Article
Sustainable Geoinformatic Approaches to Insurance for Small-Scale Farmers in Colombia

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Abstract: This article presents a low-cost insurance system developed for smallholder farms in disaster-prone regions, primarily using free Earth observation (EO) data and free open source software’s (FOSS), collectively termed “sustainable geoinformatics.” The study examined 30 farms in Risaralda Department, Colombia. A digital elevation model (12.5 m pixels) from the ALOS PALSAR satellite sensor was used with a geographic information system (GIS) to map the terrain, drainage, and geohazards of each farming district. Google Earth Engine (GEE) was used to carry out time-series analysis of 15 EO and weather datasets for 1998 to 2020. This analysis enabled the levels of risk from hydrometeorological hazards to be determined for each farm of the study, providing key data for the setting of insurance premiums. A parametric insurance product was developed using a proprietary mobile phone app that collected GPS-tagged, time-stamped mobile phone photos to verify crop damage, with further verification of crop health also provided by daily near-real-time satellite imagery (e.g., PlanetScope with 3 m pixels). Machine learning was used for feature identification with the photos and the satellite imagery. Key features of this insurance system are its low operational cost and rapid damage verification relative to conventional approaches to farm insurance. This relatively fast, low-cost, and affordable approach to insurance for small-scale farming enhances sustainable development by enabling policyholder farmers to recover more quickly from disasters.

Keywords: digital data poverty; disaster risk management; earth observation; extreme weather; GIS; machine learning; parametric insurance; small farms; sustainable geoinformatics

1. Introduction

Climate change is affecting food security via increasing temperatures, changing precipitation patterns, and greater frequency of extreme weather events [1]. According to the World Health Organization, 828 million people are affected by hunger, and 670 million people (8 percent of the world population) will still be facing hunger in 2030 [2]. This research contributes to reducing food insecurity, contributing to the United Nations Sustainable Development Goals (SDGs) of “Zero Hunger” and “Life on Land”.

Workers in low-income countries are the most affected by climate change. They struggle to find insurance as insurers begin to avoid risky regions [3]. Those who are vulnerable due to poverty, limited education, and financial exclusion are more likely to be impacted by extreme weather events [4]. Insurance can spread the risk of the losses from disasters. However, the increasing frequency and severity of extreme weather events
is making insurance much more challenging. This has led to increases in prices of the premiums charged for insurance cover, a cost barrier that low-income populations find difficult to cross [5].

The aim of this research is to develop an insurance system that is affordable to insurers and small-scale farm owners. We illustrate how this can be done using free open source software (FOSS), geographic information system (GIS), data from Earth observation (EO) satellites, and the application of machine learning and deep learning algorithms to detect features in mobile phone photos. From an insurance sector perspective, the objectives are to: (i) provide insurance access to small-scale farms, allowing them to run a viable business by increasing crop sustainability and resilience to extreme weather events; (ii) allow underwriters to predict risks, thus setting more affordable premiums; and (iii) optimize claims and verify damages using an automated system.

This study examines the feasibility of using sustainable geoinformatics and machine learning with EO satellite and mobile phone technologies, seeking to demonstrate that those technologies can be integrated into an insurance system that is affordable to small-scale farmers. Figure 1 shows how the feasibility study was conducted, with a pre-disaster underwriting stage having a better estimation of the underlying asset (i.e., crop), a better awareness of potential geohazards affecting insured farms, and a historical outlook on previous disaster events in the farming district. The diagram illustrates how a parametric insurance model estimating disaster damage can use machine learning models to detect changes in satellite images and classify mobile phone photos uploaded by impacted farmers, triggering an automated insurance payout.

**Policy and Premium Setting**

**Underwriting**
- Crop type
- Production value
- Uploaded photos
- Historical claims

**Geomorphometry**
- Slope steepness
- Position
- Soil wetness
- Terrain

**Hydrometeorology**
- Historical claims and performance of indices back them
- Frequency of disasters
- Recency of disaster

**First Notice of Loss (FNOL)**

Data collected from farmers via mobile

Two-tier image recognition based on:
1. Crop type
2. Crop health condition

Deep Learning

Automated payout

Data collected from satellite imagery

Parameteric Model

The likelihood of a specific hazard happening in an insured farm based on real-time satellite imagery data collected

**Figure 1.** Conceptual model of the insurance system and its geoinformatic components.

The organization of this manuscript is as follows. The introduction reviews the impacts of extreme weather events on farming and how such risks have been managed, including the provision of insurance for the farming sector. The next section covers the data types and analytical methods. Next comes the reporting of results, followed by a discussion, including recommendations, and conclusions.

1.1. Climate Change, Disasters, and Farming

In 2018, the UK Space Agency predicted that “Climate change is expected to result in more frequent and intensive climate-related hazards. It will also reduce the predictabili-
ity and change the geographic distribution of extreme climatic hazards, such as extreme temperatures, floods and droughts, heat waves, wild fires and storms” [6]. That prediction has largely been verified by numerous extreme weather events, often with records broken [1,7]. Therefore, many scholars focused their research on reducing risk in disaster-prone areas by building a resilient climate change ecosystem [8], in which a key factor is food security [9,10]. Other factors are decreasing the likelihood of crop failure (i.e., damaged, diseased, or destroyed [11]), as well as mitigating the risk of damage to farm infrastructure [12].

This research contributes to the shifting of the climate risk assessment framework to a sustainable climate-resilient ecosystem. This can be done by (1) predicting where and when extreme weather events are most likely and (2) ensuring farmers’ business continuity and thus the provision of sustainable livelihoods. This comes in line with the findings of the Intergovernmental Panel on Climate Change (IPCC), which asserted that climate change exacerbates land degradation [1].

1.2. Disaster Risk Management

Managing the risk of disaster has two main components: (i) reducing the risk of a disaster occurring, which requires research into the main drivers of disasters (hazards, exposure, vulnerability) to identify appropriate mitigation activities; and (ii) managing disaster risk as effectively as possible, which involves emergency management (from preparedness and early warning systems, to rapid response, then recovery, following “Build Back Better” guidelines), as well as strengthening resilience, e.g., by reducing socio-economic impacts via insurance.

Oliveira [7] conducted a systematic review of pre- and post-disaster studies and highlighted the importance of building back better in the post-disaster phase in light of the Sendai Framework. The aforementioned framework was published in 2015 by the UN Office for Disaster Risk Reduction, aiming to achieve seven global sustainable targets by 2030. In light of the above, impacts of extreme weather disasters were seen as a threat to food security and agriculture.

The term “resilience” became prominent towards the end of the last century with conceptual frameworks [13]. Lu and Yang [14] argued that disasters come with a social factor, which can be measured using social networks. Accordingly, Wu and Cui [15] monitored tweets and measured sentiment during Hurricane Sandy.

Geoinformatics and Farm Risk Management

The focus on food security has shifted the attention to secure vulnerable sources of food with advanced technologies. The suggestion of relying on information and communication technologies to increase resilience, especially in low- and middle-income countries, was introduced by many researchers followed by the emergence of a sub-discipline known as “ICT for Resilience and Sustainable Development (ICT4RS)” [4,16]. Research by Heeks and Ospina [17] introduced e-Resilience, a framework that explains the interplay between information systems and humans during disasters. They conducted a survey and reported on the usage of ICT (via mobile phones and internet-connected laptops/tablets) in relation to the respondents’ demographics. Similarly, Longo, Zardo [8] used ArcGIS version 10.4.1 software to map land cover and assess its resilience to climate change, creating the Ecosystem Service Climate Change Adaptation (ESCCA) framework.

The global abundance of freely available digital map data and Earth observation data with relatively detailed pixels (in the 3 m to 300 m range), has given scientists the opportunity to integrate many datasets at locations such as farm fields to detect, map and monitor types of vegetation coverage and hazard zones [18]. As a result, space agencies started different programs to eliminate food insecurity and protect agriculture productivity. The Global Agriculture Monitoring (GLAM) project [9] aims at monitoring crop conditions using remotely sensed data [19]. Similarly, the National Aeronautics and
Space Administration (NASA) started the “Harvest Africa” program to monitor crops and issue early warnings in the sub-Saharan Africa (SSA) region [20].

Leidig and Teeuw [21] considered disaster risk management applications of free or low-cost remote sensing data and geospatial analysis software, termed “sustainable geoinformatics.” This article is inspired by the aforementioned term and presents a low-cost EO-based farm insurance system. This is also consistent with what the UK Space Agency had stated: “EO enables accurate mapping of land use and monitoring of changes in crops and the land itself. This data is useful for finance companies that need access to data concerning land used by growers in order to be able to offer them financial products such as insurance or credit. For many small-scale producers in developing countries, these financial products are prohibitively expensive, not designed for their needs, or simply not available at all…” [6], page 11. This research examines the feasibility of using sustainable geoinformatics for disaster risk management with small farms. This has involved a combination of digital elevation data from satellite remote sensing, daily EO imagery and archive EO data from the past two decades, supported by time-stamped GPS-tagged photos from farmers’ mobile phones and data processing using deep learning. Of the various studies that focused on using geoinformatics/EO and ICT to support agriculture, the majority focused on the African continent in different scopes (e.g., West Africa, sub-Saharan Africa, etc.). Additionally, until now, no study has discussed the AI deep learning model for crop damage detection from an actuarial point of view and how that would affect the underwriting process.

1.3. Provision of Insurance for Small-Scale Farmers

Insurance helps to maintain economic stability, especially for vulnerable societies [22]. However, due to its volatility in weather conditions, many insurers stopped covering disasters such as floods [5]. The impacts of climate change are greater with small-scale farmers because they typically do not have the capacity to cope, due to their limited resources and the cost barrier that they face if they seek farm insurance [6]. This can be explained by “social identity theory,” which asserts that generations and social classes can impact climate policies [23]. Meanwhile, the development of an agricultural insurance system is a complex and multifaceted process, where production system, crop types, farm size, farm location, data availability, sales channels and other risk factors make it difficult for insurers to offer the right policy and set the right premium [24].

In agriculture, of the world’s 570 million smallholder farms, 87% are less than 2 Ha in size [25]. In addition to cost, agriculture insurance remains low in developing countries, where many small farms are concentrated, due to institutional and technological constraints [26] as well as the high cost of loss estimation/verification [27]. In the Latin American region, only 4 percent of small to medium enterprises (SMEs) working in the farming business have insurance, generally due to lack of governmental support, except for Mexico and Brazil [28]. In addition, premiums are estimated to be around USD 72 per hectare, which is a significantly high amount for smallholding farm owners. Overall, the insured farmed land in Latin America is estimated to be 29 million hectares out of a total of 138 million hectares [28]. As a result, many smallholder farmers have formed cooperative groups in order to improve productivity and spread risks, as is the case in many farming districts of Colombia, where this research is focused.

Decisions associated with disasters have been characterized as having an heuristics nature [29] instead of being data-driven. Consistently, “parametric insurance” uses indices to guide insurance payouts based on pre-defined thresholds [27]. In other words, its ultimate payment is not based on individual losses, but determined according to a measure (be it an earthquake magnitude or wind speed). In this research, the combination of EO data, GIS, geospatial analysis and machine learning methods is utilized to identify the right measure(s) per disaster type while arguing that insurance payouts can still be individualized using deep learning technology.

Parametric insurance offers payouts to claimants when a disaster exceeds a threshold measured by an index or multiple indices. The adoption of parametric insurance has been
Parametric insurance offers payouts to claimants when a disaster exceeds a threshold when it comes to agricultural products. A framework of how parametric insurance can be used in Africa was developed by Ibarra and Securities [26]. Subsequently, many studies focused on different aspects of such novel adoption in various countries. For example, Figueiredo, Martina [27] focused on methods to estimate risks by calculating the probability of a flood event happening in Jamaica using a logistic regression model. They based their study on the premise that the target variable has a binary nature: disaster/no disaster. A study by Prokopchuk [30] used temperature, humidity, and precipitation to estimate the growth level of grains within Ukraine and linked that to insurance. Inspired by the importance of predictability and the emergence of machine learning, Cesarini, Figueiredo [31] suggested integrating multiple sources of weather data then applying supervised machine learning (ML) techniques, such as support vector machines and artificial neural networks (ANNs) to classify impacts of drought and floods in the Dominican Republic between 2000 and 2019. The study of Benso, Gesualdo [22] examined weather indices in Brazil and how those affect soybean farms: they argued that disasters could be interrelated and proposed a multi-hazard risk assessment approach. During the 2023 United Nations Climate Change Conference, the former secretary of the United States, Hillary Clinton, indicated that she is pioneering new reforms of the insurance industry by working with the Arsht-Rock Foundation Resilience Center to recognize parametric insurance as a form of climate change resilience [3].

2. Materials and Methods

2.1. The Study Area

The study area for this research is the Dosquebradas farming district in Risaralda Department, Colombia (Figure 2).

Figure 2. Location of the study area in Risaralda Department, Colombia. Areas of forest are shown in dark green. The inset box indicates the area shown in detail within Figure 3 (map source: OpenStreetMap).

Farm Locations and Disaster Events

In Dosquebradas, 30 farms were surveyed (Figure 3). These were mostly growing coffee, with a few fields of avocado. Examination of disaster data on the website of Colombia’s Institute of Hydrology, Meteorology and Environmental Studies (IDEAM) (http://ideam.gov.co, accessed on 15 September 2020) yielded information about 31 disasters.
affecting Risaralda Department since 1998, e.g., event dates, areas affected, casualties (see Appendix A). Earthquakes were also included in the database because they often cause landslides, which can severely damage farm infrastructure.

Figure 3. The Dosquebradas study area (corresponding to the inset box in Figure 2): locations and areal extents of the farms included in the testing of the insurance system.

2.2. Data Sources

According to Ibarra and Securities [26], data of high quality is essential in building a parametric insurance model. Satellite imagery and digital elevation model (DEM) data were used to examine the study area, involving mapping of terrain (geomorphometry), and monitoring of land cover, crop types and weather (temperature and precipitation). After pre-processing, the various datasets were integrated using QGIS version 3.10. Archive geospatial datasets were processed using Google Earth Engine (GEE), with time-series analyses of vegetation and hydro-meteorological indices. Finally, GPS time-stamped photos provided via mobile phone apps were used for verification purposes, where deep learning was used to identify crop types and health conditions.

2.2.1. Earth Observation (EO) Imagery

Satellite EO imagery forms the basis of many global datasets on vegetation types, soil features, and land surface temperature [5]. In this feasibility study, various geoinformatic datasets were used and these are summarized in Table 1. The farming district was mapped and monitored for vegetation cover and ground surface temperature using imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS: 250 m pixels), analyzing an archive of MODIS imagery dating back to 2000. Detailed EO-based mapping of farms and
individual fields (vegetation cover, crop types, stages of crop growth and photosynthetic activity) was carried out using visible and infrared imagery from PlanetScope (3.8 m pixels) and Sentinel-2 (10 m pixels), for which archive imagery extends back to 2015.

Table 1. Geospatial datasets (VIR = visible and infraRed; VNIR = visible and near infrared).

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Type</th>
<th>Pixel Size (m)</th>
<th>Derived Indices</th>
<th>Data Provider</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALOS PALSAR (L-band radar)</td>
<td>Digital Elevation Model (DEM)</td>
<td>12.5</td>
<td>Landform types, slope steepness, floodplains, topographic wetness</td>
<td><a href="https://search.asf.alaska.edu/#/">https://search.asf.alaska.edu/#/</a>, accessed on 9 November 2020</td>
</tr>
<tr>
<td>MODIS</td>
<td>VIR imagery</td>
<td>250</td>
<td>NDVI (vegetation photosynthesis)</td>
<td><a href="https://modis.gsfc.nasa.gov/data/">https://modis.gsfc.nasa.gov/data/</a>, accessed on 9 November 2020</td>
</tr>
<tr>
<td>Sentinel-2 Multi Spectral Instrument</td>
<td>VIR imagery</td>
<td>10</td>
<td>NDVI: vegetation photosynthesis, bare ground, crop type</td>
<td><a href="https://earth.esa.int/web/sentinel/user-guides/sentinel-2-msi/product-types/level-2a">https://earth.esa.int/web/sentinel/user-guides/sentinel-2-msi/product-types/level-2a</a>, accessed on 9 November 2020</td>
</tr>
<tr>
<td>PlanetScope</td>
<td>VNIR imagery</td>
<td>3.0</td>
<td></td>
<td><a href="https://www.planet.com/products/planet-imagery/">https://www.planet.com/products/planet-imagery/</a>, accessed on 9 November 2020</td>
</tr>
<tr>
<td>Geological maps</td>
<td>GIS—1:100,000</td>
<td>1000</td>
<td>Geology Land cover type</td>
<td><a href="http://www.idealmap.gov.co/">http://www.idealmap.gov.co/</a>, accessed on 9 November 2020</td>
</tr>
<tr>
<td>OpenStreetMap</td>
<td>Open Source topography</td>
<td>Variable to 1:10 k scale</td>
<td>Topography: drainage, roads, bridges, buildings</td>
<td><a href="https://www.openstreetmap.org/#map=13/4.8540/-75.7178">https://www.openstreetmap.org/#map=13/4.8540/-75.7178</a> &amp;layers=C, accessed on 9 November 2020</td>
</tr>
<tr>
<td>Google Earth Pro</td>
<td>Maps and archive EO imagery</td>
<td>0.3–30</td>
<td>Digital globe and map with 3D visualization of terrain</td>
<td><a href="https://www.google.com/intl/en_uk/earth/versions/">https://www.google.com/intl/en_uk/earth/versions/</a>, accessed on 9 November 2020</td>
</tr>
<tr>
<td>Google Earth Engine (GEE)</td>
<td>Archive EO imagery</td>
<td>10–500</td>
<td>Search engine and data analysis platform</td>
<td>//code.earthengine.google.com/, accessed on 2 October 2020</td>
</tr>
</tbody>
</table>

2.2.2. Digital Elevation Models (DEMs) and Geomorphometrics

The ALOS PALSAR global DEM (12.5 m pixels) produced by the University of Alaska Space Facility was used to carry out geomorphometric analyses of the terrain within the two farming districts. The methodology of Argyriou, Sarris [32] and Argyriou, Teeuw [33] was used to produce DEM-derived maps of slope steepness, slope aspect, terrain wetness, drainage networks, and landform types.

2.2.3. Mobile Phone Photos

Using a customized mobile phone app, time-stamped photos with global positioning system (GPS) longitude/latitude coordinates accurate to +/-5 m were collected in September 2020 within the sampled farms. A total of 748 farm photos were saved on the InsurTech server (Figure 4) as KML files. That KML format enabled administrative users to see the locations via Google Earth, thus linking mobile phone photos to insured items on farms, as well as providing locations that could be examined using EO satellite imagery.

2.3. Data Analysis

GPS-located phone photos were collected around the boundaries of each insured farm, enabling the area of each crop type on the farm to be calculated. Thereafter, a change detection analysis could be applied to calculate the area of the “damaged” pixels and thus estimate losses. This can also be done using daily imagery from PlanetScope or other high-resolution satellite imagery (e.g., Maxar, Iceye) with pixels in the 3m to 0.3m range.
In this study, the research framework of Wagstaff [34] was followed, with its three stages: preparation, ML contribution, and impact. In preparation, the problem was identified and relevant data were collected while generating features and labeling classes. In the ML contribution, random forest (RF) was used to classify vegetation types, while LSTM was used to detect extreme weather events in the time-series analysis of the satellite data. Additionally, deep learning (DL) was used to recognize images collected from the mobile app and classify those. The impact results were presented in a parametric model where insurers would adopt a new process and become part of the InsurTech ecosystem. Those results are shared with relevant communities such as policymakers, technology developers, agriculture supply chain players and insurers who would benefit from the accessible EO capabilities. This research encouraged the adoption of the new geoinformatic approach in order to sustain small-scale farming businesses.

There were four analyses that were performed in this research: (i) terrain analysis of farming districts and individual farms, using DEM-based geomorphometrics; (ii) mapping land cover and crop types by applying a machine learning random forest (RF) algorithm on satellite imagery; (iii) time-series analysis of farming districts, monitoring hydrological indices before, during, and after historical extreme weather events, using long short-term memory (LSTM); and (iv) image recognition via computer vision to classify mobile phone photos into crop type and health condition, using deep learning (DL).

2.3.1. Mapping Terrain and Landforms: DEM Geomorphometrics

A DEM of a given landscape can be analyzed using geomorphometrics to identify key components that will have distinct morphologies. This is subject to specific Earth surface processes and thus contains predictable soil and regolith types. A freely available DEM with near-complete global coverage was used in this research: the 12.5 m-pixel ALOS PALSAR DEM (Table 1). Three geomorphometric features were mapped in the study area and calculated within QGIS version 3.10, as follows.

1. Slope steepness: Slope gradient (SG) shows the change occurring in elevation between each pixel of the DEM and its neighbors. Flat surfaces are characterized by low values, while a steep relief is indicated by higher values [35]. The direction of slope, known as the slope aspect, was also mapped because some slopes receive more rainfall as they face towards the dominant direction of winds during the wetter seasons of the year.

2. Topographic position index (TPI), showing landform types: This is a geomorphological measure that classifies landforms into 10 types: canyons and deeply incised valleys, mid-slope drainage, upland drainage, U-shaped valleys, plains, foot slopes, upper slopes, local ridges, mid-slope ridges, and high ridges [33,36].
3. Topographic wetness index (TWI): This measure determines the slope of a given field in order to estimate soil moisture and surface saturation of that area. A high TWI value indicates an accumulation of soil moisture and surface saturation [37,38]. A low TWI value indicates susceptibility to soil erosion, whereas a high TWI value indicates an area with limited moisture [33,39,40].

2.3.2. Vegetation Mapping and Monitoring

- Vegetation detection with satellite imagery: Sentinel-2 and PlanetScope imagery (Table 1) were used to discriminate between vegetation and areas of bare soil in the study areas. The detection of land cover types through machine learning predictive modeling informed our parametric insurance model and helped in price setting, as detailed later in this paper. This was done using a random forest (RF) machine learning classification algorithm [41]. High prediction accuracy and high tolerance to outliers and noise are the main advantages of RFs [41]. In addition, they estimate correlations between covariates and dependent variables by evaluating the relative importance of covariates [42]. RF classification was applied to cloud-free Sentinel-2 imagery, based on training samples, to discriminate land cover types.

- Normalized Difference Vegetation Index (NDVI): The NDVI “is the primary vegetation index for monitoring crop conditions” [9]. It is widely used due to its ability to measure photosynthesis activity and thus correlate with vegetation density and vitality [43,44]. The NDVI is derived from satellite imagery in the visible and near-infrared (VNIR) parts of the electromagnetic spectrum. The NDVI derived from MODIS can be used for assessing vegetation dynamics during the past 20 years [45]. The NDVI has been at the center of calculations pertaining to food insecurity whenever EO is used to spot anomalies in the growth of crops [9]. Bégué, Madec [9] conducted spatiotemporal analysis of NDVI performance in West Africa: impacts of extreme weather events could be evaluated based on NDVI values before, during, and after disaster events.

2.3.3. Time-Series Analysis

Datasets were sourced via Google Earth Engine (GEE) to analyze various bioclimatic and hydrometeorological indices for our study area, examining data for the past 20 years and focusing on extreme weather events affecting those areas since 1998. Monthly datasets were compiled and analyzed from various climatic data archives: Climate Hazards group InfraRed Precipitation with Station data (CHIRPS), ERA5 Climate, TerraClimate, Palmer Drought Severity Index (PDSI) and the Cloud Classification System-Climate Data Record (CCS-CDR), details of which are provided in Appendix B. Those hydrometeorological datasets were used to examine periods of extreme weather events, such as intense rainfall and flooding (La Niña), dryness, drought and wildfires (El Niño).

MODIS 16-day rolling mean and medians of NDVI, Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN), CHIRPS precipitation indices and the Palmer Drought Severity Index (PDSI) were plotted on a time-series axis. Also, periods of extreme weather were shaded in colors: blue for floods, light brown for drought, and dark red for periods with frequent wildfire (Figure 5).
2.3.4. Damage Detection via Deep Learning (DL)

For geoinformatics to contribute to social resilience and sustainable food security, local knowledge must be incorporated in the implementation of the technology. Therefore, a digital business model was adopted, where insured farmers input their data by uploading time-stamped and geotagged photos via their mobile phones. Deep learning (DL) models have been utilized as an effective way to detect objects within photos in disaster management. For example, Chaudhuri and Bose [29] applied a convolutional neural network deep learning model for geotagged photos to verify damage in buildings and survivors in the case of earthquakes. Nakalembe and Kerner [46] argued the plausibility of using deep learning models in lieu of machine learning decision trees and random forest approaches for crop-type classifications.

Long Short-Term Memory (LSTM)

A sequence learning method has been developed for this research with thousands of time steps via a recurrent neural network known as long short-term memory (LSTM) model. The batch size and time steps were used as input features, with the output being a softmax function used in the output (final) layer. The model was trained using many instances of the disaster dataset with a look-back window of day/week/month (n + 1) onward. Every time the one-step-ahead feature is predicted, its observed parameters can be used to refine the network state, before moving the time window one step (Figure 6). This procedure provides an up-to-date network, updating every time new information is available.

Figure 6. Long short-term memory (LSTM) layers.
DL was used for image recognition and classification with the photos of the mobile phone app, aiming to detect labeled crop types and verify damage due to extreme weather events. In this feasibility study, the focus was on avocado and coffee crops.

To ensure correct pre-processing, hyper-parameters were set at the start of the learning to the shape and size of the crop images, specifically, rescaling the photos to 28 rows by 28 columns since neural networks work on square images [29]. The inputs are trained images with their labels as well as a holdout sample (or subset) for testing purposes. Both sequential and activation functions were run on the training datasets to derive initial weights. A forward pass happens when the aforementioned data and parameters are passed to the model.

Mathematical operations (linear algebraic and integral) were performed to assess the correctness of model definitions in predicting the pre-known labels. Thereafter, a backward pass took place where an optimizer aimed at minimizing the loss value using differential operation. This was run sequentially until loss was at its minimum value. As a result, weights were set to predict classes of crop type and subsequently detect crop health condition, while the iterative learning process was used to set parameters (Figure 7).

Figure 7. Parameter setting and loss value optimization to derive unbiased weights.

3. Results
3.1. Terrain and Infrastructure Risks

The information provided by the detailed, farm-specific, DEM-based geomorphometric risk analysis (Figure 8) enables the insurer to evaluate the level of risk that any given farm’s infrastructure and crops are exposed to, thereby guiding the setting of premiums for any given farm. For example, in the Dosquebradas district, most farms were found to have relatively minor exposure to flood hazards. However, farms 17 and 18 showed a risk of landslides and soil erosion due to steep slopes and topographic wetness in the eastern part of the farm (Figure 9a), while in the western part of the farm, there is severe flood risk due to topographic wetness and floodplain locations (Figure 9b).
Figure 8. Landform types of Dosquebradas district produced from DEM geomorphometrics. The inset box indicates the area examined in detail within Figure 9a, b.

Figure 9. The Dosquebradas study area, with overlain outlines of the surveyed farms: (a) landslide hazard zones, with the arrow pointing at the eastern border of farms 17 and 18; (b) flood hazard zones, with the arrow pointing at parts of farms 17 and 18 at risk of flooding.
3.2. Indices and Predictions: Climate and Vegetation over Time

The Palmer Drought Severity Index (PDSI) demonstrated a constant trend in normal time and varied during extreme weather events. The most obvious downward trend was associated with wildfires, where PDSI values demonstrated a sharp decline. However, both those and periods of flooding recorded moderate inclines in PDSI values, so PDSI cannot be used to differentiate between the two types of extreme weather.

The MODIS NDVI time-series plots exhibited a constant trend during disaster-free times. During floods, the NDVI values remained constant with less volatility. When it comes to drought, an upward trend is demonstrated. Conversely, the NDVI trend sustained a sharp decline in the periods dominated by wildfires.

3.3. Deep Learning and Mobile Phone Photos of Crops

The aim of using DL is to create two-tier layers by classifying crops into: (1) coffee beans (class I) vs. avocados (class II); and (2) healthy crops vs. unhealthy (or damaged) crops. The dataset consisting of 748 photos of crops was divided into a training set and a testing set with an 80:20 split ratio in order to prevent overfitting. Our binary classification algorithm resulted in an overall 0.8473 accuracy. Table 2 shows the performance of the model based on 748 photos collected from 30 farms in the Dosquebradas study area.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>0.8473</td>
</tr>
<tr>
<td>Precision</td>
<td>0.8917</td>
</tr>
<tr>
<td>Sensitivity (recall)</td>
<td>0.9175</td>
</tr>
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<tr>
<td>Specificity</td>
<td>0.7947</td>
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4. Discussion

4.1. Parametric Insurance Model

A parametric insurance model has been developed that incorporates crop type, crop value/yield, historic claims–loss data and satellite remote sensing data, as well as photos of the crops at the time of buying the policy. To estimate the crop yield, underwriters can use tools such as the Global Agriculture Monitoring (GLAM) decision support system to quantitatively forecast crop yields or they can rely on historical production numbers and selling prices. In contrast to GLAM, the system presented here also considers geomorphometrics and historical trends (via monthly data, for 20 years) of hydrometeorological indices for risk assessment of the underlying asset (i.e., insured farm and crops). Geomorphometrics indicate the likelihood of flooding, erosion, and landslides.

Historical extreme weather disasters can be studied in terms of types, recency, frequency and monetary claims. This helps with setting acceptable ranges for the two indices included (i.e., NDVI and PDSI) for the farm to be insured at a low risk of damage to the crops and farm infrastructure.

The design of a parametric model should assist in determining outputs to be used in underwriting an insurance policy. Those outputs are:

- Actuarial rate tables—premiums, reserves, cash values and dividends.
- Interest rates.
- Loading rates, expense charges, and policy fees.
- Date bands and face amount bands.
- Premium calculation rules.
- Billing and collection rules.
- Underwriting rules.

The aforementioned outputs will be unbiased and set more fairly since those are based on indices captured from EO, geomorphometry, and topography. Additionally, for
underwriting, both policy and premium setting would change automatically as the first notification of loss (FNOL) is issued.

4.1.1. Insurance Claim Verification

The claim verification process is a tedious task that can take a long time to be processed. Machine learning and deep learning models help automate the process while cutting time and costs. In addition, the ability of the system operators to freely download and analyze globally available daily to weekly satellite EO imagery overcomes site access limitations in developing countries. Furthermore, when analyzing data-driven claims, the opportunity of prescriptive analytics emerges when insurers, re-insurers, creditors and governmental agencies aim to minimize damage to agricultural products.

4.1.2. Automated Decision Making

Having an automated hazard detection would recommend to farmers the next best course of action, through what is known as “digital nudging” [47], for example, recommending drip irrigation for areas that the 20-year NDVA records indicate are prone to drought.

4.2. Impact

This research has a direct impact on risk transfer within the agricultural supply chain. Additionally, it has a wider impact on society with fairer and inclusive effects.

4.2.1. Applications of EO for Finance and Insurance Services

It has been argued by Longo, Zardo [8] that despite having knowledge of climate change adaptation frameworks, this knowledge needs to be integrated in practice. Therefore, the focus in this research was on the farmers–insurers relationship in practical terms. Additionally, the findings can be generalized and risk can be distributed by extending it across agricultural supply chains. Actors in such supply chains can benefit from predicting extreme weather disasters (Figure 10). In addition, insurance credit can be allowed using the parametric insurance model for re-insurers. In summary, we have demonstrated how banks and agricultural fund managers can apply EO models and techniques to estimate the projected return on their financial investment in commodities.

![Main Supply Chain Actors](image)

**Figure 10.** Agriculture supply chain.

4.2.2. Moral Hazard and Information Asymmetry

When using parameters to gauge risks, both parties, insurance provider and insured farmer, would have access to similar information about parameters leading to elimination of information asymmetry. Similarly, moral hazards (mainly represented by fraudulent claims) are significantly reduced because of the widespread availability of indices provided by third-party weather agencies [22].

4.2.3. Digital Divide and Data Poverty

The “digital divide” highlights the gap between those with ready access to digital services through information and communication technologies (ICT) and those who are without such access [48]. The digital divide is caused by geographical, economic, educational, attitudinal, generational or even physical factors. It has been argued that disasters affect people unequally by harming those who are most digitally excluded, i.e. those that
are experiencing ‘Data Poverty’ \[49,50\]. Additionally, data generated from limited ICT devices and services are of low quality and can have negative effects due to their unreliability \[51\]. Furthermore, this research has contributed to digital inclusivity \[52\] within the Colombian farming community. The level of community intelligence, determined by ICT access, determines its resilience and ability to generate reliable information \[29\].

4.2.4. Sustainability

In this research, the authors were able to improve sustainability by assisting communities in hedging the risk of hunger while offering a low-cost insurance plan. This paper outlines how the insurance ecosystem may use the affordable and publicly available data and FOSS to apply DL for image classification as well as ML for mapping terrain and estimating extreme weather risks. Not only is this new process affordable for insurers and farmers, but it is also relatively rapid and accurate. Specifically, an alert is raised automatically as soon as an indicator (or a parameter) exceeds or drops below a pre-determined acceptable range driving up the likelihood of an extreme weather disaster. This automated decision is also complemented by an image recognition algorithm that uses deep learning to verify the crop type and its condition as soon as a farmer submits a claim. Finally, ML algorithms such as RF are used to capture changes in topography and approve loss claims. The findings of this paper contribute to the farming business continuity and to the rapid recovery of farmers’ livelihoods, thus boosting sustainable development and improving quality of life.

4.2.5. Policymaking

Policymakers can make use of geoinformatics and satellite data for social good. This is consistent with the framework proposed by Oktari, Munadi \[53\], who concluded that ICT artifacts are the primary driver for sustainability and policies. This research unlocks many opportunities for farmers, insurers, and credit associations in many ways. Specifically, when suggesting that insured individuals (in this research, farmers) contribute to the claim verification process, this creates social recognition and thus contributes to institutional trust and a sustainable pro-environmental attitude towards climate change policies \[23\]. In return, the InsurTech mobile application can make recommendations such as building a glasshouse or installing a new irrigation system that is suitable for the soil of a specific area, which is known as “digital nudging” \[47\] and farmers would respond to that positively. Similarly, credit/financing societies can provide loans to ensure continuation of the supply of crops in that area based on an InsurTech recommendation system. Meanwhile, more variables and data can benefit better risk modeling, such as the growth cycles of different crops being used to better estimate losses.

4.3. Limitations

There have been some challenges with technology and fieldwork for data collection.

4.3.1. Technological Challenges

In technology, when exporting interactive maps using the GEE API, the maps expired after a few days due to authentication issues with GEE. Since they are used for research purposes, the authors could not request that the maps work permanently. Instead, maps were reproduced by running Python code.

Additionally, cloud coverage hindered the use of optical satellite imagery (e.g., Sentinel-2 and PlanetScope), which prevented the investigation of photosynthetic activity in crops. On the other hand, radar satellite imagery (e.g., Sentinel-1) is able to penetrate cloud cover and can detect land surface features and crop types, although it did not perform well in areas with steep slopes. Consequently, both radar and optical satellite imagery had to be included in the damage verification component of the insurance ecosystem.
4.3.2. Data Challenges

Collecting farm data presented a challenge, which affected the deep learning model. Specifically, photos were collected during the period of COVID-19 and many restrictions were in place for our collaborators to navigate in Colombia in March–April 2020. As a result, the mobile photos dataset was relatively small (748 photos).

On the other hand, when labeling the photos, an imbalanced dataset was produced, leading to better classification of coffee beans in comparison with avocados. This was because of the imbalance between the two classes in the dataset. This has affected the accuracy of the DL model (currently at a moderate 0.85 classification accuracy). Nevertheless, there is huge potential for improvement with the app deployment and more regions signing up onto it.

4.4. Recommendations

One of the recommendations is to extend the damage detection from crops to farming infrastructure (e.g., access roads, bridges, processing facilities).

Insurance companies can benefit from automated verification of extreme weather disasters and correct triggering of claims—thus issuing a payout to the insured farmer with less administrative cost. This can be done by ongoing monitoring of EO-derived indices such as the NDVI. Finally, the use of mobile phone photos (time-stamped and GPS-located) can identify the crop, reveal its condition, and save verification costs for the insurers.

4.5. Future Agenda

4.5.1. Wider Coverage

In terms of the underlying asset (crop), the value of crop insured can be better estimated by adding the level of growth (of the crop) at the time of the disaster. This means that a farmer with damaged crops in the sowing season would not have lost the value of a whole season of the insured crop. This is because such farmers can restart the season immediately as soon as a small payout is approved by the insurer to compensate for the value of the seeds. Conversely, when a disaster happens during the harvesting season (especially toward the end of the season), a significant loss can be expected. This is because the whole season would have to be written off. The Food and Agriculture Organization (FAO) provides an interactive tool known as the “Crop Calendar” for farm planning (by country, crop, and activity).

The FAO also summarizes the output of the tool by issuing a timeline of crop calendars per country. The aforementioned factor (growth level) can feed into the insurance model to increase transparency and information symmetry.

Researchers in the future could determine whether insuring a specific product in a specific location is viable and subsequently determine the level of risk associated with it, thus setting fair insurance premiums by integrating such tools in their actuarial insurance model.

4.5.2. Multiple Data Sources

It has been argued that disasters are hard to verify unless first responders and affected people contribute to the disaster data [54]. This can be done by integrating different data sources. In data science and information systems, one of the main features is data integration. In this research, EO was used for pre- and post-disaster damage verification, along with photographic evidence from client farmer phones. However, other sources can also be used, such as scrapping online digital texts from national disaster agencies and using AI to analyze the content of such texts. This would detect any paradigm shift in the semantics describing weather indices [55]. Additionally, exchanges on social media platforms have been effective when communicating emergency situations, specifically when a shared vision and language is present [14].
5. Conclusions

This research has examined the terrain where farms are located to understand their exposure to extreme weather events based on geomorphological measures (e.g., slope steepness, topographic wetness) derived from a freely available satellite-derived global elevation model. As a result, estimating the damage that extreme weather disasters caused to farms was possible in terms of the likelihood at a given site of geohazards such as flooding, landslides and soil erosion. Satellite data were also used to determine the historical occurrences of extreme weather events within farming districts, as well as the vegetation coverage, crop types and crop health. When it comes to insurance and crop damage verification, faster decisions resulted from utilizing a mobile phone app that can provide time-stamped, GPS-located photos of crop damage, with a DL image recognition algorithm improving the verification process.

Key features of this insurance system are its low operational cost and rapid damage verification relative to conventional approaches to farm insurance. It is an affordable form of insurance for small-scale farmers, with the rapid verification and payment of claims enabling policyholders to potentially recover more quickly from disasters.

The insurance ecosystem presented here assists sustainable development in two main ways:

(i) By the use of affordable EO data and sustainable geoinformatics, resulting in low-cost insurance, affordable to smallholder farmers.
(ii) Via relatively rapid processing and verification of damage loss claims—i.e., with payouts potentially within days, rather than months—facilitating business continuity and enabling rapid recovery of farmer livelihoods.


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Informed Consent Statement: Not applicable.

Data Availability Statement: Data are publicly available through the links provided in the manuscript and Appendix B.

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Conflicts of Interest: Author Doyle Ray Oakey was employed by the company Parametrica.ai. Author Max Foxley-Marrable was employed by the company Revolution Data Platforms. Author Alan Wilkins Mercari was employed by the company Mercari Risk Management Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A. Natural Hazards in Dosquebradas, Colombia, 1998–2020 (Compiled from IDEAM Online Database)

<table>
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<tr>
<th>Disaster</th>
<th>Start Date</th>
<th>End Date</th>
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<tr>
<td>1 Drought</td>
<td>1998-01-01</td>
<td>1999-01-01</td>
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<tr>
<td>2 Flood</td>
<td>1999-01-10</td>
<td>1999-05-19</td>
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<tr>
<td>3 Earthquake</td>
<td>1999-01-25</td>
<td>1999-01-26</td>
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<td>Type</td>
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</tr>
<tr>
<td>--------</td>
<td>------------</td>
<td>----------------</td>
</tr>
<tr>
<td>4</td>
<td>Flood</td>
<td>1999-10-28</td>
</tr>
<tr>
<td>6</td>
<td>Wildfire</td>
<td>2001-08-01</td>
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<td>Drought</td>
<td>2002-01-01</td>
</tr>
<tr>
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<td>Flood</td>
<td>2002-04-24</td>
</tr>
<tr>
<td>9</td>
<td>Flood</td>
<td>2003-08-01</td>
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<tr>
<td>10</td>
<td>Flood</td>
<td>2004-01-01</td>
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<td>Flood</td>
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Appendix B. Datasets analyzed in Google Earth Engine

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<td><a href="https://www.usgs.gov/core-science-systems/nli/landsat/landsat-8">2</a>, accessed on 9 November 2022</td>
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<td><a href="https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LE07_C01_T1_SR">3</a>, accessed on 9 November 2022</td>
<td><a href="https://www.usgs.gov/core-science-systems/nli/landsat/landsat-7">4</a>, accessed on 9 November 2022</td>
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<td>USGS Landsat 5 Surface Reflectance Tier 1</td>
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<td>MOD13Q1.006 Terra Vegetation Indices 16-Day Global 250m</td>
<td><a href="https://developers.google.com/earth-engine/datasets/catalog/MODIS_006_MOD13Q1">7</a>, accessed on 9 November 2022</td>
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<td>MYD13Q1.006 Aqua Vegetation Indices 16-Day Global 250m</td>
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<td>CHIRPS Daily (v.2): Climate Hazards Group InfraRed Precipitation with Station Data</td>
<td><a href="https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY">11</a>, accessed on 9 November 2022</td>
<td><a href="https://chc.ucsb.edu/data/chirps">12</a>, accessed on 9 November 2022</td>
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<td>PERSIANN-CDR: Precipitation Estimation from Remotely Sensed Information ANN-Climate Data Record</td>
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<td>ERA5 Daily aggregates—Latest climate reanalysis produced by ECMWF/Copernicus Climate Service</td>
<td>[17](<a href="https://developers.google.com/earth-engine/datasets/catalog/ECMWF">https://developers.google.com/earth-engine/datasets/catalog/ECMWF</a> ERA5 DAILY), accessed on 9 November 2022</td>
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