011). Kurosaki and Fafchamps (2002) expressed that agricultural insurance has been used as an efficient risk management tool, for many years. Smith and Glauber (2012) asserted that many countries have implemented agricultural insurance programs both publics and privates. Agricultural insurance is a mechanism that allows farmers to stabilise their incomes, raise their farm modernization investment (higher-risk/higher-yield investments), meet their credit commitments, and be in suitable conditions for starting again in the next crop campaign (Raju and Chand, 2008; Besley, 1995; Jensen and Barrett 2017)

An insurance guarantee is enabled through a contract, where two parts, the insurer (insurance company) and the insured (farmer), signed a commitment (insurance policy) (Ray, 1981). In this policy contract, the first one agrees to compensate the second one for a covered event occurrence, according to the specific conditions detailed in the policy, as long as the insured agent has paid the corresponding insurance premium (Ahsan et al., 1982; Mahul and Stutley, 2010).

There are various insurance methods or formats for designing agricultural insurances, depending on different aspects included in the contract (Goodwin Barry K. Mahul, 2004; Turvey, 2001), they are the following:

- a) Covered event, it is the event that causes a loss and could be an extreme climatic event, pests or even an economic adverse event as price variation, and so on. The insurance policy can cover a specific peril event or multi-peril events.
- b) The compensable object, it is the “object” that is lost as consequence of the extreme event occurrence and which has to be restored; for example, the investment, the revenues, economic losses caused by price variation, the cost of feeding supplements in livestock productions, or losses caused by water shortage.
- c) Whether *in situ* verification of the covered event occurrence is required (conventional or traditional) or the verification is done through an index (index-based insurance).

Conventional agricultural insurance is and has always been hindered by asymmetries of information between the agent (farmer) and the principal (insurer), which causes moral hazard risks or adverse selection, or both (Jensen et al., 2018). Moral hazard is the behaviour of farmers managing poorly their crops because, as they have an insurance policy, they relax their crop’s labours, surveillance and inputs applications, increasing

their propensity to suffer losses (Seog, 2010; Shynkarenko, 2007; Chambers, 1989). Adverse selection occurs when only the most risk exposed farmers contract the agricultural insurance, and the insurance companies cannot differentiate them from the low-risk farmers. Both phenomena are at the root of the major problems identified in the history of agricultural insurance (Hazell, 1992).

1.4 Conventional insurance in Ecuador

Since 2010, Ecuador has implemented an agricultural insurance policy. Coined ‘Agroseguro’, its regulatory framework is defined in the Ministerial Agreement number 100, Official Register (Ecuador, 2015). This program offers premium subsidies to medium and small agricultural, livestock, aquaculture and forestry producers. It is regulated, financed and executed by the Ministry of Agriculture and Livestock of Ecuador (MAG -acronym in Spanish-), through the Agricultural Insurance Unit (UNISA -acronym in Spanish-) which was created for that purpose.

The Ecuadorian government subsidises 60% of the premium insurance cost, excluding taxes. The policy targets the main crops in Ecuador (rice, maize, banana, potato, soy bean, wheat, barley, coffee, cocoa, fava beans, beans, quinoa, sugarcane and tamarillo), and follows a schema of multi-peril insurance covering only the crops’ working costs (investment) in case of crop losses caused by drought, flood, frost, uncontrollable pests, hail, strong winds and fires. The minimum insurable area is 5000 square meters.

This insurance is mandatory for farmers who obtain credit with the public bank (BanEcuador) or who have been beneficiaries of “Plan semillas project” (a project that delivers certified seeds and technical support to farmers). Although, this insurance can be purchased by any farmer who achieves the conditions that were mentioned before.

1.5 Index-based insurance

The index-based insurance (IBI) is a financial risk transfer instrument, from farmers to insurance companies (Janowicz-Lomott and Łyskawa, 2014). Under IBI, the insurance company does not need to either verify the occurrence of a disaster nor quantify the crop damage at every insured farm that has been impacted by an extreme climatic event. Insurable hazards are identified through a highly correlated index with the actual farm losses (Zant, 2008). In other words, it establishes a threshold which indicates to the insurance company that a disaster has occurred in a given monitored region, where the

insurance index is representative (insurance influence area), triggering a compensation to all insured farmers within this geographically-defined space (Hellmuth et al., 2009; Mude et al., 2009).

According to Leeuw et al., (2014) the selected index can be climatic, vegetation, or economic. It can also be direct or indirect. It is direct, when the index is related with the effect or impact over the insured object (crop). On the other hand, it is indirect, when the index is related with the cause of the insured extreme event or with the extreme event itself.

According to Barnett and Mahul, (2007a) IBI has some advantages and demands relative to conventional agricultural insurance. The most important ones are the following:

IBI has lower operative cost, because the insurance company does not have to verify individually each one of the affected insured farms within of the insurance influence area (IIA), saving the expenses related with mobilization and expertise evaluation of the damage. In addition, a risk status assessment is not required at individual farm level but at regional, which is cheaper, and it is charged only once in the IBI implementation cost. As result of this, the time for obtaining the compensation is shorter, because once the index reaches the threshold; all insured farmers must be compensated, with no need to draft an expertise report. Depending on the insurance contract and the used index, in some cases, it is not even necessary to wait for harvest time for getting the compensations.

Because, policyholders have less opportunity for obtaining anticipated information about the insured climatic event or the index, IBI is less prone to adverse selection. In addition, as farmers do not have any influence over the climatic event occurrence, and the compensation is based on a regionalised administrative and technical unit, dispensing with farm level impacts, chances for adverse selection are negligible.

The IBI application area must be relatively homogeneous, i.e., that the index influence area must have low spatial variability, enabling a unique index value to be used as representative loss indicator of the entire administrative unit.

Depending on the selected index, the IBI is more suitable for extensive cultivation systems; with consolidated or large field crops, especially those using vegetation indexes. Generally, IBIs are only for a single peril and the insured extreme event should have a regional impact, for example drought and floods. The phenomena with a limited impact as hail, pests, or frost are very difficult to be included in an IBI design.

The IBI implementation could have a high cost related to technical innovations, gathering data and legal regulation processes. Moreover, IBI requires a solid climatic database with a temporal extension that affords accurately characterisation of the extreme climatic events and the selected index.

The main concern with IBI implementation is basis risk (Clement et al., 2018), which occurs when the selected index does not correlate accurately with actual crop losses (Woodard and Garcia, 2008). In other words, some insured farmers could be compensated even when they have not been affected and some other farmers could not obtain any indemnity although they have been impacted by an extreme event (Conradt et al., 2015). To avoid basis risk, the index has to be selected carefully, it has to be related to the extreme climatic event and or to the impact over the crop (Chantararat et al., 2013). Additionally, the index has to be representative for the entire IIA, for which the variability of the IBI implementation area has to be deeply assessed (Elabed et al., 2013).

Many authors agreed that IBI is a viable and efficient risk management tool for transferring production risk in spite of its limitation (Jensen and Barrett, 2017; Jensen et al., 2018; Takahashi et al., 2016). Small and medium farmers in developing countries could use it. Mude et al., (2009), Sandholt et al., (2002), Skees and Collier (2008) and McIntosh et al., (2013), remarked that the use of weather and vegetation indexes for livestock, grassland and crops in many African countries has been successful for improving policyholders welfare. It is also evidenced in the study of Chantararat et al., (2017), who assessed the impact welfare of an index-based livestock insurance in Kenya. There are many other experiences of IBI pilots throughout the world. For example, Ukraine (Shynkarenko, 2007), Mongolia (Olivier and Skees, 2007), China (Wu et al., 2001; Liu et al., 2010), México (Fuchs and Wolff, 2011), India (Raju and Chand, 2008) (Daron and Stainforth, 2014) ; Kazakhstan (Breustedt et al., 2008; Khan et al., 2017), and Spain (Maestro et al., 2016) among many others.

In the last years, important technological advances in remote sensing, geographical information systems, satellite and drones imagery, smart weather stations, mobile apps, among others, have positioned IBI as an attractive risk transfer instrument (Carter et al., 2016). Not only for farmers (Patt et al., 2009), but also for many stakeholders (Jensen and Barrett, 2017), such as local and regional governments, insurance and reinsurance companies, financial institutions or lenders and even for agricultural suppliers. According

to Farrin and Miranda (2015) when insurance uptake rate is high, the credit uptake and high technology adoption is also high, and on the contrary, the credit default rate is low. However, Hill et al., (2013) and Clarke, (2016) emphasized that the demand of this financial product could decrease if the customers were not well informed about IBI products. Even though IBI technologies are increasingly reliable and accurate, they could be hard to understand by policyholders (Takahashi et al., 2016). Patt et al., (2010) and Trærup (2012) remarked that unattractive premium prices, a poor understanding and trust lack of IBI could discourage farmers to contract this product. Patt et al., (2009), Carter et al., (2008) and Binswanger-Mkhize (2012) underlined that the IBI design has to be oriented for covering the specific risk management necessity of the farmers and it has to be accompanied with an informative strategy for making IBI products more efficient and attractive.

1.6 Rice crop in Ecuador and Babahoyo canton

In Ecuador approximately 350,000 ha of rice are cultivated every year (Aguilar et al., 2015). This area varies from year to year because of many factors, the main ones being: world and regional market trends, international and local prices, and production problems e.g., pests, or adverse climatic events (El Niño phenomenon). All these factors could cause rice crop substitution for more profitable ones (FAO, 2018).

Montaño, (2005) mentioned that Ecuador had 400,000 ha of rice in 2005, but FAO, (2018) pointed out a decrease trend of rice-cultivated area in the last years. This area was around 363,000 ha for 2014, 2015 and 2016, falling down considerably to 291,167 ha in 2017 (Aguilar et al., 2018, 2015). This concerns the government, because rice plays an important role in Ecuadorian food security (Pinstrup-Andersen, 2009). The daily rice consumption per person is 115g, requiring an annual production of 660,000 tonnes (Montaño, 2005). Additionally, rice-production in Ecuador offers employment to 22% of the economically active population, involving around 140,000 families. For these reasons, Ecuadorian government must support rice-producers through giving them technical advice, credit lines for farm modernisation, and risk management mechanisms.

Rice is the annual crop with most cultivated area at national level and the third one of the crops in general, only behind cocoa and African palm. In South America, Ecuador is also the third producer (based on cultivated area) after Brazil and Colombia (Aguilar et al., 2018). The main rice producing provinces in Ecuador are Guayas and Los Rios with the

55 and 37% respectively, of the total cultivated rice area during rainy season at national level. In Babahoyo canton, rice cultivation occupies 45% of the total agricultural lands (IEE, 2009; MAGAP, 2014).

1.7 Research stages for designing an IBI

This research has been developed in the following four stages, as shown in Fig. 1:

Figure 1. Scheme of the research goals and stages of the thesis

1.7.1 Determination of agro-ecological homogeneous zones (AHZs) for index based insurance design (IBI)

One of the most important conditions for acceptable index performance is having sufficient knowledge of the insurance influence area (IIA) in which this index works, due to the spatial variability in soil and climatic characteristics (Vedenov and Barnett, 2004). Furthermore, the surface of the homogenous areas should be representative to make the application of index-based insurance feasible (de Leeuw et al., 2014).

Researchers have developed new methods for remote sensing technologies that minimise the bias found in NDVI temporal series to eliminate the effects that have no relationship with vegetation changes within the process of established index values (Barraza, 2012).

To establish loss thresholds from satellite imagery, we have to sample representative pixels where the crop of interest is located, in critical stages that represent NDVI

variations in the study area both temporally and spatially. If we have land usage information, we can focus sampling only on the crop area of interest. If we also have soil characteristics, better results can be obtained by stratifying the sample into different main homogeneous areas with similar topographic soil and climatic conditions, anticipating land variation and their effects on index values (Milich and Weiss, 2000). Therefore, we can reduce basis risk because index values will have a higher correlation with losses that depend on the soil conditions of each homogeneous class (Tan, 2005).

The physical and chemical characteristics of the soil as well as the topographical and climatic parameters directly influence the availability of soil water content for crops, the crop conditions and yield (Lascano et al., 2007). Therefore, we need to analyse which of these variables are the most important and identify those that have little influence on the spatial variability of the data. This approach will facilitate identifying homogeneous areas with similar characteristics that will be reflected on a more robust index.

The study area of this stage is in the Coastal region of Ecuador. In this country, there is a subsidised conventional agricultural insurance (Agroseguro) in which the main insured crops are rice and hard maize, both in terms of insured value and subsidies (Ecuador, 2015). Ecuador is a small (276,841 km²) but very heterogeneous country, featuring many soil types, landforms, climates and microclimates. Although the Coastal region is more regular than the Andean region, it is still necessary to determine different homogeneous areas that have similar topographic, soil and climatic conditions.

Traditional approaches to homogenise a soil characteristics map in the context of insurance are based on a combination of experience and intuitive surveyor criteria, which is supported by extensive expertise on soils, crops and climate (Bourennane et al., 2014). However, depending on different expert judgements, the results could be different (Taylor et al., 2009).

The aim of this stage is to generate a map of homogeneous classes for areas cultivated with rice and maize in several provinces of Ecuador, to create a basis for the implementation and management of index-based insurance (IBI). To this end, we have used principal component analysis (PCA) statistical method to delineate homogeneous areas based on soil characteristics, temperature and precipitation. The resulting map was compared to two other maps based on an expert classification and a simple combination

of precipitation and temperature without considering some chemical soil characteristics. A detailed discussion of the three maps is presented, taking into account the accuracy and the number of classes that best fit the needs of index-based crop insurance.

1.7.2 Evaluation of agro-ecological variability effects on an eventual index-based insurance design for extreme events

As we mentioned before, IBI's main limitation is basis risk, which is the inherent risk related to an inaccurate correlation between an index measure and a real farmer's losses (Mobarak and Rosenzweig, 2013; Binswanger-Mkhize, 2012).

Basis risk can be found in different situations. For example, when some insured farmers obtain compensation without any crop losses or do not obtain it when they are actually hit by them. Clarke et al. (2010) mentioned that basis risk could also occur when all insured farmers pay the same premium price, but a group of them have significantly more loss events than those of the others, i.e., the risk exposure status of insured farmers varies.

To avoid basis risk in IBI implementation, it is necessary to account for the variability in the area of insurance application (Stoppa and Hess, 2003; Hertzler, 2004). For this reason, White et al. (1992) claimed that effective crop condition monitoring is very desirable, and must be based on a solid sampling and statistical design that allows one to estimate the status, trends and conditions of the phenomena that affect crops.

We used NDVI as crop failure indicator, because, following Rulinda et al. (2012), the Normalized Difference Vegetation Index (NDVI) is the most widely used vegetation index, and is based on the normalized difference of near infra-red (NIR) and red spectral reflectance (Pettorelli et al., 2005). The relationship of NDVI with vegetation state is well known, and it can also be used as crop state indicator, biomass estimator and drought monitoring (Son et al., 2012; Subash et al., 2011 and Gu et al., 2007).

In the index-based insurance field, as is evidenced in the studies of Trangmar et al. (1986), Barraza (2012) and Mude et al. (2009), the standard methodology of NDVI sampling is determined by administrative regions and land use. Moreover, most studies have focused on climate as the main source of variability, leaving out the probable soil and topographic variability effect on index values.

Thus, it is very important to have information regarding also soil and topographic properties that could afford researchers a better explanation of vegetation index variation across study areas. Some soil and topographic properties cannot be easily amended through a similar management crop system, such as soil texture, structure, altitude and slope. Some authors such as Cambardella et al. (1994) and Letey (1985) found that soil and topographic variables jointly with climate have an important effect on crop conditions, which are correlated with NDVI values (Gu et al., 2007).

This study was performed in the context of an IBI implementation assessment in Babahoyo canton, Ecuador. This insurance design attempts to reduce basis risk through a proper discrimination of insurance influence area (IIA) variability, produced by the interaction of soil, topography (slope, altitude), crop and climate. IIA is a region where a determined index is representative. In this case, we used the resulting map of the former stage (AHZs) for determining IIA. This map aggregated zones with similar soil, topographic and climatic characteristics (Arias et al., 2018).

Our proposed IBI design will use NDVI as occurrence indicator of extreme events; in this case, they are drought and flood, which are the most frequent and largest events susceptible to be detected through NDVI.

For this reason, this stage aims to design an efficient stratified NDVI sampling, considering the soil, topographic, and climatic variability found in the study area that could reduce basis risk of an eventual IBI design, as well as using an adequate sampling density. The stratification criterion was based on AHZs map.

1.7.3 Design of an NDVI index-based insurance for covering economic impacts in rice cultivation

Extreme climatic events have increased both in frequency and intensity (Sivakumar et al., 2005), making more difficult for farmers to maintain their crop productions (Cai et al., 2014; Isch, 2011). These phenomena are associated to climate change, and they could affect very strongly small farmers, especially in tropical countries, having a negative impact over main cereals crops as maize, rice, and wheat which are the base of feeding in many developing countries (Harvey et al., 2014).

As it was mentioned before, FAO and Un-Habitat, (2010) reported that of the 29 most important disasters occurred in Ecuador in the last twenty years, 59% had climatic origin; also, according to Centre for Research on the Epidemiology of Disasters-CRED (2015), the most common extreme climatic events in Ecuador are flood and drought. The climatic phenomena are very important both in economic losses and in the number of people affected, and entail obvious risks to agricultural production.

One effective tool for transferring production risk from farmers to other entities is agricultural insurance, permitting farmers face their credit commitments and stay in the agricultural business (Patt et al., 2009). An interesting kind of agricultural insurance is IBI, which does not need field losses verification, but it uses a highly losses-correlated index, as occurrence indicator of a sinister (Carter et al., 2011).

Index-based agricultural insurance is a promising means to provide coverage to large agricultural areas around the world (Mobarak and Rosenzweig, 2013). However, the technical, economic and administrative hurdles are significant. In the former stage, significant differences were found between AHZs. Thus, it is necessary to consider them in index-based insurance (IBI) design to reduce basis risk.

A major problem with index-based insurance design results when the index does not correlate with losses in the IIA, which is the area for which a determinate index is representative (Elabed et al., 2013).

IBI only can be applied in relatively homogeneous areas, because its main principle is based on the use of the only one index along the IIA, but these conditions of homogeneity are rarely accomplished, much more in a field as agriculture that is generally heterogeneous. To reduce basis risk as much as possible, it is necessary to know in detail the variability of IIA, including soil, topographic and climatic conditions that could affect the index measure.

Recapitulating, we assessed the soil and climatic variability in the study area, grouping similar soil and climatic conditions in homogeneous areas through the map of AHZ by principal components, showed in the first stage. From this map, we found two main AHZs (*f7* and *f15*) over rice crop area in Babahoyo canton; which based on a statistical analysis revealed differential NDVI responses over rice cultivation in them.

The aim of this stage was to design a NDVI index-based insurance for drought and flood impacts in Babahoyo canton. We used AHZ map for dividing the IIA in two homogeneous zones (*f7* and *f15*). Then, we defined two thresholds, one physiologic (only based on crop affectation) and other economic (based on crop affectation and economic variables). These two thresholds have been determined in two scenarios; scenario 1, when we used a differentiated production cost for each AHZ and scenario 2, when we used the same production cost (weighted average) for both zones *f7* and *f15*. Then, we calculated the occurrence probability, for each AHZ (*f7* and *f15*), bellow each one of these threshold for scenarios 1 and 2. Finally, the premium cost was calculated for each possible combination AHZs-scenarios.

1.7.4 Generation of a drought risk map for rice cultivation using GIS: case study in Babahoyo canton (Ecuador)

Climate change, which has a significant influence on local and regional climatic regimes (Holman et al., 2011), produces extreme weather events with increasing intensity and frequency; furthermore, climate change affects hydrological and water resource systems (Pachauri et al., 2014; Arnell & Reynard, 1996). Most of the world's annual crop losses are due to weather events e.g., drought, flooding, frost, hail, etc. (Fraisie et al., 2006), constituting one of the main production risks and uncertainty factors that impact the performance and management of agricultural systems (Sivakumar and Motha, 2008).

Consequently, this pressure has increased risks related to agricultural and livestock production (Kgakatsi and Rautenbach, 2014). To reduce hazards and economic losses that could jeopardise farmers' incomes and threaten their business continuity, it is very important to implement agricultural risk management plans through governmental and research institutions.

Currently, agricultural insurance schemes are widely used to transfer farmers' yield risks (Trærup, 2012). However, in functional risk management plans, agricultural insurances must be integrated with a detailed monitoring system, that relates many sources of information and tools. For instance, index influence areas, crop production risk maps, crop yields, claim statistics, etc.; for avoiding asymmetric information, adverse selection and systemic risk (Stoppa & Hess, 2003; Kalogirou, 2002).

According to Iglesias, Garrote, Cancelliere, Cubillo, & Wilhite, (2009) and Hoag, (2009), drought is one of the most important extreme weather events that threatens agricultural production and affects mostly at regional levels. However, it is not only extreme drought events that can affect crops; even a short delay of the beginning of the rainy season date or a water scarcity in a critical crop stage could produce a significant yield loss (Habiba et al., 2012).

Hayes et al., (2011) identified different categories of drought: meteorological, climatic, atmospheric, hydrological and agricultural drought. The last of these is a shortage of soil water available for crops, which depends not only on precipitation but also on soil water retention capability, crop type and phenological stage (McKee et al., 1993). Therefore, soil water availability at any given time is determined not only by precipitation, but also by evapotranspiration, infiltration, runoff, soil texture, effective depth and slope (Lascano et al., 2007).

Optimal crop production conditions are based on numerous factors that encourage proper crop development; these factors are rooted in topographic, physical and chemical soil characteristics and climate, some of which can be modified or managed by farmers at different levels to achieve optimum crop requirements. Higher levels of divergence from optimal conditions can be compensated through larger investments.

Drought risk models have been assessed through different approaches mainly based on drought indices. For example, many authors have obtained drought risk categories from values of different vegetation indices (Dalezios et al., 2014). Another group of researchers have preferred to use climatic indices based on precipitation (Shahid & Behrawan, 2008; Strzepek, Yohe, Neumann, & Boehlert, 2010) or combined with temperature (Wu and Wilhite, 2004). Finally, a combination of both can also be found (Chopra, 2006).

Our goal is to generate a DRM based on a specific water availability analysis and on soil conditions for the selected crop. This model applies a new approach that replaces drought indices commonly used in risk models, such that the DRM can be adjusted to consider irrigation projects in drought risk analyses.

This case study focuses on rice crops in Babahoyo canton. To reveal soil effects on risk levels, we compare our adjusted DRM with another that does not consider soil

characteristics (DRcM). An NDVI imagery set and spatially referenced drought insurance claims are used to validate and compare the DRM to the DRcM. A novel statistical analysis based on insurance data is presented.

1.8 Research gaps

Even though the Ecuadorian government has implemented successfully a conventional agricultural insurance (Agroseguro). There still are zones where this insurance is not feasible due to difficult accessibility or remoteness of the crop fields. Additionally, the conventional insurance does not cover the gross margin loss.

The government through the Ecuadorian Spatial Institute (IEE) and the Agriculture and Livestock Ministry (MAG) has generated an important georeferenced dataset, which includes soil, geomorphological, geological, land use and climatic maps at 1:25,000 and 1:250,000 scales. This information and the imagery availability of the study area, jointly with the rice-producers' necessity of a risk management financial tool, make IBI an interesting alternative for being study.

1.9 General and specific Objectives

Index-based insurance (IBI) should be applied to large regions, which have to be relatively homogeneous. In this sense, homogeneous area is a land portion with similar characteristics of topography, soil and climate. The aim of this thesis is to study whether it is feasible to implement an IBI for rice cultivation in Babahoyo canton. This could overcome most a priori drawbacks identified with previous experience with IBI and provide rice growers in Ecuador with protection against the main climatic hazards, i.e. floods and droughts. With this purpose, the following questions should be answer through the specific objectives:

Is it possible to determine agro-ecological homogeneous zones (AHZs), from an agro-ecological map of Ecuadorian Coastal region?

- a) To evaluate different methods to aggregate agro-ecological characteristics

Then, we have proposed as case study rice cultivation in Babahoyo canton using NDVI as occurrence indicator. Are the differences, indicated by AHZs, reflected in the selected index (NDVI) and is NDVI an adequate flood and drought indicator?

- b) To assess if reflectance of bare soil and NDVI of rice crop have different response in each AHZ in Babahoyo canton
- c) To test NDVI as drought and flood occurrence indicator on rice cultivation and to determine the risk status for each AHZ

Is it technically and economically feasible to design an IBI for rice cultivation in Babahoyo canton?

- d) To evaluate NDVI as quantifier of yield reduction caused by drought and flood, and to quantify the possible economic losses
- e) To propose an IBI design for drought and flood in Babahoyo canton

In some cases, IBI is not feasible for technical, economic or political reason. Thus, is there an alternative for agricultural risk management in Babahoyo canton?

- f) To generate a drought risk map for rice cultivation in Babahoyo canton

1.10 Research context and publications

National secretary of superior education, science, technology and innovation (SENESCYT -acronym in Spanish-) of the Ecuadorian government financed this research. The study was developed in the centre of studies and researches for agricultural and environmental risk management (CEIGRAM -acronym in Spanish-) of the Universidad Politécnica de Madrid.

This research was supported by Direction of research and multi-sectorial data generation (DIGDM -acronym in Spanish-) of the General coordination of the national information system (CGSIN -acronym in Spanish-) of Ecuadorian agriculture livestock and forestry Ministry (MAG -acronym in Spanish-). This collaborating occurred in the framework of two internships in the mentioned Direction. In these internships, we participated in workshops with DIGDM and Agroseguro, where, we disserted the partial results of our research, collected cartographic data, and adjusted our methodology according stakeholders' requirements.

This thesis has motivated two scientific publications, and two additional papers, which are currently in publication process. Moreover, we have participated in some national and international scientific congresses, which are listed below.

- **Valverde, O., Tarquis, A. M., and Garrido, A. n. d.** NDVI Index-based insurance covering economic impacts in rice cultivation. (To be submitted).
- **Valverde-Arias, O., Garrido, A., Saa-Requejo, A. Carreño, F., Tarquis, A.M. n.d.** Agro-ecological variability effects on an index-based insurance design for extreme events. *Geoderma*. (under review, 2nd round).
- **Valverde-Arias, O., Garrido, A., Villeta, M., Tarquis, A.M., 2018.** Homogenisation of a soil properties map by principal component analysis to define index agricultural insurance policies. *Geoderma* 311, 149–158. <https://doi.org/https://doi.org/10.1016/j.geoderma.2017.01.018>
- **Valverde-Arias, O., Garrido, A., Valencia, J.L., Tarquis, A.M., 2018.** Using geographical information system to generate a drought risk map for rice cultivation: Case study in Babahoyo canton (Ecuador). *Biosyst. Eng.* 168, 26–41. <https://doi.org/https://doi.org/10.1016/j.biosystemseng.2017.08.007>
- **Valverde, O., Garrido, A and Tarquis, A.M.** “Index-based insurance design for drought and flood events in rice cultivation”, PICO presentation at European Geosciences Union, General Assembly. April 9th, 2018. Vienna-Austria. 2018.
- **Valencia, J. L., Villeta, M., Valverde O., Saa-Requejo, A., Garrido, A. and Tarquis, A. M.** Rice Drought Risk Map validation using agricultural insurance data: a novel approach. PICO presentation at European Geosciences Union, General Assembly. April 9th, 2018. Vienna-Austria.
- **Valverde O., Tarquis, A. M., Garrido, A., Carreño, F. and Saa-Requejo, A.** Efecto de la variabilidad del suelo sobre el NDVI en el cultivo de arroz en el diseño de un seguro agrícola indexado para sequía. Oral presentation at Foro Mundo UNIGIS 2017, Universidad San Francisco de Quito, November 17th, 2017. Quito-Ecuador.
- **Valverde O., Garrido, A., Saa-Requejo, A., Tarquis, A. M.** NDVI stratified sampling to determine threshold of losses by drought in a rice crop. A case study in Babahoyo canton, Ecuador, poster at Pedometrics, June 26th- July 1st, 2017. Wageningen-Netherlands.
- **Valverde O., Tarquis, A. M., Garrido, A., and Saa-Requejo, A.** NDVI stratified sampling to determine threshold losses in rice crop, a case study in Babahoyo canton, Ecuador. Oral presentation at European Geosciences Union, General Assembly. April 24th, 2017. Vienna-Austria.

- **Valverde O., Tarquis, A.M., and Garrido, A.** oral presentation of “Rice crop risk map in Babahoyo canton (Ecuador)”; and poster of “Homogenisation of soil properties map by Principal Component Analysis”, at European Geosciences Union, General Assembly. April 22nd, 2016. Vienna-Austria.
- **Valverde O., Tarquis, A. M., Villeta, M., and Garrido, A.** Determination of homogeneous areas in a pedo-climatic index for index insurance in Ecuador. Poster at Pedometrics. September 14-18th, 2015. Cordoba-Spain.

2 MATERIALS AND METHODS

2.1 Determination of agro-ecological homogeneous zones (AHZs) for index based insurance design (IBI)

2.1.1 Location of study area and data acquisition

The study area is located (Fig. 2.A) in the Coastal region of Ecuador, where rice and hard maize are grown, in the provinces of Manabí, Santa Elena, Los Rios, Guayas, El Oro and Loja, with a total area of 6,290,452 ha.

This study was performed using a 1:250,000 scale agro-ecological map of Ecuador (MAGAP, 2015), which includes topographical, physical and chemical soil characteristics as well as climatic variables (isohyets and isotherms). The values of these variables are coded in a geographic database (*Shapefile* downloadable at <http://geoportal.magap.gob.ec>).

Figure 2. A) Study area location in Ecuador and South America; B) spatial location of rice and hard maize crop inside the study area

2.1.2 Description of variables

The database of map variables was generated by characterising soil units through field observation measurements, laboratory soil sample analysis and digital photo interpretation adapted from FAO (2006). We had one topographic variable, slope, which was expressed as a percentage and was obtained from a digital elevation model. Soil variables were divided into physical and chemical characteristics (see Table 1).

The soil physical characteristics are defined as follows (see units in Table 1):

- a) Texture (T) is the percentage of sand, loam and clay particles present in the soil.
- b) Effective depth (ED) is the usable soil depth for crops.
- c) Stoniness (ST) is the percentage of rocks in the soil surface.
- d) Soil drainage (D) is the amount time that water is retained in the soil profile.
- e) Ground water (GW) is the depth to the ground water table.

The chemical soil characteristics are as follows:

- f) pH is a measure of the concentration of hydrogen ions in the soil solution.
- g) Organic matter (SOM) is the organic matter content in the soil.
- h) Salinity (SS) is a measure of the electrical conductivity of the soil solution.
- i) Toxicity (Tx) is determined by the amount of CaCO_3 and Aluminium in the soil.
- j) Fertility (F) is a subjective classification that qualifies the natural fertility level of the soil based on pH, SOM, base saturation, cationic exchangeable capacity and exchangeable bases.

The climatic variables include the following: a) isotherms, which are the annual average temperature ranges, with values from 4 to 26°C, and b) isohyets, which show precipitation ranges with values from 0 to 1200 mm year⁻¹. These values correspond with those found in the study area. Both isotherms and isohyets were generated based on meteorological station data.

In the present study, rice (266,235 ha) and hard maize (310,691 ha) cultivated areas in 2014 were also used (*Shapefile* given by General Coordination of National Information System -CGSIN in Spanish- of Ministry of Agriculture and Livestock of Ecuador -MAG in Spanish-), concentrating this analysis only on those areas (Fig. 2.B).

Table 1. Description of soil variables and the corresponding code for each range

<i>Code</i>	Slope	Texture	Effective depth	Stoniness	Drainage	Ground Water	pH	Organic Matter	Salinity	Toxicity	Fertility
	<i>Range (%)</i>	<i>Description</i>	<i>Range (cm)</i>	<i>Range (%)</i>	<i>Description</i>	<i>Range (cm)</i>	<i>Description</i>	<i>(%)</i>	<i>Range (mmhos. cm⁻¹)</i>	<i>Description</i>	<i>Description</i>
1	0-5	Coarse	Superficial	<10	Excessively drained	0-20	<4.5	<1	0-2	Without	Very low
2	5-12	Moderately coarse	Shallow	10-25	Well drained	20-50	4.5-5.5	1-2	2-4	Slight	Low
3	12-25	Medium	Moderately	25-50	Moderately drained	50-100	5.6-6.5	2-4	4-8	Medium	Medium
4	25-50	Fine	Deep	50-75	Poorly drained	>100	6.6-7.4	4-10	8-16	High	High
5	50-70	Very fine	-	>75	-	-	7.5-8.5	>10	>16	-	-
6	>70	-	-	-	-	-	>8.5	-	-	-	-

2.1.3 Map generation

The study area was classified into homogeneous zones according to their agricultural and technical purposes. The variability of the study area is represented by the combination of topographic, soil and climatic variables of the agro-ecological map, which have many ranges of values or categories. The number of possible different combinations of these variables in the study area was 4036, which represents high soil variability discrimination. In the context of index-based insurance, this amount of information is not required since much of this variability is not perceptible at the imagery resolution employed to calculate NDVI because it does not have an effect over this index.

This classification aimed to aggregate unrepresentative variability in the same homogeneous class and highlight variability that could affect NDVI values in different homogeneous classes.

Therefore, the following three maps were generated:

1. A control map of the form typically used in soil surveys, created by combining the categorical soil and climate data based on expert knowledge;
2. A categorical map based solely on climatic variables; and,
3. A categorical map derived through statistical analysis of the principal components of soil and climate variables.

We then analysed the resulting maps to determinate which of them is better aligned with the purposes of index insurance. This analysis assessed the homogeneous classes, which must present variability to each other and homogeneity within themselves, and it is important to consider the number of obtained homogeneous classes.

The number of homogeneous classes in the control and climatic maps were the result of the variables that were kept in the analysis and the manner in which we grouped the ranges of these variables, based on expert criteria. The number of classes obtained in the factorial map was the result of the statistical technique of information synthesis (Principal Components Analysis) and hierarchical cluster analysis.

The optimum homogeneous classes' number is not fixed; it depends on the study area variability and work scale. The number of homogeneous classes found in a specific area is desirable information for risk managers, prior to implementing index insurance. If it was found that the study area is very heterogeneous, it could hinder or make unfeasible the implementation of this insurance.

The optimal performance of a method to homogenise soil variables also depends on the coherence for grouping similar ranges of each variable to avoid finding opposite or extreme values in the same class.

2.1.4 Control and climatic maps

To generate the control map based on expert criteria, five main variables were taken from the complete agro-ecological map database. These variables were slope, texture, effective depth, precipitation and temperature. Then, their ranges were grouped according to the similarities among their values, respecting a sequential order and expert criteria.

The expert criteria were based on the following arguments regarding the selection of the main variables.

1. The topographic property (slope) is an important factor in the spatial variation of soil attributes and the vegetation growth condition (Siqueira et al., 2010).
2. Both soil physical properties and climatic variables determine the range of possible water content (Gao et al., 2015), the range of plant-available water

content, and the movement of water in a saturated flow through the soil profile during infiltration from precipitation.

3. Precipitation is a natural water source for soil; slope joint with other physical soil properties affect the amount of water that infiltrates into the soil; texture and effective depth determine the volume of water that the soil can retain (Haghverdi et al., 2015). Temperature and evapotranspiration provide an idea of the amount of water that can be lost to evaporation and crop evapotranspiration. All these characteristics can influence the soil water status (Lascano et al., 2007).
4. Soil water status is reflected in crop water status, and crop water status can be identified by the vegetation index (NDVI) (Carlson and Ripley, 1997), which is used in index-based agricultural insurance.
5. We discarded drainage because it was already included in the relationship between texture and slope.
6. We discarded pH, organic matter, toxicity and salinity, even though, in natural conditions, they could represent a high source of spatial variability (Goovaerts, 1998), and a deficiency of any of them could affect the optimal state of crops. However, in rice and hard maize cultivated areas within the study area, these chemical soil characteristics are not far from the optimum crop requirements. Thus, in technical crop systems, farmers manage them to optimise their levels, for satisfying rice and hard maize crop requirements.
7. Groundwater and stoniness were also discarded for this analysis because if either one or both variables were affecting crops and causing soil variability, it would be reflected in the effective depth qualification. Moreover, if soil has a low percentage of stoniness, generally, it has little impact on crop growth.
8. The resulting map was spatially intersected with the 2014 rice and hard maize crop layer to extract homogeneous classes only in the areas of interest. This procedure brought together land coverage information with homogeneous classes. Thus, a number of homogeneous classes present in each crop (rice and maize) in the study area were obtained. This procedure was performed also in climatic and factorial maps.

The climatic map was generated with the same precipitation and temperature ranges as the control map, but we did not account for soil and topographic characteristics to focus on the effect produced by climate.

2.1.5 Principal component analysis (Factorial map)

Principal component analysis (PCA) is one of the most commonly used multivariate statistical techniques (Murtagh and Heck 1987, Jolliffe 2002, Rencher 2003, Abdi and Williams 2010). PCA focuses on the core structure of a single sample of observations on p variables, which are generally inter-correlated. No variable is designated as dependent, and no observation grouping is *a priori* assumed. The function of the PCA is to extract important information from datasets and to express this information through a set of new orthogonal variables.

The first principal component is the linear combination with maximal variance, which results from searching for a dimension when the observations are maximally separated. The second principal component is the linear combination with maximal variance in an orthogonal direction to the first principal component. Principal components define different dimensions from those obtained by discriminant functions or canonical varieties (Rencher, 2003).

To determine how many components should be retained, we kept the number of principal components that effectively summarise the data according to the following considerations (Rencher, 2003):

1. Retain enough components to account for the specified percentage of the total variance. The minimum recommended total variance is 70%, but this value may vary depending on the study aim.
2. Retain the components whose eigenvalues are greater than the average of the eigenvalues $\sum_{i=1}^p \lambda_i / p$. For a correlation matrix, this average is 1.
3. Use the scree plot, a plot of λ_i versus i , and look for a natural break between the large eigenvalues and the small eigenvalues.
4. Test the significance of the larger components (i.e., the component corresponding to the larger eigenvalues).

2.1.5.1 Application of PCA to a geographical database

Young (1981) developed a method that permits extending the principal component analysis to more general contexts, in which they can be used for ordinal variables. This method uses monotonically non-linear transformations to maximise the fit of the data to

the model. The Prinqual algorithm performs this task (Tenenhaus and Vachette, 1977). This algorithm generates estimation models for rescaling qualitative variables based on the following two objectives: maximising the total variance of the first principal components and minimising the eigenvalue product subject to the restriction that the variance of each variable remains fixed (minimisation of generalised variance).

The factorial map was generated from a PCA of the entire geographic database (soil and climatic ordinal characteristics) through the Prinqual algorithm. Then, we calculated the factor values for each of the 4009 records (rows) that belong to the database of the study area. We then applied a hierarchical cluster analysis over those values using the centroid method. Methods of hierarchical classification set a group with tree structures so that the clusters of the lowest levels are absorbed into higher levels. This process begins with many groups as observations; then, closer observations are grouped until we stop the process or one group contains all of the observations (Everitt, 1980) and (Hartigan, 1975).

To decide how many groups should be retained, we used three statistics:

- The Concordance correlation coefficient index (CCC) (Sarle, 1983), which seeks maximum relatives with values higher than 2 and suggests that the number of groups is appropriate.
- The pseudo F index (Milligan and Cooper, 1985), which also seeks maximum relatives to obtain suitable groups.
- The pseudo T-squared index (Milligan and Cooper, 1985), whose relative maxima indicate that the last group should not have been set up. Therefore, the suggested number of groups is equal to one plus the value that reaches the maximum statistical value.

2.2 Evaluation of agro-ecological variability effects on an eventual index-based insurance design for extreme events

2.2.1 Location of study area

Figure 3. A) Location of Ecuador in South America, B) location of Babahoyo canton in Ecuador, and C) Babahoyo canton with rice crop coverage

The study area is located in Ecuador (Fig.3 A), in Babahoyo Canton, see Fig. 3 B. Its area is 109,391 ha from which 102,517 ha correspond to agricultural lands. The study is focused on rice crop (Fig. 3 C), this crop is the most cultivated (46,556 ha) in Babahoyo canton (IEE, 2009), reaching 45% cultivated area of the Canton (MAGAP, 2014).

2.2.2 Cartographic Data

2.2.2.1 Agro-ecological Homogeneous zones map

This map was generated in the first stage; it has grouped similar soil, topographic and climatic characteristics in AHZs through principal components in Ecuadorian Coastal region (Fig. 4 A).

Figure 4. A) Agro-ecological homogeneous zones (AHZs) map from (Arias et al., 2018); B) AHZs in Babahoyo canton, C) rice crop coverage, and D) AHZs on rice cultivation area in Babahoyo canton

2.2.2.2 Rice-cultivated land in Babahoyo canton (1:25,000)

Map of cultivated area with rice for 2014 in Babahoyo canton (Fig. 4 C) was generated through pixels supervised classifications on high resolution images (RapidEye) with very high spatial resolution of 5x5 m per pixel (MAGAP, 2014b). In this Canton, rice crop is periodically cultivated over consolidated areas seldom varying year by year.

2.2.2.3 Data from satellite imagery

The product downloaded (NASA LP DAAC, 2015) and used was MODIS MOD13Q1V6 which has the following characteristics, see Table 2.

We used composite images (16 days) corresponding to the rice crop cycle (January 15th to May 15th) from 2001 to 2017, totalling 170 images. The rice crop cycle in Ecuador lasts about 120 days.

Table 2. Technical characteristics of imagery set (MODIS MOD13Q1V6)

Characteristic	Description
Temporal Granularity	16-day
Temporal Extent	2001-2017
Spatial Extent	Ecuador
Coordinate System	Projected to Universal Transverse Mercator
Datum	WGS 1984 Zone 17 S
File Format	HDF-EOS
Geographic Dimensions	1200 km x 1200 km
Number of Science Dataset (SDS) Layers	12
Rows/Columns	4800rows x 4800 cols
Pixel Size	250 m

Source: adapted from (Didan, 2015)

The HDF (Hierarchical Data Format) is a multilayer file, which includes twelve layers (Didan, 2015), only the following layers were used in this study:

Hdf:0, pixel values in this layer correspond to NDVI. The total imagery set was used (170 images), as well as two NDVI images for each rice crop cycle month along 2001-2017.

Hdf:3, pixels values in this layer corresponds to surface reflectance band 1 (red), was used only the January 1st (2001-2017) observation, totalling 17 images.

Hdf:4, pixels values in this layer corresponds to surface reflectance band 2 (NIR), of which only the image of January 1st (2001-2017) was used, totalling 17 images.

Hdf:5, pixels values in this layer corresponds to surface reflectance band 3 (blue), of which only the image of January 1st (2001-2017) was used, totalling 17 images.

Hdf:6, pixels values in this layer corresponds to surface reflectance band 7 (Medium infra-red MIR), of which only the image of January 1st (2001-2017) was used, totalling 17 images.

2.2.3 Bare soil and NDVI sampling methodology

The first criterion of stratification was the AHZs map as seen in Fig. 4 A, which overlies (using overlying ArcGIS tool *Identity*) the Babahoyo canton boundary, resulting the agro-ecological homogeneous zones of Babahoyo canton (Fig. 4 B). Then, this map was overlain with rice crop coverage (Fig. 4 C) to show AHZs on rice crops in Babahoyo canton (Fig. 4 D). The most representative AHZs found with the rice crop coverage were selected (*f7* and *f15*). The main differences between these two AHZs are related to soil and topographic characteristics, particularly their water retention capacity (Arias et al., 2018). The former step is the improvement of the standard methodology, considering the agro-ecological land characteristics (soil, topography and climate) and analysed their joint interaction with land use (rice crop coverage) and political boundary, facing an extreme event (Fig. 5 A).

Based on AHZs (*f7* and *f15*), a random points *shapefile* (RPS) was generated using an ArcGIS tool, thus fulfilling three conditions: a) avoiding a border effect by eliminating points within 80 m of a border, b) covering at least 30% of the study area, and c) avoiding sampling the same pixel by imposing a minimal distance among points. As each pixel represents 250 × 250m, the diagonal ($D = 353.55$ m) plus one meter was chosen as the minimal distance among sample points.

The NDVI and reflectance pixel values were extracted through RPS. The quality of the extracted pixels were tested through the quality layer (Didan, 2015); this layer has a quality indicator (*Rank key*) for each pixel of both NDVI and reflectance (red, blue, NIR and MIR) layers. When a pixel has the *Rank key* = 0; it indicates that this pixel has high quality and that we can use it with confidence. Thus, we eliminated all pixels with *Rank key* different to 0, see user guide of Didan et al., (2015). From the selected ones, values from the red, blue, NIR and MIR layers were extracted to study the bare soil images of the January 1st; and NDVI values from images during the rice crop cycle (January 15th to May 15th).

Only the images of January 1st (from 2001–2017) were used, because at this time, farmers are preparing land for sowing on bare soil (Moreno, 2014). This is clearly observed in the example of a very high spatial resolution image (5 × 5m) as seen in Fig. 5 B. To ensure that sampling pixels were representative of bare soil, only the observations of red, blue,

NIR and MIR that have the corresponding NDVI values less than 0.2 were used; because, a higher value could correspond to vegetation coverage.

Figure 5. Very high spatial resolution images RapidEye of study area portion (represented by black rectangle in A) and sampling random points of: B) bare soil prepared for rice sowing at January 13th, 2014 and C) rice cultivation affected by flood at March 29th, 2012 both inside of AHZs f7 and f15

Remote sensing has been used for many years in successfully mapping soil properties (M. Barnes and G. Baker, 2000; Gomez et al., 2008). For this reason, reflectance values from the imagery set of red, blue, NIR and MIR layers in each representative AHZ were sampled. These bands were included in the analysis, as some soil properties are better determined using the visible spectrum (blue and red), while other properties are better determined using the near and medium infra-red spectrum (Viscarra Rossel et al., 2006).

Then, NDVI values during the rice crop cycle were sampled as was mentioned previously. In this manner, we can study if the differences between the AHZs are also statistically significant for the NDVI values. In this case, stratification could be used for differencing

premium cost in each AHZ in an eventual IBI design. In other words, a calculation of rice crop lost probability should be applied for each AHZ and not at cantonal level. This could make the IBI sustainable in time and more attractive to farmers.

2.2.4 Statistical analysis of bare soil and NDVI

First, a statistical descriptive analysis was conducted to test the normality of the data set. Then, an analysis of variance (ANOVA) was applied, in which the variability factor was the AHZ, for a data set of bare soil reflectance (red, blue, NIR and MIR bands). ANOVA for NDVI_ave, AHZ and time (years) were the variability factors. The least significant difference test of Fisher (Williams and Abdi, 2010) was performed to determine the degree of significance of the differences in the variability factors.

For the first data set (red, blue, NIR and MIR bands), we used the January 1st image during the period 2001–2017. These values are expressed in percentage ratios with values of from 0 to 1. For the second data set, we used an NDVI average (NDVI_ave) of the rice crop cycle (January 15th to May 15th) during the same years. This study started with a sampling density of 30% to study the differences between the AHZs.

To determine the minimal sampling percentage needed to maintain the differences observed, but conserve the sampling representativeness, NDVI_ave values of lower sampling densities (5, 10, 15, 20 and 25%) in the same imagery data set were used. Then, we performed an ANOVA in which the variability factors were the sampling densities and AHZs. This analysis allowed us to suggest an accurate sampling density that could be more adequate for practical purposes in IBI design.

2.2.5 Effect of Agro-ecological variability on failure probability in a rice crop

In the case that the NDVI_ave of both AHZs (*f7* and *f15*) are significantly different, the risk status of each AHZ was calculated. This consisted in determining the percentage of the NDVI_ave observations under the occurrence threshold (0.4) for each AHZ. Then, these two percentages were evaluated via a Z-test (Polasek, 2013). If the Z is outside of the critical rate range ($Z \leq z_{0.025} = -1.96$ and $Z \geq z_{0.975} = 1.96$), the two percentages are significantly different from each other. The risk assessment is in-depth addressed in the next stage.

An NDVI_{ave} threshold of 0.4 for crop failure was taken from Valverde-Arias et al. (2018). We presented a complete analysis of this threshold value in subsection 2.3.5.

2.3 Design of an NDVI index-based insurance for covering economic impacts in rice cultivation

2.3.1 Location of study area

This stage focus on in the same case study (Babahoyo canton-Ecuador) that the former one, over rice-cultivated area, see Fig. 3 A, B and C.

2.3.2 Cartographic data

2.3.2.1 Agro-ecological homogeneous zones map

We used the agro-ecological homogeneous zones (AHZs map) generated in first stage of this study.

2.3.2.2 Data from satellite imagery

We used the same NDVI product that in the former stage; MODIS MOD13Q1V6, their characteristics are shown in Table 2.

Imagery corresponds to January to May, when rainfed rice is cultivated, one image for each 16 days from 2001-2017 totalling 170 images (17 years x 5 months x 2 per month). The rice crop cycle in Ecuador takes 120 days, but the sowing date usually is around January 15th and sometimes it is delayed. Because of this, we included also May in the study.

In this stage, we used only Hdf:0 layer, which corresponds to NDVI.

2.3.3 Statistical analysis

NDVI values over rice along its crop cycle were analysed (NDVI_{ave}, which is the average of all NDVI measures of rice crop cycle -January to May- for each observation point), during period 2001 to 2017. We sampled 30% of the total pixels of rice crop in Babahoyo canton, resulting in 31,756 observations: 13,498 in zone *f7* and 18,258 in zone *f15*, having as variability factors AHZs (*f7* and *f15*) and years (2001-2017).

Descriptive statistics were applied to the data set, including the normality test of (Kolmogorov-Smirnov) which is recommended for more than 50 observations (Razali and Wah, 2011). If dataset fits to a normal distribution, an analysis of variance ANOVA will be applied for comparing means of two factors of variability (zones and years). If data set does not fit a normal distribution, we will determine which distribution this dataset fits; and we could apply the non-parametric test of (Kruskal-Wallis) for comparing median of AHZs and years. If significant differences were found among years, it could be used the Least Significance Difference (LSD) multiple rank test for means (Williams and Abdi, 2010) or Bonferroni test for medians, for grouping years that are not significant different into categories of very low, low, normal, high and very high years, according to their NDVI_ave mean or median.

2.3.4 Rice-yield estimation through NDVI_ave

For quantifying economic losses in rice cultivation, it is necessary to evaluate the correlation between NDVI_ave and rice yield. According to Huang et al., (2013) remote sensing products can be used for generating yield estimation models that could dispense with variables as crop management, fertilizer applications, among others, with good results in rice-yield prediction even at province level. Quarmby et al., (1993) mentioned that rice and maize yield could be estimated accurately by a simple linear regression between NDVI and yield; and Son et al., (2014) suggested that the use of multi-temporal NDVI data, for estimating rice-yield in large scale, should be a possible and accurate alternative.

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 in which they have sampled yield across mapped rice areas. Thus, 369 georeferenced rice-yield observations (t/ha) for 2014-2017 rainfed cycles (January to May) in the study area over AHZs *f7* and *f15* (see, Fig. 6), were available. Thus, we used these rice-yield observations for correlating them with their corresponding spatial and temporal NDVI_ave values, obtaining a rice-yield estimation model (Huang et al., 2013; Quarmby et al., 1993; Son et al., 2014). We used the following equation:

$$Y = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(X-\mu)^2}{2\sigma^2}} \quad [1]$$

Where:

σ = Standard deviation

σ^2 = Variance

X = independent variable (NDVI_ave)

Y = dependent variable (estimated rice yield)

μ = Arithmetical Mean of NDVI_ave in years 2014-2017

For evaluating the robustness of this model, it was performed RMSE (%) and R-squared coefficient.

Figure 6. Agro-ecological homogeneous zones *f7* and *f15* over rice cultivation area with yield observations in Babahoyo canton

2.3.5 Thresholds determination

We know that the index is capable of detecting rice crop affection produced by extreme climatic events (drought and flood). In addition, we determined if the index is sensitive enough for differencing some levels of crop affection. These affection levels were:

a) Total loss, when the crop is deeply affected and the farmers cannot even recover their investment

b) Physiological impact, when crop is hard affected but farmers can recover at least part of their investment, and.

c) Economic impact, when the crop impact still allows farmers to recover their investment although do not obtain any gross margin.

We determined the physiologic threshold, which is the NDVI_{ave} value more representative in years affected by extreme climatic events. For this purpose, we selected the years with the lowest NDVI_{ave} means or medians, according to LSD multiple rank or Bonferroni test, which we named very low years (Rulinda et al., 2012; Valverde-Arias et al., 2018). Then, we contrast if these years actually have been affected by extreme climatic events (drought and flood), through the climatic application of National Oceanic and Atmospheric Administration (NOAA, 2018).

For the economic threshold, we set an NDVI_{ave} value that let farmers cover at least their production cost. Thus, we regarded the sale price at farm gate for a tone of rice and the production cost divided in two scenarios: scenario 1 (when we consider differentiated production cost of AHZs *f7* and *f15*) and scenario 2 (non-differentiated production cost of AHZs).

According to CGSIN of MAG, there are officially three different rice-crop production systems in Ecuador for rainfed agriculture and two for irrigated agriculture in 2017. Each of them has different production costs as shown in Table 3, which depend on the level of farm modernization and whether they are rainfed or irrigated.

Table 3. 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

Since, we are assessing rice-production in rainy season (January-May); under normal conditions, irrigation is not required. Therefore, we used production costs of rainfed agro-systems. From rainfed production systems, we have chosen only the non-technical and semi-technical systems because these systems are more exposed to suffer the impacts of extreme climatic events and they should be insured. Thus, for the scenario 1, we assigned

to *f7* the production cost of a non-technical production system (1022 USD/ha) and for *f15* the semi-technical production cost (1629 USD/ha), see Table 3. Moreover, for Babahoyo canton (*cantonal*), we have used a weighted average production cost of these two systems (1259 USD/ha). In addition, for the scenario 2, we used the weighted average (1259 USD/ha) for all of them (*f7*, *f15*, and *cantonal*).

2.3.6 Risk assessment in AHZ

Firstly, after finding the distribution that fits our data for each AHZ and *cantonal*, we simulated through these distributions a determined number of NDVI_ave values. Secondly, we compared the frequency of observed NDVI_ave values with the estimated ones. Third, we evaluated the basis risk of the estimation through Adjusted R-squared coefficient (Vedenov and Barnett, 2004).

Lastly, we calculated the proportion of events equal or under each threshold (physiologic and economic) for each estimated distribution (*f7*, *f15* and *cantonal*). Finally, we compared if these proportions of *f7* and *f15* are statistical different or not. This analysis was performed through the Z- test of two independent proportions, which consists in contrasting if these two proportions that came from two different populations are equal (Pardo et al., 1998; Polasek, 2013).

1. Hypothesis:

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

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, they were extracted independently two random samples with n_1 and n_2 sizes, with success probability p_1 and p_2 respectively. They are constant in each extraction. Positive events are 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

$$P = \frac{n_1 P_1 + n_2 P_2}{n_1 + n_2} \quad [2]$$

$$Z = \frac{P_1 - P_2}{\sqrt{P(1-P)\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \quad [3]$$

4. Critical ratio

Bilateral:

$$Z \leq \alpha/2 Z$$

$$Z \geq 1-\alpha/2 Z$$

5. Decision.- Reject H_0 if contrast statistics falls in critical rate or $p \leq \alpha$

2.3.7 Insurance contract design

2.3.7.1 Indemnity calculation

The indemnity is the amount of money that an insured individual receives when a covered hazard occurs. In this case, we have two insuring options: the first one is the working capital, where the insured amount corresponds to the money necessary for recovering the investment (production cost) that a farmer has spent. The second is the gross margin, where the ensured amount is the money that a farmer would obtain selling his production after covering his production cost, in a normal year.

In other words, for the first option the compensation will cover the yield reduction between the economic threshold and physiologic threshold. While for the second case, the compensation will cover the difference between the expected yield in a normal year and the yield obtained at the economic threshold.

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

$$I_{sz} = Y_z \times P - Pc_{sz} \quad [4]$$

Where:

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

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

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

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

Y_z is obtained applying Equation [1]. P was calculated from rice-price monthly variation along the last two years. This value is assumed to be constant (371 USD/t) for both AHZs and *cantonal*, and for both scenarios 1 and 2.

To estimate Pc_{sz} , we evaluated two scenarios. Scenario 1, when production cost was differentiated for each z zone ($f7$, $f15$ or *cantonal*); and scenario 2, where we used the same production cost for all z zones ($f7$, $f15$ or *cantonal*).

2.3.7.2 Premium determination

The commercial premium value CP_{sz} is equal to net premium multiplied by a factor covering the insurance company profit and loading cost. The net premium or risk premium NP_{sz} has to cover the expected compensations that insurance company would have to pay over the analysed period. The net premium is calculated as a percentage of I_{sz} , this percentage corresponds to the probability of having a NDVI_ave equal or under the physiologic and economic threshold in n years (Jasiulewicz, 2001; van de Ven et al., 2000). It was expected that the probability of occurrence is different for each AHZ ($f7$ and $f15$) and when the NDVI_ave measure is made without differencing zones (*cantonal*). We calculated differentiated premium rates for each one of these cases.

$$NP_{sz} = I_{sz} \times Pr_{sz} \quad [5]$$

$$CP_{sz} = NP_{sz} (1 + (\beta_1 + \beta_2)) \quad [6]$$

Where:

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

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

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

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

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

The commercial premium value CP_{sz} in index-based insurance, generally is subsidized by the government in around 60%, to small farmers in developing countries (Peter Höppe, 2007).

2.4 Generation of a drought risk map for rice cultivation using GIS: case study in Babahoyo canton (Ecuador)

2.4.1 Location of the study area

The study area is located in Babahoyo canton, Ecuador (see Fig. 7); its area is 109,391 ha from which 102,517 ha correspond to agricultural lands and 6874 ha are urban, protected and non-agricultural lands (miscellaneous lands, water bodies, etc.). Babahoyo canton is administratively divided in five rural districts that are Babahoyo, Caracol, Fbres Cordero, La Unin, and Pimocha.

The agricultural land of the Babahoyo canton is mainly cultivated with rice, banana and soybean which reach 70,152 ha of the total Babahoyo canton's area (IEE, 2009). As we mentioned in second stage, rice is the most important crop with 46,556 ha, representing 45% of the total cultivated area in the canton (MAGAP, 2014).

Figure 7. Location of Ecuador in South America and Babahoyo canton in Continental Ecuador

2.4.2 Drought risk framework

There have been many studies assessing drought risk for specific crops, even in real-time (e.g. Wu, Hubbard, & Wilhite, 2004; Zhang, 2004). However, these are mainly focused on maize and located in Asia and United States. There is a need to develop studies in this field adapted to Ecuador's conditions using the available information.

Figure 8. Schematic representation of risk evaluation that was run in a geographical information system

This study integrates three principal factors that intervene in potential risk, as other authors (Shahid & Behrawan, 2008; Zhang, 2004) have mentioned: 1) *Threat* is defined as the likelihood of a drought event occurring and its spatial distribution. It is based on the historical analysis of the frequency and intensity with which an extreme event occurs. 2) *Vulnerability* is the level of exposure to a hazardous extreme event; in this case, it represents rice crop susceptibility to drought events. 3) The potential consequences of a drought event for rice crop production, referred to as *production risk*, which is derived from the evaluation of all possible interactions between threat and vulnerability.

This methodology spatially analyses the variables related to drought vulnerability and drought hazard for rice crops to evaluate drought risk. In Fig. 8, we showed the order and

sequence of this form of analysis that can be reproduced to obtain a drought risk map for any crop and area, as far as the required data are available.

A rice drought risk map is used for index-based insurance implementation and agricultural risk management. It can differentiate risk zones and set differentiated insurance premiums according to risk exposure levels.

2.4.3 Cartographic data

These cartographic data inputs correspond to published thematic maps in vector format (*.shp*), which were used for map algebra, and are described below:

2.4.3.1 Soil map of Babahoyo canton (1:25,000)

Table 4. Variables included in soil map database, classified by characteristic, symbol, quantitative or qualitative type and the unit or number of ranges used respectively.

Characteristics	Name	Symbol	Type	Unit
Topographic	Slope	S	Quantitative	%
	Texture	T	Quantitative	%
	Effective depth	ED	Quantitative	cm
Physical	Stoniness	ST	Quantitative	%
	Soil drainage	D	Qualitative	1-4 ranges
	Ground water	GW	Quantitative	cm
	pH	pH	Quantitative	-
Chemical	Organic matter	OM	Quantitative	%
	Cationic exchange	CEC	Quantitative	meq.100g ⁻¹
	Salinity	SS	Quantitative	mmho.cm ⁻¹
	Toxicity	Tx	Qualitative	1 to 4 ranges
	Fertility	F	Qualitative	1 to 4 ranges
Climatic	Annual isotherm	It	Quantitative	°C
	Vegetative period	Vp	Quantitative	Humid days.year ⁻¹

This map (IEE, 2009a) was generated by taxonomic soil characterisation (Soil Survey Staff, 2010) through field observation measurements, laboratory soil sample analysis and

digital photo interpretation, adapted from FAO (2006). The variables contained in the geodatabase of soil map are showed in Table 4.

2.4.3.2 Land evaluation map for rice cropping, 1:250,000 (LEM)

Also called agro-ecological zoning for rice cropping (MAGAP, 2014a), this map assesses the land suitability for a specific type of land use. In this map, rice crop requirements were compared with land characteristics (FAO, 1991; FAO, 1984).

There are many levels of land evaluation that could include biophysical, chemical, climatic, economic and social analyses of land variables (Rossiter, 1996; Manna, Basile, Bonfante, De Mascellis, & Terribile, 2009). In this case, MAGAP (2014a) adapted the methodology, focusing on the main limitation (Van Ranst and Debaveye, 1991), analysing topographic, physical and chemical soil characteristics, and climatic variables (temperature and vegetative period) of the soil map. The four categories of suitability included in this map are *suitable*, *moderately suitable*, *marginally suitable* and *unsuitable* for rice cropping.

2.4.3.3 Irrigation requirement map (1:50,000)

This map indicates the necessity for irrigation water based on climatic conditions, and analysed rainfall versus potential evapotranspiration. This map has five categories of irrigation requirement: indispensable, necessary, complementary, facultative and unnecessary. In Babahoyo canton, we only found complementary, facultative and indispensable categories. **Facultative**: 2-4 deficit months, **complementary**: 5-7 deficit months and **indispensable**: 11-12 deficit months. The climate department of CGSIN of MAG generated this map.

2.4.3.4 Map of climate types of Continental Ecuador (1:50,000)

We can find two climate types in Babahoyo canton (MAGAP, 2003): Tropical Megathermal Humid and Tropical Megathermal Semi-humid. We used this map to delimit the spatial extent of drought hazard categories.

2.4.3.5 Operative irrigation projects OIP (1:50,000)

This map represents graphically the influence area of private, public and cooperative irrigation projects that are currently operating in Ecuador. The map is updated

periodically according to the availability of new cartographic data. We used the area corresponding to Babahoyo canton, last updated in 2012 (MAGAP, 2012).

2.4.3.6 Rice cultivated land in Babahoyo canton (1:25,000)

We used a map of the rice-cultivated area in Babahoyo canton in 2014 (MAGAP, 2014b). In this canton, we can find a consolidated area that is periodically cultivated with rice and that comprises a great part of the canton.

2.4.4 Drought vulnerability evaluation (DVE)

In this study, we considered two factors that affect the drought vulnerability of the rice crop to a specific production risk. The first factor was **rice crop location** (RCL) in suitability categories, which indicates soil qualities that farmers have to manage for cropping rice; and the second was **climatic analysis** (CA), which includes temperature, precipitation and categories of irrigation requirement.

2.4.4.1 Rice crop locations within suitability categories for rice cropping

While, we did not use the LEM (MAGAP, 2014a) directly, we adapted it by applying the same land evaluation methodology to a 1:25,000 soil map database (IEE, 2009a). Also for our adaptation, we did not evaluate climatic variables, leaving them for use in *a posteriori* analysis, as is shown in Table 5.

Then, we intersected the adapted LEM with rice crop coverage for 2014 in Babahoyo canton, in turn obtaining the location of rice crops over suitability categories. According to their locations, we can determine whether farmers are planting rice in suitable areas or not. Where the latter is the case, farmers must invest to improve soil characteristics. Therefore, when a drought event occurs, farmers are more vulnerable to experiencing economic losses as the investments made are greater than those needing to be applied to a suitable area (Kalogirou, 2002; De la Rosa, Mayol, Diaz-Pereira, Fernandez, & de la Rosa Jr., 2004).

The suitability categories were adapted from previous research (FAO, 1984; Ranst & Debaveye, 1991) and divided into four categories: suitable, moderately suitable, marginally suitable and unsuitable. The details of their definition are shown in Appendix I.

Table 5. Matrix for soil characteristic classification in rice cropping suitability categories

SOIL VARIABLES	SUITABILITY CLASSIFICATION			
	Suitable	Moderately suitable	Marginally suitable	Unsuitable
<i>Slope</i>	0 - 5%	5 - 25%	25 - 40 %	> 40%
<i>Texture</i>	Clay(> 60%), Clay, Silty clay, Clay loam (> a 35% clay), Clay loam (< 35% clay), Loam, Silty loam, Silty clay loam	Sandy clay, Sandy clay loam	Sandy loam (fine to coarse), Silty	Sand (fine, medium, coarse), Loamy sand
<i>Effective Depth</i>	Shallow/ Moderately deep/ Deep	Superficial	-	Very superficial
<i>Stoniness</i>	Without/ Very few	Few	Frequent	Abundant/ Stony to rocky
<i>Drainage</i>	Well drained/ Moderately drained/ Poorly drained	-	-	Excessively drained
<i>Ground Water</i>	Without evidence/ Deep/ Moderately deep/ Shallow/ Superficial	-	Very superficial	-
<i>pH</i>	Neutral / Practically neutral/ Slightly acidic	Moderately acidic / Slightly alkaline	Acidic/ Mildly alkaline	Very acidic/ Alkaline
<i>Toxicity</i>	Without or null	Slight	Medium	High
<i>Organic Matter</i>	High/ Medium	Low	-	-
<i>Salinity</i>	Non-saline/ Slightly saline	Saline	Very saline	Extremely saline
<i>Fertility</i>	High/ Medium/ Low	Very low	-	-

Source: adapted from (INIAP, 2008) and (MAGAP, 2014a)

2.4.4.2 Climatic analysis

The first climatic variable analysed was temperature. The study area is located between isotherms of annual average temperature from 23 to 26°C; according to INIAP (2008) and Sánchez et al., (2014), the optimal temperature range for rice crops is 22 to 30°C, and thus, the entire study area falls within an optimum range of temperatures for rice cropping, as is shown in Fig. 9 A. Therefore, temperature does not represent a variable source

among the categories or a limitation for rice cropping. As such, it was excluded from the vulnerability analysis.

Figure 9. A) Isotherms in study area, B) zones of irrigation requirement

We did not use the vegetative period from soil map database although this variable denotes the number of humid days (humid day = $\text{real evaporation} \times [\text{potential evapotranspiration}]^{-1} \geq 0.75$) in a year; however, it does not specify the distribution of these days in a year and even more importantly along the crop cycle. Water availability levels in critical stages of the rice cycle are determinant.

We used irrigation requirement categories (Fig. 9 B). However, to assess water supplies in the cycle of a rice crop (Geerts et al., 2006), each irrigation zone was characterised based on monthly precipitation data for a twenty year period (Zhang, 2004). This information was drawn from meteorological stations of each category of irrigation requirements in the study area.

Water availability levels from precipitation in each irrigation zone were compared with crop water requirement for each phenological stage (Acevedo et al., 2011) for a pooled culture system (rice cultivated in artificially flooded lands), which is the culture system most commonly used in Babahoyo canton, according to Moreno (2014). Rice crops in a pooled culture system require water for rice evapotranspiration (800-1240 mm) according to INIAP (2008), as well as water for maintaining adequate pool levels at each rice farming stage.

As is shown in Table 6, we grouped the ten rice phenological stages into four stages in accordance with the water requirements of rice crops (the most common cultivars used in Babahoyo Canton: INIAP-7, INIAP-11, INIAP-14, INIAP-415, INIAP-15 and INIAP-16) in pooled culture systems (FAO, 2004; INIAP, 2008).

Table 6. Precipitation requirement to crop water consumption and for maintaining pool levels

Month	Accumulated days	Phenological stage	Precipitation (mm)	Pool water level (cm)
January	30	Sowing- Panicle	200	10
February	60	Panicle-Heading	850	25
March	98	Heading-Flowering	450	15
April	120	Flowering-Maturity	75	5

2.4.4.3 Drought vulnerability categories

For this step, we evaluated interactions between crop location and climate analysis to obtain four vulnerability categories of drought, based on soil conditions and water availability levels, following Araya, Keesstra & Stroosnijder (2010) and Shahid & Behrawan (2008), as is shown in Table 7. The four categories of drought vulnerability registered include the following: low, moderate, high and very high. Definitions of these categories are shown in Appendix II.

Table 7. Qualification matrix for drought vulnerability analysis

Crop location in suitability areas	Irrigation requirement zones		
	Facultative	Complementary	Indispensable
Suitable	Low drought vulnerability	Low drought vulnerability	Moderate drought vulnerability
Moderately suitable	Low drought vulnerability	Moderate drought vulnerability	Moderate drought vulnerability
Marginally suitable	High drought vulnerability	High drought vulnerability	High drought vulnerability
Unsuitable	Very high drought vulnerability	Very high drought vulnerability	Very high drought vulnerability

2.4.5 Drought hazard evaluation (DHE)

A drought hazard is defined the likelihood of a drought event occurring in a given region (He et al., 2011); here, we examine Babahoyo canton.

Drought in Ecuador (Cadier et al., 1994) is caused by an anomalous northern oscillation of the cold Humboldt current, which is contrary to the El Niño phenomenon. This produces floods in coastal regions and an anticyclonic system that blocks the action of fronts, convective systems and depressions, which occur over the highlands and western foothills of the Andes Mountains.

Based on historical climate analysis and climate forecast through model TL959 A1b 2039 (MAE, 2010), the current drought hazard in Babahoyo canton is characterized as 0.4 being 1.0 the most hazardous level and 0 an absence of hazards.

Nevertheless, it is very difficult to determine the extent of a drought event. Therefore, we used a climatic map of Ecuador that indicates that Babahoyo canton is divided into two climatic zones: Tropical Mega-Thermal Semi-humid over the majority of rice crop land and Tropical Mega-Thermal Humid over a small portion of land in the eastern Babahoyo canton. Thus, we followed He et al. (2011) and assigned *low drought hazard* (0.2) category to the Tropical Mega-thermal Humid zone (with wetter weather conditions) and the *moderate drought hazard* (0.4) category to the Tropical Mega-thermal Semi-humid zone.

2.4.6 Drought risk analysis

In this phase of the study, we qualified drought risks based on interactions between obtained categories of drought vulnerability and hazard including soil factors (Fig. 8) to create a drought risk map (DRM) as is shown in Table 8.

We also generated a drought risk map (DRcM) that considers the vulnerability of water availability and drought hazards from climate alone (see Fig. 8). The purpose of this map is to compare it to the DRM, to observe the effects of soil variables on drought risk and to determine which model better represents drought risks facing rice crops.

Drought risk categories include the following (Zhang, 2004): low, moderate, high and very high. Each is explained in detail in Appendix III.

Table 8. Qualification matrix for drought risk analysis

<i>Vulnerability categories</i>	<i>Hazard categories</i>	
	Low drought hazard	Moderate drought hazard
Low drought vulnerability	Low drought risk	Moderate drought risk
Moderate drought vulnerability	Moderate drought risk	Moderate drought risk
High drought vulnerability	High drought risk	High drought risk
Very high drought vulnerability	Very high drought risk	Very high drought risk

2.4.7 Risk maps adjustment

DRM and DRcM were generated based on natural soil and climatic conditions found in Babahoyo canton. Nevertheless, we counted with a map of irrigation influence area of public and private irrigation projects. In a normal rainy season, irrigation is not required but during a drought event. Thus, we assume that farmers within irrigation influence area could have access to irrigation. Then, we removed vulnerability of these areas caused by water availability, but we have kept those that are caused by soil variables in DRM.

2.4.8 Drought risk map novelty: approach and validation

Most risk models analyse the interaction between major risk factors (vulnerability and hazard) using different approaches according to their aims, scales, and degrees of data availability. Almost all of them are estimated based on drought indices, vegetation indices, climatic indices or a combination of both as mentioned above.

The most commonly used climatic indicator is the SPI. This index is adequate for monitoring drought as a precipitation deficit and makes predictions for a defined period (Hayes, Svoboda, Wilhite, & Vanyarkho, 1999). However, in many works, SPI is expressed in terms of a standard deviation (SD) from a normal distribution (Khan et al., 2008) with a “normal period” having values of -1 to +1 SD (Edwards, McKee, Doesken, & Kleist, 1997; Wu, Hayes, Weiss, & Hu, 2001). This can present problems when the precipitation distribution does not fit a normal distribution (Guttman, 1999).

At the same time, the SPI definition better fits concepts of hydrological drought than those of agricultural drought. This implies that when drought vulnerability is evaluated, we must determine the current availability of water for cropping at each phenological stage. While some researchers have tried to use other climatic variables to define new indices, such as the Palmer Drought Severity Index (PDSI) (Shahid & Behrawan, 2008; Strzepek, Yohe, Neumann, & Boehlert, 2010; He, Lü, Wu, Zhao, & Liu, 2011; Li, Ye, Wang, & Yan, 2009) or the Crop Moisture Index CMI (Wu and Wilhite, 2004) the same problems have arisen as a result. Blauhut, Gudmundsson, & Stahl (2015) reported that the SPI and PDSI do not always correlate well with drought effect reports, suggesting that they must be improved upon.

Risk models based on vegetation indices are frequently used. Many authors have obtained drought risk categories from values of the NDVI or of the Vegetation Condition Index (VCI) (Prathumchai, Honda, & Nualchawee, 2001; Belal, El-Ramady, Mohamed, & Saleh, 2014). The aim of these models is mainly to monitor vegetation conditions in the same way as climatic indices, using vegetation indices as an integrated measure of precipitation, water availability and crop patterns. However, they do not combine concepts of vulnerability and threat.

The DRM includes rain levels in each of the three precipitation zones of the study area, thus more accurately determining water supplies available for cropping. Moreover, it considers the effects of soil characteristics on production risks when triggered by drought. This is especially important for this case study, in which climatic conditions are not very limiting for this crop. The adjusted DRM considers irrigated rice crop areas experiencing reduced vulnerability resulting from water availability approaching real farming conditions. Additionally, the DRM addresses rice crops currently facing drought risks, and it does not act as a drought monitoring system.

To validate our approach, we used an NDVI imagery dataset and agricultural insurance data. To our knowledge, the latter data have not been used in a crop DRM evaluation. A comparison of these maps, in which the difference is the inclusion of soil characteristics, was conducted and is explained in section 2.1.11.

2.4.9 Validation data

2.4.9.1 NDVI data from satellite imagery

MODIS imagery (MOD13Q1V6 - 250 m_16_days_NDVI layer) for 2001 to 2014 was downloaded to obtain an NDVI database of the study area. Images corresponding to the rice crop cycle were selected to include two images per month and a total of 140 images (14 years x 5 months x 2 per month). The average of NDVI images corresponding to the same month was chosen as representative of that month.

Although rice crop cycle is normally located from January to April, some years the sowing date is delayed due to the rain pattern. For this reason, we have considered as rice crop cycle five months, from January to May, in the NDVI calculations.

Then, geographic reference points were randomly selected for each risk category (two for DRcM and 4 for DRM), covering 30% of the area. NDVI series values were extracted from each point.

2.4.9.2 Agricultural insurance data

Data used to validate the model include the following: insured area of rice crops in the winter (January to March), area of rice crops affected by drought, and claim reports of drought for each rural district of Babahoyo canton. The rural districts of Babahoyo canton are Babahoyo, Caracol, Fébres Cordero, La Unión and Pimocha. These data cover the period running from the onset of agricultural insurance in 2010 to the winter of 2014. This information was provided through the Agroseguro project, which trades conventional agricultural insurance in Ecuador. This insurance is promoted, managed and subsidised by the Ecuadorian government (Ecuador, 2015).

2.4.10 Adjusted DRM and DRcM validation

To validate the adjusted DRM and DRcM, we compared the resulting maps with NDVI imagery set data. Our evaluation is based on correspondence between risks of each category (4 categories for the DRM and 2 categories for the DRcM) with drought events in these areas (Pontius et al., 2008) as measured from NDVI values.

As concluded by many authors (Quarmby, Milnes, Hindel, & Sileos, 1993; Huang, Wang, Li, Tian, & Pan, 2013), NDVI has being used as a rice yield estimator and as an index for

monitoring agricultural drought (Tonini, Jona Lasinio, & Hochmair, 2012; Son, Chen, Chen, Chang, & Minh, 2012).

In this study, the NDVI average value (NDVI_ave) for rice crop cycle (from January to May) was used to estimate drought event occurrence. For this purpose, a NDVI_ave threshold value was selected to indicate that any lower observation is related to a drought case. NDVI_ave was selected for this analysis due to the variability that monthly NDVI values present along crop cycle depending on the crop stage. According to García & Martínez (2010), these values in rice crop varies from 0.36 to 0.71.

To set this threshold, NDVI_ave values corresponding to years of maximum drought claims for agricultural insurance were selected (2013 and 2014). The mean of NDVI_ave for these years was chosen as the drought threshold.

Then, the entire NDVI database was used to quantify values under this threshold for each risk category of adjusted DRM and DRcM while considering them as drought cases. A χ^2 test was used to validate the resulting maps with a null hypothesis stating that the severity of the risk category (for DRM and DRcM) is independent of drought cases occurring in each category (Agresti, 2013).

2.4.11 Comparison between DRM and DRcM

Agricultural insurance data (mentioned in subsection 2.1.9.2) for each of the five districts of Babahoyo canton were used to evaluate which map explains the data more accurately.

Beginning with the DRM, each group or clusters (k) corresponds to the following risk categories: 1= low drought risk, 2= moderate drought risk, 3= high drought risk and 4= very high drought risk. For each k , we know the proportion of the area in each district (i) of Babahoyo canton, defined as ($w_{i,k}$).

Analysing the campaigns from 2010 to 2014, there are two years considered by the Government as severe drought: 2013 and 2014. Based on this, we have classified these as *dry years*, corresponding with a higher number of claim reports on droughts to the insurance company. The rest of the years are classified as *regular years*. To differentiate both type of years (s) we assigned $s=1$ to a dry year and $s=2$ to a regular one.

In each district i , in year type s , the insured rice area is ($N_{i,s}$), and from these a certain area is reported to be affected by drought ($n_{i,s}$). In Equation [7], $m_{i,s}$ is the proportion of area of district i that claimed to suffer drought events in a year type s .

$$m_{i,s} = \frac{n_{i,s}}{N_{i,s}} \quad [7]$$

Secondly, we named the probability of a drought event occurring in a k category in a year s as $(p_{s,k})$, independently of the district. To estimate these probabilities, the system of equations showed in [8] are solved by the method of maximum likelihood (Amemiya, 1977).

$$\sum_{k=1}^4 p_{s,k} w_{i,k} = m_{i,s} \quad 0 \leq p_{s,k} \leq 1 \quad \forall i = 1, \dots, 5; s = 1, 2 \quad [8]$$

The insured area in district i , during a year type s , belonging to category k , is designated as $(h_{i,s,k})$, estimated as:

$$h_{i,s,k} = N_{i,s} \times w_{i,k} \quad [9]$$

Finally, we will refer to insured area affected by drought, in district i , during a year type s , belonging to category k as $(u_{i,s,k})$. These variables present two restrictions:

$$\begin{aligned} \sum_{k=1}^4 u_{i,s,k} &= n_{i,s} \\ 0 \leq u_{i,s,k} &\leq h_{i,s,k} \end{aligned} \quad \forall k = 1, \dots, 4 \quad [10]$$

Thus, the likelihood that $n_{i,s}$ (district i , type of year s) are affected by drought ($L(n_{i,s})$), over $N_{i,s}$ insured hectares, was:

$$L(n_{i,s}) = \sum_{u_{i,s,1}=0}^{\min(n_{i,s}, h_{i,s,1})} \sum_{u_{i,s,2}=0}^{\min(n_{i,s}-u_{i,s,1}, h_{i,s,2})} \sum_{u_{i,s,3}=0}^{\min(n_{i,s}-u_{i,s,1}-u_{i,s,2}, h_{i,s,3})} \prod_{k=1}^4 \Pr[B(p_{s,k}, h_{i,s,k}) = u_{i,s,k}] \quad [11]$$

Where, $\Pr$ is the probability and B refers to the binomial distribution. This likelihood is based on four risk categories (k) coming from DRM map. We named it as $L(n_{i,s})_{\text{DRM}}$.

We repeated the same procedure for results obtained for DRcM, but in this map there are two risk categories k : 1= low drought risk and 2= moderate drought risk. The type of year (s) and the districts (i) will be the same as shown earlier. Thus, we defined $w'_{i,k}$ as the proportion of the area in district i that belong to k category. The proportion $m_{i,s}$ is the same as defined in equation [7], as it came from the same agricultural insurance data.

Now, the probability of a drought event occurs in a year type s in a risk category k ($q_{s,k}$) will be estimated by maximum likelihood method solving the system of equations [12] (Amemiya, 1977):

$$\sum_{k=1}^2 q_{s,k} w'_{i,k} = m_{i,s} \quad 0 \leq q_{s,k} \leq 1 \quad [12]$$

The insured area in district i , during a year type s , belonging to category k coming from DRcM map ($h'_{i,s,k}$), was estimated as:

$$h'_{i,s,k} = N_{i,s} \times w'_{i,k} \quad [13]$$

Then, the insured area affected by drought, in district i , during a year type s , belonging to category k will be named as $u'_{i,s,k}$. These variables present two restrictions:

$$\begin{aligned} \sum_{k=1}^2 u'_{i,s,k} &= n_{i,s} \\ 0 \leq u'_{i,s,k} &\leq h'_{i,s,k} \end{aligned} \quad \forall k = 1, 2 \quad [14]$$

Analogous to equation [11], the likelihood that $n_{i,s}$ is affected by drought, over $N_{i,s}$ insured area, was:

$$L(n_{i,s}) = \sum_{u'_{i,s,1}=0}^{\min(n_{i,s}, h'_{i,s,1})} \prod_{k=1}^2 \Pr[B(q_{s,k}, h'_{i,s,k}) = u'_{i,s,k}] \quad [15]$$

This likelihood is based on two risk categories (k) coming from DRcM map, we named it as $L(n_{i,s})_{\text{DRcM}}$.

To know which map (DRM or DRcM) better explains the 2010-2014 agricultural insurance data, the logarithm (log) of the ratio of both likelihoods (R_L) were used as shown in equation [16]. The calculation of the likelihood on DRM map ($L(\text{DRM})$) is based on equation [11] and on DRcM map ($L(\text{DRcM})$) based on equation [15]. Therefore:

$$R_L = \log\left(\frac{L(\text{DRM})}{L(\text{DRcM})}\right) = \log\left(\frac{\prod_{i,s}(L(n_{i,s})_{\text{DRM}})}{\prod_{i,s}(L(n_{i,s})_{\text{DRcM}})}\right) \quad [16]$$

If R_L is higher than zero, the new map has improved the explanation of agriculture insurance data.

3 RESULTS AND DISCUSSION

3.1 Determination of agro-ecological homogeneous zones (AHZs) for index based insurance design (IBI)

3.1.1 *Spatial analysis of the resulting control map*

In the control map (Fig. 10), we found 193 different classes in the study area, including 51 classes for the rice layer crop and 97 classes for the hard maize crop. This map has the variability that we imposed according to expert criteria, differentiating classes by soil and climate variability. To plot this map, we used the letter *t* followed by the number of each obtained class (e.g., *t1*).

This variability reflected different characteristics found in the study area because of different soil-forming factors. As an applicable tool for index-based insurance, this real soil variability may be excessive; however, this information could be important for aiding index-based insurance management.

We observed that current soil usage fits very well with areas in which the soil and temperature crops requirements were satisfied (rice and maize), although this was not the case for precipitation. We found large rice and maize crop areas inside very low levels of precipitation but with good soil characteristics, indicating that low precipitation was not a strong cropping limitation. Therefore, climatic information, particularly precipitation, is not representative of water availability in the crop cycle.

For example, the rice crop class *t23*, which represented 36% (96,552 ha) of the total rice crop area, had slope ranges from 0% to 12%, with fine to very fine texture, a superficial and shallow effective depth, and a temperature of 23-26°C, which all meet the optimal rice requirements. However, precipitation had a range of 0-500 mm year⁻¹, which is below the lower bound of the required range.

3.1.2 Spatial analysis of the resulting climatic map

Figure 11. A) Study area with homogeneous classes of the climatic map; B) homogeneous classes of the climatic map intersected with rice and maize layer

The climatic variables map has 11 homogeneous classes in the total area: three classes for the rice crop layer and seven classes for the hard maize layer (see Fig. 11 A, B). This map had few classes, because climatic variables are spatially more stable than soil variables, i.e., temperature does not have much variation over the Coastal region of Ecuador. Although having few classes is adequate for managing index-based insurance, but to lose information of soil variability is not desirable, because we would fail to explain some index value variation due to soil characteristics. To plot this map, we use the letter *c* followed by the number of each obtained class (e.g., **c1**).

Inside areas cultivated with rice, we found two groups with a temperature of 20-26°C. For the maize crop, we found three groups with a temperature of 11-19°C. This finding was due to maize crop tolerates lower temperature than rice.

We found rice and maize crops distributed in three precipitation groups with a range of 0-1200 mm year⁻¹, which means that isohyets were not fitting well with the coverage of these crops. This result was, in part, due to their different scales (isohyets 1:250,000 and

crop layer 1:25,000). In addition, the precipitation ranges are obtained from annual averages, so they do not always represent adequately the crop water availability in their cycle. Additionally, some farmers have irrigation, which is not evident in a map with natural precipitation conditions. Finally, few farmers cultivate in low water availability conditions, especially maize, without irrigation despite their low yields because these farmers have no other options.

3.1.3 PCA results for the factorial map

After implementing the PCA on the database, we retained five principal components with the eigenvalue criterion, retaining values greater than 1. These first five components captured 71% of the total variability.

Table 9. Pattern matrix, correlation between transformed variables with retained factors

Transformed variables	Factor1	Factor2	Factor3	Factor4	Factor5
PH Trans.	0.95	-0.04	-0.11	0.06	0.01
SALINITY Trans.	0.92	-0.02	-0.07	-0.03	-0.02
GROUND_WATER Trans.	-0.91	0.01	0.06	-0.02	-0.02
CODPRECI Trans.	0.02	0.77	0.12	0.15	0.23
EFF_DEPTH Trans.	-0.09	0.69	-0.19	0.33	-0.10
TEXTURE Trans.	0.03	-0.64	0.45	0.37	0.06
DRAINAGE Trans.	0.02	-0.75	0.42	0.16	-0.10
SLOPE Trans.	-0.17	-0.21	0.75	0.02	0.12
TOXICITY Trans.	-0.01	0.12	0.55	-0.15	-0.54
CODISOTE Trans.	0.07	0.15	-0.69	0.19	0.07
O_M Trans.	0.05	-0.04	0.04	0.76	-0.05
FERTILITY Trans.	-0.02	0.18	-0.24	0.73	0.01
STONINESS Trans.	0.00	0.18	0.06	-0.11	0.85

A pattern matrix (Table 9) shows the correlation measurements between the obtained factors and original variables transformed by the Prinqual method. Based on the correlation pattern in Table 9, we found that each factor is influenced by different variables, as shown in Table 10.

Table 10. Representative variables of each factor

Factors	Explanation
F1	High pH and salinity; low ground water
F2	High precipitation and effective depth; low texture and drainage
F3	High slope and toxicity; low temperature
F4	High organic matter and fertility
F5	High stoniness

In Fig. 12, we plot the results of the statistics applied to define the number of groups retained from the hierarchical cluster analysis. Index values are represented on the Y-axis, and the recommended number of groups is represented on the X-axis. We can see that the pseudo F and the CCC index reached maximum values at 26 groups, whereas the pseudo T-squared reached a maximum value at 25 groups, also indicating 26 groups. Based on these results, we chose a relative partition of 26 clusters.

Figure 12. Statistics to determine the number of clusters: A) Concordance correlation coefficient index (CCC), B) Pseudo F index and C) Pseudo T-squared index

The resulting classes (26) constituted homogeneous groups, and new codification (the letter *f* followed by a cluster number e.g., *f1*) were assigned to them for plotting homogeneous areas on the map, see Fig. 13 A.

3.1.4 Spatial analysis of the resulting factorial map

Figure 13. A) Study area with homogeneous classes of the factorial map; B) homogeneous classes of the factorial map intersected with rice and maize layer

In the factorial analysis, the variability was distributed over five factors. This analysis had 26 homogeneous classes in total, 20 classes for the rice crop and 20 classes for the maize crop (Fig. 13 A, B), which is a manageable number of classes to utilise for index-based agricultural insurance.

Coherence was found in the automatic grouping ranges of each variable included in the five factors. The largest cropping areas of rice and maize were found in *f7* and *f15* classes, which jointly provide the best conditions for these two crops. For soil and topographic variables, automatic grouping ranges worked well, despite the fact that some variables had many ranges included in the same homogeneous class, as shown in the following spatial analysis for the rice and maize crop layers.

3.1.4.1 Rice

For the rice crop layer, 20 homogeneous classes were found, corresponding to 266,235 ha, with *f7* (163,441 ha) and *f15* (77,921 ha) being the most important classes and representing 61% and 29%, respectively, of the total rice cultivated area.

Class *f7* grouped the best characteristics for rice cropping (Table 11). A slope (0-5%) range was featured in 99% of this class area. Additionally, 67% of this class area had a fine to very fine texture, which is common in Ecuador. The rice crop is cultivated mainly on Vertisol soils (Soil Survey Staff, 2014), which have a high percentage of clay (>60%) and are tilling hard soils. Therefore, mechanisation is very important, though it is possible in only flat and high humidity soil conditions, for which farmers make artificial pools. The effective depth is not very important for rice cultivation because rice roots do not grow deeply into the ground; therefore, 62% of the *f7* class was at a shallow depth.

For climatic variables (Table 11), the temperature of the *f7* class was completely (100%) in the range of 20-26°C, which is optimal for rice. The precipitation, which ranged from 300 to 500 mm year⁻¹, represents 62% of the total *f7* class, whereas 26% of the class was in the range of 500-700 mm year⁻¹, 1% was below 200 mm year⁻¹ and 1% was between 700 and 800 mm year⁻¹.

Although rice requires between 800 and 1200 mm of precipitation during its crop cycle, we found cultivated areas in ranges with less water availability. This phenomenon might occur because the precipitation ranges in the database are the sum of monthly average throughout the year and do not necessarily represent the water supply during the crop cycle. Therefore, for areas cultivated in ranges with lower precipitation than the optimal requirement, their water requirements could be satisfied during the raining season, despite the subsequent dry months.

Additionally, soil maps show values of variables in natural conditions; however, farmers may modify some of those conditions to meet optimal crop requirements. Many areas with scarce precipitation for cropping may be irrigated.

Table 11. Ranges of soil and climatic characteristics found inside *f7* class

Rice crop (Class <i>f7</i>) 163 441 ha					
Codes	Description	Area (ha)	Percentage (%)	Mean	Standard Deviation
Slope ranges (%)					
1	0-5	162,144	99	1398	3170
2	5-12	1297	1	68	108
Texture					
3	Medium	54,548	33	779	1488
4	Fine	34,066	21	710	1306
5	Very fine	74,826	46	4402	6686
Effective depth (cm)					
1	Superficial	92	0.06	13	20
2	Shallow	101,280	62	1809	4169
3	Moderately	15,160	9	892	1528
4	Deep	46,909	29	853	1613
Temperature ranges (°C)					
18	20-23	352	0.2	352	-
19	23-26	163,089	100	1 217	2985
Precipitation ranges (mm.year ⁻¹)					
1	0-200	1391	1	139	293
2	200-300	17,474	11	699	1355
3	300-400	38,554	24	1928	3674
4	400-500	62,027	38	2215	5018
5	500-600	23,834	15	993	1503
6	600-700	18,095	11	952	1623
7	700-800	2066	1	230	3768

We found that the *f15* class grouped a wider range related to slope, although the majority of its area (60%) had a slope of 0-5%, 34% of the total class area was in the 5-12% slope range, and just 6% had a slope of 12-25%, despite the more difficult and more expensive cultivation. Some farmers modified these conditions but in small areas.

There was an area with a slope higher than 50%, but it did not even reach 1% of the total class area. Fine was the predominant texture, comprising 75% of the *f15* class area, which is still adequate for rice crops. For climatic variables, there was no difference between the *f7* and *f15* classes in terms of temperature, but in terms of precipitation, the *f15* class grouped more of its area (65%) in the 700-900 mm year⁻¹ range.

In general, rice is located in *f7* (62% of the total rice crop in the study area) more than in *f15*, maybe due to their slope and texture, which are very important to rice cultivation system.

Five classes were automatically discarded from the complete study area when we intersected the rice crop layer of this area. Because these classes present limitations that farmers cannot correct or because cultivation would be very expensive, farmers do not cultivate rice on those areas. These classes and their main limitations included the following: the *f19* class with high slope and toxicity; the *f21* class with abundant stoniness, high slope and highly acidic pH; the *f22* class with high slope and abundant stoniness; the *f23* class with abundant stoniness and the *f25* class with coarse soil texture.

3.1.4.2 Maize

Maize was mainly cultivated in the *f15* and *f7* classes, reaching 75% of the total area. The *f15* class has an area of 181,900 ha (59%), and the *f7* class has an area of 51,313 ha (17%). The *f6* and *f17* classes that represented just 14% of the total area follow them.

We observed that the *f15* and *f7* classes jointly provided the best soil conditions for crops and grouped variable ranges in this same manner as in rice. However, the area distribution of ranges was changed according to maize crop requirements. For example, in the *f7* class, most of its area was concentrated in the slope ranges of 0-5% (89%) and 5-12% (12%) because flat soils are good for any crop mechanisation. However, in terms of texture, the majority of its area (83%) had medium texture because for maize cultivation flat soils and very fine textures can cause diseases. In the *f7* class, deep soils are predominant (74% of the total class area), followed by moderately deep (14%) and shallow (11%) soil. Maize requires moderately deep soils.

As observed in Table 12, the *f15* class was mainly grouped in slope ranges of 12-70%, totalling 82% of the class area. Despite being not advisable for short-cycle crops, farmers implement reduced or no-tillage practices that reduce or avoid soil erosion, and some of these areas are used for maize production because farmers do not have better options for rainfed cropping. The texture of the *f15* class area was mainly fine (71%) to medium (29%). The effective depth was moderate in more than half of the area (56%), followed by shallow (29%), just 11% of the area was of superficial depth, and the latter corresponds to marginal maize crop production.

The *f7* class grouped almost its entire area (98%) in the temperature range of 18-19°C. The *f15* class grouped the majority of its area in the same range of temperature as found in the *f7* class but contained 9% of its area in the 16-18°C range and insignificant areas in a temperature range of less than 16°C. The location of maize crops in these areas can be explained because some cultivars of hard maize are tolerant to slightly lower temperatures, especially south of the study area in Loja Province, which is a low mountain region.

The *f7* class grouped a wide range of precipitation, but maize areas are concentrated in the 0-300 mm year⁻¹ range (52% of the total class area), and 29% of the total class area was in the 600-800 mm year⁻¹ range. For the *f15* class, we observed the same result, but the majority of the maize crop area (54%) was concentrated in the range of 600-900 mm year⁻¹, followed by a range of 0-300 mm year⁻¹ in 28% of the crop area.

Table 12. Ranges of soil and climatic characteristics found inside *f15* class

Maize crop (Class <i>f15</i>) 181 900 ha					
Slope range (%)					
Codes	Description	Area (ha)	Percentage (%)	Mean	Standard Deviation
1	0-5	11,383	6	670	962
2	5-12	15,850	9	311	1129
3	12-25	60,983	34	473	1405
4	25-50	51,113	28	301	691
5	50-70	36,822	20	247	476
6	>70	5750	3	77	160

Texture					
Codes	Description	Area (ha)	Percentage (%)	Mean	Standard Deviation
2	Moderately coarse	35	0.02	35	0
3	Medium	51,977	29	500	1410
4	Fine	129,870	71	268	716
5	Very fine	18	0.01	18	0
Effective depth (cm)					
1	Superficial	20,291	11	752	1777
2	Shallow	53,468	29	220	435
3	Moderately	102,420	56	394	1102
4	Deep	5721	3	94	232
Temperature ranges (°C)					
13	12-13	2	0.001	0.7	1
14	13-14	108	0.06	14	14
15	14-15	581	0.3	65	55
16	15-16	1405	1	83	105
17	16-17	5116	3	119	161
18	17-18	10,363	6	86	152
19	18-19	164,325	90	420	1061
Precipitation ranges (mm.year ⁻¹)					
1	0-200	18,787	10	368	814
2	200-300	32,059	18	276	833
3	300-400	9489	5	120	275
4	400-500	9341	5	114	297
5	500-600	14,917	8	174	390
6	600-700	57,901	32	752	1640
7	700-800	16,841	9	276	530
8	800-900	22,566	12	579	1374

We found classes that grouped unsuitable characteristics of soil and climate for maize cropping; these classes were excluded when we intersected total study areas with maize coverage, suggesting that farmers do not use those lands due to their unsuitable

conditions. This finding demonstrates that the factorial method satisfactorily grouped soil characteristics, separating suitable and unsuitable groups for cropping rice and maize. These classes and their main limitations were as follows: the *f1* class with a coarse soil texture, superficial effective depth, and excessive soil drainage. The *f13* class with very fine soil textures, superficial effective depth, poor soil drainage, superficial ground water and high salinity. The *f14* class with very fine soil textures, superficial effective depth, poor soil drainage, superficial ground water and very high salinity. The *f19* class with a high slope and toxicity, the *f25* class with coarse soil texture, and the *f26* class with a high slope, very fine soil texture and superficial effective depth.

3.1.5 Comparison of maps

To better appreciate the differences of control, climatic and factorial maps, a zone where a large rice and maize cultivated area was magnified (see in Fig. 10.B, Fig. 11.B, and Fig. 13.B; respectively). The control map presents many different classes compared to the climatic map, which only shows a few classes that represent the climatic variability missing soil variability. The factorial map grouped some of the control map classes, resulting in a lower number.

Spatially, the three maps present a certain similitude in the Southwest, where the variability in the soil is lower as it can be observed in the control map classes. Whereas along the East, the control map presented many classes, the factorial map showed fewer classes, and the climatic map presented just one class. This result means that the factorial map summarised soil characteristics better than the control map but conserved variability, which could not be found in the climatic map.

3.2 Evaluation of agro-ecological variability effects on an eventual index-based insurance design for extreme events

3.2.1 Representative agro-ecological homogeneous zones (AHZs)

In Babahoyo canton on rice crop coverage, we found seven AHZs, the most representative being *f7* with 17,110 ha and *f15* with 24,676 ha; these two zones accounted for 91% of the study area, as seen in Fig. 4 D.

As shown in Table 13, the most important agro-ecological differences between zones *f7* and *f15* are slope, altitude, texture, and effective depth as well as precipitation.

Table 13. Soil and climatic characteristics of agro-ecological homogeneous zones (AHZs) in Babahoyo canton

<i>Characteristics</i>	<i>f7</i>	<i>f15</i>
Slope	0-5%	5-12%
Altitude	1-12 m	>12-35 m
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 °C	24-25 °C
Precipitation	500-700 mm	700-900 mm
Soil Classification*	Typic Hapluderts	Vertic Eutrudepts

*According to USDA Soil Taxonomy (Soil Survey Staff, 2014)

3.2.2 Statistical analysis of soil variability

Reviewing the descriptive statistics (Table 14), skewness and kurtosis values were less than 2.0 indicating possible normality for datasets of reflectance and NDVI_ave, allowing us to continue with the analysis of variance.

Table 14. Descriptive statistics of bare soil reflectance bands (red, NIR, blue and MIR) and NDVI_ave of rice crop cycle

	<i>Reflectance</i>				<i>NDVI_ave</i>
	<i>Red</i>	<i>NIR</i>	<i>Blue</i>	<i>MIR</i>	<i>Rice crop cycle</i>
	<i>Bare soil (January 1st)</i>				<i>(January 15th– May 15th)</i>
Mean	0.285	0.368	0.244	0.231	0.468
Typical error	0.001	0.001	0.001	0.001	0.001
Median	0.283	0.374	0.255	0.229	0.487
Standard deviation	0.102	0.108	0.105	0.076	0.116
Kurtosis	1.866	1.158	-0.130	-0.056	0.559
Skewness	0.555	0.222	-0.060	0.154	-0.785
Count	6213	6213	6213	6213	31,756

As listed in Table 15, the reflectance of bare soil for the red, blue, NIR, and MIR bands is significantly different between zones *f7* and *f15*. This could be due to the different soil characteristics of each zone. According to Thomasson et al. (2001), soil properties such as texture, mineralogy, organic matter and soil moisture can be discriminated using remote sensing.

Table 15. ANOVA for agro-ecological homogeneous zones (AHZs) of bare soil reflectance bands (red, NIR, blue, and MIR)

Source	Square sum	F.D.	Mean square	F-Ratio	P-Value
Red					
<i>Inter-AHZ</i>	0.27	1	0.27	25.58	0.000
<i>Intra-AHZ</i>	64.92	6211	0.01		
<i>TOTAL (CORRECTED)</i>	65.19	6212			
NIR					
<i>Inter-AHZ</i>	0.73	1	0.73	63.22	0.000
<i>Intra-AHZ</i>	71.61	6211	0.01		
<i>TOTAL (CORRECTED)</i>	72.34	6212			
Blue					
<i>Inter-AHZ</i>	0.59	1	0.59	54.09	0.000
<i>Intra-AHZ</i>	67.88	6211	0.01		
<i>TOTAL (CORRECTED)</i>	68.47	6212			
MIR					
<i>Inter-AHZ</i>	0.05	1	0.05	9.49	0.0021
<i>Intra-AHZ</i>	35.63	6211	0.01		
<i>TOTAL (CORRECTED)</i>	35.68	6212			

Italic and bold represent significant statistical difference

The reflectance is lower with higher the soil moisture in soils with low humidity, such as those in the study area at the beginning of the rainy season (Weidong et al., 2002). For the red, NIR and blue bands, the reflectance is lower in zone *f15* than that in *f7* (Fig. 14 A, B, C) which is in agreement with Table 13. The AHZ *f15* is within a higher precipitation zone (700-900mm annually), compared to that of *f7* (500-700mm annually); thus, *f15* could have higher soil moisture content. On the other hand, the dynamics of water availability in each zone during the rice crop cycle is complex, influencing other factors. The slope and texture of the soil of *f7* could provide better conditions for retaining water as the soil has finer texture and is flatter than that of *f15*. As seen in Fig. 5 C (RapidEye scene of March 2012) during a year with excessive precipitation, zone *f7* presents some flooded areas, while zone *f15* does not show any trace of poor drainage.

The reflectance of NIR (Fig. 14 B) in *f7* (0.38) corresponds to a clay soil, according to Thomasson et al. (2001); *f15* has a reflectance of 0.36, which indicates slightly lower clay content. This difference is in agreement with the soil characteristics (Table 13) and with the statement that a finer soil texture has greater reflectance (Mouazen et al., 2005).

Figure 14. Least significant difference test (LSD) for reflectance means of agro-ecological homogeneous zones *f7* and *f15*, by Fisher: A) for red band, B) for near infra-red band NIR, C) for blue band, and D) for medium infra-red MIR

Gomez et al. (2008) used MIR to determine soil organic carbon (SOC) content and found that values less than 1% of SOC are not accurately discriminated. Along the same line, Henderson et al., (1992) mentioned that the reflectance percentage decreases when organic matter content increases. The AHZs *f7* and *f15* are in the same range of soil organic matter (2-4%), which correspond to moderate organic matter content (Krishnan et al., 1980). However, the MIR reflectance is significantly different between AHZs *f7* (0.234) and *f15* (0.227), which indicates that *f7* has more organic matter content than that of *f15* (Fig. 14 D).

3.2.3 Statistical analysis of NDVI

As seen in Table 16, both variability factors (AHZ and years) and their interaction have a significant effect on NDVI_ave, with a confidence level of 99% and p-values of less than 0.01.

According to a multiple rank test of 99% LSD (Fig.15 A), the mean of NDVI_ave for a rice crop cycle of *f7* (0.45) is significantly different to that of *f15* (0.48), showing that the variability found between these zones over bare soil also persists under rice cultivation.

Table 16. ANOVA of NDVI_ave for agro-ecological homogeneous zones (AHZs) *f7* and *f15*

Source	Sum of squares	F.D.	Mean square	F-Ratio	P-Value
<i>MAIN EFFECTS</i>					
<i>A:AHZ</i>	6.40	1	6.40	663.1	0.000
<i>B:Years</i>	108.35	16	6.77	701.35	0.000
<i>INTERACTIONS</i>					
<i>AB</i>	15.08	16	0.94	97.63	0.000
<i>RESIDUES</i>	306.30	31,722	0.01		
<i>TOTAL (CORRECTED)</i>	429.82	31,755			

Italic and bold represent significant statistical difference

Figure 15. A) Multiple rank test (LSD) for NDVI_ave means of agro-ecological homogeneous zones (AHZs) *f7* and *f15*; B) NDVI average distribution along rice crop cycle for AHZs *f7* and *f15* zones; and C) histograms of NDVI_ave data in analysed period (2001-2017) in Babahoyo for *f7* and *f15*, (t) drought affection threshold (0.4)

The variation regime of NDVI during the rice crop cycles of *f7* and *f15* analysed for the period is also different (Fig. 15 B). In *f15*, due mainly to favourable soil conditions for rice crops, the NDVI increased from 15th January (at sowing) until March, when the crop has reached its maturity (flowering). Then, it diminishes during April and May during the rice's senescence. Meanwhile, the NDVI in *f7* follows a similar pattern but present slower values compared to *f15*. As seen in Fig. 15 B. the growth of rice in *f7* is limited by soil conditions both for the crop's development and during the time that it takes to achieve maturity at April, one month later than that of *f15* (May).

3.2.4 Effect of soil variability on failure probability in rice crops

Calculating the percentage of NDVI values under the selected threshold ($t = 0.4$), we observed that *f7* had more events (25%) than that of *f15* (17%) for the analysed 17 years (Fig. 15 C). The Z-test shows that these proportions of accumulated events in each AHZ (*f7* and *f15*) are significantly different because the calculated Z value (18.06) is outside the critical rate.

As previously mentioned, the different soil characteristics of AHZs *f7* and *f15* affect their risk of extreme events (drought and flood) for rice crops at different levels. The interaction between agro-ecological characteristics and these phenomena are clear. AHZ *f7* is more affected by floods than is *f15*, due to, *f7*'s very fine texture (>50% clay), low altitude (1-12m) and flat topography, hindering the proper drainage and accentuating its flooding vulnerability. On the other hand, under drought conditions, the *f7* soil characteristics resulted in better water retention than those of *f15*, but at the same time, this water is not easily available to crops (Baver et al., 1972). Under extreme drought conditions, the Vertisol soil order (Soil Survey Staff, 2014) becomes difficult to till, presenting deep and wide cracks that can even destroy roots.

3.2.5 Sampling density effect

Several sampling densities for both AHZs were tested showing that there was no significant difference among the 5% to 30% densities (Table 17). At any of the densities tested, both AHZs were significantly different. In other words, the difference in NDVI_ave between AHZ *f7* and *f15* was always statistically significant and discriminated at all sampling densities (Fig. 16). This shows that once the sampling is stratified into two AHZs, the NDVI_ave is quite homogeneous in each AHZ, maintaining a statistically significant difference even at low sampling densities (5 and 10%).

Table 17. ANOVA for different NDVI sampling densities of agro-ecological homogeneous zones (AHZs) *f7* and *f15*

Source	Sum of squares	F.D.	Mean square	F-Ratio	P-Value
<i>MAIN EFFECTS</i>					
<i>A: Sampling density</i>	0.03	5	0.007	0.52	0.7585
<i>B:AHZ</i>	5.80	1	5.802	470.96	0.000
<i>INTERACTIONS</i>					
<i>AB</i>	0.09	5	0.018	1.49	0.1879
<i>RESIDUES</i>	1127.50	91,520	0.012		
<i>TOTAL (CORRECTED)</i>	1136.13	91,531			

Italic and bold represent significant statistical difference

In practical applications, a representative and accurate NDVI_ave value is desirable. Observing Fig. 16, any of the sampling densities provide a stable value for each AHZ. However, 5% sampling density shows a higher variance, and thus, a sampling density of at least 10% is desirable. In the context of IBI, 10% sampling density is recommended.

Figure 16. Multiple rank test (LSD) of NDVI_ave means for the interaction between agro-ecological homogeneous zones (*f7* and *f15*) and sampling densities

3.3 Design of an NDVI index-based insurance for covering economic impacts in rice cultivation

3.3.1 Statistical analysis

From descriptive statistical analysis, the kurtosis (0.56) and a skewness (-0.78) indicated that the dataset of NDVI_ave fits a normal distribution; however, the Lilliefors (Kolmogorov-Smirnov) normality test, showed: $D = 0.0802$ and a $p\text{-value} < 2.2e^{-16}$ lower than 0.05; then, we rejected the null hypothesis that the dataset comes from a normal distribution. We have found that our data fits a Generalized-minimum extreme value (GEVmin) distribution (Kotz and Nadarajah, 2000) for *cantonal* data set and for AHZs (*f7* and *f15*), as we can notice in Table 18 through the Chi-squared statistic.

As the data sets did not fit normal distributions, we used non-parametric test to determine if NDVI_ave in zones *f7* and *f15* are significantly different. The Kruskal-Wallis test for zone (Chi-squared = 345.48, F.D. = 1, $p\text{-value} < 2.2e^{-16}$), shows us that the null hypothesis of *f7* and *f15* are equal can be rejected, because the $p\text{-value}$ is lower than 0.05. The same test mentioned before, but this time for years, shows us that years are also

significant different (Chi-squared = 7507.4, F.D. = 16, p-value < 2.2e-16 is also lower than 0.05). The results of LSD and Bonferroni tests are shown in Table 19.

Table 18. Parameters of GEVmin distribution for each AHZ and cantonal and distribution adjustment statistic of maximum likelihood

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

Table 19. Fisher's Least significant difference 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	<i>Very low</i> (Years affected by extreme climatic events)
2012	0.40	2013	0.41	
2013	0.40	2016	0.42	
2016	0.40	2012	0.42	
2017	0.42	2017	0.44	<i>Low</i> (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	<i>Normal</i> (Normal years)
2005	0.49	2005	0.49	
2011	0.49	2002	0.49	
2001	0.51	2001	0.52	<i>High</i> (Years with good climatic conditions)
2009	0.51	2009	0.52	
2007	0.52	2007	0.52	
2003	0.54	2004	0.54	<i>Very High</i> (Years with very good climatic conditions)
2004	0.55	2003	0.55	
2006	0.55	2006	0.56	

3.3.2 Rice-yield estimation

The observed rice-yield was plotted versus NDVI_ave in a rice crop cycle. A normal accumulative curve was adjusted (Equation [1] in Fig. 17 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), indicating that NDVI_ave is an adequate indicator for assessing the impact of drought and flood over rice crop (Fig. 17 B).

Figure 17. A) Scatter plot of observed rice-yield and NDVI_ave, curve of Equation [1] for estimating yield; and B) correlation of observed and estimated rice-yield

In this case study, the national rice-yield average is approximately 4.2 t/ha. In the region of Babahoyo canton, it is reported to be 5.7 t/ha. Introducing an NDVI_ave of 0.4 in Equation [1], a yield of 2.6 t/ha was obtained. This result is less than 50% of the regional average. This confirms that the NDVI_ave threshold of 0.4 of Valverde-Arias et al., (2018) is a reasonable value to be used under an extreme event scenario.

3.3.3 Thresholds determination

As shown in Table 19, years 2008, 2012, 2013 and 2016 belong to the “very low category” due to their lowest NDVI_ave, both for LSD (Mean) and Bonferroni (Median) tests. NOAA, (2018) showed that these years were affected by extreme climatic events, whose

application contains and plots historical climatic data. In this case, we analysed the combined precipitation anomalies, in which (0) represents no precipitation anomaly. As we can see in Fig. 18 A and B, Babahoyo canton presented positive anomalies of precipitation (floods) in the years 2008 and 2012; and negative anomalies of precipitation (drought) in 2013 and 2016, see Fig. 18 C and D.

Figure 18. Positive anomalies of precipitation (flood) in A) year 2008, B) year 2012, E) year 2010, F) year 2017; negative anomalies of precipitation (drought) in C) year 2013 and D) year 2016, G) year 2014 and H) year 2015.

Source: NOAA, (2018)

Once, we characterised the years affected by extreme events, we could define the different impact thresholds. A threshold for total loss (when damage in rice crop produced by

extreme events reduces rice's yield to less than 0.5 t/ha, NDVI_ave = 0.26) is detectable neither at cantonal level nor at AHZs (*f7* and *f15*) level.

The physiologic threshold represents the maximum rice-crop damage detected through NDVI_ave that has been produced by an extreme event. It is the same (0.4) for both AHZs (*f7* and *f15*) and *cantonal* (see Table 20). The years when, we reached the physiologic threshold in our data set were (2008, 2012, 2013, 2016), which have been years deeply impacted by extreme climatic events, see Table 19 and Fig 18 A, B, C and D.

On the other hand, an economic threshold depends on economic factors such as rice-price, production cost, and rice-yield. Thus, it is variable and had to be adjusted to the amount that farmers must earn for meeting their expenses, as it is shown in Table 20.

Table 20. 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)						Type of Insurance		
	<i>Cantonal</i>		<i>f7</i>		<i>f15</i>		<i>Cantonal</i>		<i>f7</i>		<i>f15</i>		Occurrence verification by	<i>IBI</i>	<i>Conventional</i>
	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	Gross margin	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	Gross margin	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)

As the economic threshold represents the minimum yield that farmers must reach for covering at least its 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*); due to *f7*'s 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 20). 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. 18 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*, thus the economic threshold (0.43) is the same for AHZs and *cantonal*.

3.3.4 Risk assessment of AHZ and Babahoyo canton

It was found that NDVI_ave dataset fits a GEVmin distribution. Therefore, we have used this distribution, with specific parameters (Mode and Scale, see Table 18) for estimating NDVI_ave density frequencies for *f7*, *f15*, and *cantonal*. The basis risk for this estimation is very low, see Adjusted R-squared in Table 21. Therefore, we can use confidently these estimations for determining the proportion of events under the physiologic and economic thresholds, i.e. the occurrence probability of extreme events that warrant compensations.

Table 21. Simulation of NDVI_ave by GEVmin distribution for AHZs and cantonal, and basis risk calculation between observed (O) and estimated (E) frequencies of NDVI_ave

<i>NDVI_ave</i> <i>Class</i>	<i>Frequency</i>					
	<i>O f7</i>	<i>E f7</i>	<i>O f15</i>	<i>E f15</i>	<i>O Cantonal</i>	<i>E cantonal</i>
<i>0.08</i>	25	204	8	73	330	34
<i>0.16</i>	310	391	171	117	434	482
<i>0.24</i>	758	590	462	357	957	1228
<i>0.32</i>	1215	1098	817	869	2032	2036
<i>0.40</i>	1963	1912	1583	2125	4119	3569
<i>0.48</i>	2929	2902	4751	4417	7345	7705
<i>0.56</i>	3413	3356	6863	6300	9375	10267
<i>0.64</i>	2206	2355	3232	3690	6141	5404
<i>0.72</i>	598	653	354	310	1004	933
<i>0.80</i>	78	37	17	0	19	95
<i>0.88</i>	3	0	0	0	0	3
Total Observations	13,498	13,498	18,258	18,258	31,756	31,756
Adjusted R-Squared	$R^2_{f7} = 0.99$		$R^2_{f15} = 0.98$		$R^2_{Cantonal} = 0.98$	

The 25% of events were found under the physiologic threshold for *f7* and 17% for *f15* (see Fig. 19 B, C); and when, we do not consider AHZs (*cantonal*) 21% see Fig. 19 A. The *f7*'s probability is higher, because the soil conditions of *f7* (see Table 13) make this 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. As the same as for drought, these conditions could give to *f7* better capacity for water retaining for long time. However, when drought is extreme and the soil get dried, it becomes very hard and presents deep cracks, which affects physically the crop's roots and make soil almost impossible to be tillage, all these characteristics are typical of Vertisols (Soil Survey Staff, 2014), which is the predominant soil order of this zone.

Figure 19. Generalized-minimum extreme value (GEVmin) distribution of NDVI_ave for physiologic threshold for: A) *cantonal*, B) *f7* and C) *f15*

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 Fig.

20 A, C and E. It is because in this scenario, *f15*'s farmers have to cover the higher production cost (which corresponds to semi-technical production system); for which, they have to reach an economic threshold also higher (0.47) than that one in the *f7*.

For 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%). It is because, although that for this scenario the economic threshold is the same for both AHZs (*f7* and *f15*) and *cantonal*, their frequency distribution of NDVI_ave categories were different, accumulating different probabilities under the threshold according each case, as shown in Fig. 20 B, D and F.

Figure 20. 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*

According to Z-test (see Table 22), Z is out of the critical interval both for physiologic and economic thresholds (including scenarios 1 and 2). Then, the null hypothesis ($H_0: p_1 = p_2$) can be rejected and we can assert that the proportion of positive cases (equal or under thresholds) in *f7* are significantly different from that in *f15*. However, under the difference production cost (scenario 1) for economic threshold, the calculated Z is negative, because in this case the probability of *f15* is higher than *f7*.

Table 22. Z-test for probability of events susceptible of compensations (ESC) under physiological and economical and thresholds in AHZ (*f7* and *f15*) and cantonal

	Type of threshold	Observations	Positive events	Probability	Critical rate	Z test
Non differentiated production cost/ differentiated production cost	<i>Physiological threshold cantonal</i>	31,756	6669	0.21		
	<i>Physiological threshold f7</i>	13,498	3375	0.25	$Z \leq z_{0.025} = -1.96$ $Z \geq z_{0.975} = 1.96$	18.06
	<i>Physiological threshold f15</i>	18,258	3041	0.17		
Differentiated production cost (scenario 1)	<i>Economic threshold cantonal</i>	31,756	9209	0.29	$Z \leq z_{0.025} = -1.96$	
	<i>Economic threshold f7</i>	13,498	4320	0.32	$Z \geq z_{0.975} = 1.96$	13.59
	<i>Economic threshold f15</i>	18,258	4565	0.25		
Non differentiated production cost (scenario 2)	<i>Economic threshold cantonal</i>	31,756	9209	0.29	$Z \leq z_{0.025} = -1.96$	
	<i>Economic threshold f7</i>	13,498	3510	0.26	$Z \geq z_{0.975} = 1.96$	-21.35
	<i>Economic threshold f15</i>	18,258	6756	0.37		

3.3.5 Insurance contract design

3.3.5.1 Indemnity calculation

The indemnity for insured investment in scenario 1 is shown in Table 23. These values show us the deficit (negative numbers) that farmers face for recovering their production costs at physiologic threshold, in each AHZ (*f7* and *f15*) and *cantonal*. It means that farmers have spent more money than that they received for their production. The indemnity for *f7* is only 38 USD/ha, it is because over this scenario when a farmer reaches physiologic threshold, he could almost cover his production cost, which is also low. 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 farmer would receive as compensation in case of an extreme event.

For scenario 2, as the production cost (1259 USD/ha) is the same for each AHZ (*f7* and *f15*) and for *cantonal* and the rice-yield at physiologic threshold also is the same, the indemnity would be 275 USD/ha for all of them. In Ecuador, as has been mentioned throughout this work, it already exists an agricultural conventional insurance that covers farmer's investment; but we included this calculation as an alternative for those places where conventional insurance cannot be suitable.

Table 23. Indemnity calculation for physiologic threshold in AHZ (*f7* and *f15*) and cantonal

	Expected yield at physiological threshold (t/ha)	Price (USD/t)	Gross incomes (USD/ha)	Differentiated production cost (USD/ha)	Deficit for covering investment (USD/ha)
<i>Cantonal</i>	2.65	371.5	984.4	1259.00	-274.6
<i>f7</i>	2.65	371.5	984.4	1022.00	-37.6
<i>f15</i>	2.65	371.5	984.4	1629.00	-644.6

For economic threshold, the indemnity calculation (840 USD/ha) is equal in both scenarios 1 and 2, for *cantonal*, as shown in Table 24. Because, they used the same weighted average as production cost (1259 USD/ha). For *f7*, it is expected higher net income in scenario 1 than that in scenario 2, due to scenario 2's production cost being higher. On the contrary, for *f15* the net income is higher in scenario 2 than that in scenario 1; because in scenario 2, *f15* has lower production cost than that in scenario 1.

As we can observe in Table 24, the insured amount in scenario 1 is very close for AHZ (*f7* and *f15*) and *cantonal*, although the expected yields are different. It is because their production cost has been related with their expected yield; thus, for example, if *f15* has higher expected yield, it should be because farmers have invested more money in their crop. Thus, the difference in the premium price of these zones will be determined by the different probability of extreme events occurrence of each AHZ (*f7* and *f15*) and *cantonal*.

In scenario 2, on the contrary, we have assumed the same production cost for *f7* and *f15*; thus, *f15* has higher expected yield in normal years than that *f7*. Obviously, in this scenario *f15* obtained the highest gross margin (1223 USD/ha), having also the highest insured amount, which would be reflected in a high premium cost. On the other hand, *f7* has the lowest insured amount (640 USD/ha), so that its premium cost also should be low;

although for premium cost calculation, it is also very important the occurrence probability of the insured extreme event.

Table 24. Calculation of net incomes (gross margin) for economic threshold, for each AHZ (*f7* and *f15*) and *cantonal*, both in scenario 1 and 2

	Expected yield in normal years (t/ha)	Price (USD/t)	Gross incomes (USD/ha)	Production cost scenario 1* (USD/ha)	Gross margin Scen.1 (USD/ha)	Production cost scenario 2** (USD/ha)	Gross margin Scen.2 (USD/ha)
<i>Cantonal</i>	5.65	371	2099	1259	840	1259	840
<i>f7</i>	5.11	371	1899	1022	877	1259	640
<i>f15</i>	6.68	371	2482	1629	853	1259	1223

* Scen. 1 = Differentiated production cost, ** Scen. 2 = Non differentiated production cost

3.3.5.2 Premium determination

The premium value is related to the insured amount (the amount of money that insurance company must pay to farmers when an insured extreme event occurs) and the probability of the insured extreme events occurs in a determined period.

In general terms, it can be appreciated that premiums for economic thresholds are more expensive than that premiums for physiologic threshold, for both scenarios (1 and 2); it is because in economic threshold the insured amount is the entire gross margin. While in physiologic threshold, the insured amount only covers the reduction of the production, which is necessary for covering the investment.

When the insured amounts are similar among AHZ (*f7* and *f15*) and *cantonal*, the difference in premium cost is determined by the occurrence probability. When the differences among insured amounts of AHZ (*f7* and *f15*) and *cantonal* are wider, they have more influence over premium cost variation than the occurrence probability.

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

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

Also, for physiologic threshold in scenario 2, the insured amount is equal in all AHZ (*f7* and *f15*) and *cantonal*, thus their premium cost has been differentiated through the occurrence probability, being the highest for *f7* (85.82 USD/ha). While, when we do not differentiate the production cost, *f15* has the highest gross margin, therefore a high-ensured amount. Despite its low occurrence probability (0.25), it has a high premium price (382.29 USD/ha), but lower than that for *f15* in scenario 1 (394.66 USD/ha), where its occurrence probability is the highest (0.37).

As it can be appreciated in Table 25, after we divided the study area through AHZs map in *f7* and *f15* zones, we can perform more accurate calculations of the premium costs according to the expected yield, insured amount and occurrence probability of each AHZ (*f7* and *f15*).

The price of the premium could be expensive for some farmers, but we have to consider that this insurance will cover the more frequent and intense two extreme events that affect Babahoyo canton (drought and flood). In addition, the government, lowering the cost for farmer, would subsidize a percentage (60%) of the premium cost.

By differentiating the study area through AHZs (*f7* and *f15*), we can design an accurate insurance policy where farmers from each zone pay the corresponding premium to the risk they are facing. For example, under scenario 1 for physiological threshold, when we did not differentiate between AHZ and use *cantonal* as IIA. An average farmer (farm of 20 ha) from *f15* only would pay 72.09 USD/ha, having as compensation only 4915.68 USD which is less than half of what he would actually lose in a year when an extreme event occurs (11,796.56 USD).

Besides, if government would apply prevention policies, as promoting farms' modernization, farmer's technical training, and civil works such as dams and irrigation infrastructure that could improve the risk status of Babahoyo farmers. The occurrence probability of extreme events could be reduced or at least mitigate its impact. This could be reflected also in a reduction of the premium cost.

Table 25. 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)	Difference between insured and not insured average farm of 20 ha (USD)*
<i>Scenario 1 (Differentiated production cost)</i>								
Physiologic	<i>Cantonal</i>	0.40	274.62	0.21	57.67	72.09	1287.83	4915.68
	<i>f7</i>	0.40	37.62	0.25	9.4	11.76	1026.70	658.32
	<i>f15</i>	0.40	644.62	0.17	109.59	136.98	1683.79	11796.56
Economic	<i>Cantonal</i>	0.43	840.21	0.29	243.66	304.58	1380.83	14367.56
	<i>f7</i>	0.41	877.28	0.26	228.09	285.12	1136.05	15264.64
	<i>f15</i>	0.47	853.31	0.37	315.73	394.66	1786.86	13908.92
<i>Scenario 2 (Non differentiated production cost)</i>								
Physiologic	<i>Cantonal</i>	0.40	274.62	0.21	57.67	72.09	1287.83	4915.68
	<i>f7</i>	0.40	274.62	0.25	68.65	85.82	1293.33	4805.84
	<i>f15</i>	0.40	274.62	0.17	46.68	58.36	1282.34	5025.52
Economic	<i>Cantonal</i>	0.43	840.21	0.29	243.66	304.58	1380.83	14367.56
	<i>f7</i>	0.43	640.28	0.32	204.89	256.11	1361.44	10756.72
	<i>f15</i>	0.43	1223.32	0.25	305.83	382.29	1411.91	21408.08

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

3.4 Generation of a drought risk map for rice cultivation using GIS: case study in Babahoyo canton (Ecuador)

3.4.1 Adapted land evaluation map for rice cropping

From the adapted LEM for rice cropping in Babahoyo canton, we found 35,555 ha to occupy the suitable category, 40,158 ha to occupy the moderately suitable category, 17,172 ha to occupy the marginally suitable category and 9,632 ha to occupy the unsuitable category. Suitable and moderately suitable categories were found to account for 70% of the area of Babahoyo canton. These results indicate that Babahoyo canton includes favourable topographic and soil conditions for rice cropping. We only found adverse conditions for rice cropping along high slopes east of the canton, as this area includes foothills of the Andes Mountains.

3.4.2 *Rice crop location suitability categories*

Degrees of suitability of the rice crop locations according to the adapted LEM are as follows: 23,308 ha of rice fields occupy the suitable category; 15,303 ha of rice fields occupy the moderately suitable category; 6798 ha of rice fields occupy the marginally suitable category, and only 550 ha of rice fields occupy the unsuitable category. We also found 597 ha to occupy the “0” category, which corresponds to a rice crop area in officially non-agricultural lands.

The rice crop area mainly extends across suitable and moderately suitable land that accounts for 83% of the rice farming area. This means that soil variables are determinants when farmers select land for rice cropping based on particular rice farming requirements (slope and texture in particular). Applying the pooled culture system, which is widely used for this crop, requires access to flat soils of a very fine texture to form pools and to maintain pool water levels over a certain length of time.

About risk levels, this map provides a clear account of soil conditions that farmers must work with to cultivate rice, investments necessary to manage such conditions and degrees of crop susceptibility to drought events. It represents a first measure of vulnerability that we complement with a water availability evaluation.

3.4.3 *Availability water characterisation for rice cropping in irrigation requirement zones*

Fig. 21 shows how crop irrigation requirements are matched with precipitation levels for each irrigation requirement category throughout the crop cycle. We find that for the facultative category, crop requirements are satisfied at all stages of the rice crop cycle while for the complementary category, crops require irrigation in February, when requirements are higher than they are during any other stage. In the case of the indispensable category, we found water deficits for February and March. These two months are crucial for rice production, as they correspond with maximum vegetative development stages. Water deficits in these months could severely limit rice-cropping capacities if farmers do not properly manage available water or do not use irrigation. From these results, when a drought event occurs with the same intensity and magnitude in the study area, effects on the different irrigation categories can vary. Such information could not be inferred from the SPI, which only monitors drought patterns (Wu et al., 2004).

Figure 21. Monthly water precipitation in each irrigation requirement category and water requirement during growth stages of rice

3.4.4 Drought vulnerability map

We found 2509 ha that exhibit low levels of drought vulnerability; 36,101 ha that exhibit moderate levels of drought vulnerability. 6798 ha that exhibit high levels of drought vulnerability and 550 ha that exhibit very high levels of drought vulnerability, see Fig. 22 A. Areas of moderate drought vulnerability account for 78% of the total rice crop area in Babahoyo canton. In the DVE, we can appreciate the combined effects of soil and climatic patterns on drought vulnerability.

The pooled culture system affects drought vulnerability levels in Babahoyo canton, as this system is more water intensive and renders rice crops more susceptible to water shortages. The MAG of Ecuador should consider switching from the pooled culture system to the use of a conventional culture system that is less water intensive. Such considerations should evaluate the technical and economic feasibility of such a change and consider farmers' views.

Figure 22. Model that used soil and climate to generate drought risk map: A) drought vulnerability map, B) drought risk map DRM, C) adjusted DRM. Model that used only climate to generate drought risk map: D) drought hazard map, E) operative irrigation projects used to adjust DRM and DRcM, F) drought vulnerability map only based in water availability, G) drought risk map DRcM only based in climatic vulnerability and hazard, and H) adjusted DRcM

From our drought vulnerability map, we can diagnose the current state of rice crops according to soil characteristics and water availability levels. In this way, we can differentiate between potential effects of drought on each forms of vulnerability.

3.4.5 Drought risk map (DRM)

As is shown in Fig. 22 B, from the DRM, we found only 71 ha that occupy the low drought risk category; 38,538 ha that occupy the moderate drought risk category; 6798 ha that occupy the high drought risk category, and 550 ha that occupy the very high drought risk category.

From the DRcM shown in Fig. 22 G, we found 510 ha that exhibit low levels of drought risk and 45,448 ha that exhibit moderate levels of drought risk, but we did not find indications of high and very high drought risk areas. Therefore, this model is limited in that it does not account for risks related to soil characteristics, which are also very important.

3.4.6 *Adjusted drought risk map*

Fig. 22 C shows the adjusted DRM. We extracted climatic limitations and drought hazards for the study areas that are irrigated. We identified 9492 ha in the low drought risk category; 29,118 ha in the moderate drought risk category; 6798 ha in the high-risk category, and 550 ha in the very high-risk category. After adjustments are made, we can observe the real conditions of rice crops in Babahoyo canton. We appreciate that with the current OIP (Fig. 22 E), 20% of the rice crop area has improved in terms of risk levels from moderate to low drought risk levels. With new irrigation projects, we could increase this area to 23,308 ha, as determined under the suitable category of the adapted LEM.

For high- and very high-risk categories, even when we provide irrigation to these areas, their risk status does not change because their main risk factors are related to the soil. Hence, we recommend (especially for areas of very high drought risk) that rice should not be cultivated in these areas, as farmers are assuming too many risks. Additionally, it is difficult for farmers to secure agricultural insurance that covers their crops, and when they do, resulting premiums are very expensive.

The results of the adjusted DRcM (Fig. 22 H) are as follows: 19,558 ha in the low drought risk category and 26,400 ha in the moderate drought risk category. For irrigated areas, the low-risk category increases to 41%.

In the intersected adjusted DRM with political divisions, we can determine the rice crop area exposed to drought risks in each district of Babahoyo canton (Table 26). For example, Babahoyo district exposure levels are very low, as 98% of the rice cropping area is exposed to low and moderate drought risks. In contrast, 31% and 15% of the La Unión district is exposed to very high and high drought risks, respectively. This information shows us that should a drought occur, large areas of rice cropping land in La Unión could be affected by drought.

Table 26 shows that Babahoyo and Caracol are the districts with the smallest proportions of area exposed to drought risks while La Unión is the most exposed followed by Fébres Cordero and Pimocha. In absolute terms, Fébres Cordero (3864 ha) is the district with the largest area of high drought risk, followed by Pimocha with 2558 ha; La Unión is the district with largest area of very high drought risk at 409 ha.

Table 26. Proportion of each drought risk category in rural districts of Babahoyo canton

District <i>i</i>	Risk categories <i>k</i>					Total area (ha)
	Low drought risk	Moderate drought risk	High drought risk	Very high drought risk		
	(0*)	(1)	(2)	(3)	(4)	
	Percentage (%) DRM					
Babahoyo	0.87	40.59	57.73	0.65	0.15	14,297
Caracol	0.64	0.00	95.96	2.99	0.41	2735
Fébres Cordero	0.75	11.02	58.61	29.51	0.12	13,097
La Unión	1.62	5.38	47.04	15.16	30.81	1327
Pimocha	2.23	14.40	65.82	16.94	0.62	15,099
	Percentage (%) DRcM					
Babahoyo	0.87	41.80	57.33	0.00	0.00	14,297
Caracol	0.64	1.10	98.26	0.00	0.00	2735
Fébres Cordero	0.75	41.40	57.85	0.00	0.00	13,097
La Unión	1.62	26.91	71.47	0.00	0.00	1327
Pimocha	2.23	51.48	46.30	0.00	0.00	15,099

* Category 0 correspond to non-agricultural lands as urban or protected lands but that however are being cultivated with rice

When soil crop requirements are removed from the adjusted DRcM (Table 26), we obtain only two risk categories. This reduction in the number of categories does not have evident repercussions for districts with a small percentage of drought-exposed area such as the Babahoyo and Caracol districts, where the elimination of high and very high-risk categories has hardly increased low and moderate category areas. However, for the remaining districts with larger exposed areas, there is a considerable increment.

3.4.7 Validation of the resulting maps

From the results of the NDVI_{ave} analysis for dry years, a threshold based on the mean value (0.4) was considered as the most representative one for drought years. This threshold is consistent with the work of Rulinda, Dilo, Bijker, & Stein (2012) for monitoring vegetative drought, which mentioned that NDVI pixels with a difference of -0.1 from the monthly NDVI average, could be considered as a drought risk area. In our case, we have a general monthly NDVI average of 0.49; therefore, all NDVI values under 0.39, approximately 0.4, would be a drought case. Other studies (Gu et al., 2007; Subash,

Ram Mohan, & Banukumar, 2011) agreed that NDVI values lower than 0.5 correspond to crop drought conditions.

According to our χ^2 test (Table 27), the null hypothesis stating that both factors are independent is rejected for the adjusted DRM and DRcM. Thus, NDVI_ave values under the threshold are not independent of risk categories of the adjusted DRM and DRcM. This implies that the riskier a category is, the higher the percentage of drought events becomes (see Table 27) in both risk maps.

Table 27. Proportion of drought events occurred in 2001-2014 in risk categories of DRM and DRcM in Babahoyo canton

Adjusted DRM categories	NDVI_ave<0.4 (%)	NDVI_ave>=0.4 (%)	
			$\chi^2 = 39.79 > 16.27$
1	19.91	80.09	$\chi^2 (F.D.=3, \text{prob.}=0.001) = 16.27$
2	22.59	77.41	
3	24.98	75.02	
4	27.86	72.14	
Adjusted DRcM categories	NDVI_ave<0.4 (%)	NDVI_ave>=0.4 (%)	
			$\chi^2 = 166.46 > 10.83$
1	18.72	81.28	$\chi^2 (F.D.=1, \text{prob.}=0.001) = 10.83$
2	25.44	74.56	

The results of our estimation of p_{sk} (for each category k in s years) for the adjusted DRM are shown in Table 28. We found that this estimation confirms our expected results for each risk category. For dry years, the probability of drought events is very marked according to each risk category. We found high probability levels for the high and very high risk categories, lower probability levels for the moderate category 2 and very low probability levels for the low risk category.

According to these results, we recommend that rice not be cultivated under category 4 due to a very high likelihood of production losses in a dry year, and in the event that agricultural insurance is applied, we should differentiate between insurance premiums based on categories of drought risk. For categories 1 and 2, premiums should be lower than they are for categories 3 and 4.

Table 28. Likelihood of a drought event occurring in drought risk categories

Agroseguro data (2010-2014)	Low drought risk (1)	Moderate drought risk (2)	High drought risk (3)	Very high drought risk (4)
Dry Years (2013-2014)	0.010	0.20	0.50	0.99
Regular years (remaining years)	0.005	0.04	0.05	0.70

On the other hand, in regular years, the probability of a drought event occurring in each risk category is not as obvious as it is for dry years, as in regular years, the occurrence and locations of drought events becomes more uncertain (Aimin, 2010). Thus, the probability of a drought event occurring in the first three risk categories is very low, although there are differences between categories 1, 2 and 3. However, for category 4, the probability is very high. For a regular year, the probability of a drought event occurring must be categorised under the riskiest category.

The results of our estimation of q_{sk} (for the two categories k for s year) for the adjusted DRcM are shown in Table 29. Drought events are most common under the drought risk category, which is the riskiest category. We also appreciate the difference between dry and regular years, as the likelihood of drought events is higher in dry years.

However, this model does not account for drought events occurring in dry years, as it does not include categories 3 and 4. Category 2 assumes this probability but it does not agree with levels of risk exposure that this category represents. This is confirmed by R_L , which presents a value much higher than 0 (**212.22**), meaning that the partitioned cluster in 4 categories explains the insurance data better than that with 2 categories. In other words, the adjusted DRM corresponds better with agricultural insurance data than the adjusted DRcM.

Table 29. Likelihood of a drought event occurs in drought risk categories

Agroseguro data (2010-2014)	Low drought risk (1)	Moderate drought risk (2)
Dry Years (2013-2014)	0.005	0.46
Regular years (remaining years)	0.001	0.1

From this validation, we can assert that our risk map assessment serves as an accurate representation of drought risks facing rice cropping. The scale of this map is semi-detailed (at the district level), which is very appropriate for the purposes of agricultural risk management.

4 CONCLUSIONS

4.1 General and specific conclusions

The NDVI index-based insurance is a technically feasible tool for rice-producers in Babahoyo canton, whose farms currently cannot be covered by traditional insurance. Alternatively, it could serve farmers who, despite being a conventional insurance's policyholder, wants or needs to extend their insurance coverage to cover also their gross margin. With our IBI design, the most important extreme climatic events (drought and flood) are covered. In the following points, I return to the main thesis's objective and summarise the main specific findings.

Is it possible to determine agro-ecological homogeneous zones (AHZs), from an agro-ecological map of Ecuadorian Coastal region?

- The control map summarises the real variations in soil, topographic and climatic characteristics. This map was defined based on technical criteria for grouping values of selected variables: slope, texture, effective depth, temperature and precipitation. These variables are the most important variables in the database that reflect soil water content. Accordingly, with these criteria, this method successfully reduced soil variability to 193 homogeneous classes, which could be useful information for managing index-based insurance. The separation into groups by different precipitation ranges did not correspond with crop soil usage, because we found large cultivated areas with rice and maize inside different ranges of precipitation, even in unsuitable ranges, but almost always under optimal soil conditions. This means that isohyets information is not representative of the soil water availability in crop cycles. Additionally, some of these areas with insufficient water may be irrigated.
- The climatic map adequately represents climatic variation with only 11 homogeneous classes in the study area. Summarising the information to few classes is adequate for managing index-based insurance, but we missed important variability of soil characteristics that could influence index values variations.
- PCA is a convenient and effective method for homogenising efficiently soil characteristics without expert judgement. However, the results must be validated by a spatial analysis with the current land usage.

- The factorial map assembles climatic topographic and soil variables by PCA, obtaining 26 homogeneous classes in the total study area. This method has generalised efficiently climatic, topographic and soil characteristics of the complete dataset, obtaining fewer classes than the control map but retaining the importance of soil variability. Twenty homogeneous classes in each crop are a manageable number of classes to implement index-based insurance; furthermore, we obtained two predominant classes (*f7* and *f15*), which must be the basis of sampling to establish the threshold index in the study area.
- The main homogeneous classes in the factorial map (*f7* and *f15*) corresponded with the optimal rice and maize requirements for soil and topographic variables, which was reflected in the land use. Precipitation, in this case, did not represent the availability of water in the complete study area. The temperature was not a source of variability for the rice crop because all the cultivated area with rice was in the optimum range for this crop. A similar phenomenon was observed for maize cultivation, though integrating a wider range of temperatures due to the broader temperature tolerance of maize.
- Further efforts are necessary, for generating accurate climatic information. Especially precipitation and water availability data in the vegetative period of these crops. The spatial distribution of irrigated areas is also required to explain some cultivated areas in unsuitable ranges of precipitation.

Are the differences, indicated by AHZs, reflected in the selected index (NDVI) and is NDVI an adequate flood and drought indicator?

- The differences between the AHZs *f7* and *f15*, as already observed in the agro-ecological map database, are obvious over bare soil using satellite imagery. Statistically significant differences for the reflectance means of *f7* and *f15* for the red, blue, NIR and MIR bands were found.
- AHZs *f7* and *f15*, which mainly differ in terms of soil, topographic and climatic characteristics have a reflection in response to rice crop growth. This effect has been detected over the NDVI average of the rice crop cycle (NDVI_ave), and significant differences in the NDVI_ave of AHZs *f7* and *f15* were found.
- The percentage of values under the threshold of NDVI_ave of 0.4, related to rice crop failure, in AHZs *f7* and *f15* are statistically significantly different: 25% and

17%, respectively. These results clearly show a higher crop failure probability in *f7* than in *f15*. In the context of IBI implementation, it is necessary to adjust the premium price for each AHZ; otherwise, insurance would not be sustainable as the *f15* farmers will eventually leave.

- Significant differences among sampling densities were not found, because of the very low intra-variability of AHZ and the high AHZs inter-variability. In other words, NDVI_ave is quite homogeneous inside each AHZ and very different between AHZs *f7* and *f15*. For practical purposes in IBI implementation, a 10% sampling density is recommended, as it presents adequate accuracy and representativeness, as found in this case study.

Is it technically and economically feasible to design an IBI for rice cultivation in Babahoyo canton?

- We have found two levels of impacts resulting from climatic extreme events over rice cultivation. The first one is the physiological impact that is determined by physiologic threshold; it occurs when a climatic event is extreme. Our proposed insurance contract will cover losses of the crop's working capital. In addition, the second is the economic impact, which is determined by economical threshold when the climatic event is moderate, and our proposed insurance policy will cover the crops' gross margin.
- The design of differentiated premium calculation, based on the risk status and insured amount of each AHZ (*f7* and *f15*), allows farmers to pay an insurance premium that fits as much as possible with their risk status and to receive compensations that effectively could 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 multi risk status of Babahoyo canton, has been reduced in our IBI design, through dividing this canton into *f7* and *f15* zones, reducing in this way the possible bias caused for not discriminating Babahoyo variability.
- The cost for contracting an insurance policy might be in some cases unaffordable, but farmers have the security that they are paying for the risk that they are facing and for the expected compensation that they will receive when an insured hazard

happens. Besides, this kind of insurance is most of the times partially subsidized by the government, especially in developing countries as Ecuador, which could make this insurance affordable to farmers.

Finally, is there an alternative for agricultural risk management in Babahoyo canton?

- Babahoyo canton is generally characterised by good soil and topographic characteristics for rice cropping. Regarding climatic characteristics, temperatures in the study fall within an optimum range. Precipitation levels of the facultative irrigation category are enough, but those of the complementary and indispensable categories must be managed to supply a water deficit during one or two deficit months of the rice crop cycle. A drought risk map was generated by evaluating soil, climatic and land use cartography data through a geographic information system.
- Drought vulnerability levels for rice cropping in Babahoyo canton are predominantly moderate (76%), as many soil characteristics are adequate for rice cropping and soil water retention, and in regular years involving enough precipitation management, farmers can supply water requirements to their rice crops.
- Drought risks are mostly moderate under natural conditions, accounting for 82% of the rice cropping area in Babahoyo Canton. This is due to the presence of largely suitable soil conditions for rice cropping with sufficient water supplies made available from precipitation falling in almost all crop cycle months in regular years and with moderate drought hazards found for nearly all areas of the canton.
- The adjusted DRM shows us that under current irrigation projects, much of the cultivated area (83%) is subjected to low and moderate levels of drought risk. However, it also shows that 15% of the rice crop area is exposed to high levels of drought risk, while 1.2% is exposed to very high levels of drought risk for soil variables. We thus recommend that farmers not cultivate rice in these areas. For areas of the high and very high drought risk categories, there is a 50% and 99% probability of losing crops, respectively.
- Both maps (the DRM and DRcM) have properly classified the study area into different drought risk categories based on our NDVI analysis. However, the

former explains more precisely insurance data, highlighting the importance of considering soil characteristics.

- The adjusted DRM can be used via index-based insurance implementation to help set premium values and to prevent adverse selection. For agricultural risk management, this map can allow the government to identify rice farming areas susceptible to drought risks; in turn, the government can focus on those most vulnerable to drought events. The model of the adjusted DRM can be enhanced according to new and more accurate data.
- The developed map can provide risk managers, farm extension agents and policy makers with important information on the extent to which rice farms face production risks triggered by drought. Based on this information, they can make informed decisions to mitigate the effects of drought on rice crops by implementing policies, mitigation work, grants and subsidies.

4.2 Limitations and further research

4.2.1 *Limitations during research*

The main limitation was data availability. Even though, we could count on high quality cartography data, we missed robust climatic data from weather stations in the study area. We solved this limitation obtaining complete climatic data, but with lower spatial resolution.

With access to complete conventional insurance data (Agroseguro), a comparison between their performance and our IBI design in Babahoyo canton might have been possible. Although, Agroseguro collaborated actively with our research, they could not be allowed to give us insurance companies' data due to confidentiality restrictions.

Another limitation was the relatively short time that we had for performing this research, leaving out the analysis of financial-economic scenarios of the proposed IBI design. This might have resulted in more efficient results, and perhaps lower costs.

4.2.2 *Limitations in proposed IBI product*

The main limitation found for IBI implementation was that this methodology is limited to homogeneous areas as alluvial plains of Ecuadorian Coastal region, being technically

very difficult to apply in high spatially heterogeneous regions as Ecuadorian highlands in Andean Mountains or in the Amazon.

This type of insurance is additionally conditioned to consolidated and extensive crops. Because, if we use moderate resolution imagery over multi-crop coverage lands, increasing the error caused by mixing pixels with different land use. This could affect the accuracy of the index.

The commercial premium cost is unaffordable for farmer without a government subsidy.

4.2.3 Further research

A natural continuation of the thesis goals should be the analysis of the financial-economic scenarios in IBI design. Including these scenarios could help us understand better the insurance companies' financial management. It would let us calculating different scenarios of insurance companies' profitability, for setting more accurate premium prices, incentivising the insurance contracting. With more contracted policies, policy prices might be lower.

It is very important to launch a pilot IBI for validating my design before the implementation can upscale, thus revealing unexpected inconsistencies or inaccuracies. It is thus necessary to test this IBI design in the field with a group of Babahoyo rice-producers for calibrating and validating this design in one or two rainy seasons.

Another research line should be to test the use of higher spatial resolution images, which could solve the limitation of that IBI is suitable only for consolidated or extensive crops. This is because with higher spatial resolution it might be possible a higher spatial discrimination of land use. Additionally, it could expand the index insurance to more spatial variability regions as highlands of Ecuadorian Andean Mountains. Currently, it is limited only to the scientific field, due to, the high cost of high-resolution imagery and its short historical dataset.

REFERENCES

- Abdi, H., Williams, L.J., 2010. Principal component analysis. *Wiley Interdiscip. Rev. Comput. Stat.* 2, 433–459.
- Acevedo, R., González, I., Cabello, M.C., Larenas, V., Urbina, L., 2011. Recommendations manual for flooded rice crop from planting, 2d ed. Fundacion Chile, Santiago. Chile.
- Agresti, A., 2013. *Categorical Data Analysis*, Second Edi. ed. Wiley Interscience, Gainesville, Florida.
- Aguilar, D., Alava, D., Burbano, J., Garcés, A.L., Jácome, D., Leiva, D., Simbaña, B., Yépez, R., 2018. Estimación de superficie sembrada de arroz (*Oryza sativa* l.), maíz amarillo duro (*Zea mays* l.) y soya (*Glycine max*) en las épocas del año 2017, en las provincias de: Guayas, Los Ríos, Manabí, Santa Elena, Loja y El Oro. Quito-Ecuador.
- Aguilar, D., Andrade, D., Alava, D., Burbano, J., Díaz, M., Garcés, A.L., Jiménez, W., Leiva, D., Loayza, V., Muyulema, W., Pérez, P., Ruiz, V., Simbaña, B., Yépez, R., 2015. Estimación de superficie sembrada de arroz (*Oryza sativa* l.) Y maíz amarillo duro (*Zea mays* l.) En las épocas de invierno y verano año 2015, en las provincias de Manabí, Los Ríos, Guayas, Santa Elena, Loja y El Oro. Quito-Ecuador.
- Ahsan, S.M., Ali, A.A.G., Kurian, N.J., 1982. Toward a Theory of Agricultural Insurance. *Am. J. Agric. Econ.* 64, 510–529. doi:10.2307/1240644
- Aimin, H., 2010. Uncertainty, Risk Aversion and Risk Management in Agriculture. *Agric. Agric. Sci. Procedia* 1, 152–156. doi:10.1016/j.aaspro.2010.09.018
- Akter, S., 2012. The Role of Microinsurance as a Safety Net Against Environmental Risks in Bangladesh. *J. Environ. Dev.* 21, 263–280. doi:10.1177/1070496512442505
- Amemiya, T., 1977. The maximum likelihood and the nonlinear three-stage least squares estimator in the general nonlinear simultaneous equation model. *Econom. J. Econom. Soc.* 45, No. 4, 955–968.
- Araya, A., Keesstra, S.D., Stroosnijder, L., 2010. A new agro-climatic classification for

- crop suitability zoning in northern semi-arid Ethiopia. *Agric. For. Meteorol.* 150, 1057–1064.
- Arias, O.V., Garrido, A., Villeta, M., Tarquis, A.M., 2018. Homogenisation of a soil properties map by principal component analysis to define index agricultural insurance policies. *Geoderma* 311, 149–158.
doi:<https://doi.org/10.1016/j.geoderma.2017.01.018>
- Arnell, N.W., Reynard, N.S., 1996. The effects of climate change due to global warming on river flows in Great Britain. *J. Hydrol.* 183, 397–424.
- Barnett, B.J., Mahul, O., 2007. Weather Index Insurance for Agriculture and Rural Areas in Lower-Income Countries. *Am. J. Agric. Econ.* 89, 1241–1247.
doi:[10.1111/j.1467-8276.2007.01091.x](https://doi.org/10.1111/j.1467-8276.2007.01091.x)
- Barraza, K.B., 2012. Estrategias innovadoras para la gestión del riesgo de sequía es sistemas ganaderos extensivos. Universidad Politécnica de Madrid.
- Baver, L.D., Gardner, W.H., Gardner, W.R., 1972. *Soil Physics*. New York, John Wiley & Sons Ltd.
- Belal, A.-A., El-Ramady, H.R., Mohamed, E.S., Saleh, A.M., 2014. Drought risk assessment using remote sensing and GIS techniques. *Arab. J. Geosci.* 7, 35–53.
doi:[10.1007/s12517-012-0707-2](https://doi.org/10.1007/s12517-012-0707-2)
- Bendix, J., Trachte, K., Palacios, E., Rollenbeck, R., Göttlicher, D., Nauss, T., Bendix, A., 2011. El Niño meets la Niña - anomalous rainfall patterns in the “Traditional” El Niño region of Southern Ecuador. *Erdkunde* 65, 151–167. doi:DOI: [10.3112/erdkunde.2011.02.04](https://doi.org/10.3112/erdkunde.2011.02.04)
- Besley, T., 1995. Chapter 36 Savings, credit and insurance, in: *Handbook of Development Economics*. Elsevier, pp. 2123–2207.
doi:[https://doi.org/10.1016/S1573-4471\(05\)80008-7](https://doi.org/10.1016/S1573-4471(05)80008-7)
- Binswanger-Mkhize, H.P., 2012. Is there too much hype about index-based agricultural insurance? *J. Dev. Stud.* 48, 187–200.
- Blauhut, V., Gudmundsson, L., Stahl, K., 2015. Towards pan-European drought risk maps: quantifying the link between drought indices and reported drought impacts. *Environ. Res. Lett.* 10, 14008.

- Blöschl, G., Ardoin-Bardin, S., Bonell, M., Dorninger, M., Goodrich, D., Gutknecht, D., Matamoros, D., Merz, B., Shand, P., Szolgay, J., 2007. At what scales do climate variability and land cover change impact on flooding and low flows? *Hydrol. Process.* 21, 1241–1247. doi:10.1002/hyp.6669
- Bourennane, H., Couturier, A., Pasquier, C., Chartin, C., Hinschberger, F., Macaire, J.-J., Salvador-Blanes, S., 2014. Comparative performance of classification algorithms for the development of models of spatial distribution of landscape structures. *Geoderma* 219–220, 136–144. doi:http://dx.doi.org/10.1016/j.geoderma.2014.01.001
- Breustedt, G., Bokusheva, R., Heidelbach, O., 2008. Evaluating the potential of index insurance schemes to reduce crop yield risk in an arid region. *J. Agric. Econ.* 59, 312–328. doi:10.1111/j.1477-9552.2007.00152.x
- Bullock, J.M., Dhanjal-Adams, K.L., Milne, A., Oliver, T.H., Todman, L.C., Whitmore, A.P., Pywell, R.F., 2017. Resilience and food security: rethinking an ecological concept. *J. Ecol.* 105, 880–884. doi:10.1111/1365-2745.12791
- Bunge, H.-P., Grand, S.P., 2000. Mesozoic plate-motion history below the northeast Pacific Ocean from seismic images of the subducted Farallon slab. *Nature* 405, 337.
- Cadier, É., Gomez, G., Calvez, R., Rossel, F., 1994. Inundaciones y sequias en el Ecuador. *Sci. Publ. Inst. Rech. pour le Développement* 107–116.
- Cai, W., Borlace, S., Lengaigne, M., van Rensch, P., Collins, M., Vecchi, G., Timmermann, A., Santoso, A., McPhaden, M.J., Wu, L., England, M.H., Wang, G., Guilyardi, E., Jin, F.-F., 2014. Increasing frequency of extreme El Nino events due to greenhouse warming. *Nat. Clim. Chang.* 4, 111–116.
- Cambardella, C.A., Moorman, T.B., Parkin, T.B., Karlen, D.L., Novak, J.M., Turco, R.F., Konopka, A.E., 1994. Field-Scale Variability of Soil Properties in Central Iowa Soils. *Soil Sci. Soc. Am. J.* 58, 1501–1511. doi:10.2136/sssaj1994.03615995005800050033x
- Cardona, O., 2007. Diagnóstico de la gestión financiera del riesgo y propuesta de instrumentos financieros factibles de retención y transferencia. Bogota-Colombia.
- Carlson, T.N., Ripley, D. a., 1997. On the relation between NDVI, fractional vegetation

- cover, and leaf area index. *Remote Sens. Environ.* 62, 241–252.
doi:10.1016/S0034-4257(97)00104-1
- Carter, M., Cheng, L., Sarris, A., 2011. The Impact of Inter-linked Index Insurance and Credit Contracts on Financial Market Deepening and Small Farm Productivity. Unpubl. manuscript, Univ. California, Davis.
- Carter, M.R., Barrett, C.B., Boucher, S., Chantarat, S., Galarza, F., Mcpeak, J., Mude, A., Trivelli, C., 2008. Insuring the Never Before Insured: Explaining Index Insurance through Financial Education Games. October 1–8.
- Carter, M.R., Cheng, L., Sarris, A., 2016. Where and how index insurance can boost the adoption of improved agricultural technologies. *J. Dev. Econ.* 118, 59–71.
doi:https://doi.org/10.1016/j.jdeveco.2015.08.008
- Centre for Research on the Epidemiology of Disasters-CRED, 2015. EM DAT The International Disaster Database [WWW Document]. URL
<http://www.emdat.be/database>
- Chambers, R.G., 1989. Insurability and Moral Hazard in Agricultural Insurance Markets. *Am. J. Agric. Econ.* 71, 604–616. doi:10.2307/1242016
- Chantarat, S., Mude, A.G., Barrett, C.B., Carter, M.R., 2013. Designing index-based livestock insurance for managing asset risk in northern Kenya. *J. Risk Insur.* 80, 205–237.
- Chantarat, S., Mude, A.G., Barrett, C.B., Turvey, C.G., 2017. Welfare Impacts of Index Insurance in the Presence of a Poverty Trap. *World Dev.* 94, 119–138.
doi:https://doi.org/10.1016/j.worlddev.2016.12.044
- Chopra, P., 2006. Drought risk assessment using remote sensing and GIS: a case study of Gujarat. ME thesis, Indian Inst. Remote Sensing, Dehradun Int. Inst. Geo-information Earth Obs. Netherlands.
- Clarke, D.J., 2016. A theory of rational demand for index insurance. *Am. Econ. J. Microeconomics* 8, 283–306. doi:10.1257/mic.20140103
- Clement, K.Y., Botzen, W.J.W., Brouwer, R., Aerts, J.C.J.H., 2018. A global review of the impact of basis risk on the functioning of and demand for index insurance. *Int. J. Disaster Risk Reduct.* 28, 845–853.

- doi:<https://doi.org/10.1016/j.ijdr.2018.01.001>
- Conradt, S., Finger, R., Spörri, M., 2015. Flexible weather index-based insurance design. *Clim. Risk Manag.* 10, 106–117.
doi:<https://doi.org/10.1016/j.crm.2015.06.003>
- Dalezios, N.R., Blanta, A., Spyropoulos, N. V, Tarquis, A.M., 2014. Risk identification of agricultural drought for sustainable Agroecosystems. *Nat. Hazards Earth Syst. Sci.* 14, 2435–2448. doi:10.5194/nhess-14-2435-2014
- Daron, J.D., Stainforth, D.A., 2014. Assessing pricing assumptions for weather index insurance in a changing climate. *Clim. Risk Manag.* 1, 76–91.
doi:10.1016/j.crm.2014.01.001
- De la Rosa, D., Mayol, F., Diaz-Pereira, E., Fernandez, M., de la Rosa Jr., D., 2004. A land evaluation decision support system (MicroLEIS DSS) for agricultural soil protection: With special reference to the Mediterranean region. *Environ. Model. Softw.* 19, 929–942. doi:<http://dx.doi.org/10.1016/j.envsoft.2003.10.006>
- de Leeuw, J., Vrieling, A., Shee, A., Atzberger, C., Hadgu, K.M., Biradar, C.M., Keah, H., Turvey, C., 2014. The potential and uptake of remote sensing in insurance: a review. *Remote Sens.* 6, 10888–10912.
- Didan, K., 2015. MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006. NASA EOSDIS Land Processes DAAC.
doi:10.5067/MODIS/MOD13Q1.006
- Didan, K., Barreto, A., Solano, R., Huete, A., 2015. MODIS Vegetation Index User's Guide (MOD13 Series) Version 3.00, (Collection 6).
- Ecuador, 2015. Acuerdo Ministerial No. 100, Agroseguro. Registro Oficial Año III No. 362, 27 de agosto, Quito-Ecuador.
- Edwards, C.D.C., McKee, T.B., Doesken, N.J., Kleist, J., 1997. Historical analysis of drought in the United States, in: 7th Conference on Climate Variations, 77th AMS Annual Meeting.
- Elabed, G., Bellemare, M.F., Carter, M.R., Guirkingner, C., 2013. Managing basis risk with multiscale index insurance. *Agric. Econ. (United Kingdom)* 44, 419–431.
doi:10.1111/agec.12025

- Espinoza Villar, J.C., Ronchail, J., Guyot, J.L., Cochonneau, G., Naziano, F., Lavado, W., De Oliveira, E., Pombosa, R., Vauchel, P., 2008. Spatio-temporal rainfall variability in the Amazon basin countries (Brazil, Peru, Bolivia, Colombia, and Ecuador). *Int. J. Climatol.* 29, 1574–1594. doi:10.1002/joc.1791
- Everitt, B., 1980. *Cluster Analysis*. Second, 2 nd. ed. London, Wiley, London.
- FAO, 2018. Seguimiento del mercado del arroz de la FAO. Comer. y mercados, FAO XXI, 9. doi:I9243ES/1/0I4294S/1/
- FAO, 2006. *Guidelines for soil description*, 4th ed. Rome.
- FAO, 2004. Rice and water: a long and diversified story, in: *Rice Is Life*. International Year of Rice 2004. Food and Agriculture Organization of the United Nations, Rome, Italy, p. 2.
- FAO, 1991. *Guidelines: land evaluation for extensive grazing*, Soils Bulletin 58. Food & Agriculture Org., Rome, Italy.
- FAO, 1984. *Guidelines: land evaluation for rainfed agriculture*, Soils Bulletin 52. Food & Agriculture Org., Rome, Italy.
- FAO, Un-Habitat, 2010. *On solid ground. Addressing land tenure issues following natural disasters*.
- Farrin, K., Miranda, M.J., 2015. A heterogeneous agent model of credit-linked index insurance and farm technology adoption. *J. Dev. Econ.* 116, 199–211. doi:<https://doi.org/10.1016/j.jdeveco.2015.05.001>
- Fraisse, C.W., Breuer, N.E., Zierden, D., Bellow, J.G., Paz, J., Cabrera, V.E., y Garcia, A.G., Ingram, K.T., Hatch, U., Hoogenboom, G., 2006. AgClimate: A climate forecast information system for agricultural risk management in the southeastern USA. *Comput. Electron. Agric.* 53, 13–27.
- Fuchs, A., Wolff, H., 2011. Concept and unintended consequences of weather index insurance: the case of Mexico. *Am. J. Agric. Econ.* 93, 505–511.
- Fuhrer, J., Beniston, M., Fischlin, A., Frei, C., Goyette, S., Jasper, K., Pfister, C., 2006. Climate risks and their impact on agriculture and forests in Switzerland, in: Wanner, H., Grosjean, M., Röthlisberger, R., Xoplaki, E. (Eds.), *Climate Variability, Predictability and Climate Risks: A European Perspective*. Springer

- Netherlands, Dordrecht, pp. 79–102. doi:10.1007/978-1-4020-5714-4_5
- Gao, L., Shao, M., Peng, X., She, D., 2015. Spatio-temporal variability and temporal stability of water contents distributed within soil profiles at a hillslope scale. CATENA 132, 29–36. doi:http://dx.doi.org/10.1016/j.catena.2015.03.022
- García, S., Martínez, L., 2010. Método para la identificación de cultivo de arroz (*Oryza sativa* L.) con base en imágenes de satélite. Agron. Colomb. 28, Núm. 2. doi:10.15446/agron.colomb
- Geerts, S., Raes, D., Garcia, M., Del Castillo, C., Buytaert, W., 2006. Agro-climatic suitability mapping for crop production in the Bolivian Altiplano: A case study for quinoa. Agric. For. Meteorol. 139, 399–412.
- Gergis, J.L., Fowler, A.M., 2009. A history of ENSO events since A.D. 1525: implications for future climate change. Clim. Change 92, 343–387. doi:10.1007/s10584-008-9476-z
- Gomez, C., Rossel, R.A.V., McBratney, A.B., 2008. Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: An Australian case study. Geoderma 146, 403–411.
- Goodwin Barry K. Mahul, O., 2004. Risk Modeling Concepts Relating to the Design and Rating of Agricultural Insurance Contracts. The World Bank. doi:10.1596/1813-9450-3392
- Goovaerts, P., 1998. Geostatistical tools for characterizing the spatial variability of microbiological and physico-chemical soil properties. Biol. Fertil. Soils 27, 315–334. doi:10.1007/s003740050439
- Gu, Y., Brown, J.F., Verdin, J.P., Wardlow, B., 2007. A five year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States. Geophys. Res. Lett. 34.
- Gu, Y., Wylie, B.K., Howard, D.M., Phuyal, K.P., Ji, L., 2013. NDVI saturation adjustment: A new approach for improving cropland performance estimates in the Greater Platte River Basin, USA. Ecol. Indic. 30, 1–6. doi:10.1016/j.ecolind.2013.01.041
- Guttman, N.B., 1999. Accepting the standardized precipitation index: a calculation

- algorithm. JAWRA J. Am. Water Resour. Assoc. 35, 311–322.
- Habiba, U., Shaw, R., Takeuchi, Y., 2012. Farmer’s perception and adaptation practices to cope with drought: Perspectives from Northwestern Bangladesh. *Int. J. Disaster Risk Reduct.* 1, 72–84. doi:10.1016/j.ijdr.2012.05.004
- Haghverdi, A., Leib, B.G., Washington-Allen, R.A., Ayers, P.D., Buschermohle, M.J., 2015. High-resolution prediction of soil available water content within the crop root zone. *J. Hydrol.* 530, 167–179.
doi:http://dx.doi.org/10.1016/j.jhydrol.2015.09.061
- Hartigan, J.A., 1975. Clustering algorithms. John Wiley & Sons, Inc.
- Harvey, C. a, Rakotobe, Z.L., Rao, N.S., Dave, R., Razafimahatratra, H., Rabarijohn, R.H., Rajaofara, H., Mackinnon, J.L., 2014. Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar. *Philos. Trans. R. Soc. Lond. B. Biol. Sci.* 369, 20130089. doi:10.1098/rstb.2013.0089
- Hayes, M., Svoboda, M., Wall, N., Widhalm, M., 2011. The Lincoln Declaration on Drought Indices: Universal Meteorological Drought Index Recommended. *Bull. Am. Meteorol. Soc.* 92, 485–488. doi:https://doi.org/10.1175/2010BAMS3103.1
- Hayes, M.J., Svoboda, M.D., Wilhite, D.A., Vanyarkho, O. V, 1999. Monitoring the 1996 drought using the standardized precipitation index. *Bull. Am. Meteorol. Soc.* 80, 429–438.
- Hazell, P.B.R., 1992. The appropriate role of agricultural insurance in developing countries. *J. Int. Dev.* 4, 567–581. doi:10.1002/jid.3380040602
- He, B., Lü, A., Wu, J., Zhao, L., Liu, M., 2011. Drought hazard assessment and spatial characteristics analysis in China. *J. Geogr. Sci.* 21, 235–249. doi:10.1007/s11442-011-0841-x
- Hellmuth, M., Osgoog, D., Hess, U., Moorhead, A., Bhojwani, H., (eds.), 2009. Seguros en base a índices climáticos y riesgo climático : Perspectivas para el desarrollo y la gestión de desastres. *Clima y Sociedad No . 2*. Instituto Internacional de Investigación para el Clima y la Sociedad (IRI), The Earth Institute at Columbia University, Nueva York-EEUU.
- Henderson, T.L., Baumgardner, M.F., Franzmeier, D.P., Stott, D.E., Coster, D.C., 1992.

- High Dimensional Reflectance Analysis of Soil Organic Matter. *Soil Sci. Soc. Am. J.* 56, 865–872. doi:10.2136/sssaj1992.03615995005600030031x
- Hertzler, G., 2004. Weather derivatives and yield index insurance as exotic options, in: 48th Conference of the Australian Agricultural and Resource Economics Society, Melbourne, February.
- Hill, R.V., Hoddinott, J., Kumar, N., 2013. Adoption of weather-index insurance: learning from willingness to pay among a panel of households in rural Ethiopia. *Agric. Econ.* 44, 385–398.
- Hoag, D.L., 2009. Applied risk management in agriculture. CRC Press.
- Hodell, D.A., Curtis, J.H., Brenner, M., 1995. Possible role of climate in the collapse of Classic Maya civilization. *Nature* 375, 391.
- Holman, I.P., Rivas-Casado, M., Bloomfield, J.P., Gurdak, J.J., 2011. Identifying non-stationary groundwater level response to North Atlantic ocean-atmosphere teleconnection patterns using wavelet coherence. *Hydrogeol. J.* 19, 1269. doi:10.1007/s10040-011-0755-9
- Howden, S.M., Soussana, J.-F., Tubiello, F.N., Chhetri, N., Dunlop, M., Meinke, H., 2007. Adapting agriculture to climate change. *Proc. Natl. Acad. Sci.* 104, 19691–19696. doi:10.1073/pnas.0701890104
- Hu, H., Lei, T., Hu, J., Zhang, S., Kavan, P., 2018. Disaster-mitigating and general innovative responses to climate disasters: Evidence from modern and historical China. *Int. J. Disaster Risk Reduct.* 28, 664–673. doi:https://doi.org/10.1016/j.ijdr.2018.01.022
- Huang, J., Wang, X., Li, X., Tian, H., Pan, Z., 2013. Remotely sensed rice yield prediction using multi-temporal NDVI data derived from NOAA's-AVHRR. *PLoS One* 8, e70816.
- IEE-Instituto Espacial Ecuatoriano, 2009a. Technical report of production systems in Babahoyo canton. Quito-Ecuador.
- IEE-Instituto Espacial Ecuatoriano, 2009b. Soil map of Babahoyo Canton 1:25000 [WWW Document]. IDE IEE Geoportal, Generación geoinformación a Niv. Nac. URL http://181.211.99.244/cantonal/canton_babahoyo.html

- Iglesias, C.A., Garrote, L., Cancelliere, A., Cubillo, F., Wilhite, D.A., 2009. Coping with drought risk in agriculture and water supply systems: Drought management and policy development in the Mediterranean. Springer Science & Business Media.
- INIAP, 2008. Rice crop. Technical guide of crops. Manual 73. Instituto Nacional Autónomo de Investigaciones Agropecuarias, Quito, Ecuador.
- Instituto Geofísico, E.P.N., 2015. Instituto Geofísico - EPN - Red de Observatorios Vulcanológicos (ROVIG) [WWW Document]. URL <http://www.igepn.edu.ec/> (accessed 5.26.15).
- Isch, E., 2011. El cambio climático y el agua: efectos y medidas de adaptación. Quito-Ecuador.
- Janowicz-Lomott, M., Łyskawa, K., 2014. The New Instruments of Risk Management in Agriculture in the European Union. *Procedia Econ. Financ.* 9, 321–330. doi:10.1016/S2212-5671(14)00033-1
- Jasiulewicz, H., 2001. Probability of ruin with variable premium rate in a Markovian environment. *Insur. Math. Econ.* 29, 291–296. doi:[https://doi.org/10.1016/S0167-6687\(01\)00090-7](https://doi.org/10.1016/S0167-6687(01)00090-7)
- Jensen, N., Barrett, C., 2017. Agricultural Index Insurance for Development. *Appl. Econ. Perspect. Policy* 39, 199–219. doi:10.1093/aepp/ppw022
- Jensen, N.D., Mude, A.G., Barrett, C.B., 2018. How basis risk and spatiotemporal adverse selection influence demand for index insurance: Evidence from northern Kenya. *Food Policy* 74, 172–198. doi:<https://doi.org/10.1016/j.foodpol.2018.01.002>
- Jolliffe, I., 2002. Principal component analysis. Wiley Online Library.
- Kalogirou, S., 2002. Expert systems and GIS: an application of land suitability evaluation. *Comput. Environ. Urban Syst.* 26, 89–112. doi:[http://dx.doi.org/10.1016/S0198-9715\(01\)00031-X](http://dx.doi.org/10.1016/S0198-9715(01)00031-X)
- Kgakatsi, I.B., Rautenbach, C.J.D.W., 2014. The contribution of seasonal climate forecasts to the management of agricultural disaster-risk in South Africa. *Int. J. Disaster Risk Reduct.* 8, 100–113. doi:10.1016/j.ijdrr.2014.01.002
- Khan, S., Gabriel, H.F., Rana, T., 2008. Standard precipitation index to track drought

- and assess impact of rainfall on watertables in irrigation areas. *Irrig. Drain. Syst.* 22, 159–177. doi:10.1007/s10795-008-9049-3
- Khan, Y., Nikitina, G., Grigoruk, V., Akimbekova, G., 2017. Specifics of Agricultural Risks Insurance System in the Republic of Kazakhstan. *J. Environ. Manag. Tour.* VIII, 17–30. doi:DOI: [https://doi.org/10.14505/jemt.v8.1\(17\).02](https://doi.org/10.14505/jemt.v8.1(17).02)
- Kotz, S., Nadarajah, S., 2000. *Extreme Value distribution: Theory and applications*, 1st ed. Imperial College Press, London.
- Kripalani, R.H., Kulkarni, A., 1997. Climatic impact of El Niño/La Niña on the Indian monsoon: A new perspective. *Weather* 52, 39–46. doi:10.1002/j.1477-8696.1997.tb06267.x
- Krishnan, P., Alexander, J.D., Butler, B.J., Hummel, J.W., 1980. Reflectance Technique for Predicting Soil Organic Matter1. *Soil Sci. Soc. Am. J.* 44, 1282–1285. doi:10.2136/sssaj1980.03615995004400060030x
- Kurosaki, T., Fafchamps, M., 2002. Insurance market efficiency and crop choices in Pakistan. *J. Dev. Econ.* 67, 419–453. doi:[https://doi.org/10.1016/S0304-3878\(01\)00188-2](https://doi.org/10.1016/S0304-3878(01)00188-2)
- Lascano, R.J., Sojka, R.E., Adamsen, F., Hook, J., Cardon, G., Letey, J., Baltensperger, D., Ransom, M., Krishnan, H., Ulery, A., 2007. *Irrigation of agricultural crops*. American Society of Agronomy.
- Letey, J., 1985. Relationship between Soil Physical Properties and Crop Production, in: Stewart, B.A. (Ed.), *Advances in Soil Science*. Springer New York, New York, NY, pp. 277–294. doi:10.1007/978-1-4612-5046-3_8
- Li, Y., Ye, W., Wang, M., Yan, X., 2009. Climate change and drought: a risk assessment of crop-yield impacts. *Clim. Res.* 39, 31–46.
- Liu, B., Li, M., Guo, Y., Shan, K., 2010. Analysis of the Demand for Weather Index Agricultural Insurance on Household level in Anhui, China. *Agric. Agric. Sci. Procedia* 1, 179–186. doi:<https://doi.org/10.1016/j.aaspro.2010.09.022>
- M. Barnes, E., G. Baker, M., 2000. Multispectral Data for Mapping Soil Texture: Possibilities and Limitations. *Appl. Eng. Agric.* 16, 731. doi:<https://doi.org/10.13031/2013.5370>

- MAE Ministry of Environment of Ecuador, 2010. Future vulnerability analysis of Ecuador facing climate changing, cantonal level. Quito-Ecuador.
- Maestro, T., Bielza, M., Garrido, A., 2016. Hydrological drought index insurance for irrigation districts in Spain. Spanish J. Agric. Res. 14. doi:10.5424/sjar/2016143-8981
- MAGAP-Ministerio de Agricultura Ganaderia Acuacultura y Pesca, 2014a. Map of estimated area of rice and maize cultivation in the provinces of Guayas, Santa Elena, Los Rios, Manabí, El Oro and Loja in 2014 [WWW Document]. Geoportal del Agro Ecuatoriano. URL http://geoportal.agricultura.gob.ec/catalogo_datos/visualizador.html
- MAGAP-Ministerio de Agricultura Ganaderia Acuacultura y Pesca, 2014b. Map of Agro-ecological zoning of rice cultivation in Continental Ecuador [WWW Document]. Geoportal del Agro Ecuatoriano. URL http://geoportal.agricultura.gob.ec/catalogo_datos/visualizador.html (accessed 11.12.16).
- MAGAP-Ministerio de Agricultura Ganaderia Acuacultura y Pesca, 2012a. Resultados 2012. Quito-Ecuador.
- MAGAP-Ministerio de Agricultura Ganaderia Acuacultura y Pesca, 2012b. Map of location of government irrigation Systems 1: 50000 [WWW Document]. Geoportal del Agro Ecuatoriano. URL http://geoportal.agricultura.gob.ec/catalogo_datos/visualizador.html (accessed 10.8.12).
- MAGAP-Ministerio de Agricultura Ganaderia Acuacultura y Pesca, 2003. Map of Climate types of Continental Ecuador 1: 250000 [WWW Document]. Geoportal del Agro Ecuatoriano. URL http://geoportal.agricultura.gob.ec/catalogo_datos/visualizador.html (accessed 12.13.16).
- MAGAP, 2015. Mapa Agroecológico del Ecuador Continental escala 1:250000 [WWW Document]. URL <https://geoportal.magap.gob.ec/>
- Mahul, O., Stutley, C., 2010. Government Support to Agricultural Insurance. Challenges and Options for Developing Countries, 1st ed. The World Bank,

- Washington, DC. doi:10.1596/978-0-8213-8217-2
- Manna, P., Basile, A., Bonfante, A., De Mascellis, R., Terribile, F., 2009. Comparative Land Evaluation approaches: An itinerary from FAO framework to simulation modelling. *Geoderma* 150, 367–378.
doi:http://dx.doi.org/10.1016/j.geoderma.2009.02.020
- Mcintosh, C., Sarris, A., Papadopoulos, F., 2013. Productivity, credit, risk, and the demand for weather index insurance in smallholder agriculture in Ethiopia. *Agric. Econ. (United Kingdom)* 44, 399–417. doi:10.1111/agec.12024
- McKee, T.B., Doesken, N.J., Kleist, J., 1993. The relationship of drought frequency and duration to time scales, in: *Proceedings of the 8th Conference on Applied Climatology*. American Meteorological Society Boston, MA, USA, pp. 179–183.
- Milich, L., Weiss, E., 2000. GAC NDVI interannual coefficient of variation (CoV) images: ground truth sampling of the Sahel along north-south transects. *Int. J. Remote Sens.* 21, 235–260.
- Milligan, G., Cooper, M., 1985. An examination of procedures for determining the number of clusters in a data set. *Psychometrika* 50, 159–179.
doi:10.1007/BF02294245
- Mobarak, A.M., Rosenzweig, M.R., 2013. Informal risk sharing, index insurance, and risk taking in developing countries. *Am. Econ. Rev.* 103, 375–380.
- Montaño, M., 2005. Estudio de la aplicación de Azolla Anabaena como bioabono en el cultivo de arroz en el Litoral ecuatoriano. *Rev. Tecnológica ESPOL Vol.* 18, 147–151. doi:ISSN : 0257-1749
- Moreno, B., 2014. Yield rice in Ecuador. First quarter 2014. Quito-Ecuador.
- Morton, J.F., 2007. The impact of climate change on smallholder and subsistence agriculture. *Proc. Natl. Acad. Sci.* 104, 19680 LP-19685.
doi:https://doi.org/10.1073/pnas.0701855104
- Mouazen, A.M., Karoui, R., De Baerdemaeker, J., Ramon, H., 2005. Classification of Soil Texture Classes by Using Soil Visual near Infrared Spectroscopy and Factorial Discriminant Analysis Techniques. *J. Near Infrared Spectrosc.* 13, 231–240.
doi:10.1255/jnirs.541

- Moy, C.M., Seltzer, G.O., Rodbell, D.T., Anderson, D.M., 2002. Variability of El Niño/Southern Oscillation activity at millennial timescales during the Holocene epoch. *Nature* 420, 162.
- Mude, A., Barrett, C.B., Carter, M.R., Chantarat, S., Ikegami, M., McPeak, J.G., 2009. Index based livestock insurance for northern Kenya's arid and semi-arid lands: the Marsabit pilot. Available SSRN 1844758.
- Nakanishi, H., Black, J., 2018. Implicit and explicit knowledge in flood evacuations with a case study of Takamatsu, Japan. *Int. J. Disaster Risk Reduct.* 28, 788–797. doi:<https://doi.org/10.1016/j.ijdr.2018.02.008>
- NASA LP DAAC, 2015. MOD13Q1: MODIS/Terra Vegetation Indices 16-Day L3 Global 250m Grid SIN V006 [WWW Document]. USGS Earth Resour. Obs. Sci. Center. Sioux Falls, South Dakota. doi:10.5067/MODIS/MOD13Q1.006
- NOAA, N.O. and A.A., 2018. Anomalies of GPCC Precipitation [WWW Document]. Phys. Sci. Div. Earth Syst. Res. Lab. URL <https://www.esrl.noaa.gov/psd/cgi-bin/data/composites/printpage.pl> (accessed 2.8.18).
- OECD, 2011. Managing Risk in Agriculture. doi:<https://doi.org/https://doi.org/10.1787/9789264116146-en>
- OECD, 2009. Managing Risk in Agriculture. doi:<https://doi.org/https://doi.org/10.1787/9789264075313-en>
- Olivier, M., Skees, J., 2007. Managing Agricultural Risk At The Country Level : The Case Of Index-Based Livestock Insurance In Mongolia (No. 4325). The World Bank. doi:10.1596/1813-9450-4325
- Pachauri, R.K., Allen, M.R., Barros, V.R., Broome, J., Cramer, W., Christ, R., Church, J.A., Clarke, L., Dahe, Q., Dasgupta, P., 2014. Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.
- Pantaleoni, E., Engel, B.A., Johannsen, C.J., 2007. Identifying agricultural flood damage using Landsat imagery. *Precis. Agric.* 8, 27–36. doi:10.1007/s11119-006-9026-5
- Pardo, A., Merino, A.P., Castellanos, R.S.M., 1998. Análisis de datos en psicología II,

- Análisis de datos en Psicología II. Pirámide.
- Patt, A., Peterson, N., Carter, M., Velez, M., Hess, U., Suarez, P., 2009. Making index insurance attractive to farmers. *Mitig. Adapt. Strateg. Glob. Chang.* 14, 737–753. doi:10.1007/s11027-009-9196-3
- Patt, A., Suarez, P., Hess, U., 2010. How do small-holder farmers understand insurance, and how much do they want it? Evidence from Africa. *Glob. Environ. Chang.* 20, 153–161. doi:10.1016/j.gloenvcha.2009.10.007
- Peter Höpfe, 2007. Scientific and Economic Rationale for Weather Risk Insurance For Agriculture, in: Sivakumar, M.V.K., Motha, R.P. (Eds.), *Managing Weather and Climate Risks in Agriculture*. Springer, Berlin, Heidelberg, pp. 367–375. doi:https://doi.org/10.1007/978-3-540-72746-0_27
- Pettorelli, N., Vik, J.O., Mysterud, A., Gaillard, J.-M., Tucker, C.J., Stenseth, N.C., 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends Ecol. Evol.* 20, 503–510. doi:https://doi.org/10.1016/j.tree.2005.05.011
- Piao, S., Ciais, P., Huang, Y., Shen, Z., Peng, S., Li, J., Zhou, L., Liu, H., Ma, Y., Ding, Y., Friedlingstein, P., Liu, C., Tan, K., Yu, Y., Zhang, T., Fang, J., 2010. The impacts of climate change on water resources and agriculture in China. *Nature* 467, 43. doi:doi:10.1038/nature09364
- Pinstrup-Andersen, P., 2009. Food security: definition and measurement. *Food Secur.* 1, 5–7. doi:10.1007/s12571-008-0002-y
- Polasek, W., 2013. *Multivariate Analysis for the Biobehavioral and Social Sciences: A Graphical Approach* by Bruce L. Brown, Suzanne B. Hendrix, Dawson W. Hedges, Timothy B. Smith. *Int. Stat. Rev.* 81, 463–465. doi:10.1111/insr.12042_5
- Pontius, R.G., Boersma, W., Castella, J.-C., Clarke, K., de Nijs, T., Dietzel, C., Duan, Z., Fotsing, E., Goldstein, N., Kok, K., Koomen, E., Lippitt, C.D., McConnell, W., Mohd Sood, A., Pijanowski, B., Pithadia, S., Sweeney, S., Trung, T.N., Veldkamp, A.T., Verburg, P.H., 2008. Comparing the input, output, and validation maps for several models of land change. *Ann. Reg. Sci.* 42, 11–37. doi:10.1007/s00168-007-0138-2
- Prathumchai, K., Honda, K., Nualchawee, K., 2001. Drought risk evaluation using

- remote sensing and GIS: a case study in Lop Buri Province, in: Paper Presented at the 22nd Asian Conference on Remote Sensing. p. 9.
- Quarmby, N.A., Milnes, M., Hindel, T.L., Sileos, N., 1993. The use of multi-temporal NDVI measurements from AVHRR data for crop yield estimation and prediction. *Int. J. Remote Sens.* 14, 199–210. doi:10.1080/01431169308904332
- Raju, S.S., Chand, R., 2008. Agricultural Insurance in India Problems and Prospects. *Natl. Cent. Agric. Econ. Policy Res. NCAP Worki*, 77.
- Ranst, E. Van, Debaveye, J., 1991. Land Evaluation. Part II, Methods in land evaluation. State Universite Gent, Gent-Belgiun.
- Ray, P.K., 1981. Agricultural insurance. Theory and practice and application to developing countries. Pergamon Press.
- Razali, N.M., Wah, Y.B., 2011. Power comparisons of Shapiro-Wilk, Kolmogorov-Smirnov, Lilliefors and Anderson-Darling tests. *J. Stat. Model. Anal.* 2 (1), 21–33.
- Rencher, A.C., 2003. Methods of multivariate analysis. John Wiley & Sons.
- Rondeaux, G., Steven, M., Baret, F., 1996. Optimization of soil-adjusted vegetation indices. *Remote Sens. Environ.* 55, 95–107. doi:https://doi.org/10.1016/0034-4257(95)00186-7
- Rossiter, D.G., 1996. A theoretical framework for land evaluation. *Geoderma* 72, 165–190. doi:http://dx.doi.org/10.1016/0016-7061(96)00031-6
- Rulinda, C.M., Dilo, A., Bijker, W., Stein, A., 2012. Characterising and quantifying vegetative drought in East Africa using fuzzy modelling and NDVI data. *J. Arid Environ.* 78, 169–178. doi:http://dx.doi.org/10.1016/j.jaridenv.2011.11.016
- Sánchez, B., Rasmussen, A., Porter, J.R., 2014. Temperatures and the growth and development of maize and rice: a review. *Glob. Chang. Biol.* 20, 408–417.
- Sandholt, I., Rasmussen, K., Andersen, J., 2002. A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status. *Remote Sens. Environ.* 79, 213–224. doi:http://dx.doi.org/10.1016/S0034-4257(01)00274-7
- Sanyal, J., Lu, X.X., 2004. Application of Remote Sensing in Flood Management with Special Reference to Monsoon Asia: A Review. *Nat. Hazards* 33, 283–301.

- doi:10.1023/B:NHAZ.0000037035.65105.95
- Sarle, W.S., 1983. SAS Institute Inc., Technical Report A-108, Cubic Clustering Criterion. Cary, NC:
- Seog, S.H., 2010. The economics of risk and insurance, 1st ed. Wiley-Blackwell.
- Shahid, S., Behrawan, H., 2008. Drought risk assessment in the western part of Bangladesh. *Nat. Hazards* 46, 391–413.
- Shannon, H.D., Motha, R.P., 2015. Managing weather and climate risks to agriculture in North America, Central America and the Caribbean. *Weather Clim. Extrem.* 1–7. doi:<http://dx.doi.org/10.1016/j.wace.2015.10.006>
- Shynkarenko, R., 2007. Introduction of Weather Index Insurance in Ukraine-Obstacles and Opportunities, in: 101st Seminar, July 5-6, 2007, Berlin Germany. European Association of Agricultural Economists.
- Siqueira, D.S., Marques Jr., J., Pereira, G.T., 2010. Corrigendum to "The use of landforms to predict the variability of soil and orange attributes" [*Geoderma* 155 (1–2) (2010) 55–66]. *Geoderma* 156, 410. doi:<http://dx.doi.org/10.1016/j.geoderma.2010.02.017>
- Sivakumar, M., Motha, R., Das, H., 2005. Natural Disasters and Extreme Events in Agriculture. Impacts and Mitigation. Springer, Berlin, Heidelberg, Berlin. doi:<https://doi.org/10.1007/3-540-28307-2>
- Sivakumar, M.V.K., Motha, R.P., 2008. Managing weather and climate risks in agriculture. Springer Science & Business Media.
- Skees, J.R., Collier, B., 2008. The potential of weather index insurance for spurring a green revolution in Africa. *Glob. Ag Risk Inc* 53.
- Smith, V.H., Glauber, J.W., 2012. Agricultural Insurance in Developed Countries: Where Have We Been and Where Are We Going? *Appl. Econ. Perspect. Policy* 34, 363–390. doi:10.1093/aep/pps029
- Soil Survey Staff, 2014. Keys to soil taxonomy, 12th ed. ed. USDA-Natural Resources Conservation Service, Washington, DC.
- Soil Survey Staff, 2010. Keys to soil taxonomy, 11th ed. ed. United States Department of Agriculture, Washington, DC.

- Son, N.T., Chen, C.F., Chen, C.R., Chang, L.Y., Minh, V.Q., 2012. Monitoring agricultural drought in the Lower Mekong Basin using {MODIS} {NDVI} and land surface temperature data. *Int. J. Appl. Earth Obs. Geoinf.* 18, 417–427. doi:<https://doi.org/10.1016/j.jag.2012.03.014>
- Son, N.T., Chen, C.F., Chen, C.R., Minh, V.Q., Trung, N.H., 2014. A comparative analysis of multitemporal MODIS EVI and NDVI data for large-scale rice yield estimation. *Agric. For. Meteorol.* 197, 52–64. doi:<https://doi.org/10.1016/j.agrformet.2014.06.007>
- Stoppa, a, Hess, U., 2003. Design and use of weather derivatives in agricultural policies: the case of rainfall index insurance in Morocco. *Int. Conf. Agric. Policy Reform WTO Where Are We Head.* 23–26.
- Strzepek, K., Yohe, G., Neumann, J., Boehlert, B., 2010. Characterizing changes in drought risk for the United States from climate change. *Environ. Res. Lett.* 5, 44012.
- Subash, N., Ram Mohan, H.S., Banukumar, K., 2011. Comparing water-vegetative indices for rice (*Oryza sativa* L.)–wheat (*Triticum aestivum* L.) drought assessment. *Comput. Electron. Agric.* 77, 175–187. doi:<http://dx.doi.org/10.1016/j.compag.2011.05.001>
- Takahashi, K., Ikegami, M., Sheahan, M., Barrett, C.B., 2016. Experimental Evidence on the Drivers of Index-Based Livestock Insurance Demand in Southern Ethiopia. *World Dev.* 78, 324–340. doi:<https://doi.org/10.1016/j.worlddev.2015.10.039>
- Tan, K.H., 2005. Soil sampling, preparation, and analysis, 2nd ed. Taylor & Francis Group, Greensboro, Georgia.
- Taylor, J.A., Coulouma, G., Lagacherie, P., Tisseyre, B., 2009. Mapping soil units within a vineyard using statistics associated with high-resolution apparent soil electrical conductivity data and factorial discriminant analysis. *Geoderma* 153, 278–284. doi:<http://dx.doi.org/10.1016/j.geoderma.2009.08.014>
- Tenenhaus, M., Vachette, J.L., 1977. PRINQUAL: Un programme d’alyse en composantes principales d’un ensemble de variables nominales ou numériques. CESA, Jout-en-Josas, France.
- Thomasson, J.A., Sui, R., Cox, M.S., Al-Rajehy, A., 2001. Soil reflectance sensing for

- determining soil properties in precision agriculture. *Trans. ASAE* 44, 1445.
- Tonini, F., Jona Lasinio, G., Hochmair, H.H., 2012. Mapping return levels of absolute NDVI variations for the assessment of drought risk in Ethiopia. *Int. J. Appl. Earth Obs. Geoinf.* 18, 564–572. doi:<http://dx.doi.org/10.1016/j.jag.2012.03.018>
- Trærup, S.L.M., 2012. Informal networks and resilience to climate change impacts: A collective approach to index insurance. *Glob. Environ. Chang.* 22, 255–267. doi:[10.1016/j.gloenvcha.2011.09.017](https://doi.org/10.1016/j.gloenvcha.2011.09.017)
- Trangmar, B.B., Yost, R.S., Uehara, G., 1986. Application of Geostatistics to Spatial Studies of Soil Properties, in: Brady, N.C.B.T.-A. in A. (Ed.), . Academic Press, pp. 45–94. doi:[https://doi.org/10.1016/S0065-2113\(08\)60673-2](https://doi.org/10.1016/S0065-2113(08)60673-2)
- Trenberth, K.E., 1997. The Definition of El Niño. *Bull. Am. Meteorol. Soc.* 78, 2771–2778. doi:[10.1175/1520-0477\(1997\)078<2771:TDOENO>2.0.CO;2](https://doi.org/10.1175/1520-0477(1997)078<2771:TDOENO>2.0.CO;2)
- Turvey, C.G., 2001. Weather Derivatives for Specific Event Risks in Agriculture. *Appl. Econ. Perspect. Policy* 23, 333–351. doi:[10.1111/1467-9353.00065](https://doi.org/10.1111/1467-9353.00065)
- Ullah, R., Jourdain, D., Shivakoti, G.P., Dhakal, S., 2015. Managing catastrophic risks in agriculture: Simultaneous adoption of diversification and precautionary savings. *Int. J. Disaster Risk Reduct.* 12, 268–277. doi:[10.1016/j.ijdrr.2015.02.001](https://doi.org/10.1016/j.ijdrr.2015.02.001)
- Valverde-Arias, O., Garrido, A., Valencia, J.L., Tarquis, A.M., 2018. Using geographical information system to generate a drought risk map for rice cultivation: Case study in Babahoyo canton (Ecuador). *Biosyst. Eng.* 168, 26–41. doi:<https://doi.org/10.1016/j.biosystemseng.2017.08.007>
- van de Ven, W.P.M.M., van Vliet, R.C.J.A., Schut, F.T., van Barneveld, E.M., 2000. Access to coverage for high-risks in a competitive individual health insurance market: via premium rate restrictions or risk-adjusted premium subsidies? *J. Health Econ.* 19, 311–339. doi:[https://doi.org/10.1016/S0167-6296\(99\)00028-4](https://doi.org/10.1016/S0167-6296(99)00028-4)
- Vedenov, D. V, Barnett, B.J., 2004. Efficiency of Weather Derivatives as Primary Crop Insurance Instruments. *J. Agric. Resour. Econ.* 29, 387–403.
- Viscarra Rossel, R.A., Walvoort, D.J.J., McBratney, A.B., Janik, L.J., Skjemstad, J.O., 2006. Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. *Geoderma*

- 131, 59–75. doi:<http://dx.doi.org/10.1016/j.geoderma.2005.03.007>
- Vuille, M., Bradley, R.S., Keimig, F., 2000. Climate Variability in the Andes of Ecuador and Its Relation to Tropical Pacific and Atlantic Sea Surface Temperature Anomalies. *J. Clim.* 13, 2520–2535. doi:10.1175/1520-0442(2000)013<2520:CVITAO>2.0.CO;2
- Wauters, E., Winsen, F. van, Mey, Y. de, Lauwers, L., 2014. Risk perception, attitudes towards risk and risk management: evidence and implications. *Agric. Econ. (Zemědělská Ekon.* 60, 389–405.
- Weidong, L., Baret, F., Xingfa, G., Qingxi, T., Lanfen, Z., Bing, Z., 2002. Relating soil surface moisture to reflectance. *Remote Sens. Environ.* 81, 238–246.
- White, D., Kimerling, J.A., Overton, S.W., 1992. Cartographic and Geometric Components of a Global Sampling Design for Environmental Monitoring. *Cartogr. Geogr. Inf. Syst.* 19, 5–22. doi:10.1559/152304092783786636
- Wilke, a. K., Morton, L.W., 2015. Climatologists' Communication of Climate Science to the Agricultural Sector. *Sci. Commun.* 37, 371–395. doi:10.1177/1075547015581927
- Williams, L.J., Abdi, H., 2010. Fisher's least significant difference (LSD) test. *Encycl. Res. Des.* 218, 840–853.
- Woodard, J.D., Garcia, P., 2008. Basis risk and weather hedging effectiveness. *Agric. Financ. Rev.* 68, 99–117. doi:10.1108/00214660880001221
- Wu, H., Hayes, M.J., Weiss, A., Hu, Q., 2001. An evaluation of the Standardized Precipitation Index, the China-Z Index and the statistical Z-Score. *Int. J. Climatol.* 21, 745–758. doi:10.1002/joc.658
- Wu, H., Hubbard, K.G., Wilhite, D.A., 2004. An agricultural drought risk-assessment model for corn and soybeans. *Drought Mitig. Cent. Fac. Publ. Paper* 37, 27.
- Wu, H., Wilhite, D.A., 2004. An Operational Agricultural Drought Risk Assessment Model for Nebraska, USA. *Nat. Hazards* 33, 1–21. doi:10.1023/B:NHAZ.0000034994.44357.75
- Young, F., 1981. Quantitative analysis of qualitative data. *Psychometrika* 46, 357–388. doi:10.1007/BF02293796

- Zant, W., 2008. Hot Stuff: Index Insurance for Indian Smallholder Pepper Growers. *World Dev.* 36, 1585–1606. doi:10.1016/j.worlddev.2007.09.006
- Zhang, J., 2004. Risk assessment of drought disaster in the maize-growing region of Songliao Plain, China. *Agric. Ecosyst. Environ.* 102, 133–153. doi:http://dx.doi.org/10.1016/j.agee.2003.08.003

APPENDICES

Appendix I

Description of suitability categories adapted from FAO, (1984) and Ranst & Debaveye, (1991)

Suitable: land units without or with slight soil limitations, soil requires no or little improvement to obtain at least up to 0.8 of the maximum potential yield, thus farmers only have to make minor investments to obtain optimum yields.

Moderately suitable: land units with moderate soil limitations, with any labour of soil improvement i.e., in natural conditions, we expect to obtain from 0.6 to 0.8 of the maximum potential yield. Farmers have to invest a moderate amount of money to obtain an optimum yield.

Marginally suitable: land units with severe soil limitations, such that in natural conditions we expect to obtain from 0.4 to 0.6 of the maximum potential yield. With enough investment to correct the severe soil limitations, farmers can obtain optimal potential yields, but only in favourable conditions of weather and market. Therefore, the production risk increases considerably (Hoag, 2009).

Unsuitable: land units with very strong limitations that cannot be corrected with current technologies at an acceptable cost. In natural conditions, we expect from 0.2 to 0.4 of the maximum potential yield.

Appendix II

Description of drought vulnerability categories adapted from Shahid & Behrawan, (2008):

Low vulnerability: rice crop areas located over lands with suitable soil conditions and a sufficient water supply. This category also accepts the complementary requirement of irrigation with optimum soil conditions for rice cropping and the lands with moderate soil conditions for rice cropping with an adequate supply of water in all cultivation stages.

Moderate vulnerability: rice crop zones located over lands with good soil conditions, but with an indispensable requirement of irrigation; or over moderate soil conditions but with a complementary irrigation requirement in one crop stage.

High vulnerability: this category is determined by severe limitations of soil conditions and/or a high requirement of water in the crop cycle.

Very high vulnerability: rice crop zones located in areas that are very susceptible to losses because of strong soil limitations that farmers have to manage for cropping, adding in the possible lack of water in the crop cycle.

Appendix III

The categories of risk are described below (Zhang, 2004):

Low drought risk: lands with good soil and topographic characteristics for rice cropping and good water storage. Where farmers do not have to invest much money to manage those characteristics, and the crop must be in optimal condition to face pests and water stress. Additionally, with a suitable supply of water during the entire rice crop cycle by precipitation and if it is necessary by irrigation.

Moderate drought risk: lands with moderate soil and topographic conditions for rice cultivation and water storage. Where farmers have to modify some soil characteristics to meet crop requirements, where they need to invest more money to achieve adequate conditions. With a suitable supply of water during the entire rice crop cycle by precipitation and irrigation or when facing a moderate drought hazard.

High drought risk: lands with marginal soil conditions, where farmers have to make large investment to produce rice and they are very exposed to risk of losses, due to soil conditions or a precipitation deficit during the crop cycle, and they do not have access to irrigation. Farmers have a high likelihood of losing their investment, also placing much pressure on natural resources, and increasing the risk of pollution by pesticides and fertilisers.

Very high drought risk: lands cultivated with rice that do not meet rice crop requirements, in which soil conditions have been modified to obtain closer to crop requirements, with very large investments, but where the crop is very susceptible to pests and weather. It is very difficult for farmers to obtain the optimum potential yield. Farmers have a very high likelihood of losing their investment due to soil conditions and water deficits in the crop cycle.