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A Climate Change Vulnerability Assessment among Small Farmers: A Case Study in Western Honduras

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ABSTRACT

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Climate change is now affecting every known society. Small farmers in Low Income Countries (LICs) are especially vulnerable to climate change patterns because they depend heavily on rain, seasonality patterns, and known temperature ranges. To help build climate change resilient communities among rural farmers, the first step is to understand the impact of climate change on the population. This dissertation aims to use information and communication technology (ICT) to assess climate change vulnerabilities among rural farmers. To achieve this overall goal, this dissertation first proposes a comprehensive Climate Change Vulnerability Assessment Framework (CCVAF) that integrates both community level and individual household level indicators. The CCVAF was instantiated into a GIS-based web application named THRIVE for different decision makers to better assess how climate change is affecting rural farmers in Western Honduras. Qualitative evaluation of the THRIVE showed that it is an innovative and useful tool. The CCVAF and its instantiation provides an important initial step towards building climate change resilience among rural farmers. It is the first attempt to provide a comprehensive set of the indicators with related measurements and data sources for climate change vulnerability assessment. The framework thus contributes to the knowledge base of the climate change vulnerability assessment. It also contributes to the design science literature by providing guidelines to design a class of climate change vulnerability assessment solutions. To the best of our knowledge, the CCVAF is the first generalizable artifact that can be used to build a group of ICT-based climate change vulnerability assessment solutions. Another knowledge contribution of this dissertation is its reproducibility by making the input and output

data available to the research and practitioner community through a GeoHub. For practical contributions, the framework can be easily used by researchers and practitioners to consistently design a vulnerability assessment tool, starting with the set of indicators organized by the three-level determinants, and following specific spatial data analysis and models. Such an ICT-based tool adds practical values to tackle climate change challenges.

DEDICATION

I first dedicate this dissertation to my Lord and Savior, my strength, and my hope. I also dedicate this dissertation to my wonderful children Christian and Isabella. I love you both to the moon and back. Mom has not been a normal mom so thank you for being patient and loving me always despite my craziness. To all my supporting family Mom, Dad, Carmen, Karina, Tia Teresa, Tia Gloria, Ruth, Benny, and Virgilio for being there for me even though my dream seemed so crazy and far beyond my reach. To all my friends especially Huda, Clarissa, Luis, Jovita, Shawnika, Denise, and Marisol who have given me words of encouragement and have been there for me always.

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CHAPTER 1: INTRODUCTION

Climate change is now affecting every known society. According to the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5), climate change has a clear human influence with the highest anthropogenic greenhouse gas emissions (GHG) in history, diminishing snow levels and ice caps, rising sea levels, and warming atmosphere and oceans. Higher intensity extreme climatic events and more frequent occurrences are also observed and expected (IPCC, 2014; Schmidhuber & Tubiello, 2007; UN, 2018).

Disadvantaged people, such as rural poor and smallholder producers in developing countries, are at a higher risk as the changes in climate patterns will impact crop yields and undermine food security, especially among subsistence farmers who generally produce low yields and are least able to cope with their effects (Altieri et al., 2015; Antle, 1995; FAO, 2017; IPCC, 2014; P. Jones & Thornton, 2003; Kang et al., 2009; Misra, 2014; Schmidhuber & Tubiello, 2007; UN, 2018; World Bank, 2013). According to FAO (2017), climate change affects food security in four dimensions: food availability, food access, food utilization and food stability (FAO, 2017).

Climate change is also expected to the slow economic growth of nations and regions. In recent studies of 134 countries, a temperature rise of 1° C was expected to significantly reduce the per capita GDP by 9 % (World Bank, 2013). Developing and least developed countries often suffer from frequent extreme climatic events. Poverty reduction efforts in these countries are more difficult as planned resources are diverted towards disaster relief, creating new poverty traps and hunger hotspots (IPCC, 2014; P. Jones & Thornton, 2003; Morton, 2007; Thomalla et al., 2006; World Bank, 2013). For example, when Djibouti suffered from a severe drought in 2011, the country lost 20 years of its development effort and its poverty level rose to the level seen in 2002 (World Bank, 2013). Changes in weather patterns, such as drought or heavy rains leading to flooding, are also projected to generate an increase in human migration especially in developing countries because the population in these countries has less adaptive capacity to climatic variability (FAO, 2017; IPCC, 2014; Milman et al., 2018).

Agriculture is still a main source of income and food security in many developing and low-income countries, especially in rural areas (Baca et al., 2014). As temperatures increase, the need for irrigation water also increases. Water stress affects smallholder and subsistence farmers in developing countries (Morton, 2007). Even with a moderate increase in temperature (1 - 2 °C) in tropical regions, maize, rice, and wheat yields are expected to be negatively impacted (Morton, 2007). For example, P. Jones & Thornton (2003) tested a third-order Markov rainfall model to simulate how rainfall variability would impact maize production in the Latin America and African regions. The model shows a 10% decrease in maize yields by 2055, which can be disruptive for rural communities who depend on maize for subsistence and livestock feed (P. Jones & Thornton, 2003). The change in climate may also alter the dynamics of pest populations as temperature increases directly influence their reproduction (Altieri et al., 2015). For example, Arabica coffee, one of the most important crops in the Mesoamerican region, is seriously threatened by the increase in temperature and resulting pest infestations. Ethiopia and Kenya have already seen a shift in the distribution of wild coffee and a reduction in yields (Baca et al., 2014).

Subsistence agriculture is an approach that has changed little over the centuries, utilizing few mechanical or industrial inputs and with little technical assistance. Its goals are primarily food production for home use and local sales for household cash needs. It is generally practiced on small land holdings, and is a common scenario among the Central American region (Bouroncle et al., 2017; Holland et al., 2017; Imbach et al., 2017). These small farmers depend heavily on rain and are highly vulnerable to any change in precipitation or climate patterns. Many of these farmers are already food insecure and live in precarious conditions. For this reason, they are a priority in climate change adaption plans (Holland et al., 2017; Morton, 2007).

Climate change adaptation focuses on strengthening resilience and reducing vulnerability (FAO, 2018). Many planned processes, proposed or new policies, and technological innovations (Altieri et al., 2015; FAO, 2018; Misra, 2014; Neil Adger et al., 2005) have been advanced to deal with the impact of climate change, especially those that affect food production, and adaptation has become an anticipatory measure. Climate change adaptation should involve the local communities, civil society, international

organizations, governments at the local, regional and national level (Neil Adger et al., 2005). Policy makers need to identify vulnerable populations to understand the shocks and stressors they may be facing now and in the future, and allocate possible adaptation resources to them (Bouroncle et al., 2017). They need to assess these populations' adaptive capacity and identify vulnerabilities. Information is often limited due to the difficulty of obtaining data about these vulnerable populations, and their expected shocks and stresses, particularly those faced by marginal communities of small farmers in low-income countries. To assess the adaptive capacity of a population, both primary and secondary data are needed. Primary data are collected at the individual household or community level. Secondary data are usually generated by governments and can be used to estimate adaptive capacity locally or regionally. The data challenge exists as the "availability, quality, consistency and reliability" of these data can be limited (Holland et al., 2017). To help build climate change resilient communities among rural farmers, the first step is to understand the impact of climate change on the population, its land, and its agricultural practices. This dissertation aims to use information and communication technology (ICT) to assess climate change vulnerabilities among rural farmers. More specifically, the ICT will be used to collect both primary and secondary data for rural farmers in low-income countries and use these data for understanding the climate change vulnerabilities of the targeted population.

1.1 Research Problem and Research Questions

As described earlier, this dissertation aims to use information, communication, and technology (ICT) to assess climate change vulnerabilities among rural farmers. To achieve this overall objective, this dissertation seeks to answer the following research questions:

1. What determinants and variables need to be analyzed to assess climate change vulnerability?

2. How can climate change exposure and sensitivity be measured using geospatial technology?

3. What determinants and variables are needed to measure the adaptive capacity of the communities?

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While reviewing empirical studies on climate change, it is clear a large portion of the analyses focus on identifying the possible damage and areas where climate change impact will disproportionally affect agriculture, especially in developing countries at higher climate risk (Altieri et al., 2015; Antle, 1995; Arbuckle et al., 2015; Howden et al., 2007; Imbach et al., 2012, 2017; Morton, 2007; Tan & Shibasaki, 2003). While expected impacts are well studied, mechanisms for identifying vulnerable areas are not. For this reason, innovative ways to measure and identify vulnerable areas are needed on dimensions that may be disproportionately impacted by climate change, such as various aspects of the natural environment – the focus of this dissertation. With the advancement of new spatial technologies, Geographic Information Systems (GIS), Remote Sensing (RS) and Artificial Intelligence (AI) with its subsets Machine Learning and Deep Learning are now and can be widely used for a wide swath of analyses critical to successfully understanding and managing environmental and agricultural vulnerability. These include crop productivity and yield estimations, crop management challenges (Huang et al., 2018; Sahu et al., 2011; Singh et al., 2015a; Tan & Shibasaki, 2003), environmental vulnerability and degradation assessments (Hassan et al., 2015; Mohamed et al., 2013), soil degradation, moisture and erosion measurements (Diodato & Ceccarelli, 2004; Jain & Das, 2010; Song et al., 2016), agricultural early warning and decision support system (DSS) (Rembold et al., 2017; Suksa-Ngiam et al., 2016), deforestation (Ahmadi, 2018; DeFries et al., 2007; P. Kumar et al., 2010; Yoshikawa & Sanga-Ngoie, 2011), climate change risk assessment and adaptation (Kunapo et al., 2016; Rizzi et al., 2012) droughts (AghaKouchak et al., 2015; Bagheri, 2016; Mishra & Nagarajan, 2011), forest fires (Caceres, 2011; Chuvieco & Salas, 1996; Erten & Kurgun, 2002a; Jaiswal et al., 2002a), systems to monitor vector-borne animal and plant diseases, and other environmental epidemiological applications (Khormi & Kumar, 2014; VoPham et al., 2018). The next section provides a broader look into the environmental factors considered to assess climate change vulnerability.

CHAPTER 2: LITERATURE REVIEW

This literature review contains a review of two major sections of research:

2.1 Vulnerability and Climate Change

2.2 Exposure and Sensitivity Determinants

2.1 Vulnerability and Climate Change

The word vulnerable has its origins in the Latin noun *vulnus* which means wound. *Vulnus* led to the Latin verb *vulnerare* which means to wound and to the Latin adjective *vulnerabilis* which means vulnerable (Kelly & Adger, 2000; Luna, 2018; Merriam-Webster, 2019). Today, the term vulnerability is extensively used in a wide variety of research areas including poverty and development, food security, emergency preparedness, economic development, climate change and recently also has been used in moral philosophy and bioethics. It is a term being conceptualized differently depending on the domain being used, evolving throughout time with no consensus on its meaning. Of particular importance, its subject, and the identification of vulnerable populations, has been generously labeled as vague. In some cases, the difference in conceptualizations can become problematic in climate change research. Scholars from different fields collaborate and a consistent terminology is needed for improved collaboration and communication (Brooks, 2003; Füssel, 2007; Luna, 2018). Vulnerability also describes the analysis to measure powerlessness, marginality and how susceptible a group or individual can be to a harmful situation being caused by multiple stressors and pathways (Adger, 2006). Vulnerability has become a central concept to climate change research as the effects of climate change are being widely observed and the development of vulnerability assessments are being used to raise awareness, develop policies and to monitor of adaptation measures (GIZ, 2013, 2014; Hinkel, 2011). If one intends to create a vulnerability assessment (to encourage a change in a community or inform policy makers), one must determine the methodology to measure vulnerability.

Empirical studies show the use of a variation of the basic formula to measure vulnerability: "Vulnerability = Risk + Response" or "Vulnerability= Baseline + Hazard + Response" (Moret, 2014).

One of the main objectives of this dissertation is to develop a framework to assess and identify the vulnerability of households in the area under study. As the vulnerability and adaptation literature grows and uses a wide array of concepts (Brooks, 2003), it is important to start by defining several concepts that will be part of this vulnerability analysis: vulnerability, exposure, resilience, sensitivity, and adaptive capacity. This dissertation will use the definitions provided by (IPCC & Edenhofer, 2014; McCarthy & IPCC, 2001) as follows:

- **Vulnerability:** "The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity"

- **Exposure:** "The nature and degree to which a system is exposed to significant climatic variations"

- **Resilience:** "The capacity of social, economic, and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganizing in ways that maintain their essential function, identity, and structure, while also maintaining the capacity for adaptation, learning, and transformation"

- **Sensitivity**: "Sensitivity is the degree to which a system is affected, either adversely or beneficially, by climate-related *stimuli*. The effect may be direct (e.g., a change in crop yield in response to a change in the mean, range, or variability of temperature) or indirect (e.g., damages caused by an increase in the frequency of coastal flooding due to *sea-level rise*)."

- **Adaptive capacity:** "The ability of systems, institutions, humans, and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences." (IPCC & Edenhofer, 2014)

When developing a vulnerability assessment, empirical studies show different approaches can be used. (Below et al., 2012) identifies three ontological approaches: theory-driven, data-driven and combination of empirical and theoretical. The theory-driven approach uses a literature review to select the

variables being measured, but this approach provides a level of uncertainty as to whether the variables being chosen can really measure vulnerability. The data-driven approach selects the variables being measured through expert opinion or through the correlation of past events, but this approach does not assess the variables through a benchmark but limits itself to expert opinion. The third approach is a response to the weaknesses of the other approaches. Two specific examples are the Livelihood Vulnerability Index proposed by (Hahn et al., 2009) and the Vulnerability assessment using an Indicator approach proposed by (Gbetibouo et al., 2010) (Below et al., 2012). Both approaches will be described in more depth in following subsections. (Gbetibouo et al., 2010) mentions the use of two very similar approaches: the econometric approach and the indicator approach. The econometric approach uses metrics as consumption or yields mainly measuring loss but does not completely target exposure, sensitivity and adaptive capacity which are the three main vulnerability dimensions. The indicator approach uses specific indicators or a combination of them to measure vulnerability to compute indices or weighted averages but again this approach is limited to the actual variables selected for the assessment being useful for monitoring and evaluation (M&E) purposes (Gbetibouo et al., 2010). (Below et al., 2012) proposes an activity-based adaptation index (AAI) which is a different approach starting with a quantitative assessment of previous adaptation processes.

2.1.1 Climate Change Vulnerability Assessment

A Climate Change Vulnerability Assessment (CCVA) is a commonly used tool to help define interventions for climate change adaptation plans and are generally used to measure the vulnerability of communities or natural systems (e.g. watersheds) exposed to climatic phenomena prioritizing the intervention needed (Bouroncle et al., 2017; GIZ, 2013). Several authors emphasize the importance of shifting from measuring the vulnerability of a given geographic location but instead focusing on the assessment of variables and specific stressors (Füssel, 2007) . The changes in an agricultural livelihood during a period due to exposure, sensitivity and adaptive capacity define the vulnerability of that livelihood (Bouroncle et al., 2017). Vulnerability is determined by the farm's biophysical features and the

farmer's socioeconomic condition (Altieri et al., 2015). Vulnerability is hard to observe or measure directly, but can be deduced by estimating exposure, sensitivity and adaptive capacity using qualitative and quantitative information with indicators and variables (GIZ, 2013). The potential impact (PI) is the combination of sensitivity and exposure that may occur if adaptation is not considered when a change in climate happens. Previous CCVA studies done in the Central American region, have mainly focused on specific groups such as cooperatives or on specific crops such as coffee, but lack a real definition on where the adaptation efforts should focus geographically or how these groups of farmers should adapt (Bouroncle et al., 2017). (Bouroncle et al., 2017), developed a "quantitative indicator-based CCVA" of municipalities (second level of administrative division) in El Salvador, Guatemala, Honduras, and Nicaragua. The study represents the PI as the "expected absolute change in climatic suitability for crops" including exposure using bioclimatic variables and General Circulation Models from IPCC. The Adaptive Capacity Index (ACI) was also mapped for all the municipalities in the study based on three conditions: "basic need satisfaction, resources for innovation and resources for transforming innovation into actions" (Bouroncle et al., 2017). The sum of PI and ACI resulted as the Vulnerability Index (VI) for every municipality resulting in three quantiles (low, medium, and high) which helps to identify the most vulnerable municipalities. The study results show Honduras has most of its territory with medium to low Adaptive Capacity, except for the areas with high population density which has high Adaptive Capacity. Honduras also scores with higher VI as a result of higher PI and lower ACI (Bouroncle et al., 2017).

The approach chosen to conduct a CCVA determines the unit under evaluation (e.g., households, watersheds, or communities), the scale (e.g., country, community, household), and the availability of data. The two commonly used approaches are: Top-Down and Bottom-Up. The Top-Down approach uses global and regional scenarios to assess possible impact starting with an analysis of the impacts of climate change. The Bottom-Up approach focuses first on the people affected and its study unit is smaller (e.g., communities) and typically the people in the communities are part of the assessment but also, they are providers of data and may assist in the analysis integrating local knowledge in the process. A combination

of top-down and bottom-up approaches has also been useful in the past increasing the acceptance to results (GIZ, 2013, 2014).

2.1.2 Livelihood Vulnerability Index

A livelihood may be defined as an environment comprised of assets allowing a means of living (Krantz, 2001) and which provides adequate levels of food and cash. The term Sustainable refers to the production of resources in the long-term without compromising the resources for future generations. A livelihood may become sustainable if one has access to land ownership, or livestock, or fishing, hunting or any source of stable employment that allows a stable source of income. The Sustainable Livelihoods Approach (SLA) uses five types of assets: natural, social, financial, physical, and human capital, all useful in supporting a household to withstand shocks (Chambers & Conway, 1992; Hahn et al., 2009). However, the SLA only addresses sensitivity and adaptative capacity. With changes in climate, this approach is no longer feasible as it does not address the complex changes the environment is experiencing. A new approach is needed to integrate exposure and household adaptation. The Livelihood Vulnerability Index (LVI) combines methods estimating the impacts climate change is having in different communities using several indicators to measure exposure, variability, adaptive capacity, and sensitivity. (Hahn et al., 2009) uses seven major components: socio-demographic profile, livelihood strategies, social networks, health, food, water, natural disasters, and climate variability. The LVI applies an equal weighted average approach and each subcomponent has an equal weight (Hahn et al., 2009) but this equal weighting is seen as a weakness, given it is hard to assume all the subcomponents can have an equal effect (Below et al., 2012).

2.1.3 Indicator Approach

(Gbetibouo et al., 2010) focuses on the farming sector in South Africa and proposes the integration of biophysical and socioeconomic indicators from the farming regions under study. But this approach is also subjective as it is limited to the selection of specific variables. Seeking to reduce

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subjectivity, two steps were followed: a) literature review on different vulnerability assessments; and b) indicators were assessed through an expert panel using a criterion to identify which ones were relevant, adequate, easy to grasp, and had data available to measure them. Through the assessment indicators measured exposure (frequency of past climate extremes, predicted change in temperature and rainfall), sensitivity (irrigation rate, land degradation index, crop diversification index, share small-scale), and adaptive capacity (share of farmers in farms, literacy rate, HIV prevalence, farm income, infrastructure index). The values are then normalized and then weighted depending on the indicator and using a principal component analysis (PCA) method (Gbetibouo et al., 2010). But according to (Below et al., 2012) the determination of every weight is through the data structure and may result in contradictory weights (Below et al., 2012).

2.1.4 Activity-based adaptation index (AAI)

Vulnerability is also measured by how a community is able to adapt through responses and the availability of resources (Adger et al., 2003) but its measurement is challenging as many of the variables used are uncertain (Below et al., 2012). Agriculture is highly sensitive to climate changes as is regularly seen by the impact of meteorological phenomena El Niño and La Niña, so it is crucial to identify adaptation options (Howden et al., 2007). Adaptation can be seen as the reduction of dependence by the diversification of food production (Adger et al., 2003) through the incorporation of different varieties/species with higher resistance to heat waves, alteration of fertilizer rates, changing irrigation timings, "harvesting" water, undertaking soil moisture conservation, and many others (Howden et al., 2007). In order to obtain better results, adaptation should follow local-level analysis. (Below et al., 2012) proposes an activity-based adaptation index (AAI), which is a quantitative assessment to measure adaptation determinants linking local livelihood indicators. This approach analyzes poverty levels and different strategies taken by the household through socioeconomic variables with a further statistical analysis using factor analysis and multiple regression (Below et al., 2012).

2.2 Exposure and Sensitivity Determinants

While reviewing empirical studies on climate change, it is clear a large portion focuses on identifying the possible damages and areas where its impacts will be the most intense predominantly agriculture in developing countries (Altieri et al., 2015; Antle, 1995; Arbuckle et al., 2015; Howden et al., 2007; Imbach et al., 2012, 2017; Morton, 2007; Tan & Shibasaki, 2003). For this reason, innovative ways to measure and identify vulnerable areas are needed and are needed on dimensions that are affected by climate change, such as the environmental factors which this research paper addresses. With the advancement of new spatial technologies, Geographic Information Systems (GIS), Remote Sensing and Artificial Intelligence with its subsets Machine Learning and Deep Learning are now widely used for crop productivity and yield estimations, crop management (Huang et al., 2018; Sahu et al., 2011; Singh et al., 2015a; Tan & Shibasaki, 2003), assessing environmental vulnerability and degradation (Hassan et al., 2015; Mohamed et al., 2013), assessing soil degradation, moisture and erosion (Diodato & Ceccarelli, 2004; Jain & Das, 2010; Song et al., 2016), agricultural early warning and decision support system (DSS) (Rembold et al., 2017; Suksa-Ngiam et al., 2016), assessing deforestation (Ahmadi, 2018; DeFries et al., 2007; P. Kumar et al., 2010; Yoshikawa & Sanga-Ngoie, 2011), climate change risk assessment and adaptation (Kunapo et al., 2016; Rizzi et al., 2012) droughts (AghaKouchak et al., 2015; Bagheri, 2016; Mishra & Nagarajan, 2011), monitoring forest fires risk (Caceres, 2011; Chuvieco & Salas, 1996; Erten & Kurgun, 2002a; Jaiswal et al., 2002a), and monitoring vector-borne diseases and other environmental epidemiological applications (Khormi & Kumar, 2014; VoPham et al., 2018). The next section provides a broader look into the factors considered to assess climate change vulnerability.

2.2.1 Forest Disturbances

A forest disturbance is an environmental fluctuation that disturbs the normal health of a forest ecosystem and impacts the resources available through it (van Lierop et al., 2015). It is expected that climate change will deeply impact forest ecosystems through abiotic disturbances agents such as fires, snow, wind, and droughts, as well as through biotic disturbances such as insect outbreaks and pathogens.

Both types of disturbances affect forest growth, survival, yields and wood quality. Another source of forest disturbance include deforestation due to a change in land use. A disturbance disrupts the potential of the ecosystem to provide a service to a community and affects its resilience with the grave consequence of lasting impacting its balance (FAO (3), 2019; Seidl et al., 2017; van Lierop et al., 2015). Among the key environmental disturbances affecting forests are temperature variability, wind speed, atmospheric moisture and water availability (Seidl et al., 2017).

This study will include as part of its vulnerability assessment the study of the following disturbances: fire, deforestation, droughts and insect outbreaks and each disturbance will be described in following sections.

2.2.1.1 Fire and Forest Fire Risk Zones

A forest fire is a natural ecological process and is a traditional agricultural practice in Honduras for land management, regenerating grasslands and eliminating pests (Caceres, 2011; Lineal & Laituri, 2013). But this practice may have adverse consequences as uncontrolled fires can easily spread into national parks or surrounding areas affecting the livelihood of the population and the air quality of the area (Brandt, 1966; Davies et al., 2009; Lineal & Laituri, 2013). In recent years, we have seen an increase in forest fires most likely due to changes in land use, although climate changes should also be considered since variation in precipitation changes the fuel conditions which increases fire risks (Chuvieco, 1999). According to (Seidl et al., 2017), climate change has a direct and indirect effect on a forest fire as it may affect the fuel moisture, the ignition source, the speed of fire spread, the fuel availability, flammability and fuel continuity.

Since its inception, GIS and Remote Sensing have demonstrated their value as tools to observe or study active or historic forest fires. This is because they can correlate different variables to further develop models resulting in forest fire risk zone maps (Adab et al., 2013; Caceres, 2011; Chuvieco et al., 2019; Chuvieco & Congalton, 1989a; Erten & Kurgun, 2002a; Giglio et al., 2016; Yin et al., 2004).

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In recent years, wildfire activity has increased and the response to those events requires access to timely information for resource allocation, budgeting, management, and planning. As technology advances, improved applications capable for Earth observation are possible allowing the near-real time data monitoring and processing of fire-related data. One source of environmental data including active fire data is provided through the Moderate-resolution Imaging Spectroradiometer (MODIS) which is a sensor onboard Terra and Aqua satellites. Both satellites are part of the National Aeronautics and Space Administration (NASA) Earth Observing System (EOS) mission. MODIS uses an algorithm capable of detecting "fire pixels" containing active fire(s) when the satellite passes and classifying them as: missing data, cloud, non-fire, fire or unknown. MODIS provides daily active fire data and 500m tile burned area. To make this data available, two systems were developed: the MODIS Rapid Response (MRR) system and the Fire Information for Resource Management System (FIRMS). The MRR tool provides different resolutions for true-color imagery in near real time. FIRMS is a tool oriented towards GIS users allowing the capability of handling data in GIS desktop software (Davies et al., 2009; Giglio et al., 2016). This Dissertation uses the FIRMS tool as a source to obtain and map active fires in the area under study.

The term fire risk and fire danger can be used interchangeably depending on the authors (Chuvieco, 2003). According to FAO (1986) fire risk is "the chance of fire starting, as affected by the nature and incidence of causative agencies; an element of the fire danger in any area" and fire danger is "the resultant, often expressed as an index, of both constant and variable danger factors affecting the inception, spread and difficulty of control of fires and the damage they cause" (FAO, 1986). Other authors identify a fire risk zone as an area prone to fire hazard which can easily spread to surrounding areas (Chuvieco & Congalton, 1989a; Gai et al., 2011) consider the union of fire hazard and fire ignition as a fire risk zone (Chuvieco, 2003; Chuvieco & Congalton, 1989b). Another terminology clarification is the one provided by Chuvieco (1999) distinguishing the beginning of a fire as fire ignition or flammability and the spread of a fire as fire behavior risk or fire hazard, and both approaches require an integration of different spatial variables (Chuvieco, 1999).

Empirical studies provide different methodologies using Remote Sensing and GIS to identify fire hazard areas. Understanding the factors influencing forest fires is essential for mapping forest risk zones (Chuvieco & Congalton, 1989b; Jaiswal et al., 2002a). These factors include environmental (landcover, land use), physiographic (elevation, slope, aspect), climatic (wind, rainfall, relative humidity, temperature), soils types, water availability (Chuvieco, 1999), proximity to roads and proximity to settlements. These factors can determine where fires are more likely to start, where they can propagate, and may predict the intensity of forest fires (Caceres, 2011; Chuvieco, 1999, 2003; Chuvieco & Congalton, 1989a; Gai et al., 2011; Mohammadi et al., 2014; Sağlam et al., 2008). Other studies add unemployment rates in the area of study as a human risk factor to their model to identify if there is correlation between them and fires occurrences but found no correlation between them (Maingi & Henry, 2007). Other studies focus on identifying human risk factors including socio-economic, housing patterns, human presence variables and historical trends of human-caused fires (Martínez et al., 2009).

A common methodology to develop forest fires risk zones uses a model to calculate a fire hazard index by overlaying the spatial layers of the factors listed previously to quantify the level of risk. This approach uses a hierarchical scheme having some layers with greater influence weighted higher according to the impact they have to increase the risk of fire (Caceres, 2011; Chuvieco, 2003; Chuvieco & Congalton, 1989b; Erten & Kurgun, 2002a; Gai et al., 2011; Jaiswal et al., 2002a; Sağlam et al., 2008). Recent studies incorporate the use of logistic regression, linear regression, and artificial neural networks, (Chuvieco, 1999, 2003; Martínez et al., 2009; Mohammadi et al., 2014) or spatial-temporal analysis (Sağlam et al., 2008) for fire occurrence prediction at different scales.

2.2.1.2 Deforestation

Deforestation has grave implications for the availability of water locally. It also introduces variations of local climate patterns affecting crop productivity, thereby endangering communities that depend on agricultural products for their survival. Through general circulation models (GCMs), it can be predicted that a drastic loss of tropical forest will itself result in warming between 0.1 – 0.7 °C. Forest

changes. especially the reduction of tropical forest, affect the climate locally, regionally, and globally. Some factors to measure the sensitivity of a regional climate may include soil type, vegetation, topography, climatology, and forest cover distribution. Using Remote Sensing, it is possible to observe the changes in evapotranspiration comparing areas with existing forest versus areas which have been converted to pasture or growth of crops (Lawrence & Vandecar, 2015). The development of forest cover maps allows the delineation of remaining forest, and the identification of land use change through remotely sensed imagery. Land cover monitoring is possible using the seven bands available in the MODIS sensor, which provides an improved spectral option and accuracy in comparison to previous sensors. Methodologies to map land cover include fuzzy estimations, plant density isolines, empirically calibrated estimates, and regression tree algorithm for tree canopy cover estimation (Hansen et al., 2003). As technology advances, the recent combination of spatial science and artificial intelligence (AI) has formed the science field of geospatial artificial intelligence (geoAI) (Maher, 2018; VoPham et al., 2018) providing the opportunity to develop Models for Land Cover Classification using Deep Learning.

2.2.2 Drought and Soil Moisture

Drought is a climatic condition impacting human activities, ecosystems, agricultural production, and industrial activities, among others. Its effects may have devastating consequences in developing countries which may be affected by famines and migration of populations from impacted communities in search of food (Berg & Sheffield, 2018). The IPCC defines drought as "a period of abnormally dry weather long enough to cause a serious hydrological imbalance" (IPCC, 2012). It is a phenomenon affecting the global water cycle in its regional variability (AghaKouchak et al., 2015) starting with a reduction in precipitation in the long term resulting in low water levels affecting soil moisture and groundwater levels (Berg & Sheffield, 2018; Wilhite & Glantz, 1985). The scientific community has identified four approaches to measure drought: a) meteorological, b) agricultural, c) hydrological d) socioeconomic (AghaKouchak et al., 2015; Wilhite & Glantz, 1985).

Meteorological drought is the most common approach and generally identifies a "degree of dryness" and the timeframe of the event. Agricultural drought can take place in the absence of a meteorological drought when farming practices have degraded the land's water- holding capacity or utilizing plants which reduce water availability to other plants or uses. Agricultural drought includes different meteorological characteristics that may impact in agricultural production and may include "precipitation shortages", measurement of evapotranspiration, and a shift from the normal levels of precipitation. Hydrological drought focuses on the "surface or subsurface hydrology" including a change in the flow of streams and river basins. Socioeconomic drought may include the meteorological, agricultural, and hydrological droughts but focusing into the supply and demand of goods that may have been impacted by the reduction in water levels or reduction in water availability levels (Wilhite & Glantz, 1985). Recently the ecological drought is being included as a new approach focusing on the deficit of water availability stressing ecosystems (University of Nebraska - National Drought Mitigation Center, 2019).

Empirical research suggest the 1965 Palmer Drought Severity Index (PDSI) as a widely method for drought monitoring (Berg & Sheffield, 2018; Hayes et al., 2000; Wilhite & Glantz, 1985) both Internationally and in the United States. According to PDSI, drought severity is related to the difference between actual precipitation and the needed precipitation for evapotranspiration (ET) and is used to monitor prolonged periods of dry weather and evaluate conditions of long-term moisture (Wilhite & Glantz, 1985) by estimating moisture deficits during a period of time(Berg & Sheffield, 2018). But (McKee et al., 1983) mentions that a drought analysis should consider time scale, probability, precipitation deficit, and the relationship of the definition to the impacts of droughts among others. In their discussion, they mention the commonly used PDSI does not contemplate the time scale as a measuring parameter even though it exists. They propose a new definition, and an indicator called the Standardized Precipitation Index (SPI), using only one variable as the input. Their proposed definition uses standardized precipitation from different time scales thus providing a quantitative definition of drought. They define drought as a period in which the SPI has been continuously negative and being

measured as a mild drought if the SPI value falls below zero, moderate drought if the SPI value is between -1.00 to -1.49, severe drought if the SPI value is between -1.50 to -1.99 and finally extreme drought if the value is less than -2.00. Th (McKee et al., 1983).

Since its introduction in 1960, Remote Sensing has been a valuable, monitor of drought events and their ecosystem impacts. Currently there are three types of satellites in orbit: a) the high Earth orbit also called geosynchronous (GEO) satellite orbits at 35,780 km or higher and rotating in a speed of 11,100 km/hour, b) mid Earth orbit at an altitude between 2,000 – 35,780 km and rotating in a speed of 13,900 km/hour and c) low Earth orbit (LEO) at an altitude between 180 – 2,000 km and rotating in a speed of 27,500 km/hour. The geostationary orbit satellite matches the rotation of Earth and is used for weather monitoring, communications, helping locate ships and aircrafts or monitoring solar activity. The medium Earth orbit is the orbit used by the Global Positioning System (GPS) satellites and serves better for the observation of high latitude regions. The Low Earth orbit is the one used by many scientific and weather satellites given its speed the satellite is able to pass the Earth twice in a 24-hour period with one pass in daylight and the other in darkness (Riebeek, 2019). Using remote sensing common drought-related variables are able to be regularly reviewed including: precipitation, soil moisture, groundwater, evapotranspiration and snow cover (AghaKouchak et al., 2015). This research will not include snow as a variable to measure given the climatic zone of the area of influence is tropical.

A key parameter when studying droughts is the Soil Moisture Content (SMC). Studying SMC variations through monitoring precipitation deficit, solar radiation, soil evaporation, plant transpiration can help in forecasting climatic extremes (Berg & Sheffield, 2018; Ngo Thi et al., 2019).

2.2.3 Health Access

Honduras is a country of inequalities with weak institutions and access to health care is one of the main concerns for its population. According to the World Health Organization, the total Honduran health expenditure in 2014 per person was $400 and the total expenditure in health as a GDP percentage was 8.7% (OMS, 2020). Health is directly related to the economic status of an individual, and it has been

proven groups of individuals with lower income have higher probabilities of dying from chronic diseases and preventable diseases (Rápalo et al., 2005).

According to April's 2020 World Bank's Poverty & Equity Brief, Honduras is one of the poorest countries in Latin America and Caribbean (LAC). Approximately 48.3% of its population lives in poverty with 16.5% of its population lives with less than US$1.90 a day and approximately 50.3% lives with less than US$5.5 per day. Approximately 60.1% of its rural population lives in poverty, representing approximately 2.5 million people (The World Bank, 2020). Honduras has three main health concerns: a) prevalence of infectious diseases including leishmaniasis, TB, and HIV/AIDs, and vector borne diseases as zika, dengue, chikungunya and malaria, b) non-communicable diseases as diabetes, and high blood pressure, and c) high levels of morbidity and mortality rates due to traffic accidents and homicides (OPS/OMS, 2016; Rodríguez & Arévalo, 2018). Sadly in 2013, the United Nations defined Honduras as having the highest homicide rates in the world with a rate of 82.1 per 100,000 habitants and reducing its rates in 2014 to 60 per 100,000 habitants (OPS/OMS, 2016).

In recent years, there has been an increase in vector (often mosquito) borne infections mainly zika virus (ZIKV), dengue (DENV), chikungunya virus (CHIKV) raising global concerns as it was the declaration of ZIKV as a 2016 Public Health Emergency of International Concern (Banu et al., 2011; OPS/OMS, 2016; Paixão et al., 2018). Reports have concluded there is a direct relationship between vector borne infections and climate change as changes in temperature, precipitation and humidity affect the biology, ecology, and dispersion of the vector. The vector's geographic distribution changes as weather conditions change and may allow vectors to proliferate and expand their territory. Climate change may also change the vector's incubation periods. As droughts increase, communities may seek different ways of storing drinking water including the use of barrels or buckets. Without the proper maintenance and care, these can increase the vector's breeding sites. But in other areas where rainfall increases may create any container as a new breeding site expanding the mosquito population (Banu et al., 2011; Paixão et al., 2018).

The Honduran Health Ministry offers its services in their own centers with their own doctors, nurses, and personnel but it is estimated only 50-60% of the population has access to these services. The Social Security Institute covers approximately 18% of the economically active population and the private sector covers approximately 10-15% of the population with capacity to pay for their expensive services. It is estimated 17% of the Honduran population does not have any access to health services (OPS/OMS, 2016). The Honduran Health Ministry Public System offers different levels of access based on the location of the centers. This study will mainly focus on the services offered in rural communities. The Rural Health Centers or CESAR (Spanish abbreviation) provides basic primary care by an auxiliary nurse and - in the best conditions - the center also includes a health volunteer and promoter. Their service is generally Mondays through Fridays from 7:00 am – 1:00 pm. The Medical-Dental Health Center or CESAMO (Spanish abbreviation) provides a higher level of health care with a multidisciplinary team formed by a doctor, nurse, auxiliary nurse social worker, a dentist, lab technician, and pharmacy assistant. Their service is generally Mondays through Fridays from 7:00 am – 1:00 pm. Both centers may also include security, cleaning and janitorial services depending on the circumstance (Transformemos Honduras, 2013). The Maternal and Child Center or CMI (Spanish Abbreviation) are public birth centers located in rural areas. These centers are staffed by an auxiliary nurse with limited resources (WHO, 2007). The CMI are generally near the CESAMO. The system also includes regional and area hospitals with higher capacity for providing different health services including emergency services, surgeries, and several medical specialties. Even though regional and area hospitals offer more health services, there are still many cases where patients are transferred to main hospital cities as Tegucigalpa and San Pedro Sula. This transfer is generally done through ambulances or private cars travelling several hours on roads not always in the best condition. Transfers through helicopters are rare and not available to the general population.

2.2.4 Socioeconomic Analysis

2.2.4.1 Economic Capacity and Access to Basic Needs

To better understand and analyze poverty, it is essential to identify the best measurement methodologies. Alkire and Foster (2011) provide a framework to measure multidimensional poverty through the selection of dimensions and their cutoffs, dimensional weights, and poverty cutoffs. Their method focuses on identifying multiple deprivations which are experienced simultaneously. This method requires data collection to individual or household level (Alkire & Foster, 2011). A similar framework is the one proposed by Alkire and Santos (2010) focusing on combination of deprivations affecting a household. The multidimensional poverty index (MPI) has three dimensions: health, education, and standard of living. Based on this index, a household is considered multidimensionally poor if the combination of its weighted ten indicators is 30% or more of the dimension (Alkire & Santos, 2010). A common method used in Latin America is the Unsatisfied Basic Needs (UBN) focusing in determining if the household has home under the minimum standard of living, access to basic sanitary services, access to basic education and the economical capacity of the household provides a minimum consumption level (Hicks, 2000). Based on the UBN framework, CEPAL/UNDP (1988) proposed the following framework:

Table 1. Unsatisfied Basic Needs (CEPAL & PNUD, 1988)

Basic Needs	Dimensions	Census Variables
Access to a House	House Quality	a) Wall material b) Floor material c) Roof material
	Overcrowding	a) Number of persons in the house b) Number of rooms in the house
Access to Basic Sanitary Service	Availability	a) Source of water in the household
	Type of Sewage Disposal Systems	a) Access to basic services b) Sewage disposal system
Access to Education	Attendance of school age children to a school	a) Age of the home members b) Attendance at school
Economical Capacity	Probability of insufficient household income	a) Age of the home members b) Last educational level attained by head of the household c) Number of persons in a household d) Employment situation

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A proposed methodology based on the CEPAL/UNDP can be seen in table 2. For a complete unsatisfied basic needs analysis, all basic needs should be incorporated. But the challenge COVID-19 caused by imposing restrictions on travel, made the measurement of access to education and economic capacity impossible. For this reason, this dissertation will only incorporate access to basic sanitary service and access to a house as part of the unsatisfied basic needs analysis.

Table 2. Proposed methodology

Basic Needs	Dimensions	Census Variables	Weight
Access to Basic Sanitary Service	Availability	a) Source of water in the household	25%
	Type of Sewage Disposal Systems	a) Access to basic services b) Sewage disposal system	
Access to a House	House Quality	a) Wall material b) Floor material c) Roof material	25%
Access to Education	Attendance of school age children to a school	a) Age of the home members b) Attendance at a school	25%
Economical Capacity	Probability of insufficient household income	a) Age of the home members b) Last educational level attained by head of the household c) Number of persons in the household d) Employment situation	25%

Table 3. Access to Basic Sanitary Service

Water Source	Distance to Water Source	Sewage Disposal System	Weight
a) Pipeline inside the house b) Pipeline reaching the yard or house property c) Bottle water		a) Toilet connected to sewer	1
a) Washing sink or open faucets b) Protected well in the household, yard, or house property		a) Toilet drains in river	2
a) Protected Public well	a) 0 to 30 minutes, walking from the household, yard, or plot b) Water reaches the household, yard, or plot through pipeline	a) Latrine with septic tank	3
a) Open well in the household b) Open well c) Water truck	a) From30 to 60 minutes walking from the house	a) Common pit latrine	4

| a) Water hole, river, creek, stream
b) Pond, lake, reservoir
c) Rainwater | a) More than 60-minute walking from house | a) No basic sanitary service or latrine | 5 |

Table 4. Access to a House with basic requirements

Floor Material	Wall Material	Roof Material	Cooking Energy	Weight
a) Dirt	a) Tin b) Daub wall	a) Straw or similar b) Waste material	a) No mud stove	5
a) Rustic Wood	a) Mud b) Wood	a) Clay tile	a) Mud or stone oven	4
a) Mud Brick	a) Brick b) Block	a) Concrete b) Galvanized sheet c) Zinc sheet	a) Traditional mud stove	3
a) Cement Floor			a) Improved mud stove	2
a) Ceramic Floor b) Granite Floor c) Cement slab			a) Electric stove b) Gas stove	1

2.2.4.2 Dependency

An important measure of vulnerability in a household is the ratio of economic dependents to the economically active population. If the dependency ratio is high, it indicates a higher burden on the economically active population to provide the services and support the dependent need. If there is a higher ratio of the young in the population it implies a need to invest in schools or child-care (United Nations (2), 2007). The measurement used in this research will follow the method provided by UN (2007):

*Dependency Ratio = 100 * ((Population 0-14) + (Population 65+)) / (Population 15-64)*

Given that the dependency ratio seeks to identify the population, which is economically dependent or dependent on services, this study will include in the dependency ratio the population with disabilities. The measurement formula used is the following:

*Dependency Ratio = 100 * ((Population 0-14) + (Population 65+) + (Population with Disability))*

(Population 15-64)

2.3 Sustainable Development Goals

Impacts of climate change need to be minimized through global solutions, as reducing greenhouse gas emissions or reducing vulnerability as development gains are undermined and already impoverished areas feel the effects with higher intensity (World Bank, 2013). To respond to climate change worldwide, 175 parties adopted the Paris Agreement at the 21st Conference of the Parties (COP21) held in Paris committing to the 2030 Agenda for Sustainable Development. Sustainable Development Goal (SDG) 13 aims to "take urgent action to combat climate change and its impact". SDG13 focuses on integrating measures to mitigate and adapt to climate change into national policies, raising awareness, improving education, and strengthening institutions capacity (UN, 2018).

It is essential to prioritize these efforts into developing sustainable adaptation measures that are more inclusive, and to integrate them with actions focused on poverty reduction and food security as well. Based on the 2030 Agenda Framework, this dissertation tries to address the needed efforts to achieve the following goals and targets:

SDG1: End Poverty in all its forms everywhere

- Target 1.5: "By 2030, build resilience of the poor and those in vulnerable situations and reduce their exposure and vulnerability to climate-related extreme events and other economic, social and environmental shocks and disasters" (UN (1), 2019).

SDG2: End hunger, achieve food security and improved nutrition and promote sustainable agriculture

- **Target 2.3:** "By 2030, double the agricultural productivity and incomes of small-scale food producers, in particular women, indigenous peoples, family farmers, pastoralists, and fishers, including through secure and equal access to land, other productive resources and inputs, knowledge, financial services, markets and opportunities for value addition and non-farm employment

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- **Target 2.4:** By 2030, ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, that help maintain ecosystems, that strengthen capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters and that progressively improve land and soil quality" (UN (2), 2019).

SDG13: Take urgent action to combat climate change and its impacts

- Target 13.1: "Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries

- Target 13.2: Integrate climate change measures into national policies, strategies, and planning

- Target 13.3 Improve education, awareness-raising and human and institutional capacity on climate change mitigation, adaptation, impact reduction and early warning" (UN (3), 2019).

2.4 Indicators to measure vulnerability and impact

The diversity of definitions of vulnerability may be a source of confusion, as many overlaps with resilience, adaptive capacity, and exposure. At the same time, there is a wide collection of methodologies available to assess vulnerability, and these include a participatory approach or indicator-based applied to different spatial and temporal scales (Hinkel, 2011) and was previously discussed. (Hinkel, 2011) defines measurement as "the systematic process of assigning a number to a phenomenon" following predefined rules which may include the use of quantitative concepts. But making the definition of vulnerability operational is a challenge as it is a theoretical concept, thus making it hard to measure. (Hinkel, 2011) proposes making vulnerability an operational concept by providing a method for "mapping it to observable concepts" instead of measuring and defining the method as an "operational definition". When assessing vulnerability, the operational definition can be called the methodology of the assessment (Hinkel, 2011).

An indicator is a widely used term and is "a function from observable variables called indicating variables to theoretical variables". The use of indicators is a way to "bridge academic work and political needs" (Hinkel, 2011) by synthesizing, quantifying, and standardizing a complex data phenomenon into a number with the possibility of communicating to stakeholders, decision makers or policy makers (FAO, 2018; GIZ, 2014; Hinkel, 2011). Indicators are useful in both measuring progress, monitoring trends, justifying funds, and communicating priorities. Different indicators are already available to monitor the adaptation process of climate change projects, but not all indicators can be used equally, especially when considering spatial or temporal variability. At the same time, adaptation indicators have a direct link to development indicators given the connection between a community adapting and its development. This shows the need to include standard indicators of both adaptation and development. An adaptation indicator should be simple, measurable, analytically sound, relevant to policy, and transparent. In order to develop an inclusive process, the framework (Figure 1) should include "natural resources and ecosystems, agricultural production systems, social and economic variables and institutions and policymaking" indicators (FAO, 2018). The main categories and subcategories are summarized in Table 5.
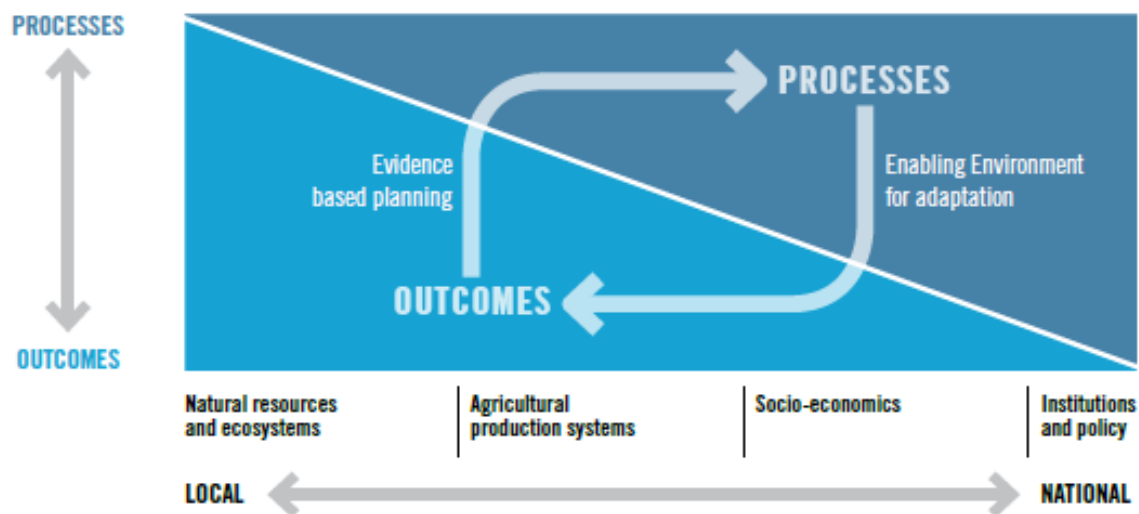
Figure 1 . The Basic Framework for Tracking Adaptation in Agriculture (FAO, 2018)

Table 5. Main and Subcategories of Indicators to Track Adaptation in Agriculture. Adapted from (FAO, 2018)

Main Categories	Subcategories	
Natural Resources and Ecosystems	1	Availability of, and access to, quality water resources for agriculture
	2	Availability of, and access to, quality agricultural land and forests
	3	Status of ecosystems and their functioning
Agricultural Production Systems	1	Agricultural production and productivity
	2	Sustainable management of agricultural production systems
	3	Impact of extreme weather and climate events on agricultural production and livelihoods
	4	Projected impact of climate change on crops
Socioeconomic	1	Food security and nutrition (vulnerability)
	2	Access to Basic Services
	3	Access to credit, government, or other sources of social protection
	4	Agricultural value addition, incomes, livelihood diversification
Institutions and Policy Making	1	Institutional and technical services
	2	Institutional capacity and stakeholder awareness

The levels of adaptation are assigned to each category and may use a score between 0 (very low adaptation and 10 (very high adaptation) and is illustrated In Figure 2.
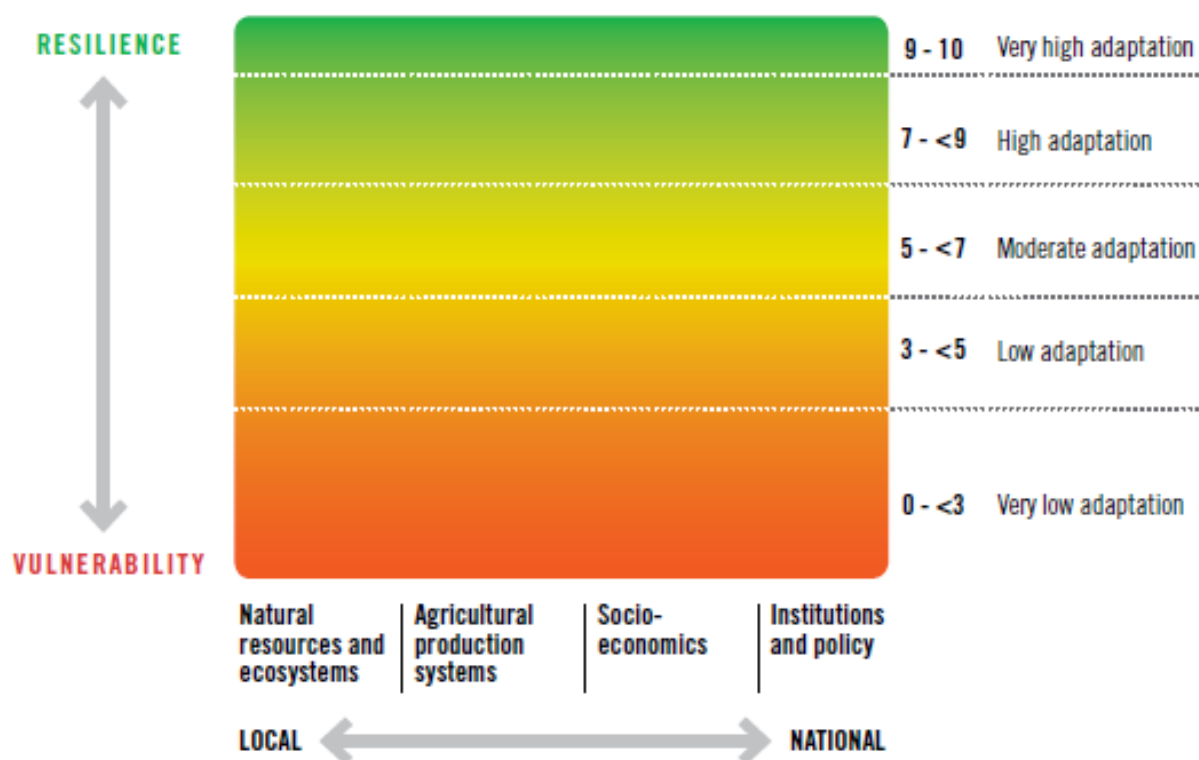
Figure 2. Levels of Adaptation Progress within an Agricultural Adaptation-Tracking Framework (FAO, 2018)

CHAPTER 3: METHODOLOGY

The impact of climate change is considered to be highly specific to location and context, and efforts to achieve resiliency of communities by increasing their adaptive capacity should also be location-based (FAO, 2018). This dissertation will use information, communication, and technology (ICT) to assess climate change vulnerabilities among rural farmers. It proposes the designing and development of a framework to identify the area's most vulnerable to climate change—a "Climate Change Vulnerability Assessment." To build this, the innovation and transfer of both technology and knowledge is crucial. The design of a system is essential for its adoption, and as such is a central focus for to researchers and practitioners—as demonstrated by the amount of behavioral research focusing on system acceptance and usage.

Design Science Research (DSR) is a widely accepted problem-solving paradigm conceptualized by (Hevner et al., 2004; Hevner & Chatterjee, 2010a), which focuses on innovative IT artifacts that may include "hardware, software, procedures and data" that contribute to knowledge (Chatterjee, 2015; Hevner & Chatterjee, 2010a). In IT research, IT artifacts become the object of study using theory to explain a) the intention to use, b) the perceived ease of use, or c) the actual usefulness of the IT-based artifact developed (Hevner et al., 2004).
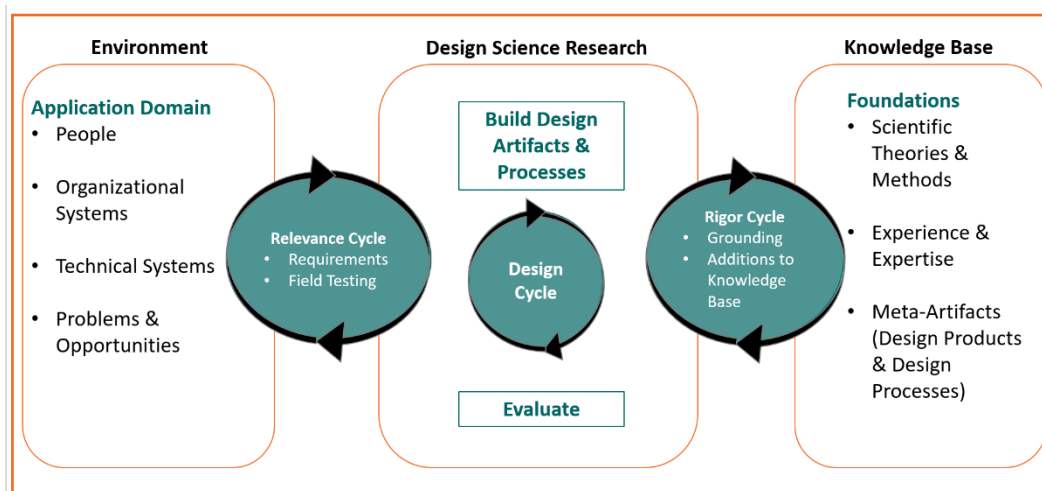
Figure 3. Design Science Research Cycles (Hevner, 2007)

This dissertation follows the DSR paradigm as it tries to 1) first understand the problem and its context, 2) design and develop innovative and useful artifacts that will help solve the problem, and 3) evaluate artifacts thoroughly. Figure 3 illustrates the DSR cycles, and Table 6 provides the DSR guidelines that will be followed in this dissertation.

The process is as follows: Knowledge is acquired through the building of the artifact. An artifact can take the form of a Construct, Model, Method, Instantiation or Theories. A **Construct** can be defined as vocabulary or symbols; a **Model** is an abstraction and representation of a system; a **Method** can take the form of an algorithm and practices; and an **Instantiation** can be either an implemented or a prototype system; a **Theory** is the base for research and allows the understanding of a phenomena (Hevner & Chatterjee, 2010b). Moreover, seven guidelines proposed by (Hevner et al., 2004) (see Table 6 below) should somehow be addressed after completing research on the design science. Design-science research incorporates a set of expert activities to build an innovative artifact (Hevner et al., 2004; Holtkamp et al., 2019). The artifact is then evaluated to improve the design and quality through an iterative process, with the main goal being the development of a useful product. It is not expected for an artifact built during design-science research to be a fully operational tool, but instead it helps define how an information system may help effectively solve a business problem (Hevner et al., 2004).

Table 6. Design Science Research Guidelines (Hevner et al., 2004)

Guideline	Description
Guideline 1: Design as an Artifact	Design science research must produce a viable artifact in the form of a construct, a model, a method, or an instantiation.
Guideline 2: Problem Relevance	The objective of DSR is to develop technology-based solutions to important and relevant business problems.
Guideline 3: Design Evaluation	The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluations methods.
Guideline 4: Research Contributions	Effective design science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.
Guideline 5: Research Rigor	Design science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.
Guideline 6: Design as a Search Process	The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.
Guideline 7: Communication of Research	Design science research must be presented effectively to both technology-oriented and management-oriented audiences.

Building and evaluating are the two main activities in a DSR information system (Venable et al., 2012). (Iivari, 2007) proposes a three-level epistemology for information systems: conceptual knowledge, descriptive knowledge, and prescriptive knowledge based on (Popper, 1978), which describes three worlds. **Conceptual knowledge** refers to concepts, constructs, conceptual frameworks, classifications, taxonomies, or typologies. **Descriptive knowledge** refers to the description of things, while **prescriptive knowledge** produces knowledge in the form of an IT artifact with a proven utility (Venable et al., 2012). An adaptation from (Peffers et al., 2007; Venable et al., 2012) can be seen in Figure 4, incorporating build-evaluate in the DSR methodology.
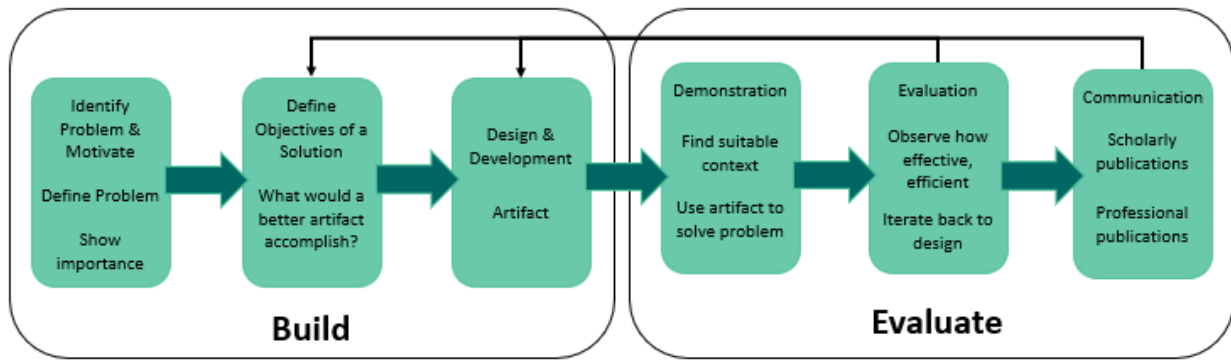
Figure 4. Build-Evaluate in DSR Methodology (adapted from Peffers et al. (2007) and Venable et al. (2012))

The following sections introduces the artifact and the instantiation proposed in this dissertation.

3.1 Artifact #1: Climate Change Vulnerability Assessment Framework

As discussed earlier, to help build climate change resilient communities among rural farmers, the first step is to understand the impact of climate change on the communities. Thus, the first artifact is a Climate Change Vulnerability Assessment Framework (CCVAF) using IT, specifically GIS and remote sensing.

The objective of any information-system-related research includes the understanding of the problem, then acquiring knowledge from the environment to develop an effective IT-based solution to

help solve it. The interaction with the people and organizations in which the research is being conducted, and where the IT-based solution will be implemented, is extremely important in order to keep the research relevant (Hevner et al., 2004). IT researchers seeking to craft relevant studies should consider focusing on the main concerns identified by practitioners and applying a more pragmatic tone when communicating its results, making the outputs of the studies of immediate and real practical value. By doing so, the proposed frameworks would be "intuitively meaningful to practitioners," allowing them to plan, organize and justify their actions (Benbasat & Zmud, 1999). To achieve this goal, this researcher maintained a close interaction for several months with the THRIVE (Transforming Household Resilience in Vulnerable Environments) team and the Design, Monitoring and Evaluation (DME) team from World Vision, a global humanitarian organization partnering with children, families, and their communities to reach their full potential by tackling the causes of poverty and injustice[1]. Such a close interaction allowed the research including the THRIVE team and the Design, Monitoring and Evaluation (DME) Team, through several Zoom or Skype meetings. better understand the practitioners' needs and processes on the vulnerability assessment based on the data collected. Their feedback was essential in the iterative development of the CCVAF, which will be discussed in Chapter 4. The framework will be evaluated using a case study in Western Honduras (see section 3.4).

3.2 Artifact 2: Web-based App (Framework Instantiation)

An instantiation is defined as an implemented or prototype system and can be the research outcome of a DSR. An instantiation can also be a test bed or serve to validate a concept through its implementation (Hevner & Chatterjee, 2010a; Nunamaker Jr. et al., 1990). For this dissertation, a web-based application was developed for the THRIVE team in World Vision, focusing on Western Honduras data as an instantiation of the proposed CCVAF. Similarly, Information system (IS) literature and practitioners' feedback were used to design the web-based applications following the DSR guidelines (Hevner et al., 2004). The Web-based application, named THRIVE, is a visualization and knowledge

platform to support decision makers in assessing climate change vulnerabilities among rural farming communities. Although the THRIVE app is built specifically for Western Honduras, its design is based on the CCVAF framework and can be easily extended to different areas around the world. The utilities of the THRIVE app will be qualitatively evaluated semi-structured interviews.

3.3 Case Study in Western Honduras

This section describes the case study background in Western Honduras. Honduras, a small low-middle-income country with more than 60.9% of its population living in poverty and one out of five Hondurans from rural communities living in extreme poverty (i.e., less than US$2.00 per day) (Ben-Davies, M.E, et al, 2013; World Bank, 2018). According to the United Nations Development Programme (UNDP), Honduras' Human Development Index (HDI) has increased to 0.617, positioning the country in the medium human development category, but it is below average compared to other Central American countries and the wider Latin American and Caribbean region. Honduras has also the lowest GNI per capita of the region (UNDP, 2018), and experienced a major political crisis in 2009 and 2017 that deepened its poverty levels further. The country has been labeled as having the highest economic inequality in Latin America (World Bank, 2018; InSight Crime, 2018).

According to (Kreft et al., 2016), the Global Climate Risk Index (CRI), developed by Germanwatch, quantifies the impacts of extreme weather events through data from the Munich RE NatCatSERVICE. This analysis uses both fatalities and economic losses due to climate change, examining absolute and relative impacts to generate an average index per country. The highest-ranked countries are the ones that are more impacted by climatic events. According to the 2017 report, Honduras, Myanmar, and Haiti are the countries with the highest CRI scores, making them the most vulnerable in the world (Kreft et al., 2016).

In 2000, the IPCC published a series of scenarios, called the Special Report on Emissions Scenarios (SRES), to be used by climate researchers. It defined the term "scenario" to imply "projections of a potential future, based on a clear logic and quantified storyline". The A2 scenario refers to a

"heterogenous world with continuously increasing global population and regionally oriented economic growth that is more fragmented and slower than other scenarios" (IPCC, 2007). Recent studies indicate that Honduras has already experienced an increase in average annual temperature of about 0.75 °C. In the projected A2 scenario developed by IPCC, it is expected that, with emissions following the same increasing pattern, the average annual temperature will increase up to 1.2°C in 2030, 2.1°C in 2050 and 4.5°C in 2100. Honduras has a rainy season from May to November, a dry period from December through April, and a hot period called *Canicula* during August. In that same A2 scenario, it is expected that average annual precipitation will decrease up to 0.3% by 2030, 13% by 2050, and 32% by 2100. Honduras' average dryness index is 1.42, classified as a humid region, but according to the A2 scenario it is expected to decrease to 1.28 by 2030. With increasing demand, its water supply will suffer a decrease of 168% by 2030, 397% by 2050, and 2,275% by 2100. With the reduction of water availability, the main hydropower plant, "El Cajon", is expected to decrease its electric generation in 22% by 2030, 39% by 2050, and 72% by 2090. For all the above reasons, it is extremely important to strengthen Honduras' climate change adaptation capacity and increase mitigation measures that may affect the agricultural sector, health of its population, and water sources (CEPAL y MiAmbiente, 2016).

The case study partnered with the team for the Honduras THRIVE (Transforming Household Resilience in Vulnerable Environments) project by World Vision. The THRIVE project supports small farmers to build their resilience in climate change through three pillars: End-To-End Business Systems of Farming, Natural Resources Management, and Emergency and Situational Awareness. The area of influence of the THRIVE project includes the "Departments" (i.e., regional governments) of Intibucá, Lempira, La Paz, Ocotepeque, Copan, Santa Barbara and El Paraiso, and 31 municipalities (the second level of the national administrative division). All Departments are in Western Honduras with corn, sorghum, and beans as their population's main agricultural products, with harvest times between May and October (Ben-Davies, M.E, et al, 2013). This study focuses on the Departments of Intibucá, Lempira, Ocotepeque, Copan, and Santa Barbara (Figure 6) with a total area of 17,303.13 km^2 and 114 municipalities (Table 7).

Table 7. Departments and Municipalities in the Study Area

Department	Municipality
Copan	Cabana, Concepcion, Copan Ruinas, Corquin, Cucuyagua, Dolores, Dulce Nombre, El Paraiso, Florida, La Jigua, La Union, Nueva Arcadia, Nueva Frontera, San Agustin, San Antonio, San Jeronimo, San Jose, San Juan de Opoa, San Nicolas, San Pedro, Santa Rita, Santa Rosa de Copan, Trinidad de Copan, Veracruz
Intibucá	Camasca, Colomoncagua, Concepcion, Dolores, Intibucá, Jesus de Otoro, La Esperanza, Magdalena, Masaguara, San Antonio, San Francisco de Opalaca, San Isidro, San Juan, San Marcos de Sierra, San Miguelito, Santa Lucia, Yamaranguila
Lempira	Belen, Candelaria, Cololaca, Erandique, Gracias, Gualcince, Guarita, La Campa, La Iguala, La Union, La Virtud, Las Flores, Lepaera, Mapulaca, Piraera, San Andres, San Francisco, San Juan Guarita, San Manuel Colohete, San Marcos de Caiquin, San Rafael, San Sebastian, Santa Cruz, Talgua, Tambla, Tomala, Valladolid, Virginia
Ocotepeque	Belen Gualcho, Concepcion, Dolores Merendon, Fraternidad, La Encarnacion, La Labor, Lucerna, Mercedes, Ocotepeque, San Fernando, San Francisco del Valle, San Jorge, San Marcos, Santa Fe, Sensenti, Sinuapa
Santa Barbara	Arada, Atima, Azacualpa, Ceguaca, Chinda, Concepcion del Norte, Concepcion del Sur, El Nispero, Florida, Gualala, Ilama, Las Vegas, Macuelizo, Naranjito, Nueva Frontera, Nuevo Celilac, Petoa, Proteccion, Quimistan, San Francisco de Ojuera, San Jose de Colinas, San Luis, San Marcos, San Nicolas, San Pedro Zacapa, San Vicente Centenario, Santa Barbara, Santa Rita, Trinidad

Figure 5. Dissertation Study Area

CHAPTER 4: FRAMEWORK

4.1 Framework Description

This dissertation proposes a Climate Change Vulnerability Assessment Framework (CCVAF) (See Figure 6) to better evaluate the different indicators for vulnerability assessment. The framework is a Model and not only describes the general phenomena being studied but also allows the possibility to understand it by studying a) specific indicators and the variables needed to measure them, and b) how those variables can provide different results depending on specific circumstances.
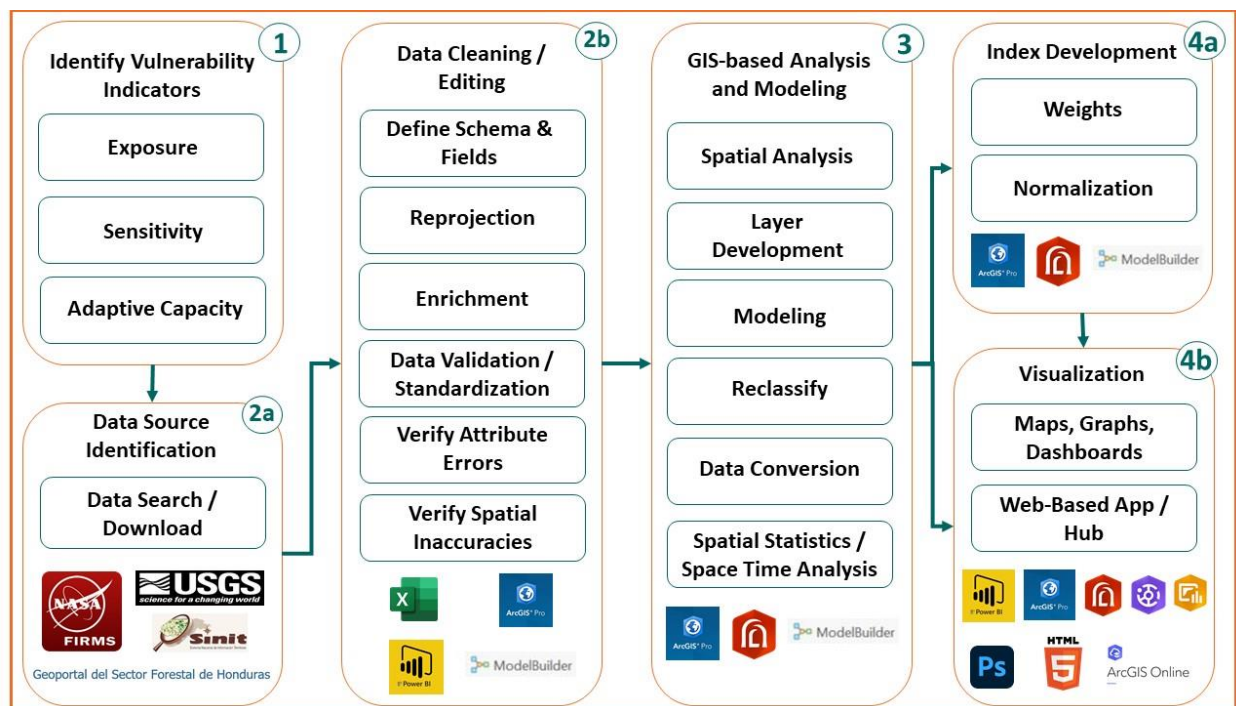
Figure 6. Steps for Measuring Vulnerability using the Proposed Framework

The framework includes four steps: 1) using a hierarchical approach to identify vulnerability indicators (Table 8), adapted from the research of (Banu et al., 2011; Below et al., 2012; Caceres, 2011; Gbetibouo et al., 2010; Hahn et al., 2009; Hirschi et al., 2011; Jaiswal et al., 2002a; Shah et al., 2013), including the methodology used by UNDP to measure Unsatisfied Basic Needs as developed in CEPAL & PNUD (1988b); 2) using GIS for data source identification and collection; 3) presenting a GIS-based

data analysis and modeling approach to measure the vulnerability indicators; and 4) creating an overall index for areas of interests, and visually displaying the indices on a web-based app.

4.2 Step 1: Identifying Vulnerability Indicators

Previous research identifies two commonly used approaches to measure vulnerability: Indicator Approach and the Vulnerability Variable Assessment Approach. The Indicator Approach uses a set of specific indicators and then calculates indices for those indicators. Meanwhile, the Vulnerability Variable Assessment Approach (VVAA) measures loss for specific variables related to stressors and is an econometric approach. But the VVAA does not fully capture vulnerability through the three determinants of vulnerability (Gbetibouo et al., 2010).

In this dissertation, the framework is based on an Indicator approach. The first step is to identify the vulnerability indicators. The concept of climatic "vulnerability" is a multidimensional process using different variables and can be classified into three categories of determinants *exposure*, *sensitivity*, and *adaptive capacity* (Below et al., 2012; Gbetibouo et al., 2010; Hahn et al., 2009; Shah et al., 2013; Yohe & Tol, 2002). **Exposure** is defined as "the nature and degree to which a system is exposed to significant climatic variations." It is a biophysical component, and it is inseparable from vulnerability. **Sensitivity** is defined as "the degree to which a system is affected, either adversely or beneficially, by climate-related stimuli." Once sensitivities are identified, interventions can be planned as a response to specific stressors seeking the improvement of communities' climate change adaptive capacity. It also allows the quantifiable reduction of vulnerability that enables the strengthening a community's adaptive capacity (Kelly & Adger, 2000). **Adaptive capacity** is defined as "the ability of systems, institutions, humans, and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences." (IPCC & Edenhofer, 2014; McCarthy & IPCC, 2001). The **Sensitivity** of a system is the degree to respond to a variation to climatic changes. Through a framework, sensitivities are identified, and interventions can be planned as a response to specific stressors seeking the improvement of

communities' adaptive capacity. A community is able to strengthen its adaptive capacity if vulnerability is quantifiably reduced (Kelly & Adger, 2000).

To develop a comprehensive set of indicators, this dissertation uses a top-down hierarchical approach (see Table 8). The highest level is the three categories of determinants described above. We then identify different components for each determinant. For example, exposure includes five components based on the literature. They are *extreme climate events*; *change in climate, forest fires, soil moisture and soil carbon*. For each component, we further identify its sub-components. For example, the *change in climate* includes two sub-components as *change in temperature* and *change in precipitation*. Lastly, for each sub-component, we identify its indicators and related measurements and data sources. For example, for forest fire, the indicator is a forest fire risk that can be measured using a Fire Risk Index of an area using Landsat 8 imagery, elevation data, settlements in the area, and roads.

Table 8 lists a comprehensive set of indicators for climate change vulnerability assessment. Depending on the area of the study, the practitioners and researchers may only select a subset of these indicators that are relevant to their study objectives. For example, in our case study, we did not include the economic capacity, financial and market access from the Adaptive Capacity determinant due to the COVID-19 travel restrictions.

4.3 Step 2: GIS Data Sources and Processing

The second step focuses on how to collect related data, and process data in a format for analysis modeling later. As shown in Table 8, many measurements for adaptive capacity are straightforward to process, while main indicators related to the exposure and sensitivity heavily rely on Geographic Information Systems (GIS) and remote sensing data.

Table 8. Vulnerability Assessment Indicators, and related measurements and data sources

Vulnerability Determinant	Component	Sub-component	Indicator	Unit of Measurement	Data Source	Source
Exposure	Extreme Climate Events	Droughts (Water Scarcity)	Frequency of Droughts	Number of Droughts	GIS/Remote Sensing Analysis	(Gbetibouo et al., 2010)
		Flood	Frequency of Flood	Number of Floods	GIS/Remote Sensing Analysis	(Gbetibouo et al., 2010)
	Change in Climate	Change in Temperature	Change in Temperature	Degrees Celsius Change	GIS/Remote Sensing Analysis	(Gbetibouo et al., 2010)
		Change in Precipitation	Change in Precipitation	mm Change	GIS/Remote Sensing Analysis	(Gbetibouo et al., 2010)
	Forest Fires	Forest Fires	Forest Fire Risk	Area in Kilometers	GIS/Remote Sensing Analysis	(Caceres, 2011; Jaiswal et al., 2002a)
	Soil Moisture	Soil Moisture	Change in Soil Moisture	Area in Kilometers	GIS/Remote Sensing Analysis	(Hirschi et al., 2011; S. V. Kumar et al., 2018)
	Soil Carbon	Soil Organic Carbon	Soil Organic Carbon	Area in Kilometers	GIS/Remote Sensing Analysis	(Angelopoulou et al., 2019; Bhunia et al., 2019; Wang et al., 2013)
Sensitivity	Deforestation	Change in Land Cover	Change in Land Cover	Kilometers of Land Cover	GIS/Remote Sensing Analysis	(Lawrence & Vandecar, 2015)
	Land Degradation Index	Percentage of Land Degradation	Percentage of Area with High Land Degradation Index	No Units	GIS/Remote Sensing Analysis	(Gbetibouo et al., 2010)
	% Irrigated Land	Percentage of Irrigated Land	Number of Farms with Irrigation Systems	Number of Farms	Does your farm have any type of irrigation system?	(Gbetibouo et al., 2010)
	% Small-Scale Farming Operation		Percentage of Area with Higher Number of Small-Scale Farming Operations	Percentage	What is the area of your farm?	(Gbetibouo et al., 2010)
	Crop Diversification Index		Number of Crop Types	Percentage	What are the crops on this farm? Do you rotate the crops?	(Gbetibouo et al., 2010)

	Socioeconomic	Economic Capacity	Number of Household Members	Number of Members	How many members live in this household?	(Below et al., 2012)
Adaptive Capacity			Number of Households where the Primary Adult is Female	Number of Households with Female Head	Who is the head of the family? Male or female	(Shah et al., 2013)
			Number of Years the Head of Household Attended less than 3 Years of School	Years	Did you go to school? If yes, what was the last grade you attended?	(CEPAL & PNUD, 1988; Shah et al., 2013)
			Number of Heads of Household whose age is under 18 and over 45	Years	What is the age of the head of household?	(CEPAL & PNUD, 1988)
			Number of Members in the Household who are Employed	Number of Members	How many members of the household are currently employed? What is the type of occupation?	(CEPAL & PNUD, 1988; Islam & Winkel, 2017)
			Number of Members Working outside the Community	Number of Members	How many members worked outside the community?	(Hahn et al., 2009)
			Number of Households Receiving Remittances on a Regular Basis	Number of Households	Do you regularly receive remittances?	(Mochizuki et al., 2014; Rajan & Bhagat, 2017)
		Dependency	Population under 14 and over 60 Years of Age	Ratio of Number of Members	How many members are under 14 and over 60?	(Below et al., 2012; Hahn et al., 2009)
			Population with Physical or Mental Disability	Ratio of Number of Members	Is there a member of the household with physical or mental illness or disability? If yes, how many?	(Shah et al., 2013)
			Number of Households with Orphans	Number of Members	Are there any children over 18 from other families living in this house because on or both of their parents died or moved to another country?	(Hahn et al., 2009)
	Access to Basic Sanitary Service	Availability	Source of Water	Kilometers	What is the household's source of water? a) well b) river c) public service d) bottle water truck	(Below et al., 2012; CEPAL & PNUD, 1988)
			Distance to the Source of Water	Kilometers	How long do you walk to the source of water? A) 0 b) 0.5 km c) 1 km d) 1.5 km e) 2 km f) more than 2 km	(Below et al., 2012; CEPAL & PNUD, 1988)
		Sewage Disposal System	Type of Sewage Disposal system	Type of Sewage	What is the type of sewage disposal system? A) toilet connected to sewer b) toilet drains in river c) latrine with septic tank d) common pit latrine e) no basic sanitary service or latrine	(CEPAL & PNUD, 1988)

	Financial Access	Access to Credit	Number of Households with Access to Credit	Number of Households	Do you have access to credit? When was the last time you received credit?	(Gbetibouo et al., 2010)
	Market Access & Analysis	Distance to Markets	Distance to Nearest Market	Minutes	How far is the nearest market?	(Below et al., 2012)
		Quality of Road	Quality of Road	Paved or Unpaved	GIS Analysis	(Gbetibouo et al., 2010)
	Health	Chronic Illness	Number of Household Members with a Chronic Illness	Number of Members	How many household members suffer from a chronic illness?	(Hahn et al., 2009)
		Access to Health Service	Number of Households with at least a Basic Health Center in a 5 km radius	Number of Households	GIS Analysis	(Hahn et al., 2009)
		Dengue, Zika, Chikungunya exposure	Number of Household with Bed Nets	Number of Households	Do you have bed nets?	(Hahn et al., 2009)
			Areas with a High Number of Cases	Area Km^2	GIS Analysis	(Hahn et al., 2009)
			Number of Members who Experienced Dengue or Similar Episode in the Last Month	Number of Members	How many of your household members suffered from Dengue, etc.?	(Hahn et al., 2009)
	Knowledge and Information	Access to Knowledge and Information	Number of Households with Access to Information and Knowledge	Number of Households	Do you have access to a reliable system for climate, weather, land or market information?	(L. Jones et al., 2019; Sorre et al., 2017)
			Number of Local Organizations and Community Leaders with Access to Information and Knowledge	Number of Local Organizations and Community Leaders	Do you have access to a reliable system for climate, weather, land, or market information?	
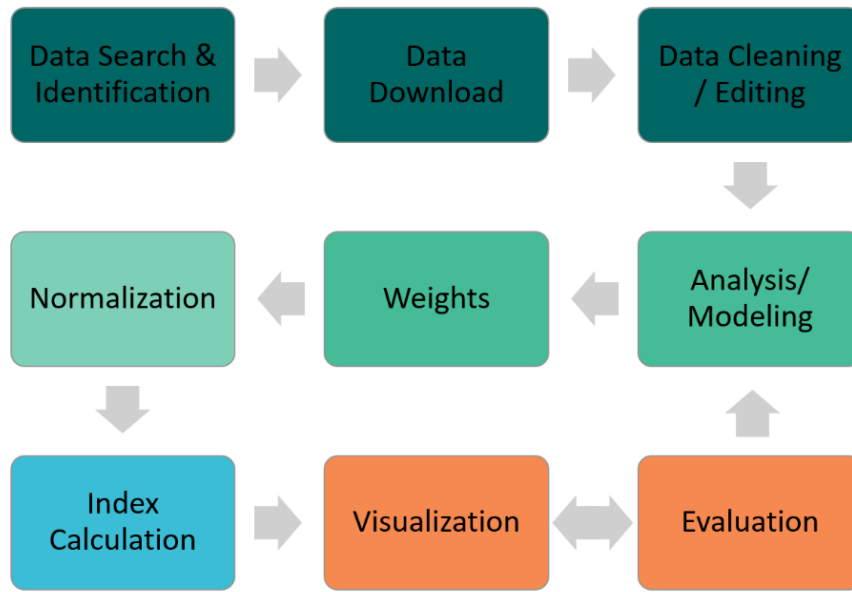
Figure 7. Data Analysis Process

These data have been extensively used to perform complex spatial analysis to mitigate climate change impacts, such as identifying fire risk zones (Jaiswal et al., 2002a), measuring environmental degradation (Hassan et al., 2015), estimating crop productivity (Tan & Shibasaki, 2003), and developing climate adaptation model tools (Kunapo et al., 2016).

Figure 7 depicts a generic data analysis process. In the next section, we elaborate how to process GIS and remote sensing data for spatial analysis and modeling.

4.3.1 Data Search and Identification

The first step of the data analysis process was to search and identify the data needed for the study. Based on the study area, our data search included the following data sources:

- *Sistema Nacional de Información Territorial* (SINIT): this is the National System for Territorial Information of Honduras. Based on Table 8, the following layers were used: International Limit Boundary; Department Boundary Polygon (1st administrative division); Municipality Boundary

Polygon (2nd administrative division); Village Boundary Polygon (3rd administrative division); Small Villages (Point Layer); National Roads, Highways; Health centers; and Schools.

- Forest fire hotspots data were obtained from NASA's Fire Information for Resource Management System (FIRMS) which distributes near-real time active fire data within 3 hours of satellite observation. Two sensors were used to collect this data: NASA's Moderate Resolution Imaging Spectroradiometer (MODIS), and NASA's Visible Infrared Imaging Radiometer Suite (VIIRS) (NASA, 2019). Three Landsat 8 scenes from September 2019, March, and April 2020 were also acquired through USGS EarthExplorer. The Census data were acquired through the National Statistics Institute (abbreviated as INE in Spanish).

- **USGS Landsat Level-2**: This type of time-series product was developed to analyze the effects of climate change and will use the USGS EROS Science Processing Architecture on Demand to obtain the imagery as it provides bulk order options. Level-2 products include **Surface reflectance-derived spectral indices**. These indices are derived from Landsat 4-5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI)/Thermal Infrared Sensors (TIRS). Some indices include the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI), and Normalized Difference Moisture Index (NDMI) (USGS (1), 2019).
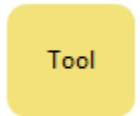
4.3.2 Data Cleaning/Editing

All the GIS data were processed using ESRI ArcGIS Pro, and, depending on the type of file, they followed a specific process using different geospatial tools. The pre-processing process may include enrichment, reprojection and cleaning. Several tools were used for data cleaning, including Microsoft Excel, Power BI, and ArcGIS Pro.

4.4 Step 3: Analysis/Modeling

The first step in analyzing data was the creation of a database use to store geospatial data or geodatabase. The processing process may include data selection, filtering, data query, creation, and export to a different format. For raster data, it was necessary to create a mosaic to use in the data classification. Raster data were converted to vector and vector data were converted to raster for use in further analysis. Other processes used with raster data included the reclassification of data and raster algebra. A main tool used for analyzing data is ESRI ModelBuilder which is a visual programming language inside ArcGIS Pro to build geoprocessing workflows. A model is represented as a diagram connecting processes and geoprocessing tools. The output of a tool becomes the input of the next process (ESRI, 2020). Three main elements will be found in the models built in this dissertation and be summarized in Table 9:

Table 9. ModelBuilder elements and descriptions. Adapted from (ESRI (2), 2020)

Element	Image	Description
Data Variable	Input Data	Data variables are model elements that store paths and other properties of data on disk. Common data variables include feature class, feature layer, raster dataset, and workspace.
Derived or output data variable	Derived Data	Derived or output data is new data created by a tool in the model. When a geoprocessing tool is added to a model, variables for the tool's output parameters are automatically created and connected to the tool.
Tool	Tool	Tools are geoprocessing tools added to the model.

The following sections explain the data analysis and modeling followed in this dissertation.

4.4.1 Exposure

The exposure determinant includes the calculation of Forest Fire Risk Zones, Soil Moisture, Soil Carbon, Extreme Climatic Events, and Changes in Climate. This dissertation will only focus on the identification of Forest Fire Risk Zones and Soil Moisture. The following sections will expand the process to develop Forest Fire Risk Zones and a Soil Moisture layer.

4.4.1.1 Forest Fire Risk Zones

One of the components defined in the exposure determinant is the identification of Forest Fire Risk Zones, which is essential for understanding the factors behind forest fires (Chuvieco & Congalton, 1989b; Jaiswal et al., 2002a). Empirical studies provide different methodologies using remote sensing and GIS to identify fire hazard areas. The influence of environmental factors (e.g., landcover, land use), physiographic factors (e.g., elevation, slope, aspect), climatic factors (e.g., wind, rainfall, relative humidity, temperature), soils, water availability (Chuvieco, 1999), proximity to roads and proximity to settlements can determine where fires are more likely to start and propagate; they may also predict the intensity of forest fires (Caceres, 2011; Chuvieco, 1999, 2003; Chuvieco & Congalton, 1989a; Gai et al., 2011; Mohammadi et al., 2014; Sağlam et al., 2008).

A common methodology used to develop Forest Fire Risk Zones uses a model to calculate a fire hazard index by overlaying the spatial layers of the factors listed previously to quantify the level of risk. This approach uses a hierarchical scheme with some layers with higher influence weighted higher according to their impact on fire risk (Caceres, 2011; Chuvieco, 2003; Chuvieco & Congalton, 1989b; Erten & Kurgun, 2002a; Gai et al., 2011; Jaiswal et al., 2002a; Sağlam et al., 2008).   Figure 8 provides a flowchart of the process followed to create a Forest Fire Risk Index Layer; the next sections will provide an expanded description of the creation of each layer.

4.4.1.1.1 Fire Hotspots

The Moderate-resolution Imaging Spectroradiometer (MODIS) is a sensor onboard orbiting satellites called Terra and Aqua. Both satellites are part of the National Aeronautics and Space Administration (NASA) Earth Observing System (EOS) mission. MODIS uses an algorithm capable of detecting "fire pixels," or hotspots, containing active fire(s) when the satellite passes, and classifying them as missing data, cloud, non-fire, fire, or unknown. MODIS provides daily active fire data and 500m tile burned area.
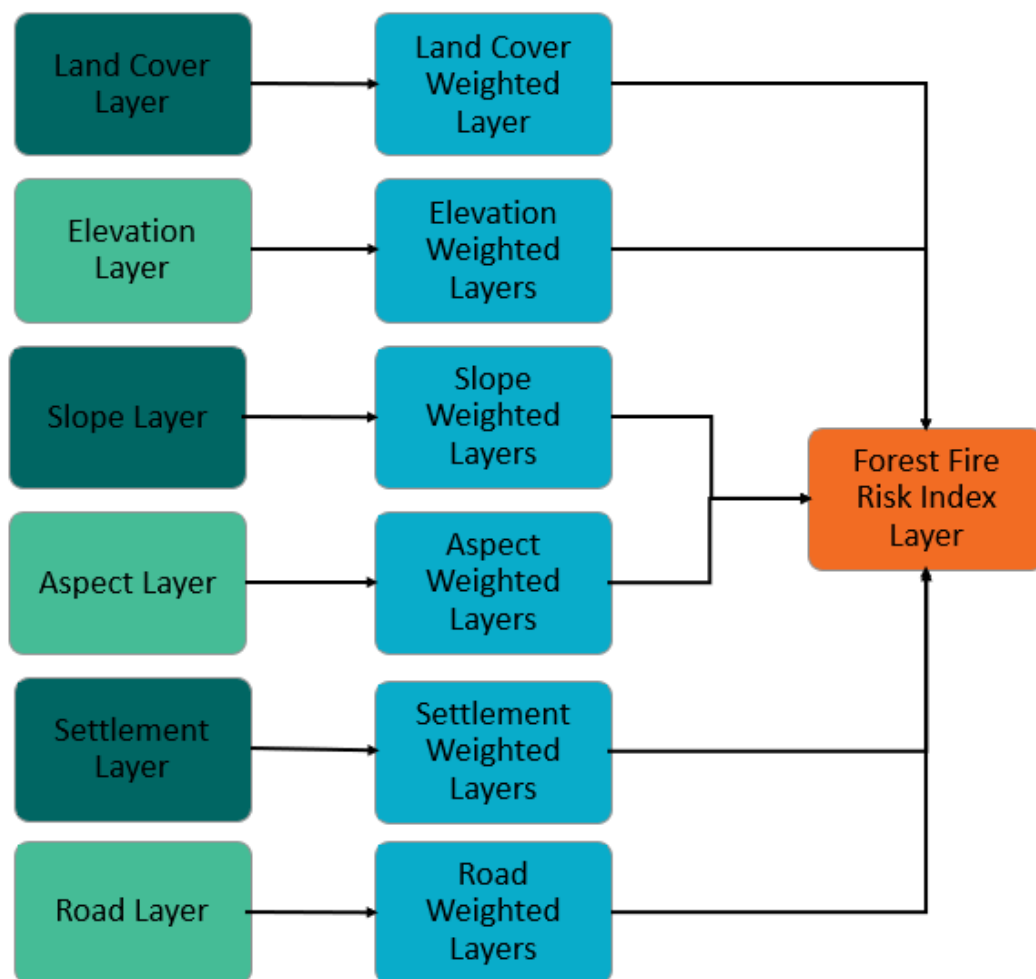
Figure 8. Process Followed to Develop the Forest Fire Risk Index Layer

To make this data available, two systems were developed: the MODIS Rapid Response (MRR) system and the Fire Information for Resource Management System (FIRMS) (Davies et al., 2009; Giglio et al., 2016). Using the FIRMS data, an initial analysis was performed to identify the active hotspots in

the area under study. A total of 33,128 hotspots for the THRIVE region were identified for the period between January 2012 and May 2020. During this timeframe, the months of March, April, and May have a higher presence of hotspots (Figure 9).
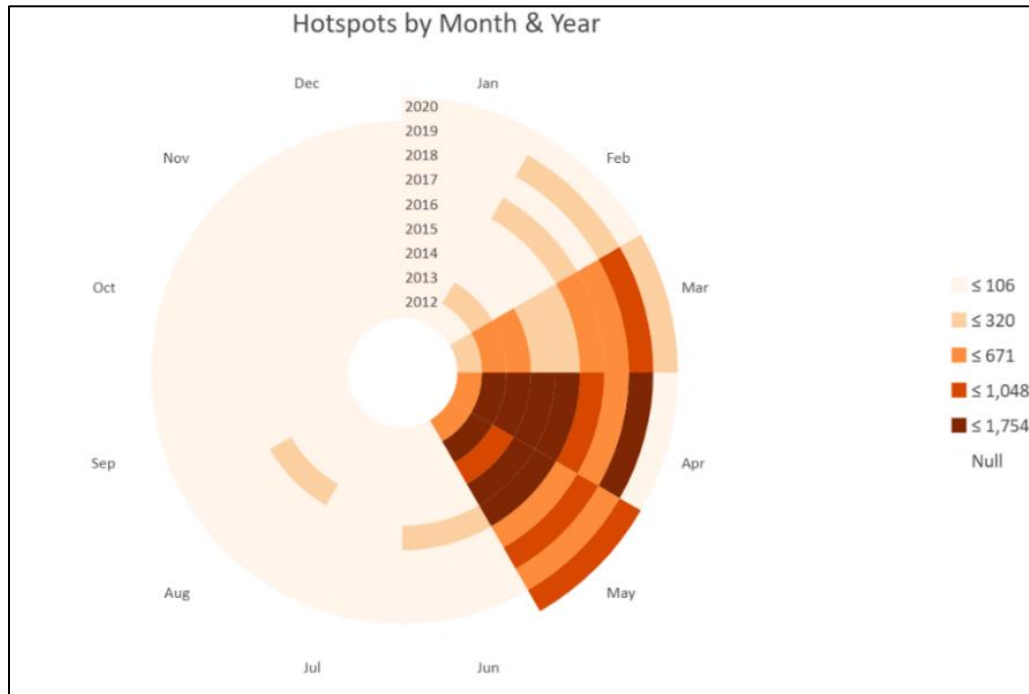
Figure 9. Clock Chart Indicating that the Months with a Higher Number of Hotspots are March, April, and May

The THRIVE region is composed of Copan, Intibucá, Lempira, Ocotepeque, and Santa Barbara, all regional Departments in western Honduras. A dashboard was developed to help visualize the hotspot data (Figure 10), providing a deeper insight into the results. Santa Barbara was the Department with the highest number of hotspots with 7,480, followed by Lempira with 3,315 and Copan with 2,481 during the same period. Quimistan, San Luis and San Pedro Zacapa from Santa Barbara, followed by Guarita from Lempira, were the municipalities with a higher number of hotspots. A higher number of hotspots were recorded in 2013 and 2019—significantly higher than the same period in 2020, probably due to the country being closed because of COVID-19.
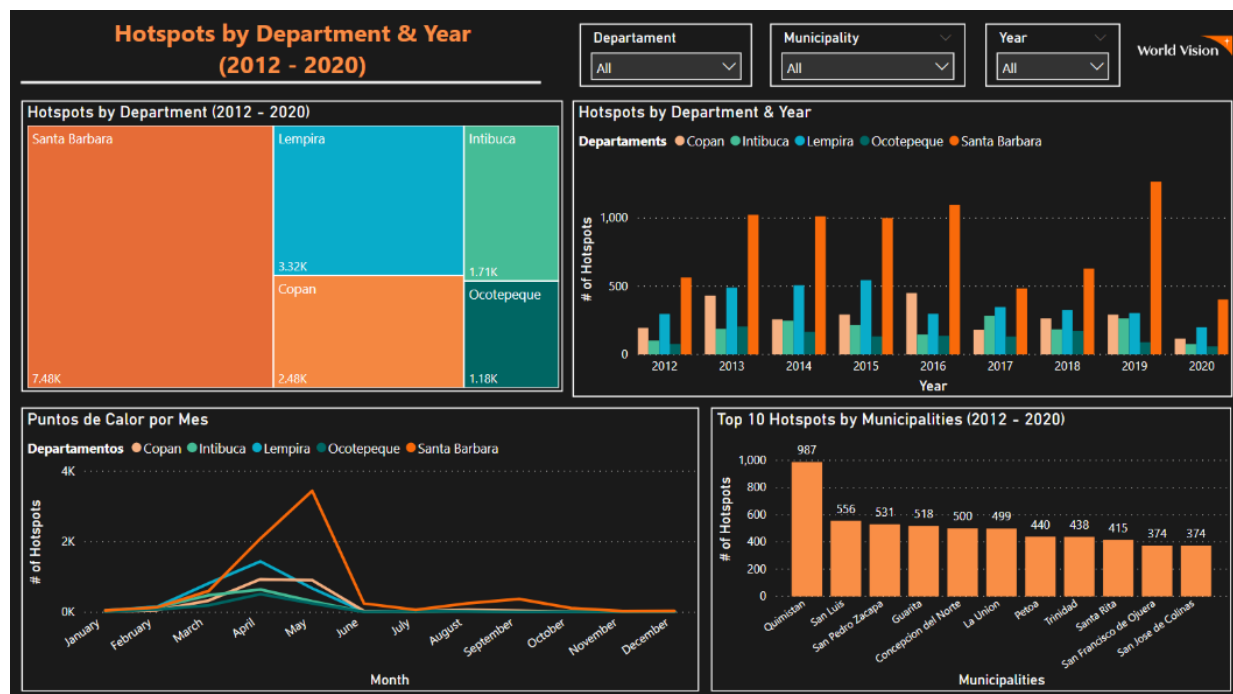
Figure 10. Fire Hotspot Dashboard

4.4.1.1.1.2 Density and Spatiotemporal Analysis

Additional analysis was performed with the Fire Hotspots Layer. An initial density map was performed using a Kernel Density tool, showing the areas with higher concentration of hotspots (Figure 11). Using the fire hotspot layer, a space time cube analysis was performed to understand if there are changes of the hotspots through time. The space time cube layer was created using an interval of 1 month and aggregated to a hexagon grid (Figure 13).
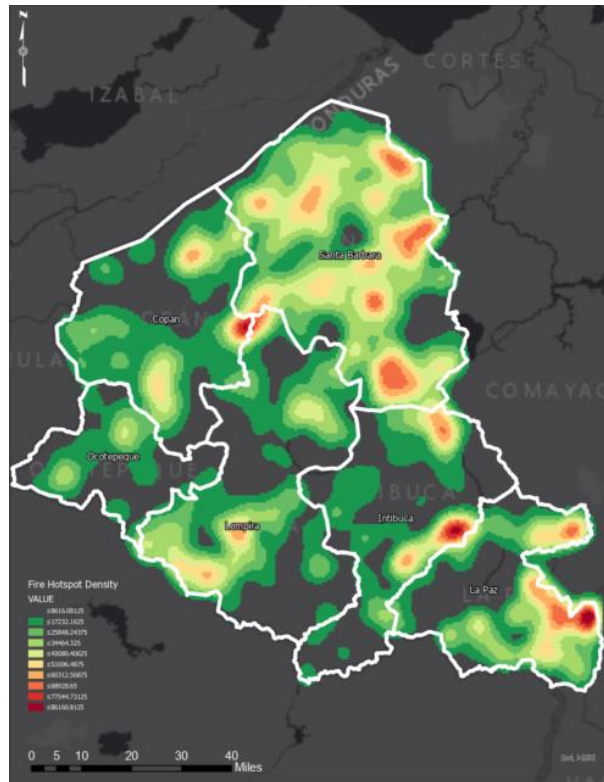
Figure 11. Fire Hotspot Kernel Density Map
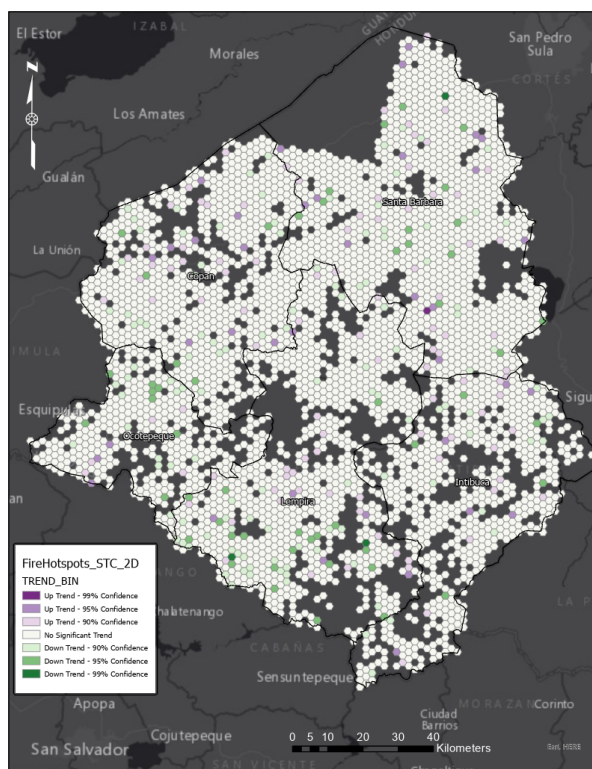
Figure 13. Space Time Cube 2D Visualization in Hexagon Grid
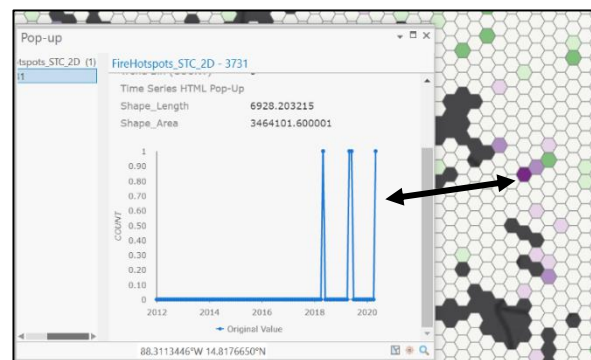
Figure 12. This Sample Shows the Results for the Up-Trend Hexagon through Time

This tool allows an important visualization of the fire hotspots by identifying the up and down trends through time. Every hexagon provides a summary of the change through time (Figure 12).

An emergent hotspot analysis (Figure 14) was also developed, showing several regions as sporadic hotspots. Based on the statistical analysis performed by the tool, less than 90% of the areas surveyed have been identified as statistically significant hotspots.
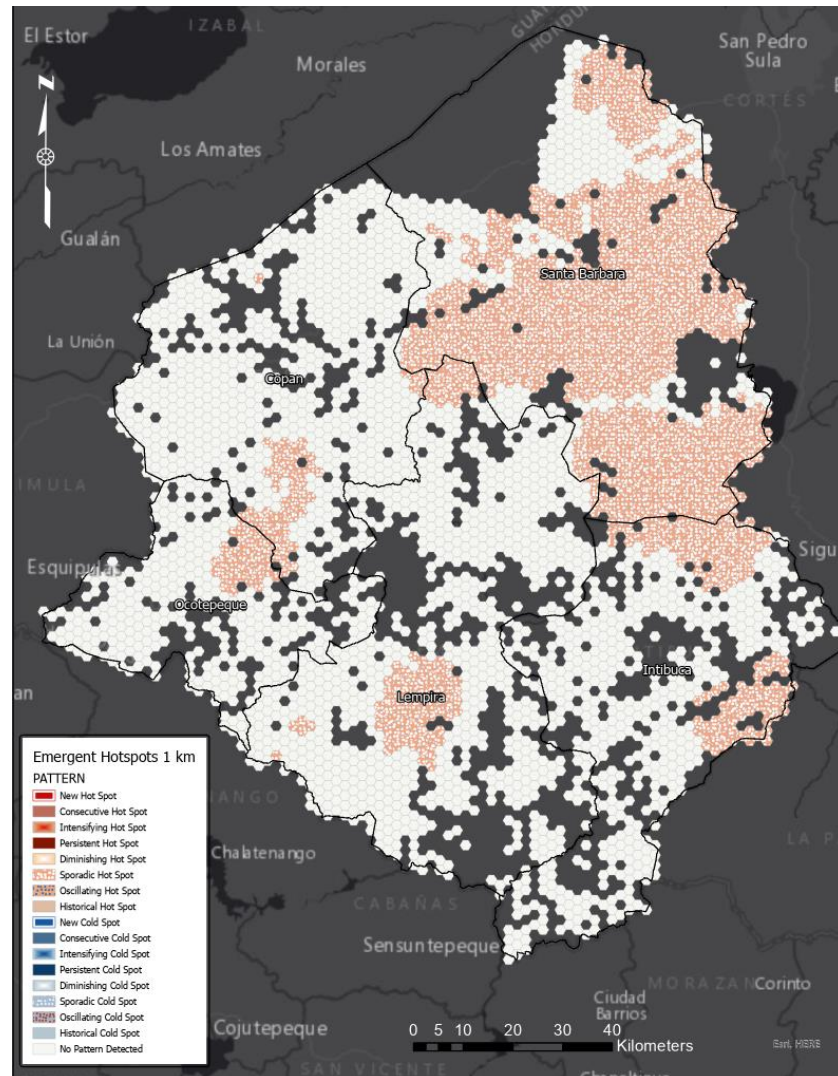
Figure 14. Emergent Hotspot Analysis within a Neighboring Distance of 1 Km

4.4.1.1.2 Topographic Data

The use of topographic variables as part of a forest risk assessment have been widely documented (Caceres, 2011; Chuvieco, 1999; Chuvieco & Congalton, 1989b; Erten & Kurgun, 2002a; Gai et al., 2011; Jaiswal et al., 2002a). Topography is a quantitative representation of an area and may include data on elevation, aspect, and slope (Estes et al., 2017). Understanding the elevation, slope and aspect may determine how a fire can behave (Chuvieco & Congalton, 1989b).

Elevation can determine the type of vegetation, temperature, precipitation, and the wind behavior (Chuvieco & Congalton, 1989b; Estes et al., 2017; Jaiswal et al., 2002a). The elevation layer (Figure 15) was obtained by creating a Digital Elevation Model (DEM) from the 1:50,000 topographic layer obtained from the Honduran Geographic Institute. The highest elevation point was in Lempira at 2,219.6 meters above sea level, and the lowest was in Santa Barbara at 95.41 meters above mean sea level. From the elevation layer it was possible to obtain the slope (Figure 16) and aspect (Figure 17) layers.
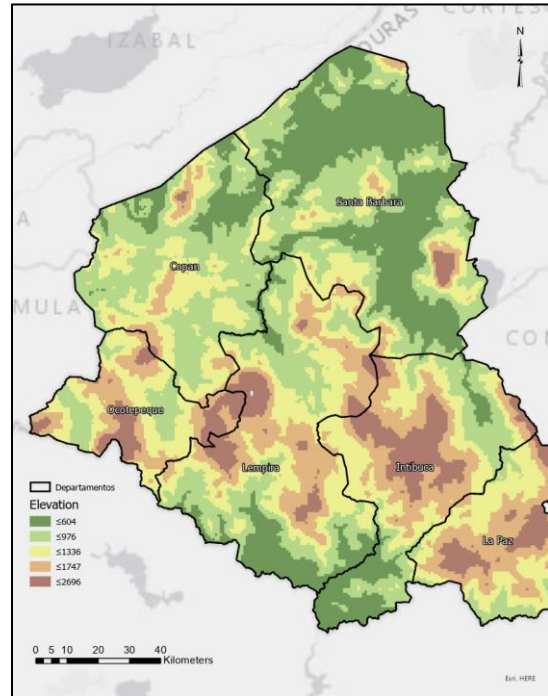
Figure 15. Elevation Map
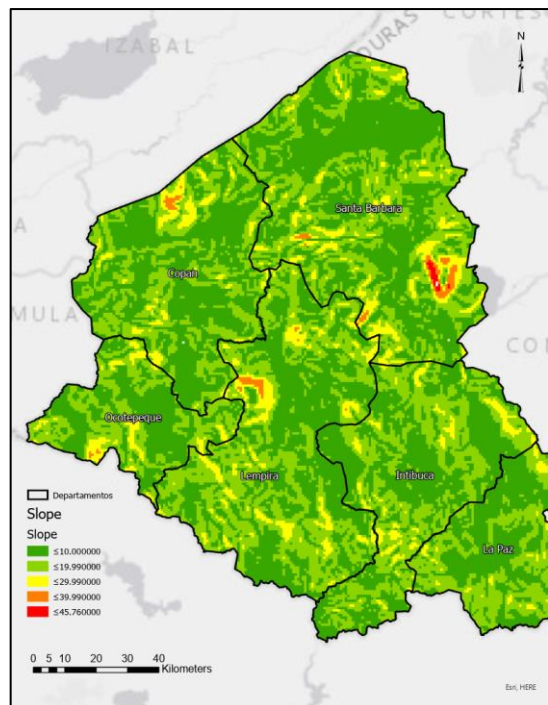
Figure 16. Slope Map

The slope may determine the rate of fire spread so it is critical for this analysis. Steep slopes have higher preheating, an increased rate of spread (Chuvieco & Congalton, 1989b; Estes et al., 2017), and higher flame length (Estes et al., 2017). From the aspect layer, it is possible to determine the amount of sun exposure (Chuvieco, 2003). According to (Estes et al., 2017), the aspect of a terrain can determine not only the solar radiation but also the moisture availability, which has a direct influence on the type of vegetation. The aspect layer map can be seen in Figure 17, and the dashboard developed to help visualize the results can be seen in
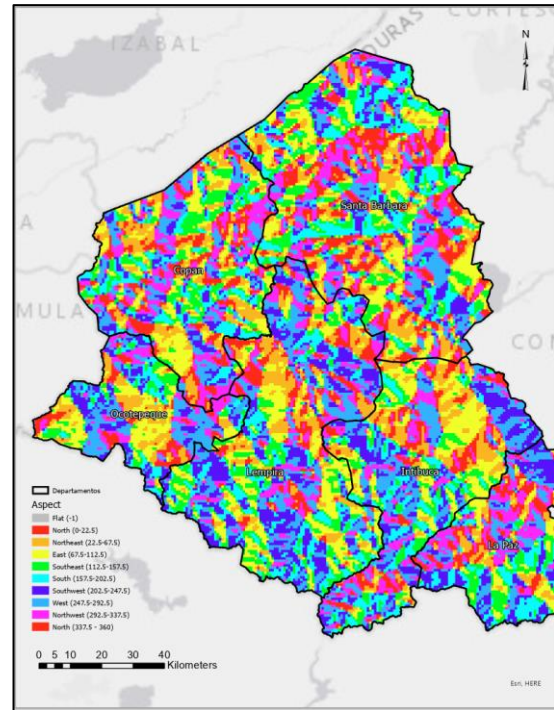
Figure 17. Aspect Map

Figure 18. Based on further analysis, the top aspects intersecting the fire hotspots were east, south, southeast, and northeast.
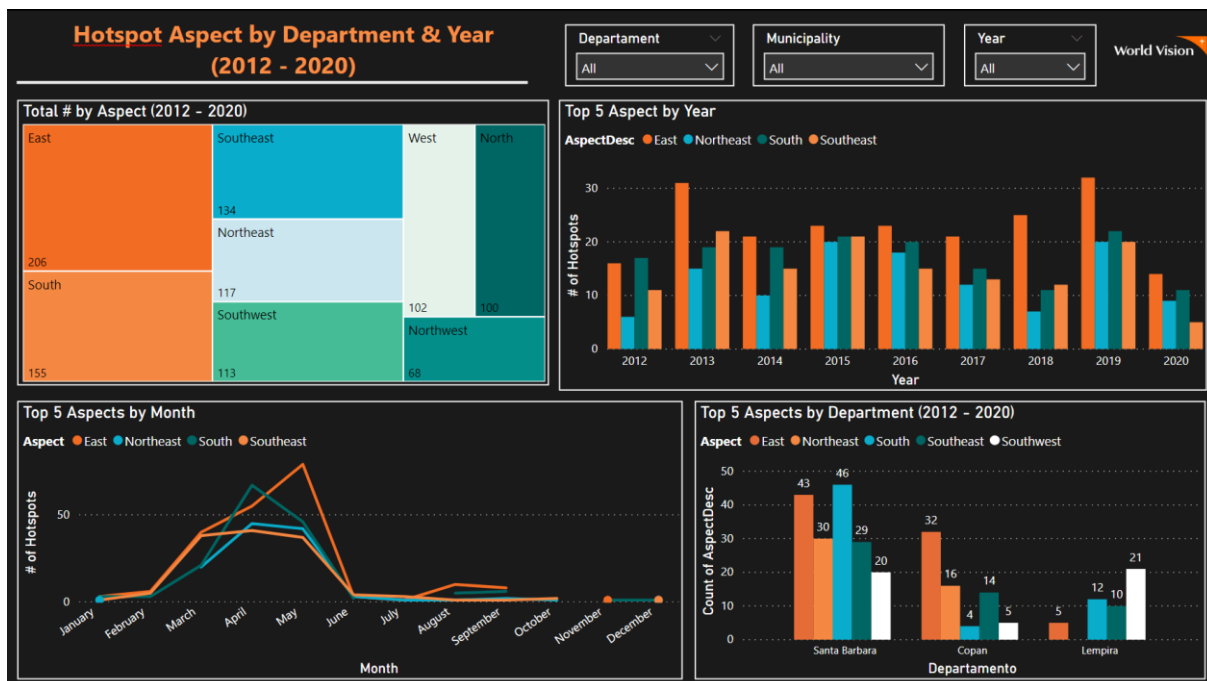
Figure 18. Hotspots Aspect by Department and Year Dashboard

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4.4.1.1.3 Landcover

Generating a landcover layer may be one of the most challenging variables in the study (Chuvieco, 1999). For this study, Landsat-8 scenes were downloaded from USGS EarthExplorer. Landsat-8 offers two sensors: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). Both are calibrated to offer a top of the atmosphere reflectance with better than 5% uncertainty, an absolute geodetic accuracy better than 65 meters, plus a 90%

Figure 19. Mosaic created from the 3 Landsat-8 scenes symbolized with Bands 5,4,3

confidence and 11 bands (see Table 9) (Department of the Interior USGS, 2019; Roy et al., 2014). Compared to previous sensors, the OLI sensor has two additional reflective bands—the shorter wavelength blue band, which improves the sensitivity to chlorophyll and water, and a new shortwave infrared band which improves cloud detection (Roy et al., 2014). Given the study area is in a tropical region, cloud cover is a huge problem when searching for imagery. USGS EarthExplorer allows the possibility of searching for imagery with low cloud cover when a filter with less than 10% of cloud cover was selected.

Even though this filter was selected, several scenes we reviewed contained areas with large portions of cloud cover. After reviewing approximately 30 scenes, three scenes were selected. All three had a processing correction level L1TP and are listed as follows: Scene 1 was acquired on April 09, 2020 (WRS Path 019, WRS Row 050); Scene 2 was acquired on March 28, 2020 (WRS Path 018, WRS Row 049); and Scene 3 was acquired on September 02, 2019 (WRS Path 018, WRS Row 50).

A mosaic was created (Figure 19) using ArcGIS Prom covering an approximate area of 100,000 KM^2, with some overlap of neighboring countries Guatemala and El Salvador.

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A supervised classification with 1,149 training samples was performed with an initial classification schema of eight classes: Water, Urban Area, Sand/Barren Land, Forest, Cloud Cover, Shrub, Burned Areas and Agriculture. After the initial classification result, an evaluation process was performed to determine if the classification was successful, allowing the reclassification of the areas identified as cloud cover and burned areas while correcting areas identified as an incorrect class. The layer was clipped using the Departments under study resulting in an area of 16,440.60 KM^2. The final layer can be seen in Figure 20. The total Forest area in all
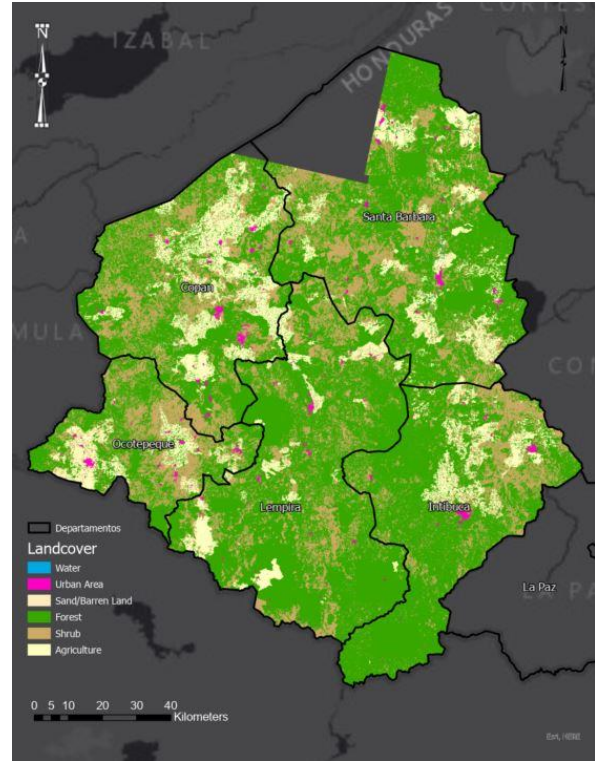
Figure 20. The resulting Landcover layer obtained through a Supervised Classification

five Departments was 10,453.05 KM^2, followed by Shrub areas with 3,982. 73 KM^2, Agriculture with 1,858.18 KM^2. Lempira has the largest area with Forest cover, followed by Santa Barbara. Copan has the largest area with Agriculture followed by Santa Barbara and Intibucá. A dashboard was developed to visualize the results (Figure 21).

Table 10. Landsat-8 OLI and TIRS Bands (μm) (Department of the Interior USGS, 2019)

Band	Wavelength (μm)	Resolution (m)
Band 1: Coastal/Aerosol	0.435-0.451	30m
Band 2: Blue	0.452-0.512	30m
Band 3: Green	0.533-0.590	30m
Band 4: Red	0.636-0.673	30m
Band 5: NIR	0.851-0.879	30m
Band 6: SWIR-1	1.566-1.651	30m
Band 10: TIR-1	10.60-11.19	100m
Band 11: TIR-2	11.50-12.51	100m
Band 7: SWIR-2	2.107-2.294	30m
Band 8: Pan	0.503-0.676	15m
Band 9: Cirrus	1.363-1.384	30m
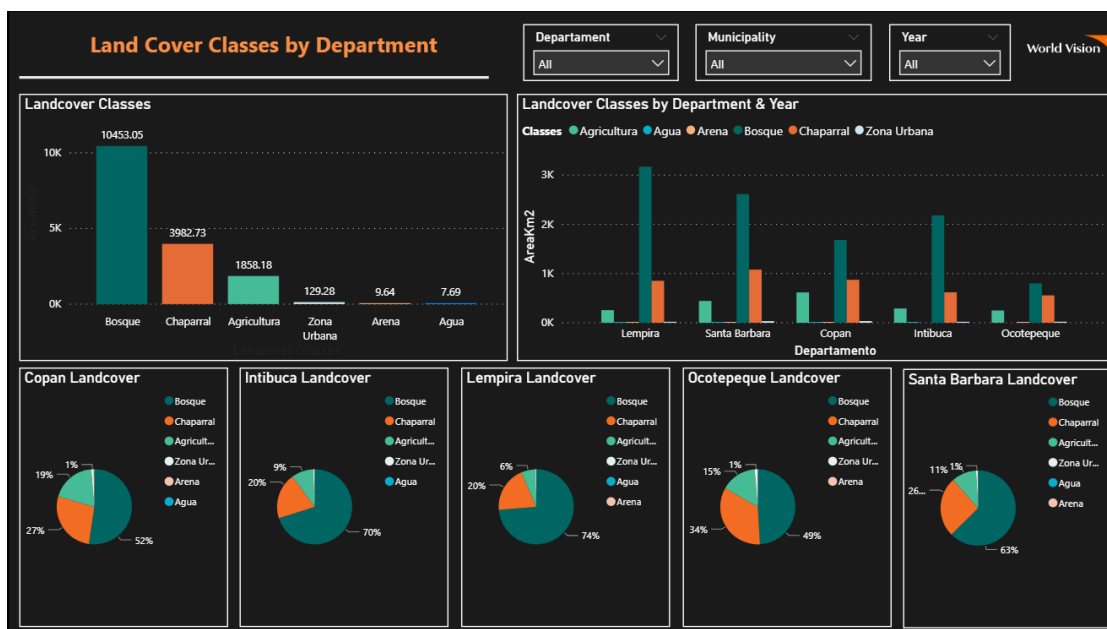
Figure 21. Land Cover Dashboard by Department

4.4.1.1.4 Settlements

When the settlement layer obtained from the National Honduran Territorial System was clipped

with the Departments under study, a total of 6,599 settlements were identified (Table 10). The

importance of identifying the settlements in the area has been previously noted (Caceres, 2011; Chuvieco,

2003; Gai et al., 2011; Jaiswal et al., 2002a) in discussions about cultural practices as a possible risk

factor for accidental fires.

Table 11. Total Number of Settlements Located in the THRIVE Area

Department	Number of Settlements	Population 2001	Population 2013	Population 2020
Copan	1,115	267,632	371,057	412,927
Intibucá	944	168,106	232,553	265,006
Lempira	1,685	233,739	321,179	363,867
Ocotepeque	585	98,330	146,430	165,482
Santa Barbara	1,418	297,100	421,337	469,579
Total	5747	1,064,907	1,492,556	1,676,861

A buffer layer was created to identify the areas less than one thousand meters, between one thousand and two thousand meters, and areas greater than two thousand meters within settlements. This layer was later weighted to be used in the Risk Index calculation.

4.4.1.1.5 Roads

The identification of roads has been an essential variable in previous fire risk analysis, as roads can be a route for fire suppression efforts and possible fire breaks (Chuvieco & Congalton, 1989b), as well as identifying areas prone to accidental fires, as roads can provide access to campsites or hiking trails (Chuvieco & Congalton, 1989b; Jaiswal et al., 2002a). Roads also increase the risk of people improperly disposing of cigarette butts, which is the cause of a very high number of fires (Jaiswal et al., 2002a; Wohlwend, 2018). A buffer layer was created to identify the areas less than one hundred meters, between one hundred and two hundred meters, two hundred and three hundred meters, and areas greater than three hundred meters. This layer was later weighted to be used in the risk index calculation.

4.4.1.2 Soil Moisture

Communities need to adapt and take proactive approaches on how changes in climate may affect their yields. The use of Remote Sensing (RS) for monitoring and assessing soil moisture using either naked-eye or microwave scans may provide a simple solution (Amani, 2016; Ngo Thi et al., 2019; Njoku & Entekhabi, 1996; Urban et al., 2018). Some studies focus on measuring specific indices, such as the Normalized Difference Vegetation Index (NDVI) (Amani, 2016; T. Chen et al., 2014; Singh et al., 2015b; Urban et al., 2018), which measures the photosynthetic value of plants; this helps identify vegetation stress, as there is a high correlation between droughts and NDVI (Amani, 2016; S. Chen et al., 2015; Rahman & Mesev, 2019). NDVI can be calculated (USGS (2), 2019; Vermote et al., 2016) as follows:

$$NDVI = (NIR - R) / (NIR + R) \text{ or}$$

$$NDVI = (Band\ 5 - Band\ 4) / (Band\ 5 + Band\ 4)$$

Other indices studied in relationship with soil moisture include the Temperature Vegetation Dryness Index (TVDI), which measures the correlation between forest canopy temperature and NDVI (Burapapol & Nagasawa, 2016), and the Land Surface Temperature (LST) index, which provides a relationship between the surface energy and water balance (Rozenstein et al., 2014). The accuracy of these indices has increased in recent years. Landsat 8, launched in 2013, is the most recently launched satellite for Earth observation (Department of the Interior USGS, 2019). Before this date, the reliability of surface temperature data had to be verified through ancillary data, as prior missions only had a single thermal band (Roy et al., 2014).

Another index for determining the vegetation water content is the Normalized Difference Moisture Index (NDMI), which provides a measurement of the vegetation's water stress levels. NDMI can be calculated (USGS (6), 2019) as follows:

$$NDMI = (NIR - SWIR) / (NIR + SWIR) \text{ or}$$

$$NDMI = (Band\ 5 - Band\ 6) / (Band\ 5 + Band\ 6)$$

To calculate NDMI, this research used the following three Landsat 8 scenes: Scene 1, acquired on April 09, 2020 (WRS Path 019, WRS Row 050); Scene 2, acquired on March 28, 2020 (WRS Path 018, WRS Row 049), and Scene 3, acquired on September 02, 2019 (WRS Path 018, WRS Row 50). ModelBuilder was used to create the process to calculate the NDMI layer (Figure 22) and its result can be seen in Figure 23.
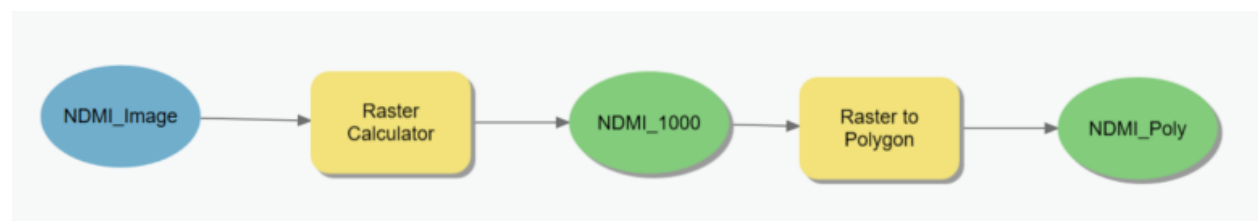
Figure 22. Model for Conversion of the NDMI and NDVI Models to Vector Layers
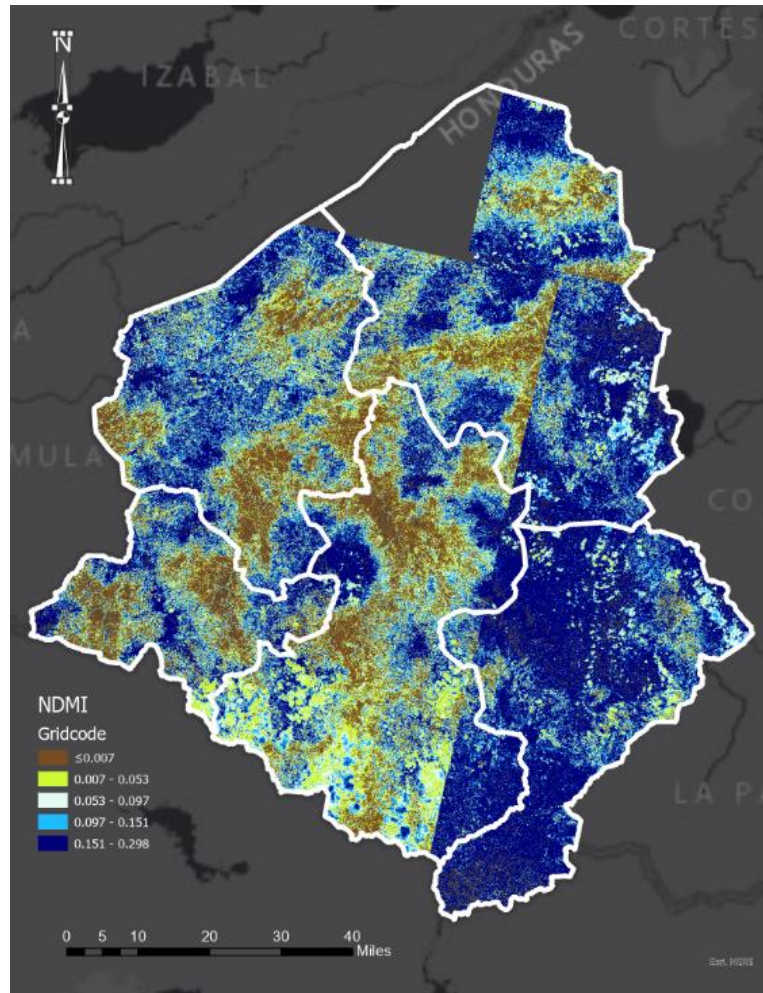
Figure 23.NDMI Layer Showing Water Stress in the Region

4.4.2 Sensitivity

The sensitivity of a system is referred to the degree climate may affect it either adversely or beneficially (IPCC & Edenhofer, 2014; McCarthy & IPCC, 2001). The sensitivity of the THRIVE region was measured by identifying the areas that have suffered deforestation and identifying the areas with small-scale farming operation. A description of how each analysis was performed is in the following sections.

4.4.2.1 Deforestation

The 2009 Land Cover layer was obtained from the National Territorial System (abbreviated as SINIT in Spanish). The 2018 Land Cover layer was obtained from the Honduran National Institute for Conservation and Forest Development's (abbreviated as ICF in Spanish) Geoportal. A comparison between those two layers shows a decrease in forest cover in the period between 2009 and 2018. A dashboard was developed to show the changes in forest cover (Figure 24).
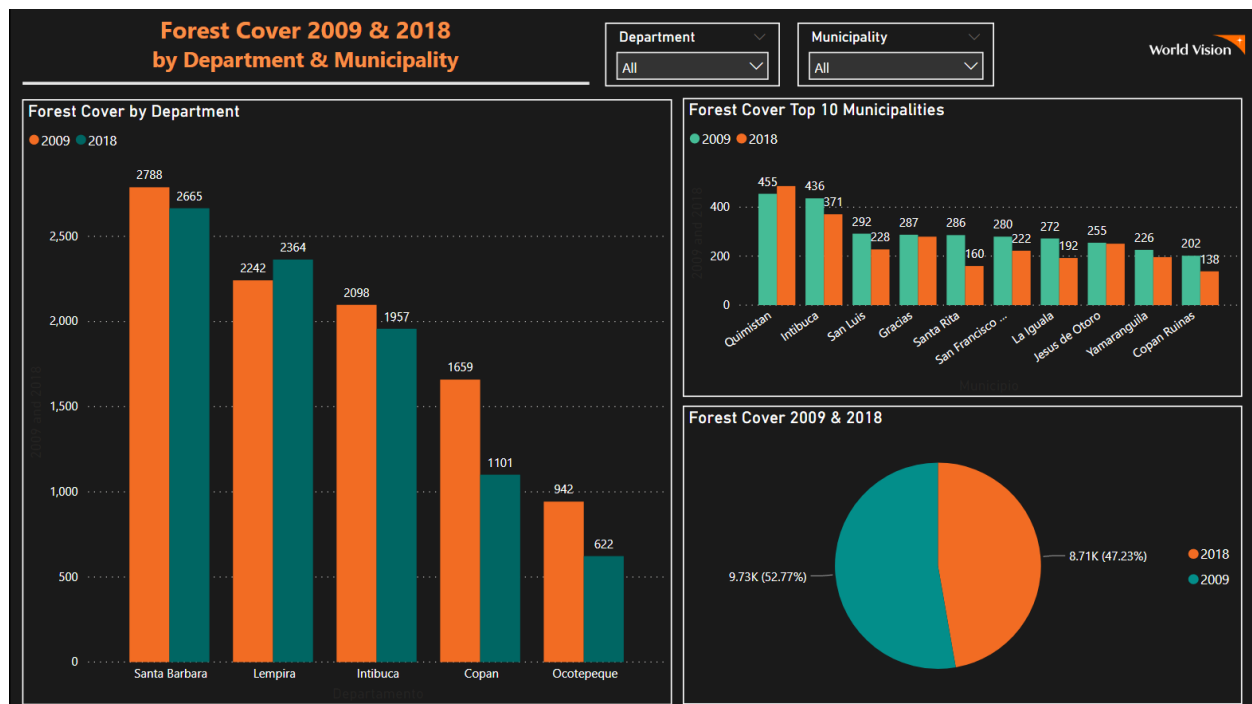
Figure 24. Forest Cover Comparison between 2009 and 2019 by Department and Municipality.

The rate of deforestation was calculated by subtracting the 2009 and 2018 forest area raster layers. ArcGIS ModelBuilder was used to reclassify the grid values and determine the areas that have seen deforestation or reforestation. The model can be seen in Figure 25, the resulting layer in Figure 26, and a dashboard in Figure 27.
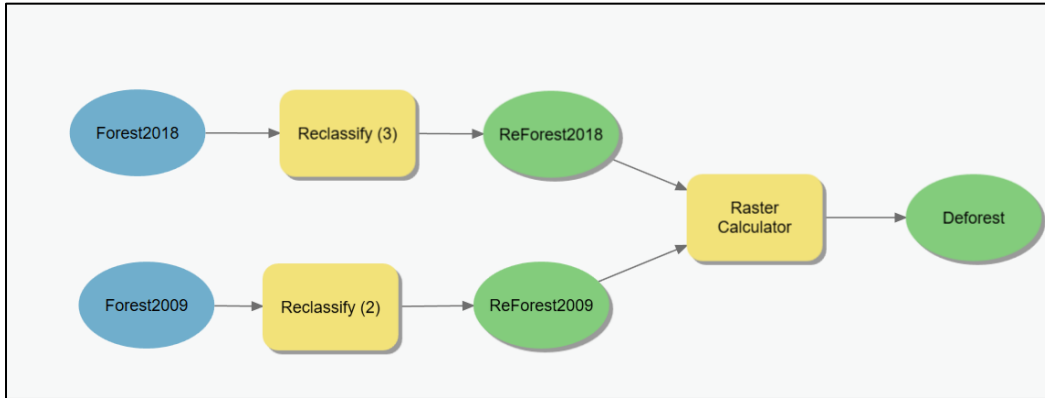
Figure 25. Deforestation Model to Calculate Deforestation or Reforestation
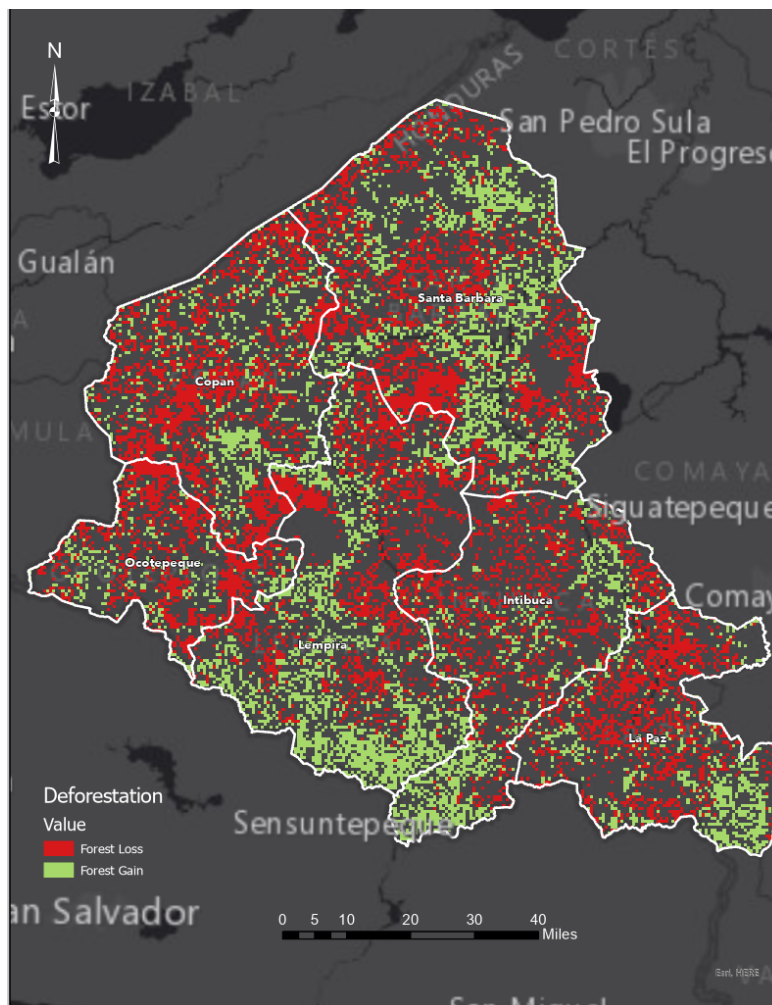
Figure 26. Resulting Layer Showing Areas of Forest Loss or Gain.
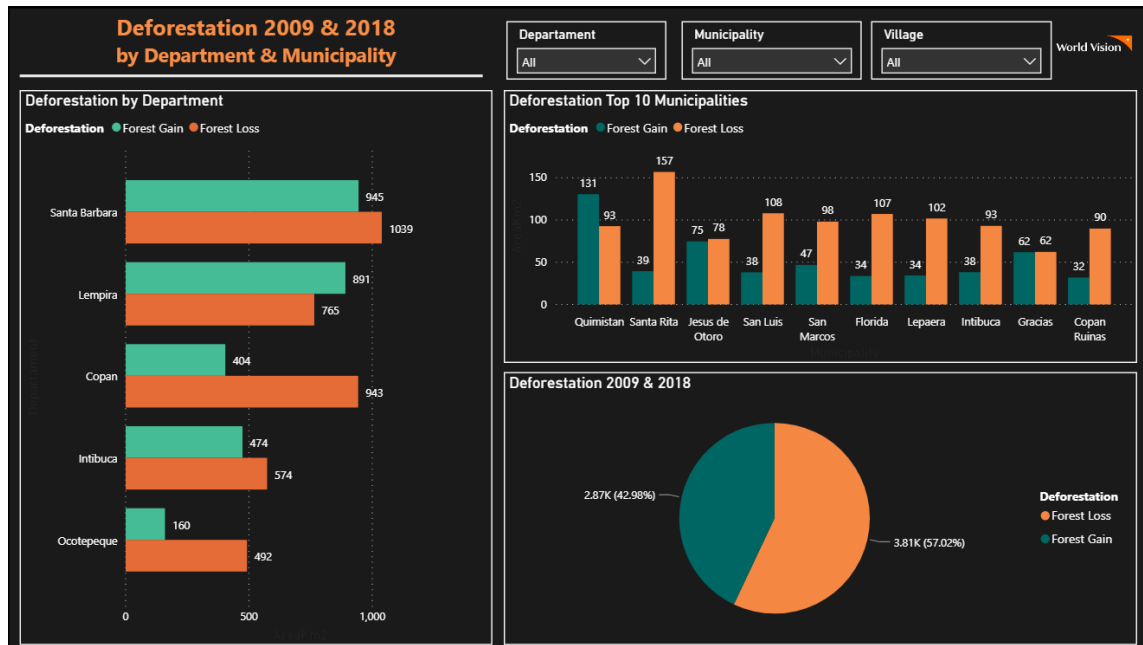
Figure 27. Dashboard Comparing Forest Loss and Forest Gain among Departments and Municipalities

When comparing the deforestation rates, all Departments experienced significant forest loss expect Lempira. Ocotepeque lost forest cover at a rate of 207%, Copan lost at a rate of 33%, Intibucá 21%, and Santa Barbara 9.9%

To weight this layer, it was necessary to identify the percentage of deforestation in comparison to the area of the village. Two fields were used, one which included the area of deforestation and another which included the village area. This process was performed using ModelBuilder and is summarized in Figure 28.
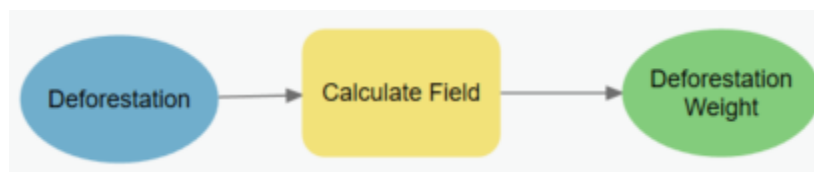
Figure 28. Deforestation weight model

The calculated field was performed through an Arcade script as follows:

```
if($feature.AreaKm2<=25)
  {return 1}
if($feature.AreaKm2>25 && $feature.AreaKm2<=50)
  {return 2}
if($feature.AreaKm2>50 && $feature.AreaKm2<=75)
  {return 3}
if($feature.AreaKm2<75)
  {return 4}
```

4.4.2.2 Percent Small-scale Farming Operation

The changes in climatic patterns are having and will have a negative effect among subsistence farmers who might already be food insecure, by reducing their crop yields. These groups have low access to financial services with limited access to technology, making them more vulnerable to extreme changes (Altieri et al., 2015; Antle, 1995; FAO, 2017; IPCC, 2014; IPCC (4), 2007; P. Jones & Thornton, 2003; Kang et al., 2009; Misra, 2014; Schmidhuber & Tubiello, 2007; UN, 2018; World Bank, 2013). Using the Land Cover layer developed previously, the small-scale farming operations were identified.
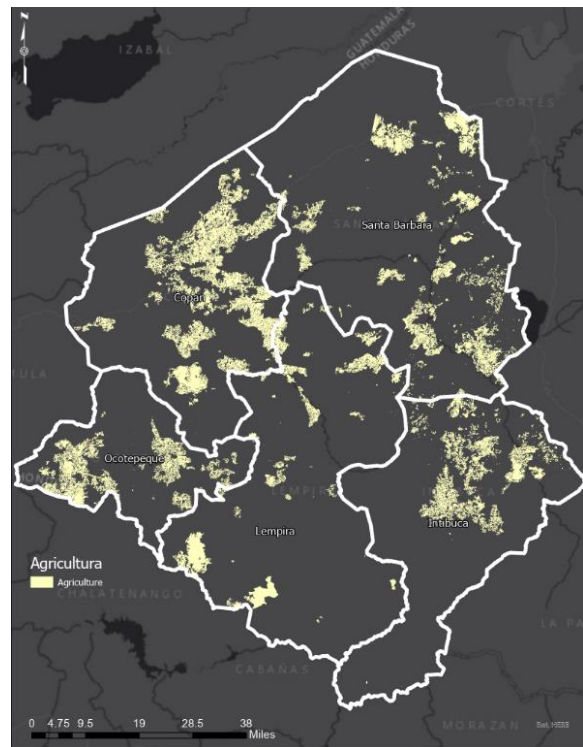
Figure 29. Agricultural land in the THRIVE region

The five Departments in the THRIVE region have approximately 1,858.20 km^2, with most of the farmers considered small-scale farmers (Figure 29). Copan has the largest area, with the top five municipalities with agricultural land being Florida, Santa Rosa de Copan, San Antonio, El Paraiso, and Nueva Arcadia; they are followed by Santa Barbara, Quimistan, San Pedro Zacapa, Santa Barbara, San Marcos and Petoa. A dashboard was developed to visualize the results of this analysis (Figure 30).
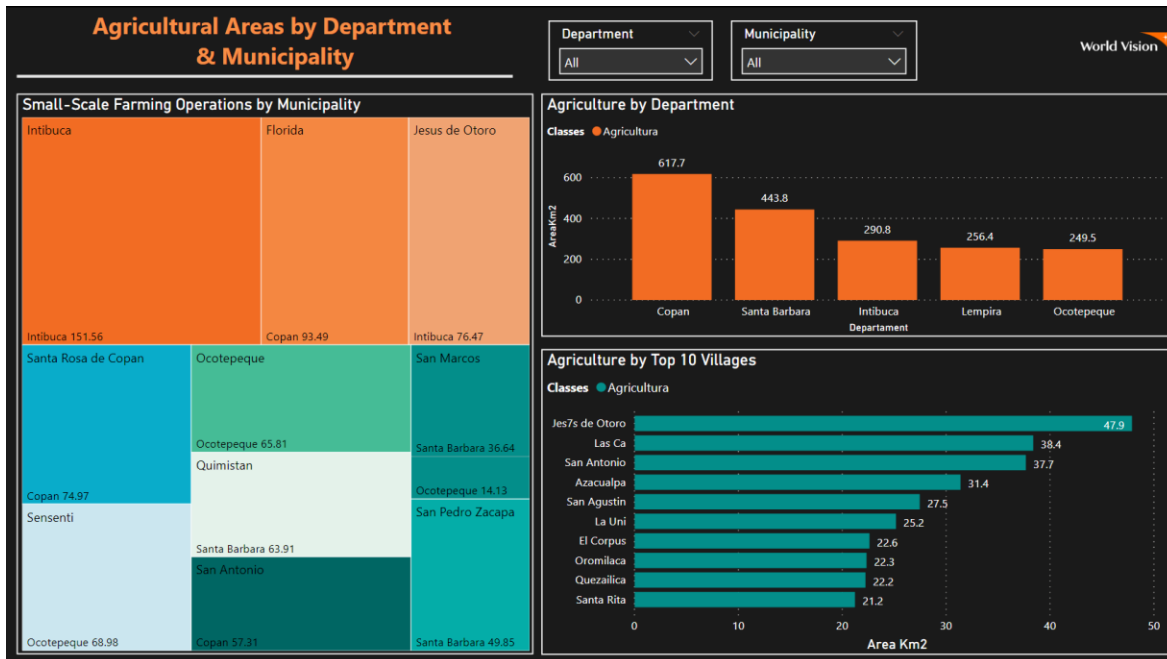
Figure 30. Small-scale Farming Operations Dashboard

To weight this layer, it was necessary to identify the percentage of the village area with agricultural land.

To perform this calculation, the area of the village and the area of agricultural land was used.

ModelBuilder was again used and is shown in Figure 31.
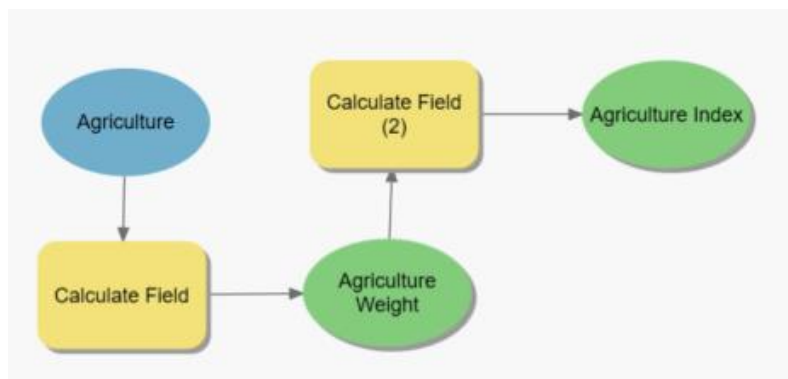
Figure 31. Agriculture Area Weight Model

The Arcade script used to calculate the Agricultural area is as follows:

```
if($feature.PercentAgric<=25)
  {return 1}
if($feature.PercentAgric>25 && $feature.PercentAgric<=50)
  {return 2}
if($feature.PercentAgric>50 && $feature.PercentAgric<=75)
  {return 3}
if($feature.PercentAgric>75)
```

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This resulted in the following layer in Figure 32:
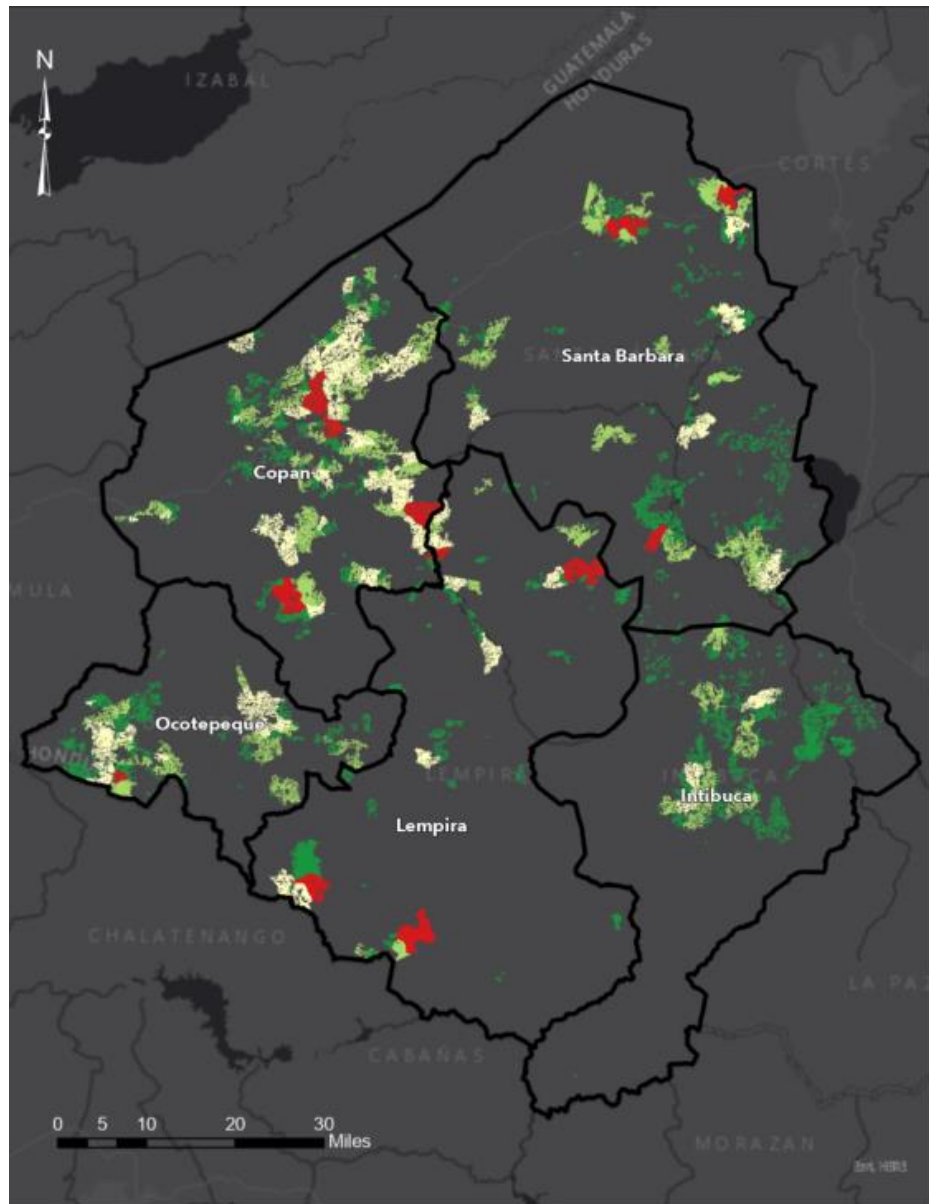
Figure 32. Weighted Small-scale Farming Operations

4.4.3 Adaptive Capacity

4.4.3.1 Health Access

To visualize and analyze the access to health care, the health centers were weighted based on the services they offered. CESAR was weighted highest as it offers only the most basic service, and the regional hospital weighted lowest as it offers better and more health services (Table 11). A model was built in ModelBuilder and can be seen in Figure 33.

Table 12. Health Services Access Weights

Health Center	Weight
CESAR	4
CESAMO	3
CMI	3
Area Hospital	2
Regional Hospital	1
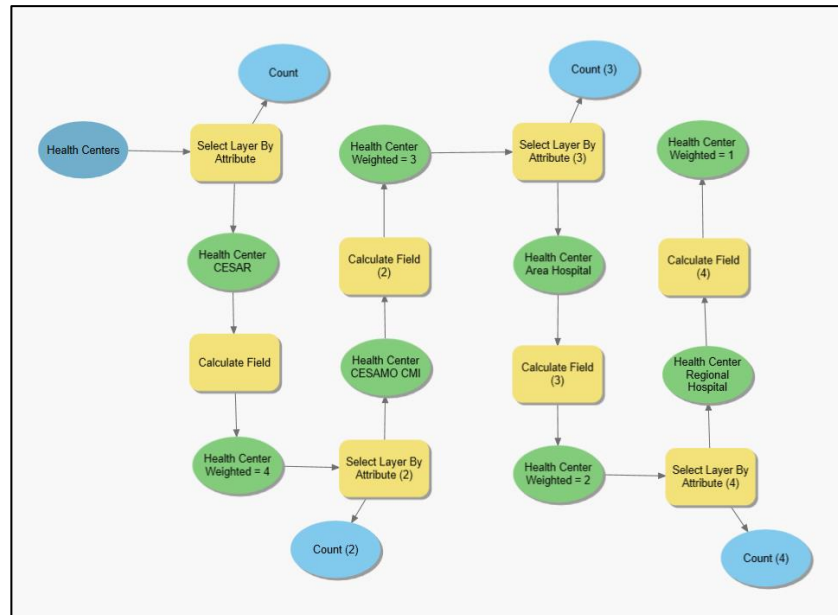
Figure 33. Health Centers Weight Model

Using the weight field, a Kernel Density Map (Figure 34) was created identifying the areas with higher health access and lower health access. Santa Barbara has the highest area with low access, followed by Intibucá and Lempira. In terms of middle access, Lempira has the highest level followed by

Copan. The Department of Copan has the highest level of health care in the region given the regional hospital is located there.
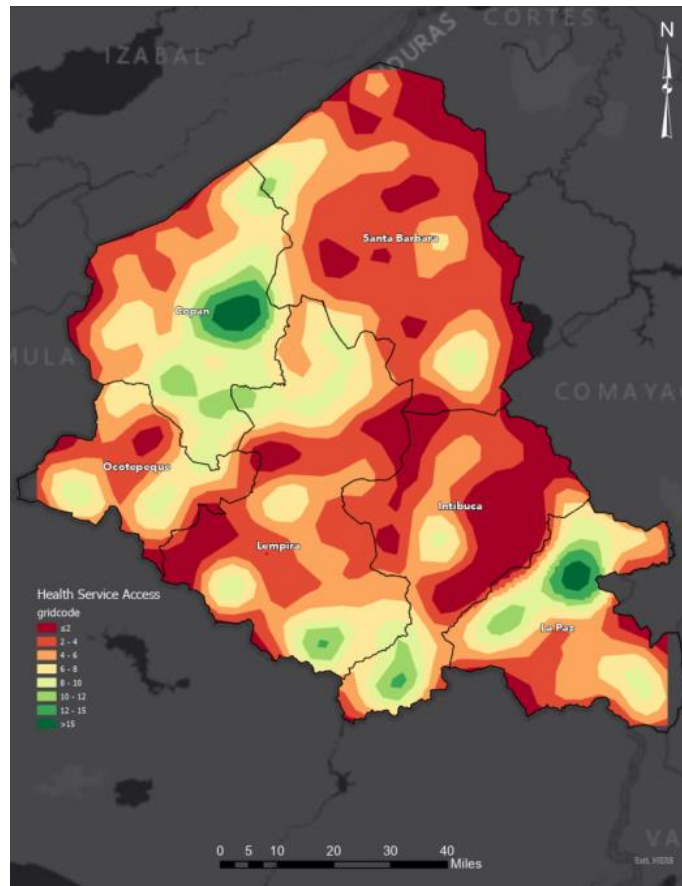
Figure 34. Health Service Access Kernel Density Map

The top municipalities with lowest health care access are Quimistan, Santa Barbara Department; Intibucá, Intibucá Department; and Jesus de Otoro, Intibucá Department. The villages with higher area of poor health care access are San Isidro, Santa Barbara Department; Jesus de Otoro, Intibucá Department; San Antonio, San Juan Department.

4.4.3.2 Socioeconomic Indicators

4.4.3.2.1 Dependency

To calculate the Dependency Ratio, a Model was developed using ModelBuilder and can be seen in Figure 35.
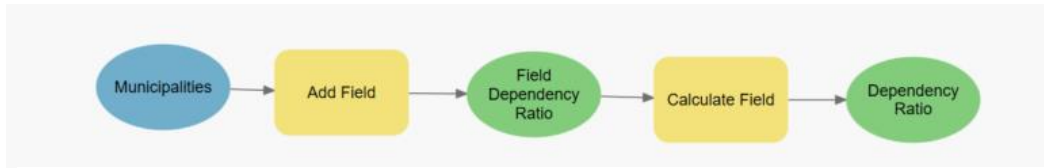
Figure 35. Dependency Ratio Model

The results of this analysis can be seen in Figure 36 (below left). A hotspot analysis was performed to identify the most dependent and vulnerable population (Figure 36 below right). The Department of Lempira was the region with highest ratio of dependency among its population, as was the case with some municipalities in the Department of Intibuca. The formula used to calculate the Dependency Ratio is as follows:

$$Dependency\ Ratio = 100 * \frac{((Population\ 0\text{-}14) + (Population\ 65+) + (Population\ with\ Disability))}{(Population\ 15\text{-}64)}$$

Table 13. Variables Used to Calculate the Dependency Ratio Layer

Where:					
Variable	**Definition**	**Variable**	**Definition**	**Variable**	**Definition**
A0_4	Age 0 – 4	**A5_9**	Age 5 – 9	**A10_14**	Age 10 – 14
A65_69	Age 65 – 69	**A70_74**	Age 70 – 74	**A75_79**	Age 75 – 79
A80_84	Age 80 – 84	**A85_89**	Age 85 – 89	**A90_94**	Age 90 – 94
A95	Age 95 +	**LimMovSi**	Limited mobility	**LimBraManSi**	Disability Arms and Hands
LimVerSi	Blind	**LimOirSi**	Deaf	**LimHablarSi**	Mute
LimCuidSi	Cannot take care of self	**RetMenSi**	Mental Disability		
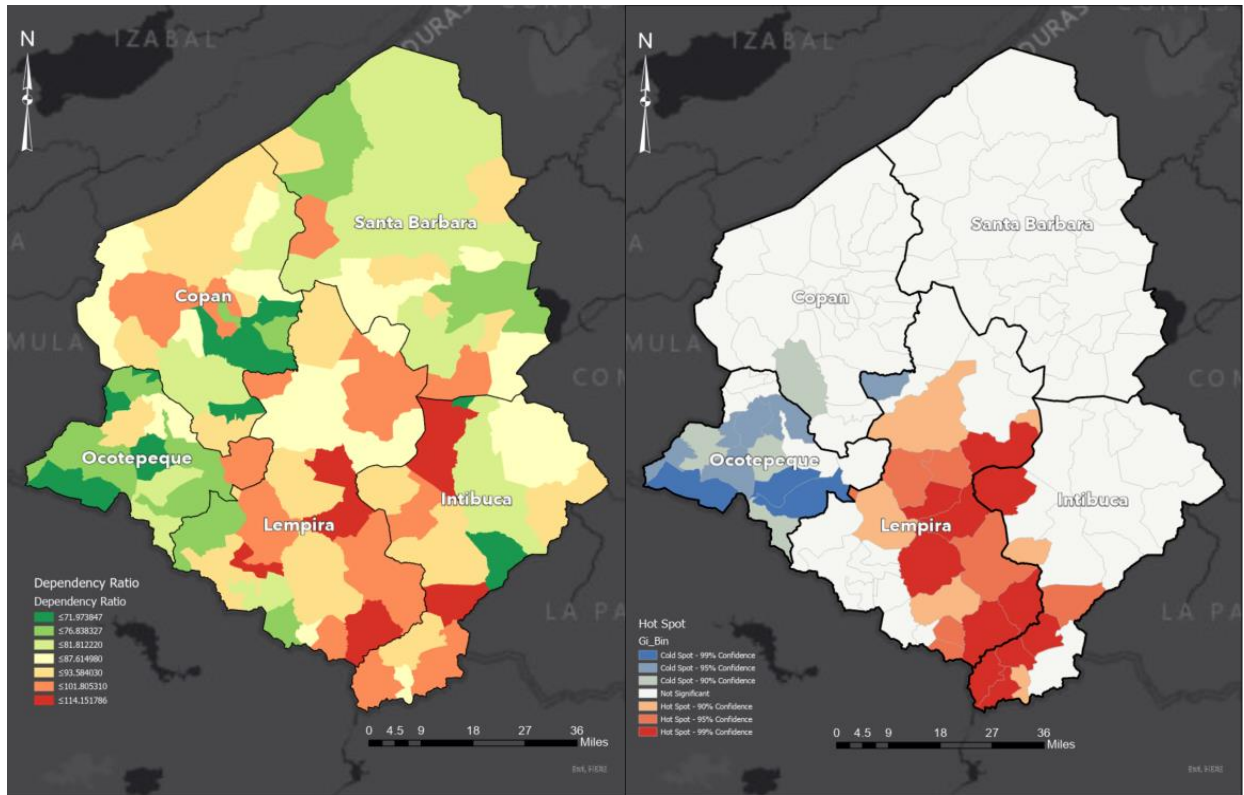
Figure 36. The Dependency Ratio Map (left) by Municipality. The Dependency Ratio Hot Spot Analysis Getis-Ord Gi* Map (right)

4.4.3.2.2 Access to Basic Sanitary Service

Using the methodology in Table 3, the Access to Basic Sanitary Service was calculated through a model as seen in Figure 37. The total population by municipality was used to determine the percentage of the population with low, medium, or high access to basic sanitary services. The results can be seen in Figure 38 (left).
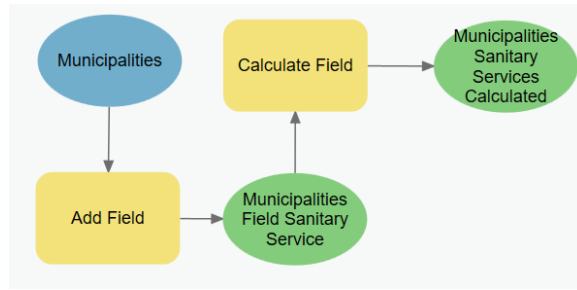
Figure 37. Access to Basic Sanitary Services

The municipalities with better access are generally larger urban areas, and the areas with lower access are municipalities with lower development rates and higher poverty levels. The municipalities with the lowest access to basic sanitary services are San Francisco Opalaca, Dolores, and San Marcos de la Sierra—all of them in the Department of Intibucá and San Francisco in the Department of Lempira. There are sixteen other municipalities in the Medium-Low Access classification. This includes Intibucá and Lempira, the Departments with the highest number of municipalities with low access to basic sanitary services. The areas with lower access can also be seen through a hotspot analysis in Figure 49 (right). The formula to calculate the Access to Basic Sanitary Service map is as follows:
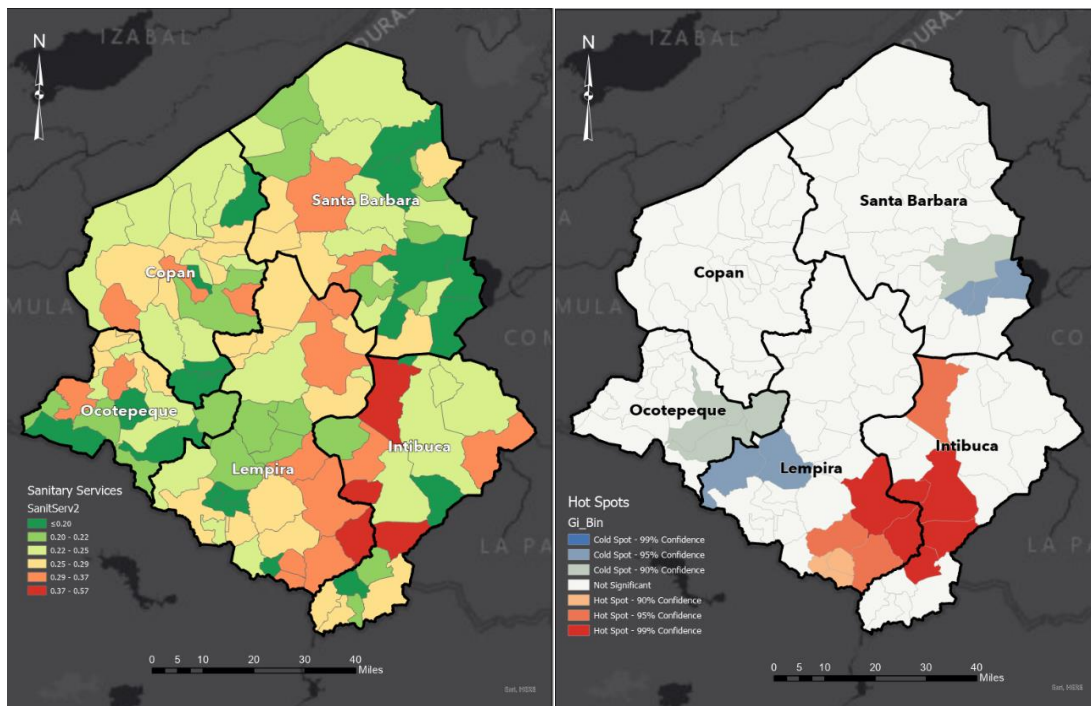
Figure 38. Access to Basic Sanitary Services Map (left) by Municipality and Hot Spot Analysis Getis-Ord Gi*
Map (right)

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(((InsidePipes* 1) + (OutsidePipes * 1) + (PipesOutsideBuilding * 1) + (NoWater! * 5) + (Well * 4) + (WellPump* 2) + (River * 5) + (Lake * 5) + (WaterSalesperson * 1) + (ToiletConnSewer * 1) + (ToiletSeptic * 1) + (ToiletDisRiver * 2) + (LatrineSimWell * 4) + (HydLatrine * 3) + (NoToilet * 5)) * 0.25)/Population)

Table 14. Variables Used to Calculate the Access to Basic Sanitary Services Layer

Where:					
Variable	**Definition**	**Variable**	**Definition**	**Variable**	**Definition**
TubDentro	Inside pipes	**TubFuera**	Outside pipes	**TubFueraEd**	Pipes outside building
NoRecAgua	Does not receive piped-in water	**PozoMalacate**	Well	**PozoBomba**	Well with pump
Rio	River	**Lago**	Lake	**Vendedor**	Salesperson
InodAlcant	Toilet connected to sewer system	**InodPzSep**	Toilet with septic tank	**InodDesRio**	Toilet discharges directly into river
LetrPzSimp	Latrine with simple well	**LetrCierreHid**	Hydraulic latrine	**NoTiene**	Doesn't have toilet
Poblacion	Population				

4.4.3.2.3 Access to a House with Basic Requirements

Using the methodology in Table 4, the Access to Basic Sanitary Service was calculated through a model seen in Figure 39. The total population by municipality was used to determine the percentage of the population with low-, medium-, or high access to a house with basic needs. The results can be seen in Figure 40. The formula used to calculate the Access to a House with Basic Needs is as follows:

(((BrickWall * 3) + (StoneWall * 3) + (CementWall * 3) + (AdobeWall * 4) + (WoodWall * 4) + (MudWall * 5) + (StickWall * 5) + (WasteWall * 5) + (ClayTileRoof * 4) + (AsbestosRoof * 3) + (ZincFoilRoof * 3) + (ConcreteRoof * 3) + (StrawRoof * 5) + (WasteWall * 5) + (AluzincRoof * 3) + (DirtFloor * 5) + (CementFloor \ 2) + (WoodFloor * 4) + (CementBrickFloor * 1) + (TerrazoFloor * 1) + (ClayFloor * 3) + (CeramicFloor * 1) + (WoodFloor * 4) + (Kerosene * 1) + (GasCylinder * 1) + (!Electricity * 1) + (DoesNotCook * 5)) * 0.25) / Population*

Table 15. Variables used to calculate the Housing with Basic Needs layer

Where:					
Variable	**Definition**	**Variable**	**Definition**	**Variable**	**Definition**
LadRafon	Brick wall	**PiedraRaj**	Stone wall	**BloqCem**	Cement wall
Adobe	Adobe wall	**Madera**	Wood wall	**Bahareque**	Mud wall
Palo	Stick wall	**MatDes**	Waste wall	**TejBarro**	Clay tile roof
LamAsbesto	Asbestos roof	**Lamzinc**	Zinc foil roof	**Concreto**	Concrete roof
Paja	Straw roof	**MatDes**	Waste roof	**LamAluzinc**	Aluzinc roof
PisoTierra	Dirt floor	**PisoCem**	Cement floor	**PisoMad**	Wood floor

PisoLadCem	Cement brick floor	PisoLadTerr	Terrazzo floor	PisoLadBarro	Clay floor
PisoCeramica	Ceramic floor	Lena	Firewood	GasKeros	Kerosene
GasChimbo	Gas cylinder	Electricidad	Electricity	Nococina	Does not cook
Poblacion	Population				
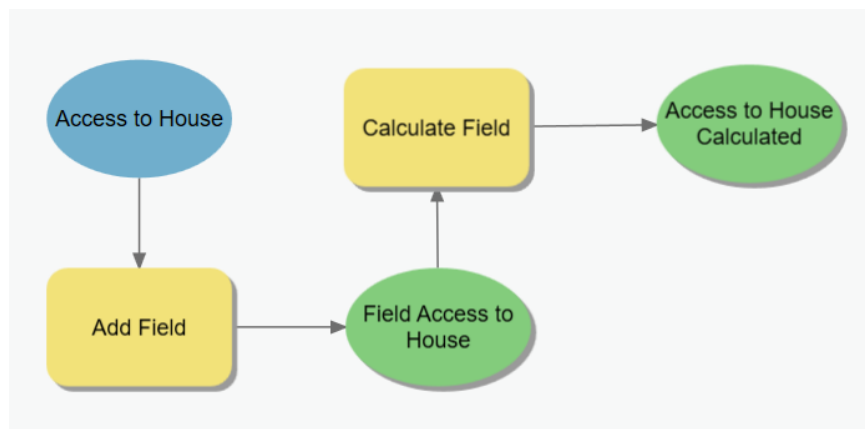
Figure 39. Access to a House with Basic Needs
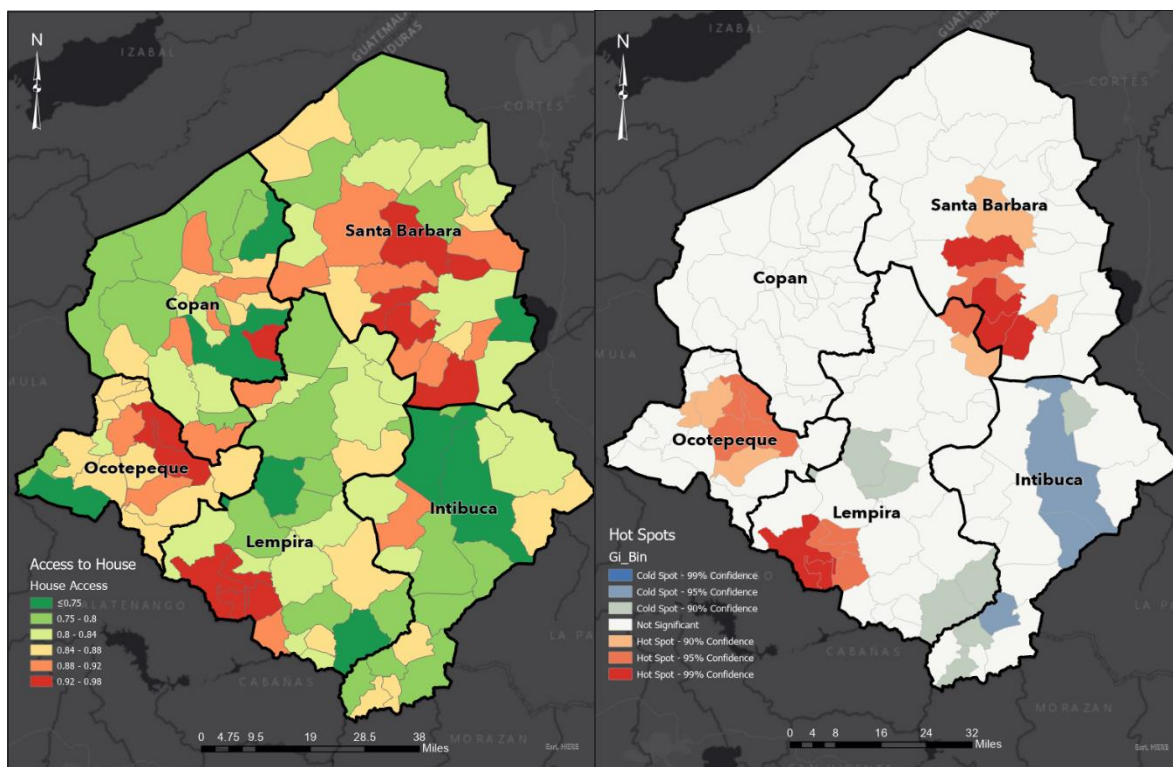
Figure 40. Access to House Results (left) and Hotspots Analysis Maps (right)

4.4.3.3 Economic Analysis

Previously, data collection in research was conducted through paper surveys collected in the field following its digitization into a database for further analysis. This process was error-prone and required several months of work from the development of the survey to the actual analysis and results. But technological advances provided a different and innovative way to perform data collection. Data collection in the field is extremely important for the success of this research, but one of the main constraints is the lack of connectivity in Honduran rural areas. A socioeconomic analysis was planned to be conducted as part of the Vulnerability Framework, but the travel restrictions imposed due to COVID-19 limited this component of the analysis.

4.5 Step 4: Index Creation and Visualization

An indicator is a widely used term and is "a function from observable variables called indicating variables to theoretical variables". The use of indicators is a way to "bridge academic work and political needs" (Hinkel, 2011), by synthesizing, quantifying and standardizing a complex data phenomenon into a number with the possibility of communicating in stakeholders, decision makers or policy makers (FAO, 2018; GIZ, 2014; Hinkel, 2011). Indicators are useful both measuring progress, monitoring trends, justifying funds, and communicating priorities (FAO, 2018). One example of the use of the indicator approach is the Sustainable Development Goals (SDGs) used to monitor progress at local, national, regional, and global level. The use of an indicator framework converts the SDGs into a management tool for countries to follow and a report card to measure progress (Sustainable Development Solutions Network, 2015). But the use of a Composite Index Approach allows the potential of showing a bigger picture when analyzing multidimensional phenomena and allows the visualization of results when presented as scores or rankings.

Empirical studies argue that the use of a Composite Index Approach may not show how indicators are interconnected, while other studies weigh the advantage of using this approach as a way to avoid precision, reliability, accuracy and validity issues (USAID (2), 2014). An example of a Composite

Index Approach is the Multidimensional Poverty Index, which groups the Millennium Development Goals indicators into dimensions, and presents a deprivation criterion to measure them. The interconnectedness of the indicators provides a better picture of the clusters of deprivation that are present in communities under study (Alkire & Santos, 2010).

This research proposes the use of the guidelines presented by ((USAID (2), 2014), which draws its guidelines from best practices in the composite indices literature and compares six assessments of Climate Change Vulnerability and Resilience Index Design: Climate Vulnerability Index (CVI), Flood Vulnerability Index (FVI), Livelihood Vulnerability Index (LVI), LVI-IPCC, Socio-Climatic Vulnerability Index (SCVI), Water Poverty Index (WPI), and Water Vulnerability Index (WVI). The steps recommended provide a benchmark, and are key steps that can be easily followed when developing indices (USAID (2), 2014):

1) *Define the purpose and theoretical/conceptual framework:* During the framing process it is essential to understand what the main motivation is to develop the index, who will use it, for what purposes will they use it, and what possible insights will occur from its use.

2) *Scope and spatial scale of analysis:* Selecting the spatial extent and comparative units at the beginning of the study is essential. The extent can be an administrative unit, a watershed, or a city.

3) *Structural design/major components:* Commonly used structured designs include a) deductive, b) hierarchical, or c) inductive.

4) *Indicator selection/criteria approach:* This decision may depend on data availability, data quality, degree of salience, and degree of audience resonance.

5) *Evaluation of data quality and potential sources of error:* Margins of error in data should be understood. Other sources of error may include measurement, coverage, and sampling errors.

6) *Data transformation:* This might include data normalization or data standardization.

7) ***Data reduction and factor retention:*** It might be recommended to reduce the number of indicators to the most significant ones. Some statistical techniques might include principal component analysis (PCA), exploratory factor analysis, or correlation methods, among others.

8) ***Weighting and aggregating methods:*** This process should be transparent and include clear documentation.

9) ***Uncertainty and sensitivity analysis:*** This type of analysis helps with indicator selection, adding transparency to the process.

10) ***Visualization of results:*** To visualize results, there can be a variety of options, including tabular form, spider or triangle diagrams, maps, or graphs.

11) ***Validation and verification:*** This process requires the engagement of stakeholders and experts. In some cases, it requires a statistical validation.

The creation of the index includes three steps. First, based on the indicators for each subcomponent, an overall index for each subcomponent is calculated. The overall index uses

$$Index = \Sigma W_1 X_1 + \cdots + W_n X_n$$

where:

W_1= weight factor

X_1= indicator

The second step will determine the weight for each component, and then calculate the overall index for each component using normalized subcomponent values.

Finally, an overall index to calculate vulnerability using

$$VI = W_{x1} I_{s1} + \cdots + W_{xn} I_{sn}$$

where W can be defined by the business users based on their specific decision context.

The following sections illustrate the development of the Fire Risk Index and the Vulnerability Index using the case study data. The classes used, indicators selected, and analysis performed can be visualized through tabular form models, graphs, and maps.

4.5.1 Fire Risk Index

A Fire Risk Index integrates several variables: 1) topographic variables (slope, elevation, and aspect) 2) socioeconomic variables (settlements and roads), and 3) land cover. But through literature review and expert advise it was determined some variables have higher influence regarding fire risk. A schematic model was developed using the variables listed below (Table 15). The Fire Risk Index formula can be summarized as follows:

$$Fire\ Risk\ Index = 1 + 75lc + 30sl + 10a + 5r + 5se + 2e$$

To conduct this modeling, ArcGIS Pro ModelBuilder was used. The following sections present the description of the models built:

Table 16. Fire Risk Index Model

Classes	Risk	Weight	References
Land Cover Layer		**75**	(Chuvieco, 2003; Chuvieco & Congalton,
Agriculture	High	2	1989; Erten & Kurgun, 2002; Estes et al.,
Shrub	High	2	2017; Gai et al., 2011; Jaiswal et al., 2002)
Forest	High	2	
Urban Area	Medium	1	
Water	Low	0	
Sand	Low	0	
Slope Layer		**30**	(Chuvieco, 2003; Chuvieco & Congalton,
>39%	High	20	1989b; Erten & Kurgun, 2002b; Estes et al.,
30-39%	Medium	15	2017; Jaiswal et al., 2002b; Sağlam et al.,
20-29%	Medium	10	2008)
10-19%	Low	5	
0-10%	Low	0	
Aspect Layer		**10**	(Chuvieco, 2003; Chuvieco & Congalton,
East	High	2	1989b; Erten & Kurgun, 2002b; Estes et al.,
South	High	2	2017; Jaiswal et al., 2002b; Sağlam et al.,
Southeast	High	2	2008)
Northeast	Medium	1	

Southwest	Medium	1	
West	Medium	1	
North	Low	0	
Northwest	Low	0	
Proximity to Roads Layer		**5**	(Chuvieco, 2003; Chuvieco & Congalton,
< 100 m	Very High	3	1989b; Erten & Kurgun, 2002b; Estes et al.,
100 – 200 m	High	2	2017; Jaiswal et al., 2002b; Sağlam et al.,
200 – 300 m	Medium	1	2008)
>300 m	Low	0	
Proximity to Settlements Layer		**5**	(Erten & Kurgun, 2002b)
< 1000 m	High	2	
1000 – 2000 m	Medium	1	
>2000m	Low	0	
Elevation Layer		**2**	(Chuvieco, 2003; Chuvieco & Congalton,
>=398	High	2	1989b; Erten & Kurgun, 2002b; Estes et al.,
6m – 398m	Medium	1	2017; Jaiswal et al., 2002b; Sağlam et al.,
<=6 m	Low	0	2008)

4.5.1.1 Land Cover

A large portion of Honduran territory, including the area under study, is considered to be forest (Flores Rodas & Mairena, 2006). Six classes were identified, and according their fire risk they were weighted based on the model (Table 11) run through ModelBuilder (Figure 41). Using the historical fire hotspots layer, it was possible to determine that 59% of the hotspots occurred in Forest areas, followed by Shrubs with 26%, and Agriculture areas with 15%. These three classes were weighted higher than the other classes.

4.5.1.2 Settlements

A multiple buffer layer was created using 1000 m, 2000 m, and 3000 m as distance parameters. Using the hotspots layer, it was possible to determine that 60% of hotspots occurred within 1000 m of a settlement, 34% occurred within 2000 m, and 6% occurred within 3000 m. The weighting process was done through ModelBuilder and can be seen in Figure 42.
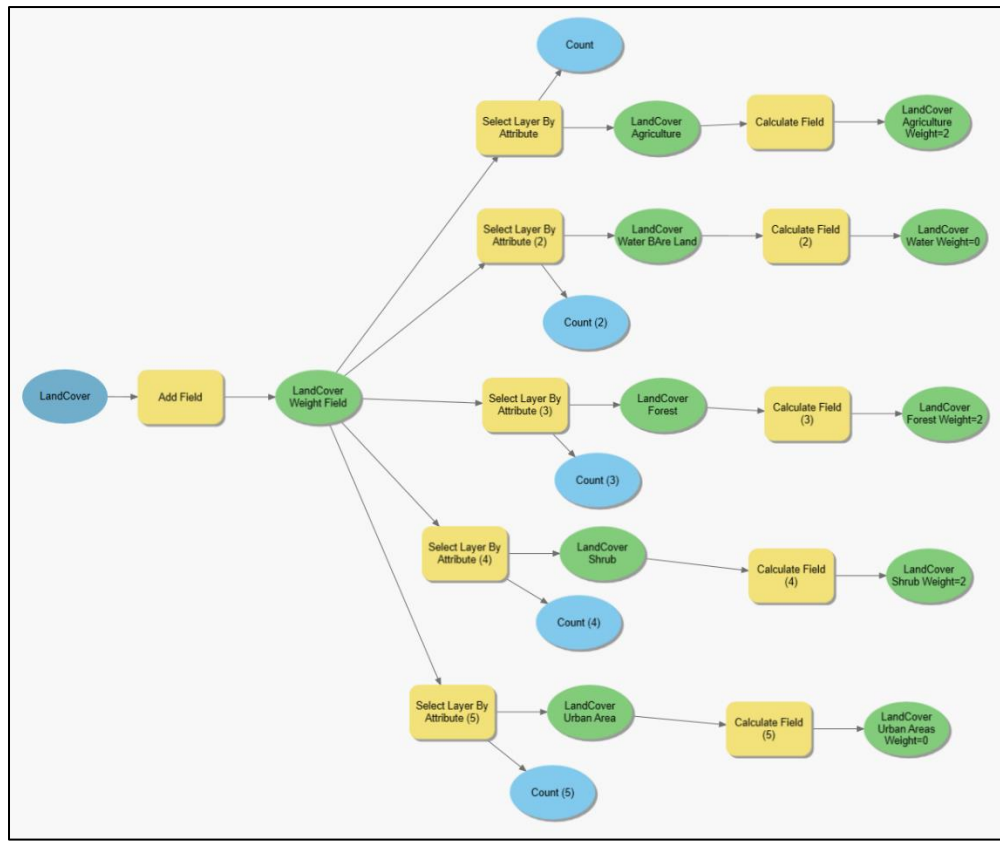
Figure 41. Land Cover Model
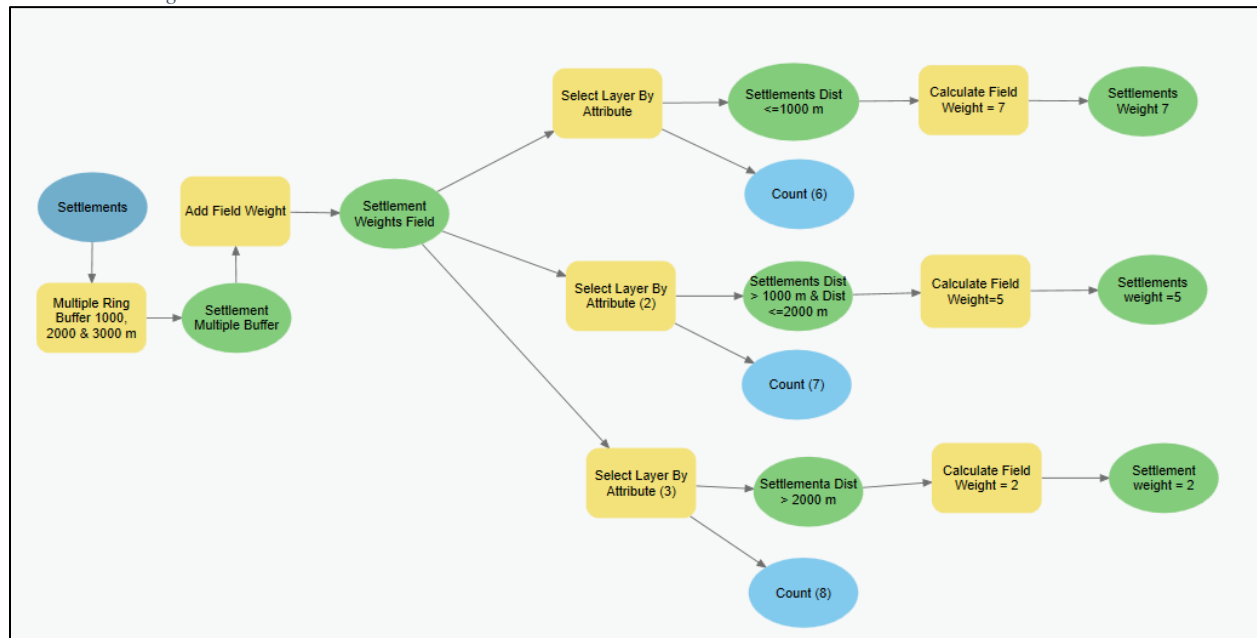
Figure 42. Settlements Model

4.5.1.3 Elevation

The elevation layer was developed through a Topo-to-Raster conversion process which generates a DEM. To perform the weighting process, it was necessary to transform the raster into a vector layer. This process was done through ModelBuilder and can be seen in Figure 43. The model includes adding the field to store the weights depending on the elevation. Based on the model on Table 15, three weights were assigned: 0, 1, and 2; 2 being the weight assigned to all the areas with an elevation greater than 2,000 meters above sea level.
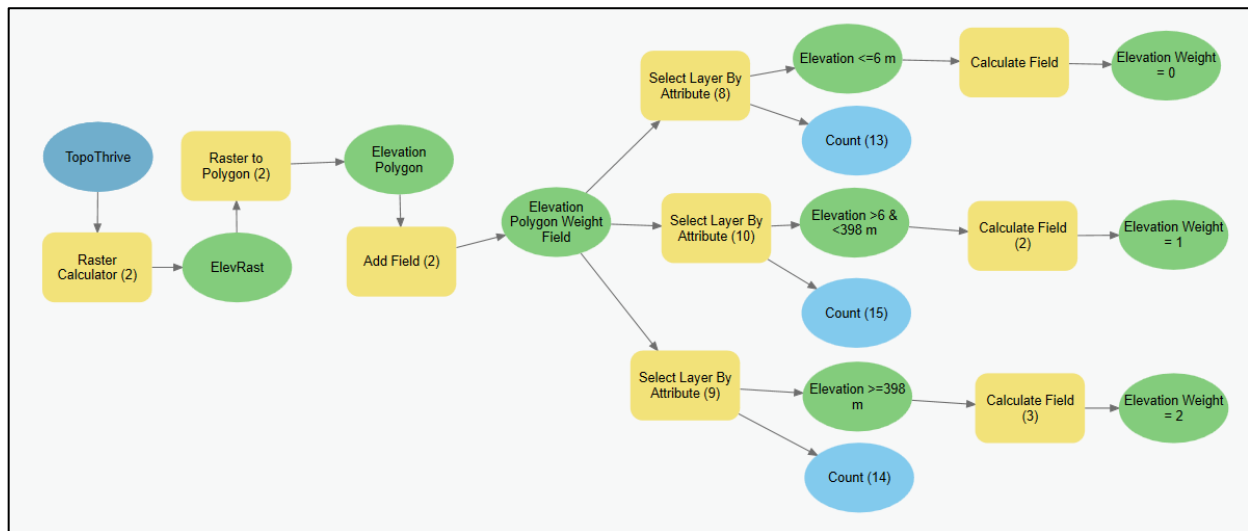
Figure 43. Elevation Model

4.5.1.4 Slope

The slope layer was generated from the DEM resulting in a raster. To weight this layer, conversion to a vector layer was necessary. As a polygon layer, it was now possible to select the slope rises and weight them accordingly, as steep slopes present a higher risk to fires. This process was performed using ModelBuilder and can be seen in Figure 44.

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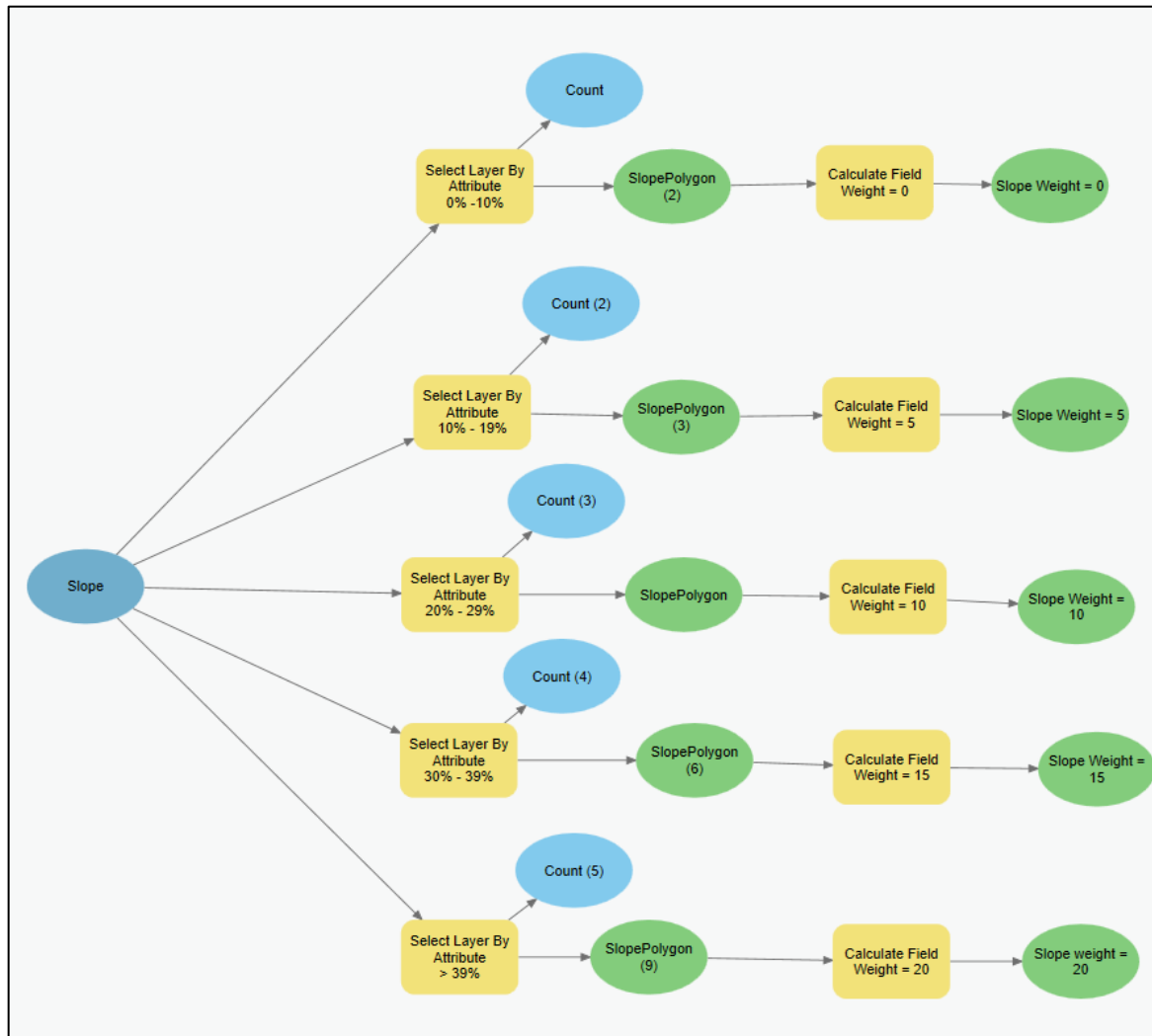
Figure 44. Slope Model

4.5.1.5 Roads

The fire risk from the roads layer was identified by creating a multiple ring buffer 100 m, 200 m, 300 m, and 400 m. It was weighted using the model described previously. The process was performed using ModelBuilder and can be seen in Figure 45.
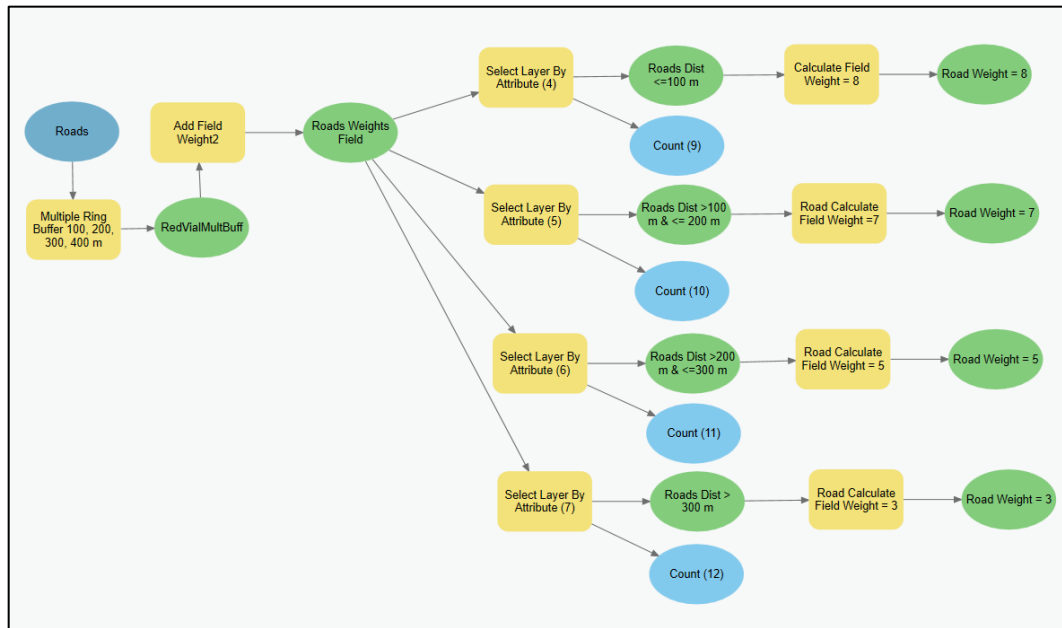
Figure 45. Roads Model

Using the weights according to their class and variable, the layers were converted to rasters and

the results can be seen below. Figure 46 illustrates the slope, elevation and aspect layers maps, and Figure

47 shows the settlement, road, and landcover layer maps.
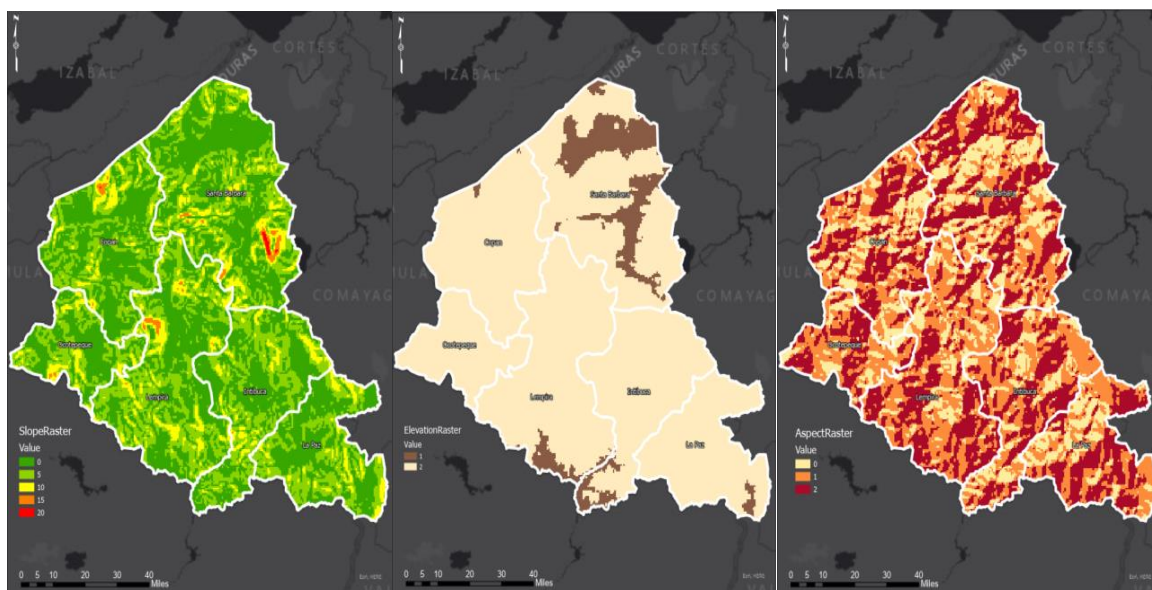
Figure 46. Raster Maps for the Slope, Elevation and Aspect Layers
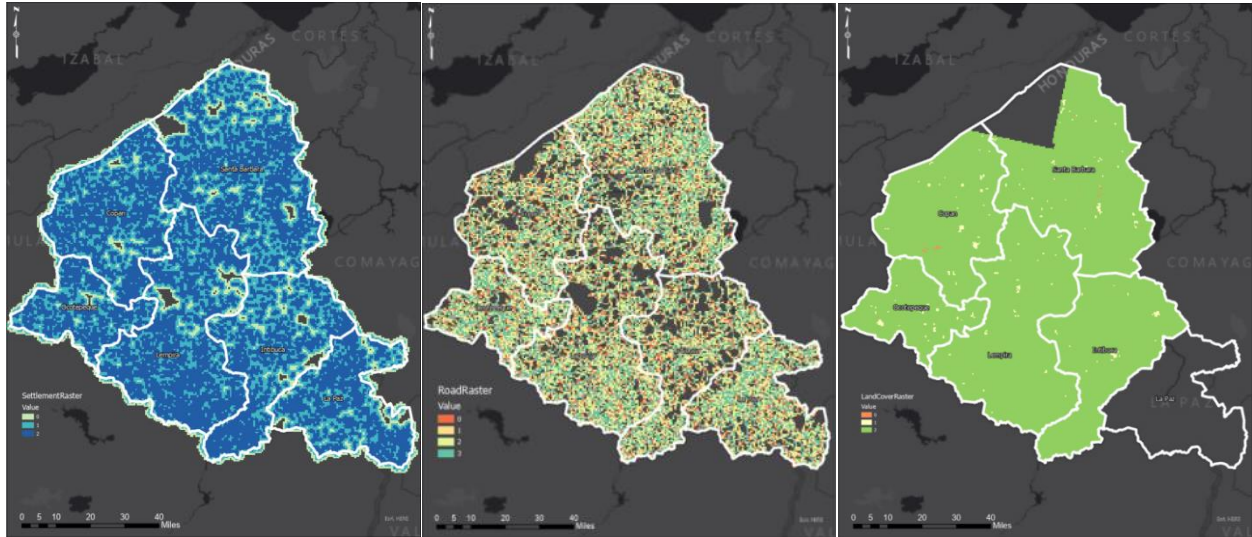
Figure 47. Raster Maps for Settlements, Roads and Landcover Layers

With the new raster layer, it was possible to calculate the Fire Risk Index using the formula above. To perform the raster conversion, reclassification, and the raster calculation, a model was created in ModelBuilder as seen below in Figure 48. The reclassification processes included adding a 0 value to the No Data and adding the THRIVE Department layer in the extent.

The formula used to calculate the Fire Risk is as follows:

*1 + 75 * ReclassificationLandCover + 30 * ReclassificationSlope%" + 10 * ReclassificationAspect%" + 5 * ReclassificationRoad%" + 5 * ReclassificationSettlements%" + 2 * ReclassificationElevation"*

Figure 48. Fire Risk Index Model

Table 17. Fire Risk Index Model Variable Definition

Where:					
Variable	**Definition**	**Variable**	**Definition**	**Variable**	**Definition**
Reclass_Land	Land Cover	**Reclass_Slope**	Slope	**Reclass_Aspe**	Aspect
Reclass_Road	Road	**Reclass_Sett**	Settlement	**Reclass_Elev**	Elevation

After running the model seen in Figure 49, the resulting layer was symbolized and can be seen in the following map:
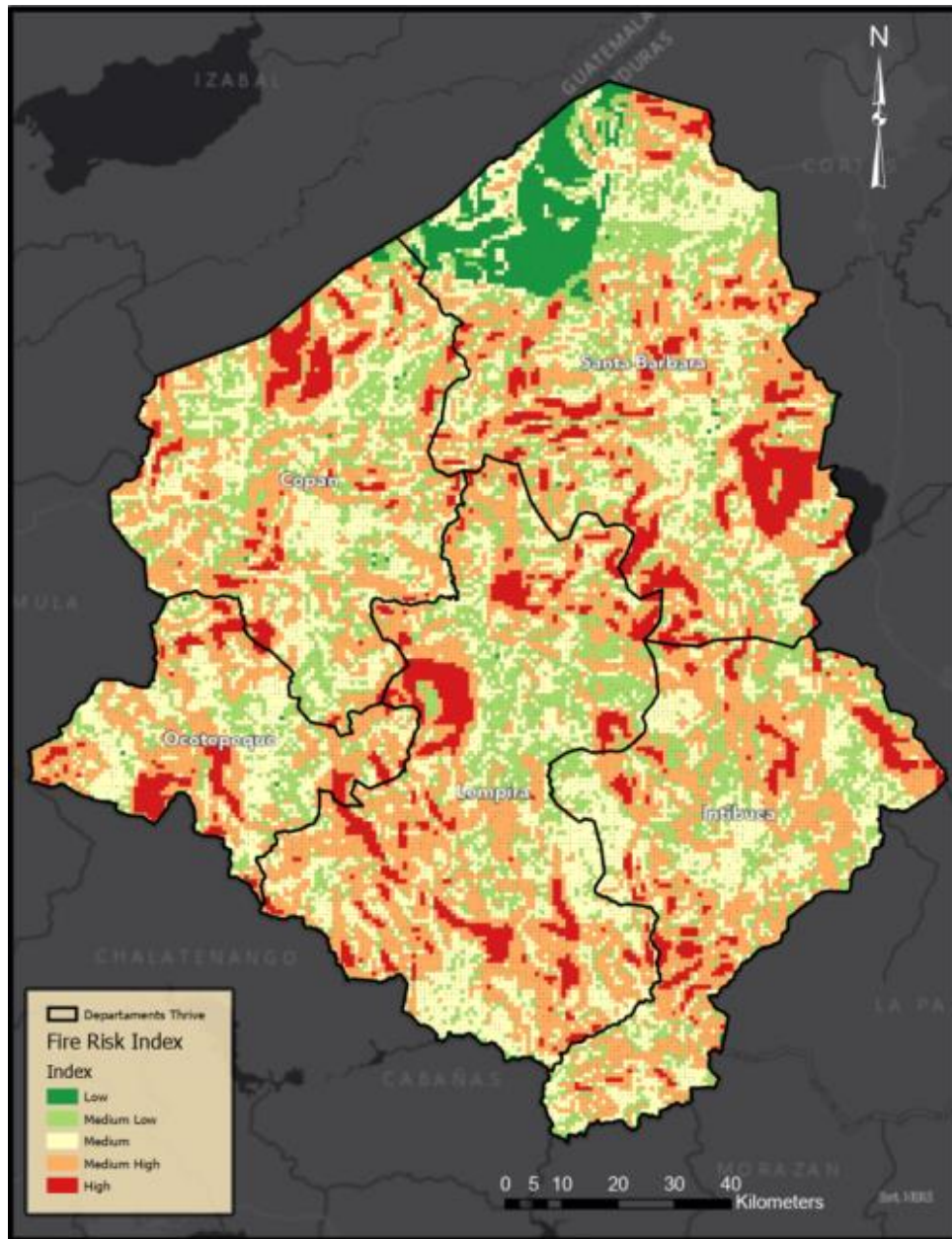
Figure 49. Fire Risk Map

The following two dashboards (Figures 50 and 51) provide some insight in the analysis results:
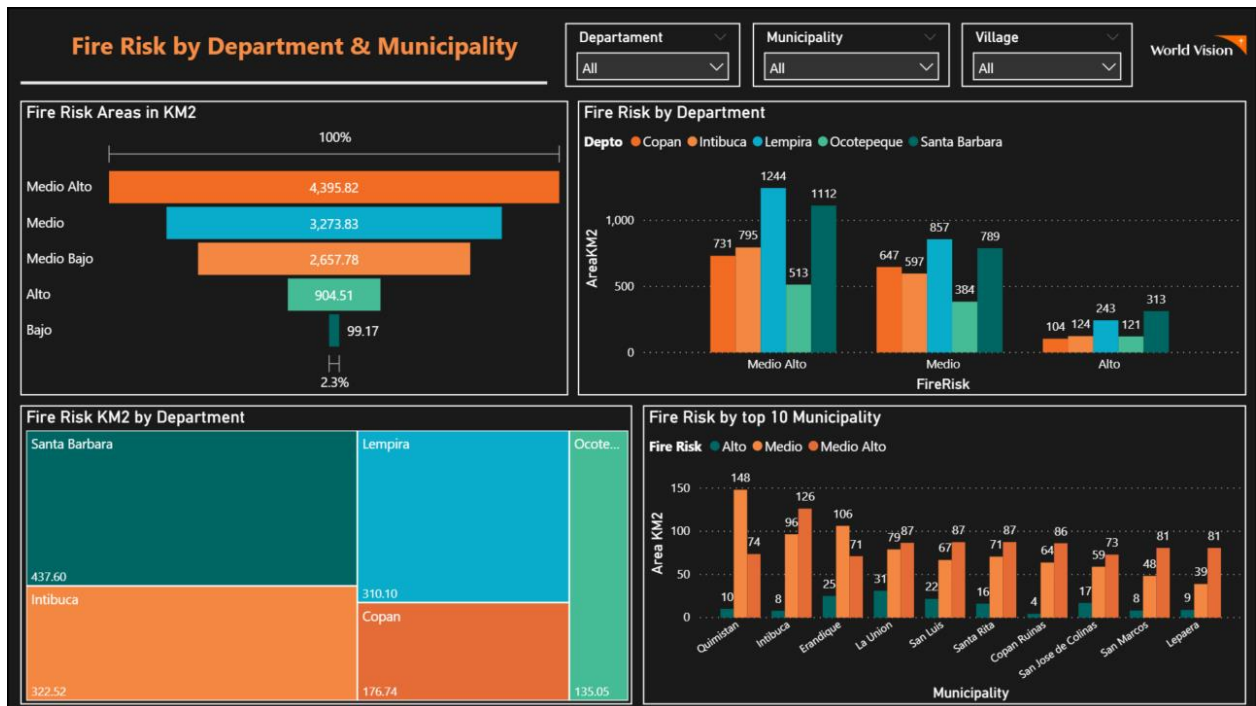
Figure 50. Fire Risk Dashboard by Department and Municipality
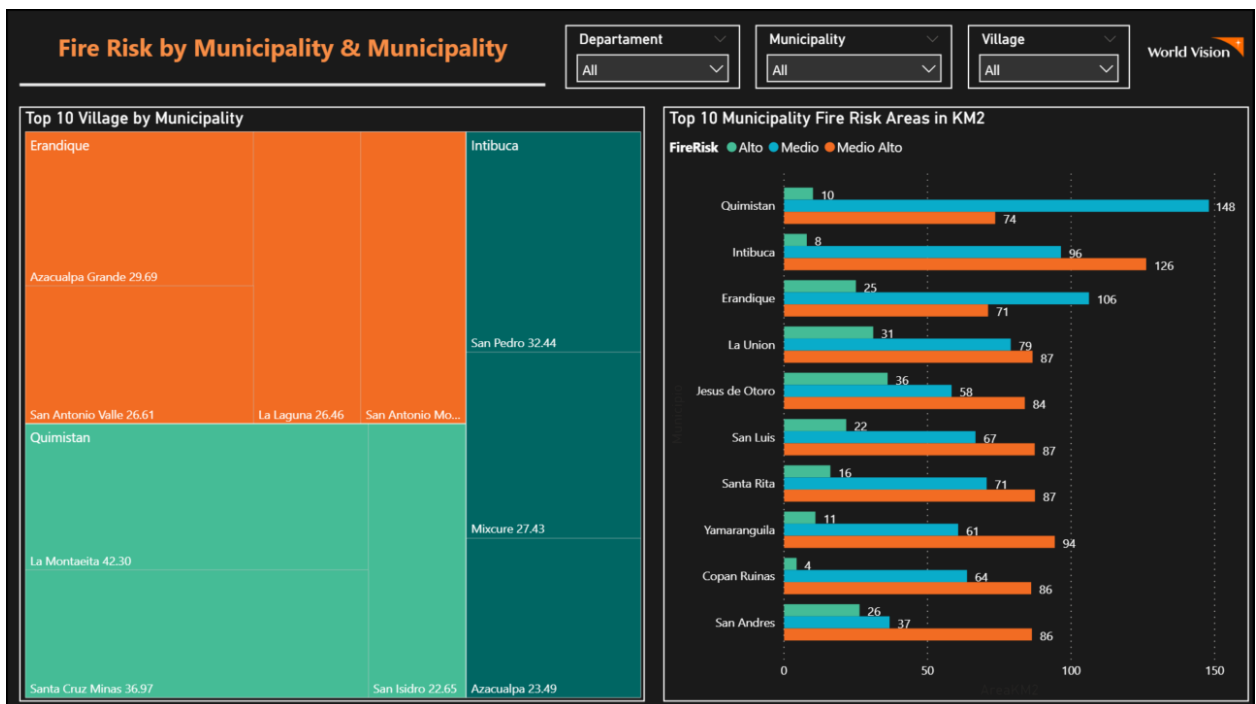
Figure 51. Fire Risk Dashboard by Municipality and Top 10 Villages

The largest area found to be a Medium High risk comprised 4,395.82 km², and Medium risk 3,273.83 km². The Department with largest risk area was Santa Barbara with 437.60 km². Quimistan, Santa Barbara was the municipality with the highest risk area followed by Intibucá, Intibucá and Erandique, Lempira.

4.5.2 Vulnerability Index

A Vulnerability Assessment Framework was proposed (Figure 6) measuring three dimensions to determine the Vulnerability Index (VI): Exposure, Sensitivity and Adaptive Capacity. The VI is a composite index allowing the determination of minimum and maximum values for each of the dimensions listed above, allowing the identification of areas with higher vulnerability levels. All the determinants have an equal weight. (Gbetibouo et al., 2010) discuss how the weights given to indicators may follow three methods: a) expert opinion, b) arbitrary choice, or c) statistics. In this case, expert opinion and judgement were used to determine the weights to be used per indicator.

The measurements calculated previously resulted in different scales. To make a correct comparison between the layers, it is necessary to normalize the indices calculated previously. The Min-Max Normalization approach was used to normalize data as per the following formula:

$$Vulnerability\ Index = \frac{(Actual\ Value - Minimum\ Value) * 100}{(Maximum\ value - Minimum\ Value)}$$

Table 18 summarizes the formulas used to perform the normalization:

Table 18. Normalization

	Component	Formula
Exposure 33%	Forest Risk	((ForestRisk- 1) * 100) / (790 - 1)
	Soil Moisture	((SoilMoisture - (-0.673)) * 100) / (0.512 - (-0.673))
Sensitivity 33%	Deforestation	((Deforestation - 1) * 100) / (4 - 1)
	Small-Scale Farming	((SmallScaleFarming - 1) * 100) / (4 - 1)
Adaptive Capacity 33%	Access to Health	((AccessHealth - 0) * 100) / (18 - 0)
	Access to House with Satisfied Basic Needs	(((HouseAccess * 1000) - 697) * 100) / (975 - 697)

	Access to Sanitary Service with Satisfied Basic Needs	((SanitaryService - 0.16) * 100) / (0.57 - 0.16)
	Dependability	((Dependability-65) * 100) / (114 - 65)

Using the recently calculated index, the layers were converted to raster and then reclassified to assign areas with no data with a value of 0. The Departments in the THRIVE region were used to an extent to make sure all the THRIVE region was included. The resulting layers were then used to calculate the vulnerability layer. This process can be seen in the model in Figure 52. The formula used to calculate the Vulnerability Index is as follows:

(((FireReclassification + SoilMoistureReclassification*0.33) +((AgricultureReclassification +

DeforestationReclassification) *0.33) + ((DependcyReclassification + SanitaryServiceReclassification +

HouseAccessReclassification + HealthReclassification) *0.33) +0.01) *100

Table 19. Vulnerability Index formula variables and definitions

Where:					
Variable	**Definition**	**Variable**	**Definition**	**Variable**	**Definition**
FireReclass3	Fire Risk Index	**SoilMReclass3**	Soil Moisture Index	**AgriReclass3**	Agriculture Index
DeforReclass3	Deforestation Index	**DependReclass3**	Dependency Index	**HealthReclass3**	Health Access
AccessReclass3	House Access Index	**SaniServReclass3**	Sanitary Serv Index		

The Department of Lempira was shown to have the highest vulnerability to climate change, followed closely by Copan and Santa Barbara. A dashboard was developed to summarize the findings from the vulnerability layer (Figure 53). The Vulnerability Index layer can be seen in Figure 54 along with the Optimized HotSpot Map.

For decision making and planning, identifying vulnerable areas is a first step. Then it becomes necessary to know what variables are influencing the high vulnerability of an area to target the best interventions. An additional analysis was performed to include all the values from the variables used to create the vulnerability assessment layer. To create this new layer, ModelBuilder was used and the model can be seen in Figure 52. First, the layers were converted into points; the points were then intersected

except for the soil moisture layer. To join the soil moisture values, a spatial join was performed using a
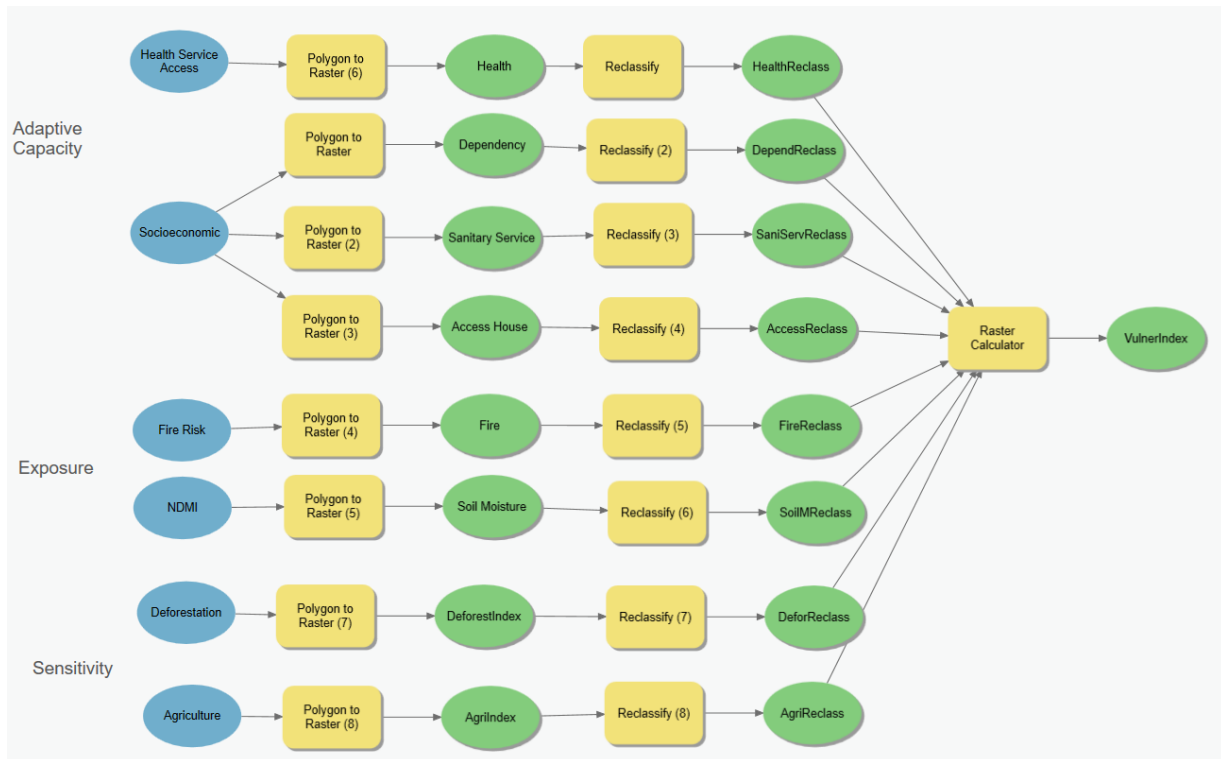
Figure 52. Vulnerability Model

match option within 400 meters from the points. Once a complete set of points was performed, a new

intersection with the Vulnerability Index layer by Village was developed.

Figure 53. Vulnerability Dashboard
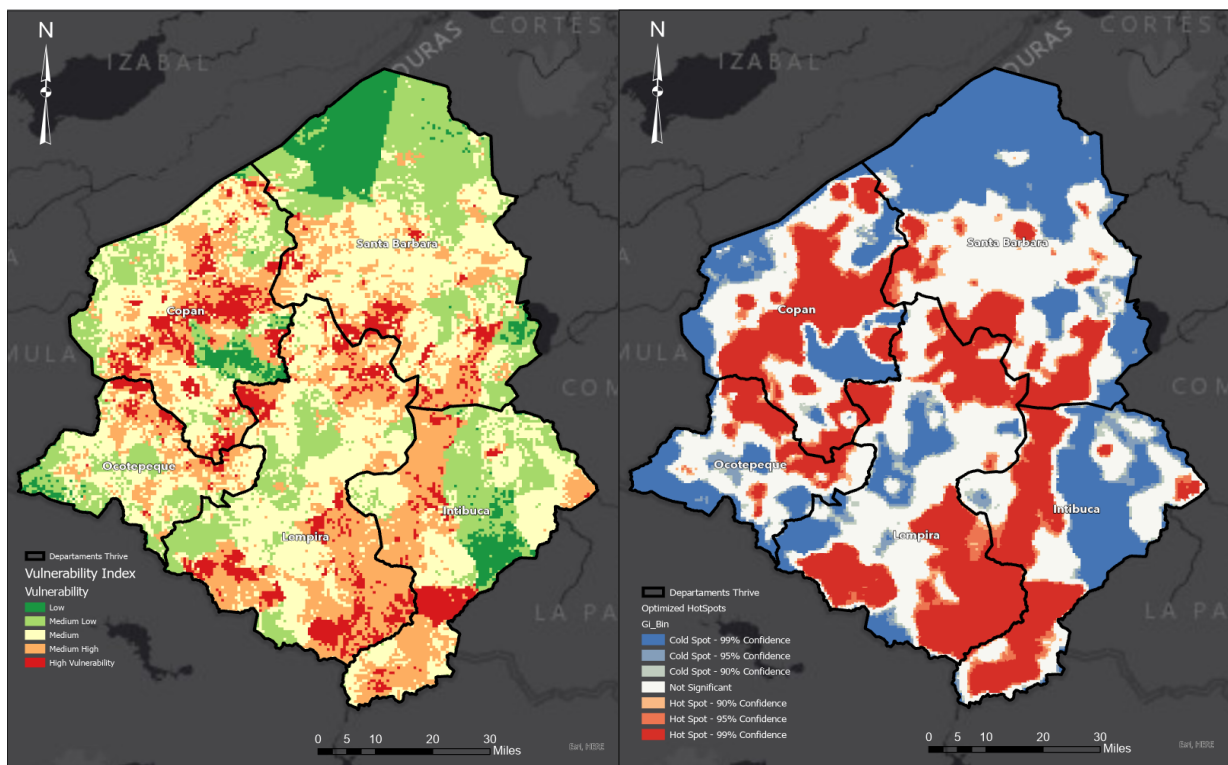
Figure 54. Vulnerability Layer Map and Optimized HotSpot Analysis
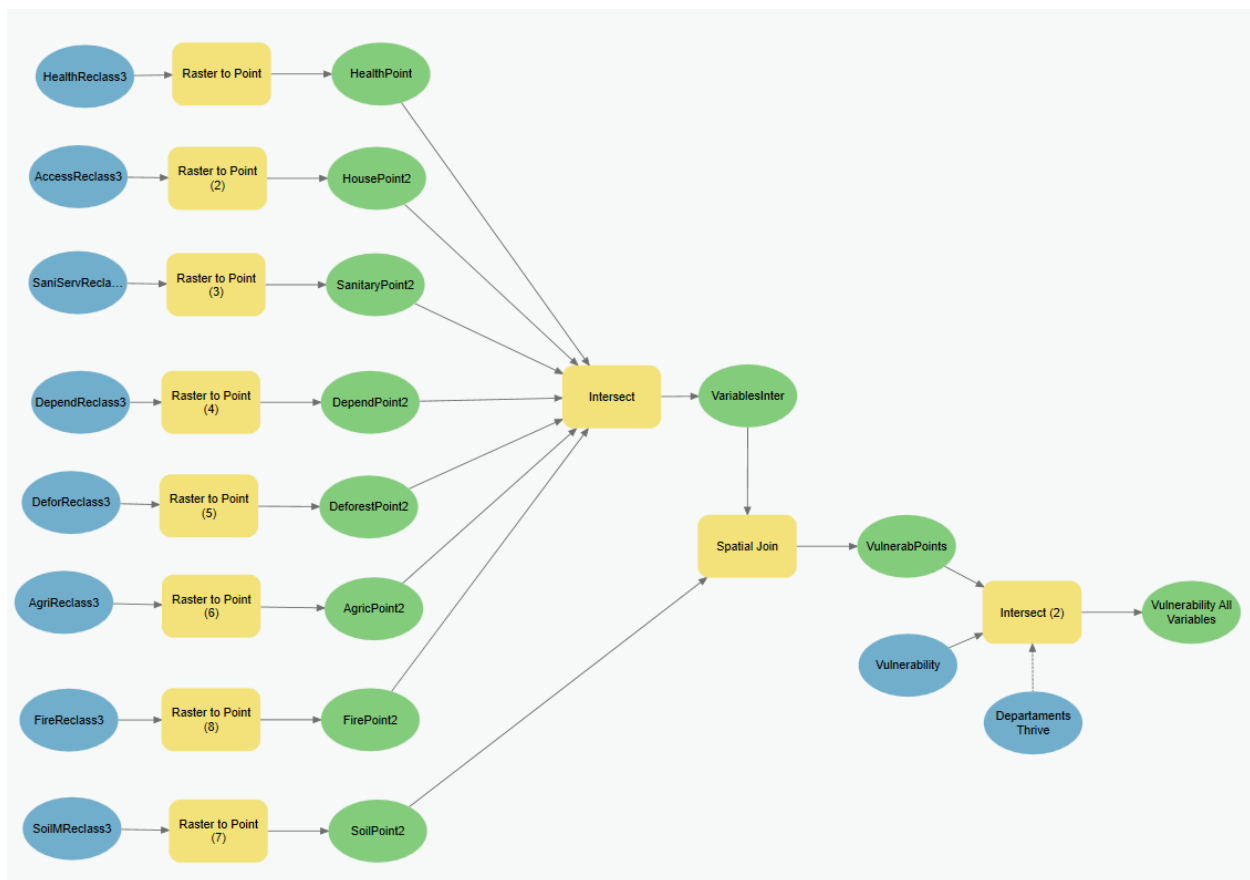
Figure 55. Model to Develop the Vulnerability Index Layer with Variables in Table

To visualize the interaction of the resulting variables with the Vulnerability Index, a new visualization was developed, and can be seen in Figure 56.
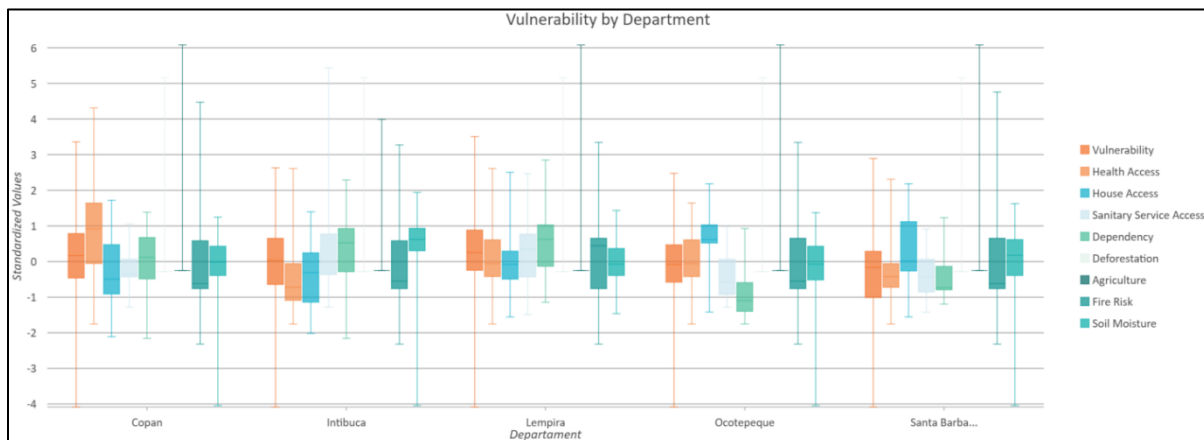
Figure 56. Vulnerability Index by Department

CHAPTER 5: WEB-BASED APP

5.1 Introduction

The THRIVE Web-Based App is a GIS-based application that aims to improve the planning, monitoring and decision making of the THRIVE team. Additionally, the THRIVE App seeks to become a platform for any user who is interested in obtaining information on how Climate Change is affecting the region identifying forest fire risk zones, deforestation, access to health, and vulnerable areas. The App has additional information that were used to develop the Vulnerability Index Layer as for example the Census data by Department, Municipality, and the land cover. The Web App allows users to explore, visualize and export information using the different tools provided.

The App was design to follow the three determinants used to calculate the Vulnerability Index: Exposure, Sensitivity, and Adaptive Capacity. The Exposure tab includes an Introduction Story Map, Hotspot Dashboard, Fire Risk Zones Dashboard, and the Soil Moisture Dashboard. The Sensitivity tab includes an Introduction Story Map, the forest loss and gain dashboard, the forest cover change app and the agriculture dashboard. The Adaptive Capacity tab includes the Introduction Story Map, the Access to Health dashboard, Access to Basic Housing, Access to Basic Sanitary Services dashboard and the Dependency Dashboard.

The App also includes a tab to visualize the Vulnerability of the area allowing the summarization by Department, Municipality and Village. When the user clicks on the Web Map includes a popup appears identifying the level of risk for each of the variables used in the analysis. Every value is color dependent on the variable value following the same color schema used in the map. Every section includes dashboard to allow users to filter by Department, Municipality or Village depending on the availability in the layer. Web Apps were also developed to allow users to print, measure, draw and export the layer table. Every section includes an Introduction to help the user understand the methodology used in the analysis and every dashboard includes a How-To section to help the user navigate throughout the App.

The Web App was developed using ESRI ArcGIS Online especially Web App builder and Operation Dashboard. The tools allow the customization of the Pop Ups using Arcade and HTML. All the Web Maps have a customized Pop Up allowing a better understanding of the layers.

5.2 Sources of Data

The GIS data used for this analysis has different sources including the following:

- Sistema Nacional de Información Territorial (SINIT): this is the National System for Territorial Information of Honduras. The layers used are as follows:
    - International Limit Boundary
    - Department Boundary Polygon (1st territorial division)
    - Municipality Boundary Polygon (2nd territorial division)
    - Village Boundary Polygon (3rd territorial division)
    - Small Villages (Point Layer)
    - National Roads, Highways
    - Health centers
    - Schools

For the forest fires hotspot data, it was obtained from NASA's Fire Information for Resource Management System (FIRMS) which distributes Near-Real Time active fire data within 3 hours of the satellite observation. Two sensors are used to collect this data NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) and NASA's Visible Infrared Imaging Radiometer Suite (VIIRS) (NASA, 2019). Three Landsat 8 scenes from September 2019, March, and April 2020 were also acquired through USGS EarthExplorer. The Census data was acquired through the National Statistics Institute (INE Spanish abbreviation).

5.3 Web-Based App Introduction

This section provides the user an Introduction to the research topic, area of influence and the methodology followed for each analysis performed.

Figure 57. Initial Screen Introduction Story Map
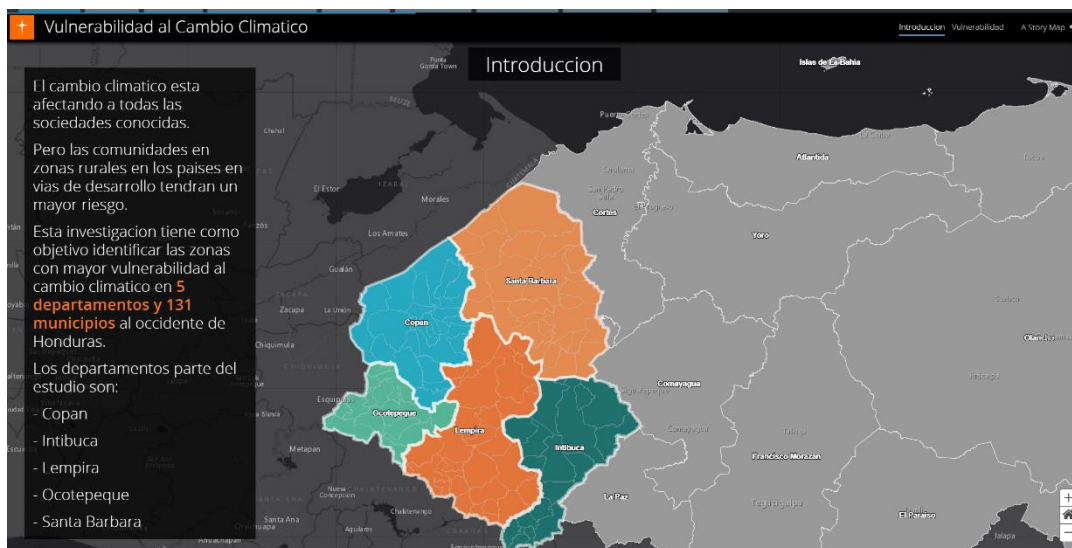
Figure 58. Area of Influence Map part of the Introduction Story Map

5.4 Exposure

This section allows the user to visualize the variables used to measure Exposure. The introduction provides the user a brief explanation of what exposure is, the different analysis that were developed to measure exposure. The Exposure section starts by showing the Fire Hotspots data allowing

the visualization through a dashboard (figure 58) with tools to filter the information by Year, Department and Municipality. It also includes a Web App (figure 59) with tools to print the map, export the table, measure, and draw.
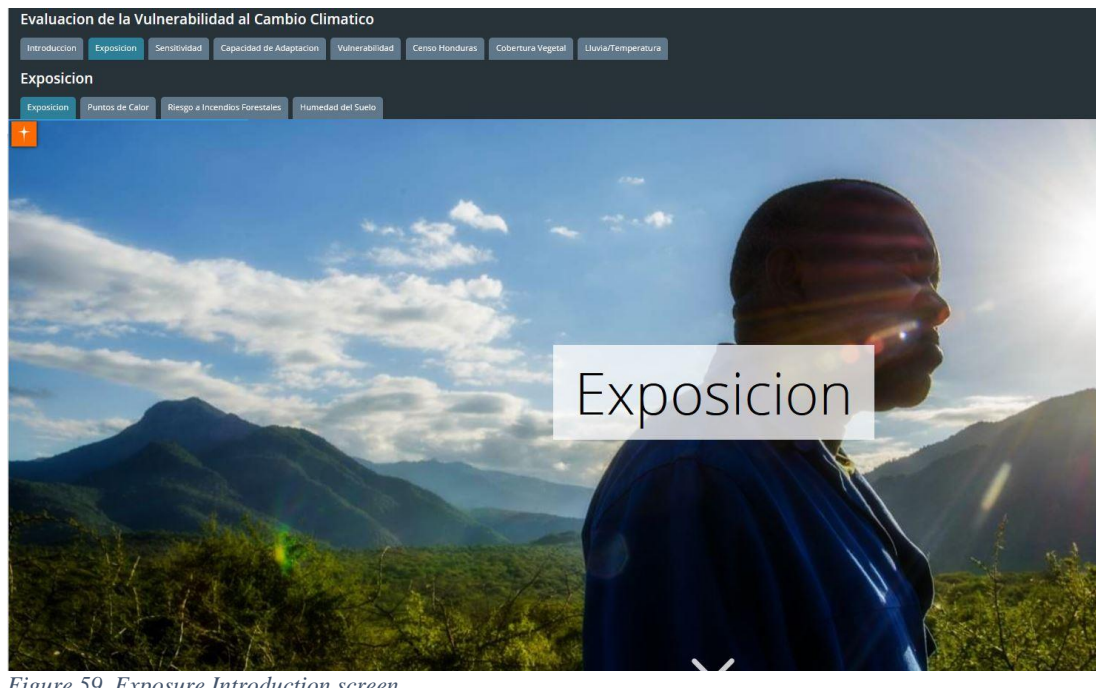
Figure 59. Exposure Introduction screen

The next option allows the visualization of the Fire Risk Layer (figure 60) which identifies the areas with high, medium-high, medium, medium-low and low fire risk. It also includes a Web App (figure 61) with tools to print the map, export the table, measure, and draw. The third option provides a visualization of the soil moisture (figure 62) analysis for the area.
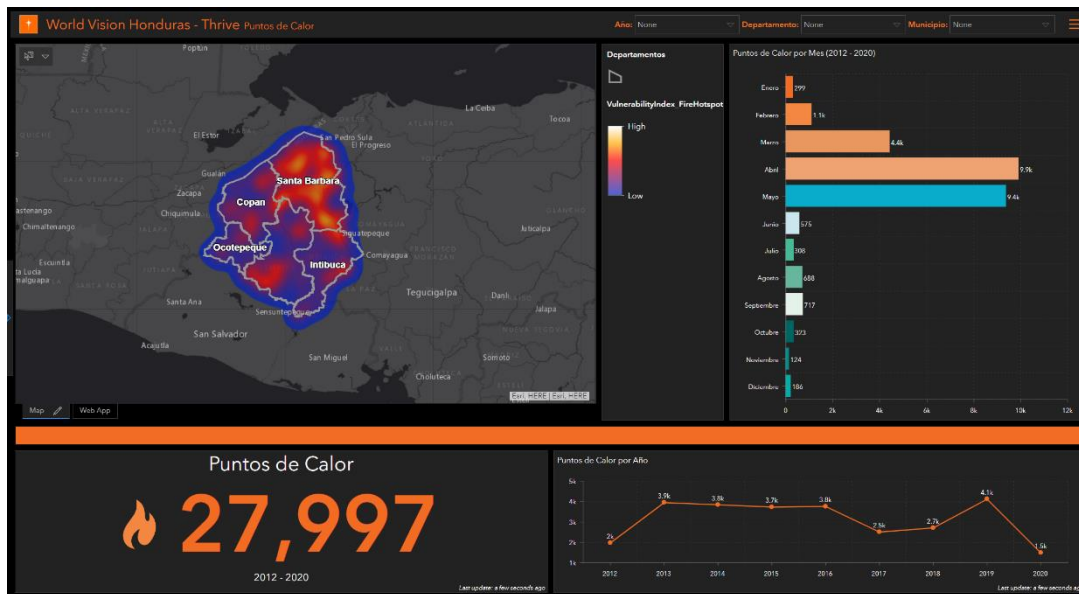
Figure 60. Hotspot Dashboard
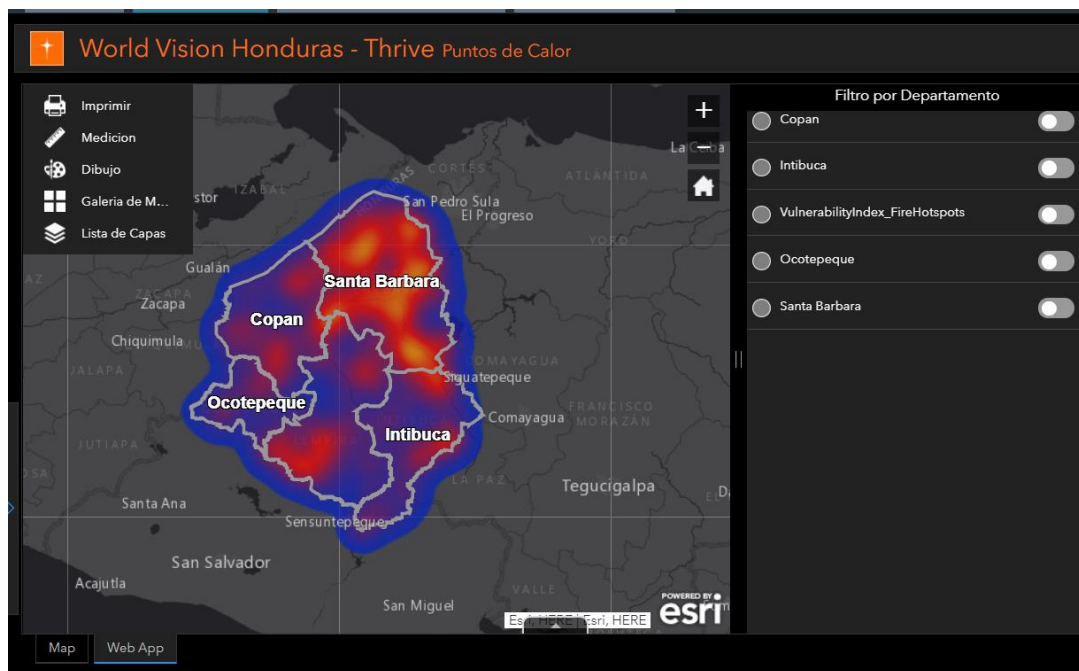
Figure 61. Hotspot Web App
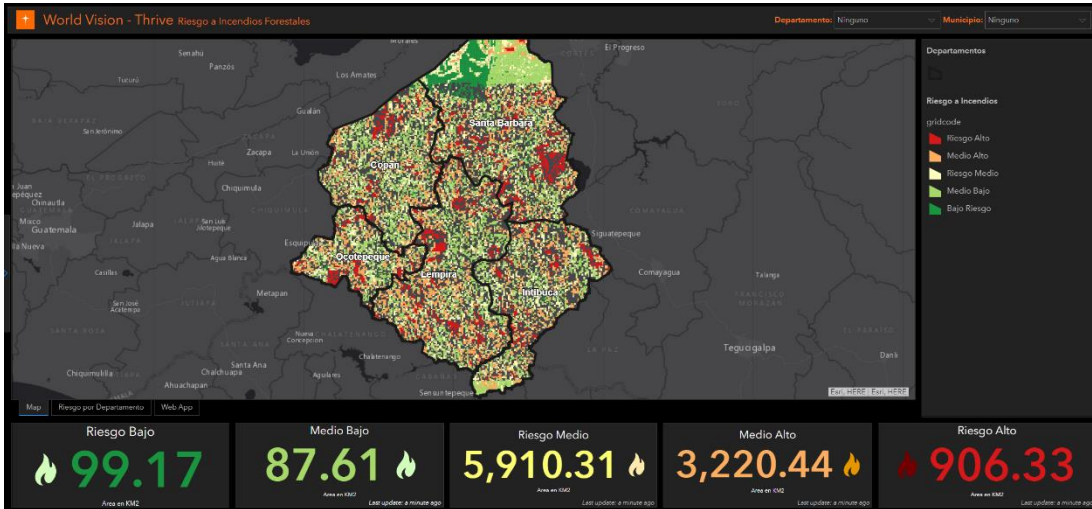
Figure 62. The Fire Risk Layer Dashboard
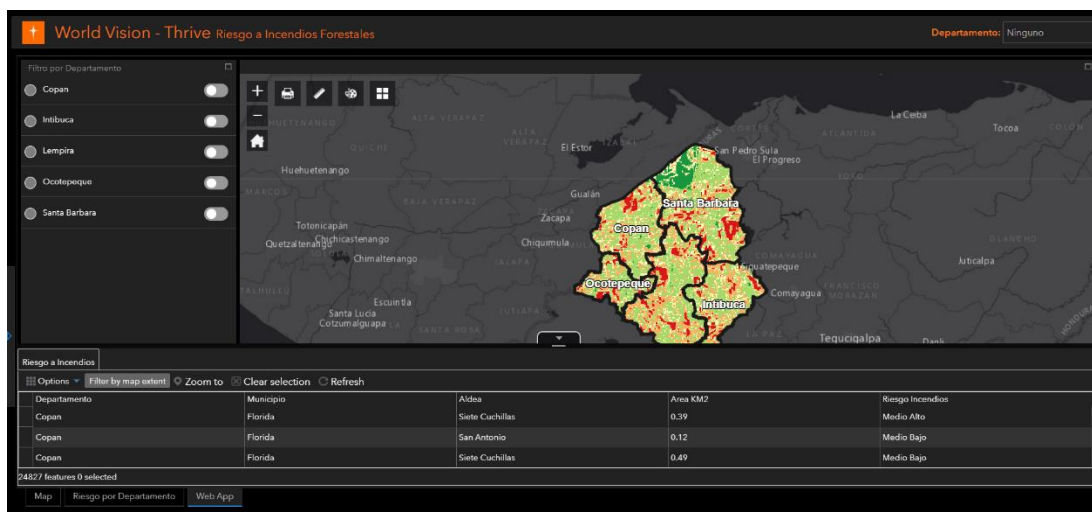
Figure 63. Fire Risk Layer Web App
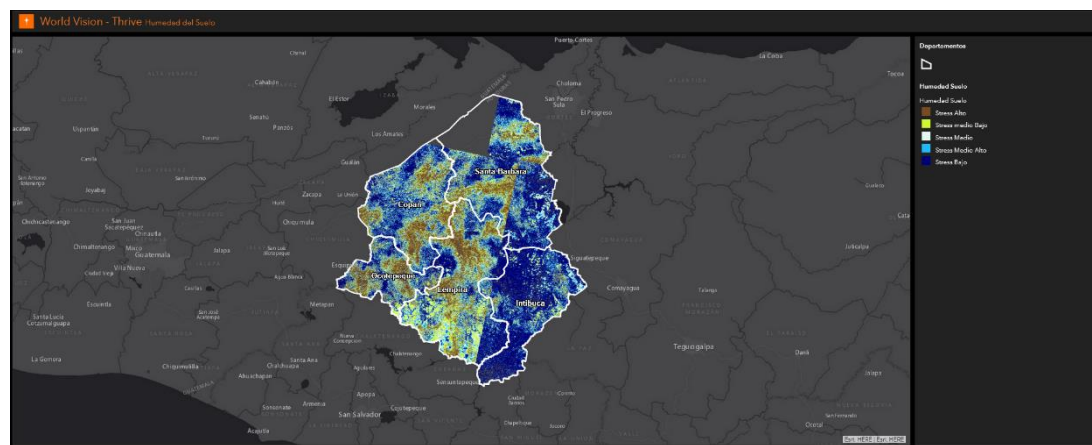
 Figure 64. Soil Moisture Dashboard

The dashboards also provide the users a how-to guide. This section is present in the dashboard

which include Web Apps. It can be accessed by clicking the blue arrow in the left section as seen in figure

63.

EXPOSICION

La exposicion es el grado en que un sistema esta expuesto a variaciones climaticas significativas (McCarthy & IPCC, 2001).

Esta investigacion tomara en cuenta los siguientes componentes como forma de medir **Exposicion**:

- el riesgo a incendios forestales
- humedad del suelo

Los puntos de calor usados en este analisis fueron obtenidos en NASA Firms.

COMO USAR ESTE DASHBOARD

A) Dashboard

Este dashboard permite la interaccion de los datos utilizando los menus ubicados en la parte superior derecha.

Departamento: Ninguno

Este menu le dara la posibilidad de filtrar la informacion dependiendo del Departamento, Municipio, o Aldea.

B) Web App

Este dashboard permite el acceso a una aplicacion adicional. Para accesar presionar la Etiqueta Web App

del Departamento, Municipio, o Aldea.

B) Web App

Este dashboard permite el acceso a una aplicacion adicional. Para accesar presionar la Etiqueta Web App

Mapa   Web App

El Web App tiene diferentes herramientas al presionar a la izquierda del Mapa y se explicaran a continuacion:

1) **Filtro:** Esta seccion permite acercar el mapa al Departamento de interes.

Filtro por Departamento

- Copan
- Intibuca
- Lempira
- Santa Barbara
- Ocotepeque

2) **Imprimir:** Esta herramienta permite la impresion del mapa que se mira en la Aplicacion. Al darle click al boton de aparecera una ventana que le preguntara la orientacion de la pagina y el

Figure 65. Side panel providing the user a how-to guide on using the dashboard. This section can be accessed by clicking on the blue arrow on the left

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5.5 Sensitivity

The sensitivity section starts with an introduction Story Map. Provides a brief definition of sensitivity and lists the analysis performed to measure sensitivity. An initial deforestation dashboard shows the area that has lost forest and the areas that has gain forest and able to filter by departments.

Figure 66. Sensitivity introduction story map
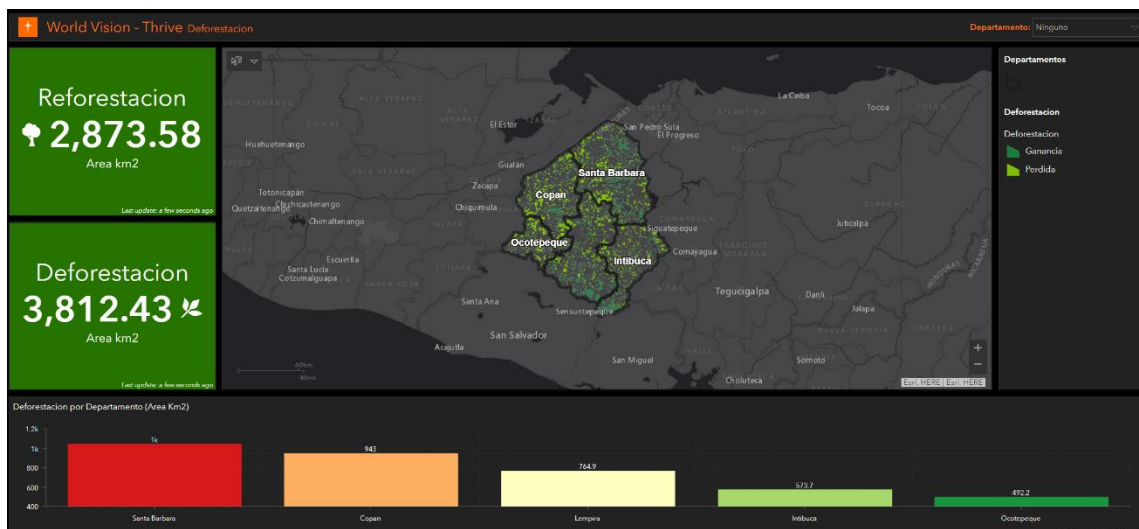
Figure 67. Deforestation dashboard
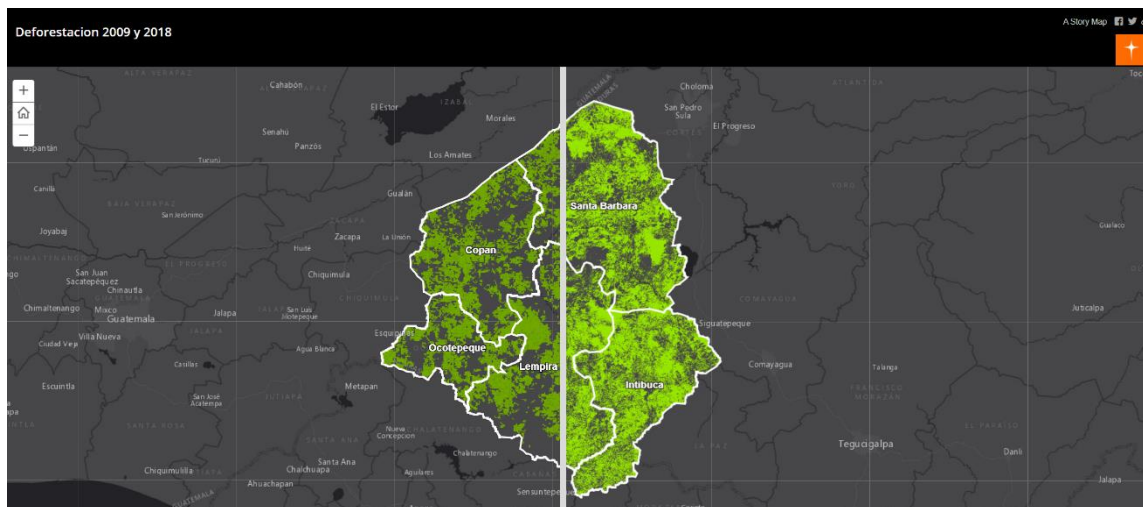
Figure 68. Web App allowing the users to compare the forest cover in 2009 and 2018.
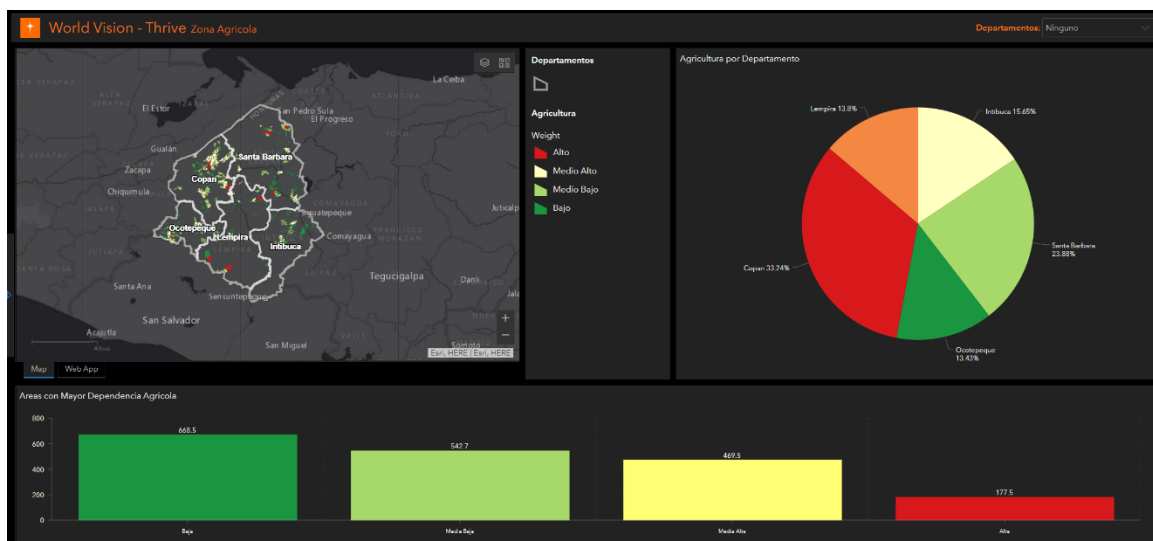
Figure 69. Small-farmer areas dashboard

5.6 Adaptive Capacity

As previous sections, the Adaptive Capacity starts with an introductory story map (figure 68). This story map provides the user a brief explanation of what adaptive capacity is and how each of the components were calculated.

Figure 70. Adaptive Capacity introductory story map

The access to health dashboard (figure 69) allows the visualization of the areas with higher or lower health access. The dashboard allows the filter by department.
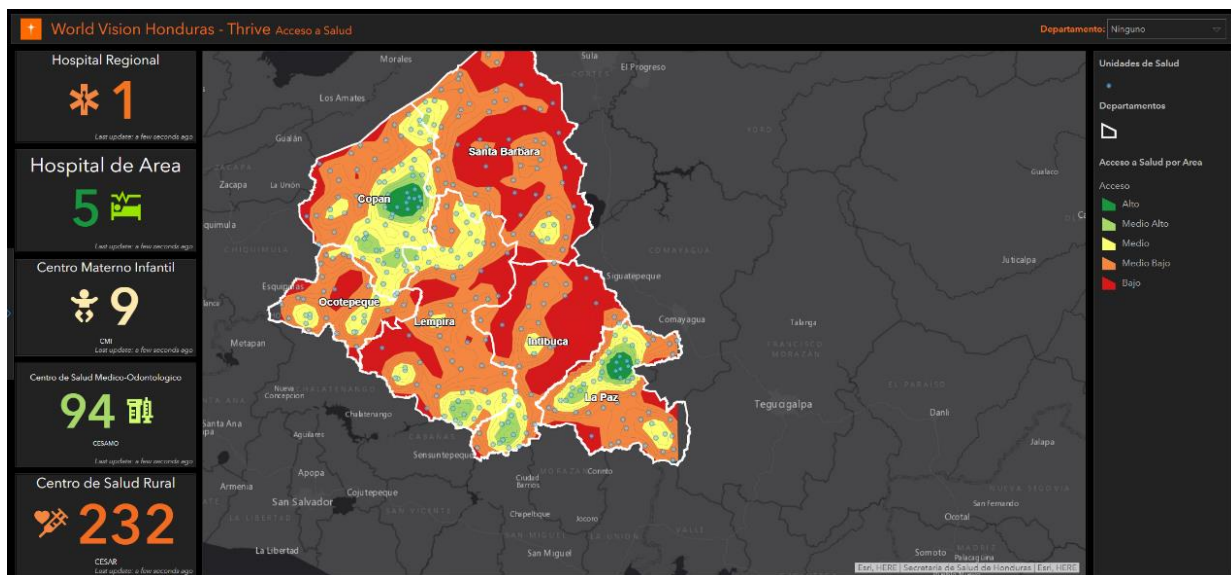
Figure 71. Access to health access dashboard
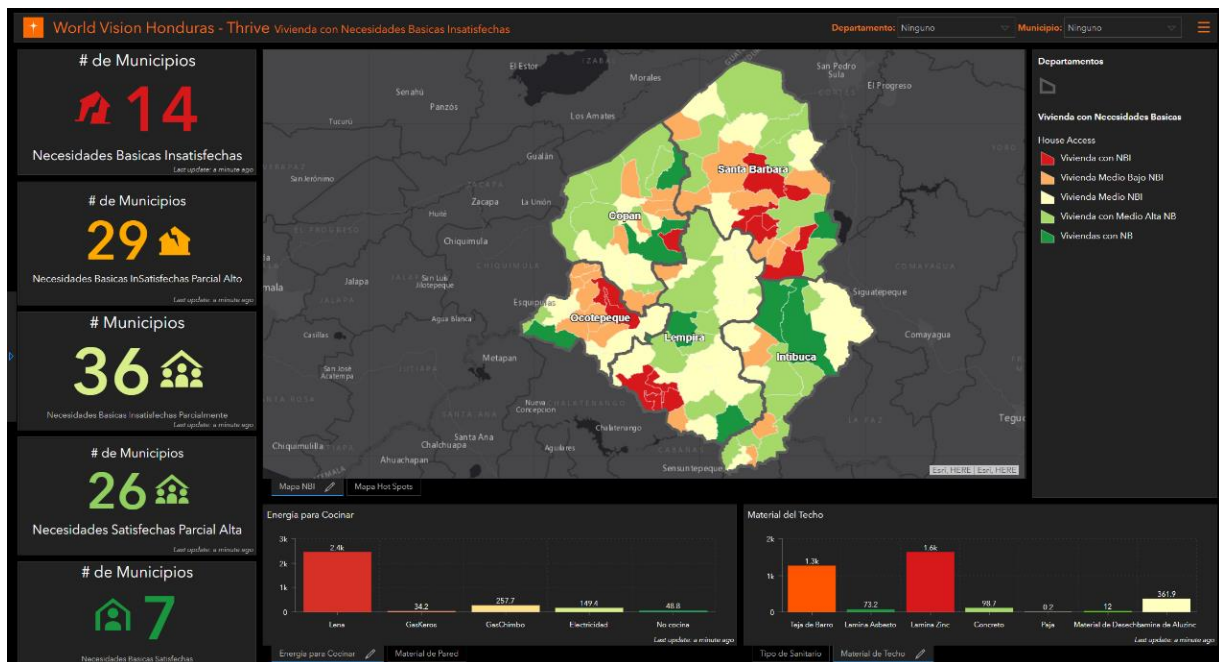
Figure 72. Access to a House with Basic Needs

The access to a house with basic satisfied needs dashboard (figure 70) allows the visualization of all the fields used to calculate this layer. This dashboard shows visualization of roof material, floor material, energy for cooking, and source of water. The access to basic sanitary service dashboard (figure 71) allows the visualization of the variables used to calculate this layer. The dashboard allows the filtering by department.
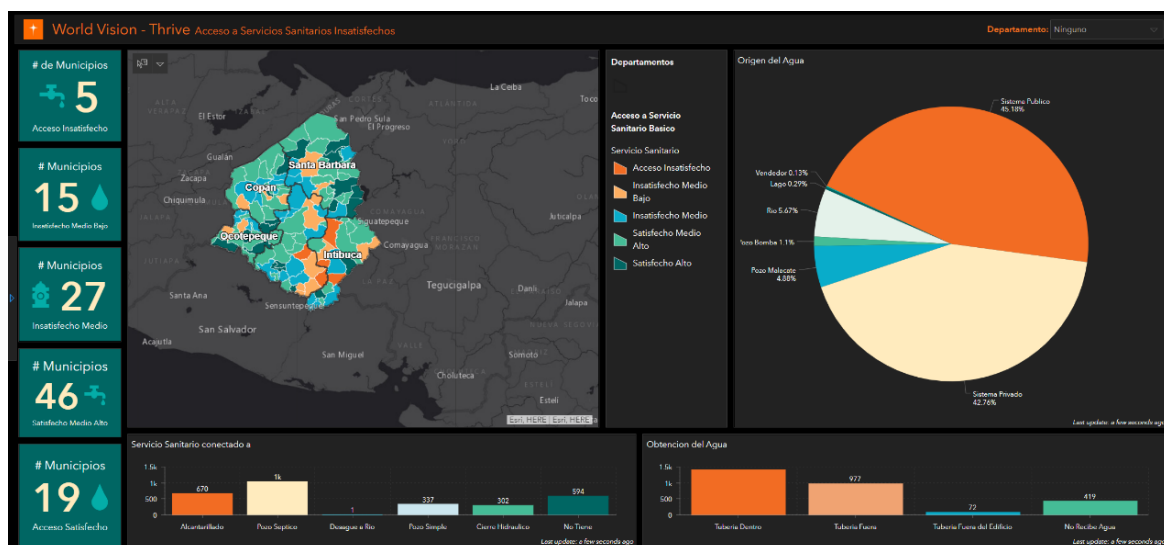
Figure 73. Access to Sanitary Service
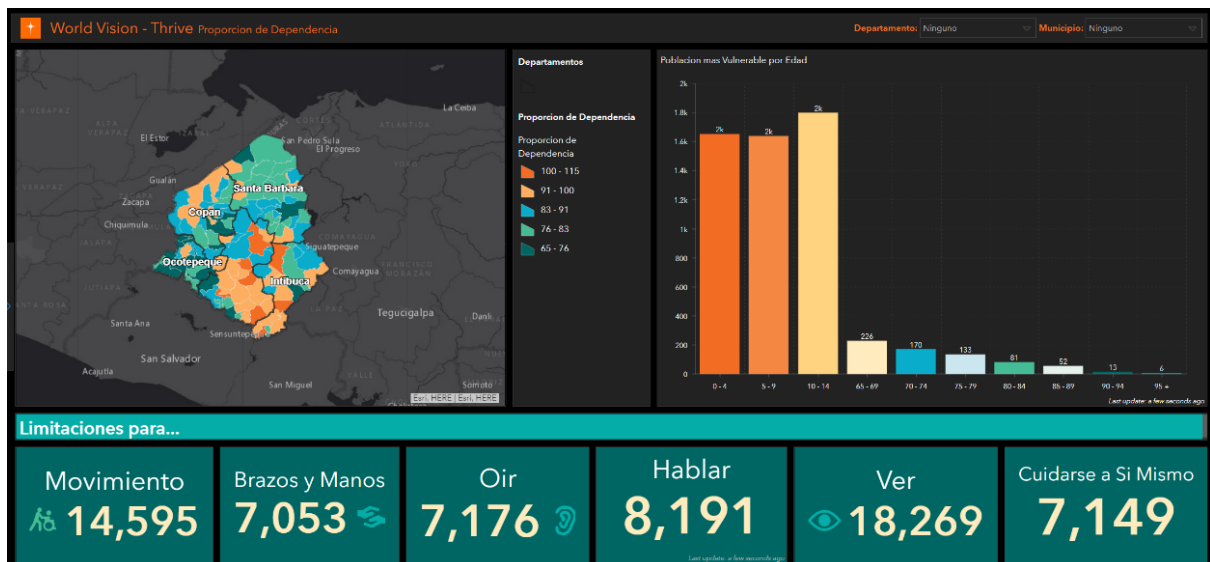
Figure 74. Dependency dashboard

The dependency dashboard (figure 72) shows the result of the analysis which identifies the location of dependent population. The dashboard allows the filtering by department and municipality. When the user clicks on the map a pop up appears providing the layer's information for population, population with physical or mental disabilities.

5.1.5 Vulnerability

The vulnerability dashboard is the result of the analysis performed with the exposure, sensitivity, and adaptive capacity layers. The final layer allows the visualization of the areas with high, medium high, medium, medium low and low vulnerability. It also shows the total area in km2 by level of vulnerability and by department. It is also possible to filter by department, municipality, and village. When the user clicks on the map, a popup will give the user a summary of the values by the different variables used in this analysis identifying the level of each variable with the message: low, medium, or high. A web app is also available allowing the user to print, measure or draw areas in the map and exporting the layer table.

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Figure 75. Vulnerability Dashboard and Web App

Figure 76. Vulnerability Pop Up summarizing the variables in the layer

5.7 Additional Layers and solutions

The app includes additional sections to provide the users with Census information for departments (figure 75) and municipalities (figure 76). Both dashboards include a how-to guide and web apps with additional tools for printing and the option of exporting the layer table, among others.
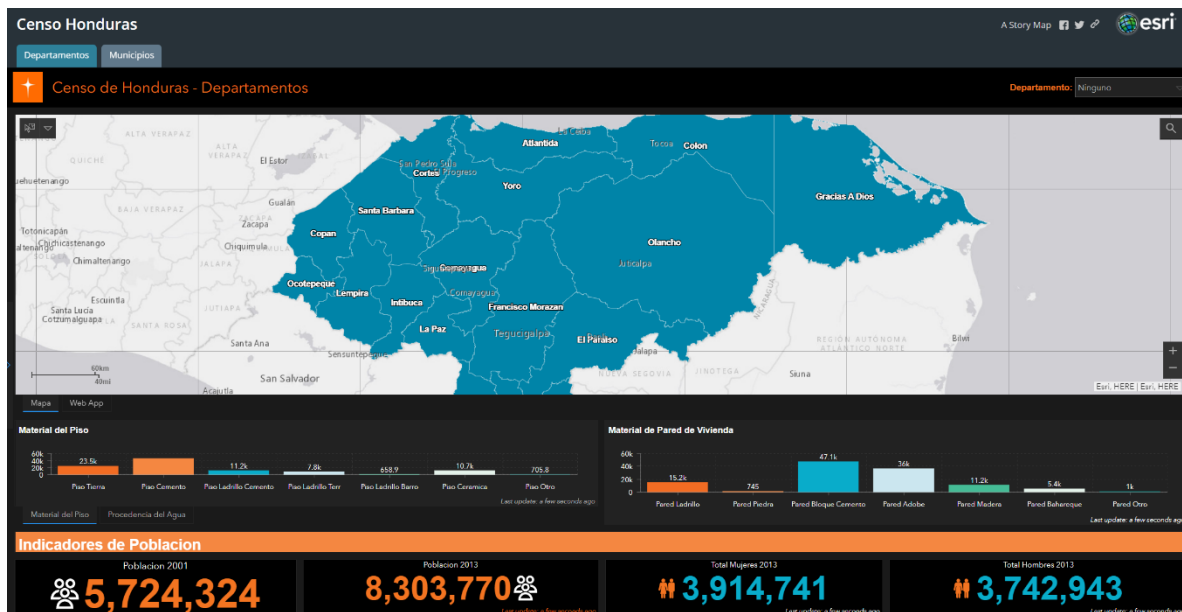
Figure 78. Department census dashboard
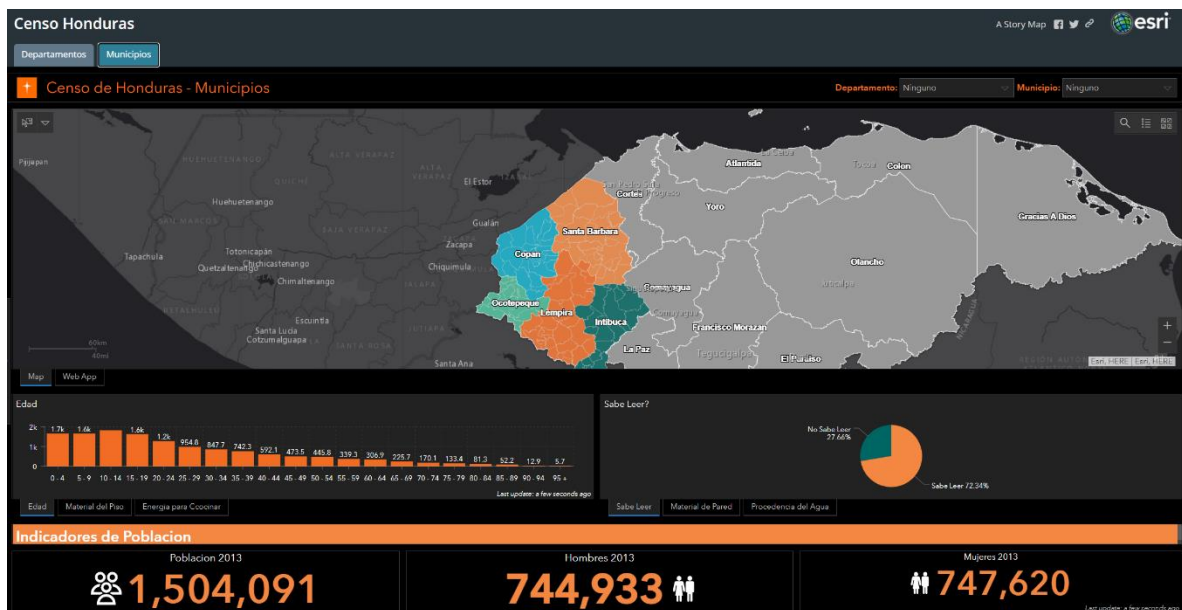
Figure 77. Municipalities census dashboard

The web app also includes the land cover dashboard (figure 77) and a tool to visualize climate data (figure 78) including precipitation and temperature, among others.
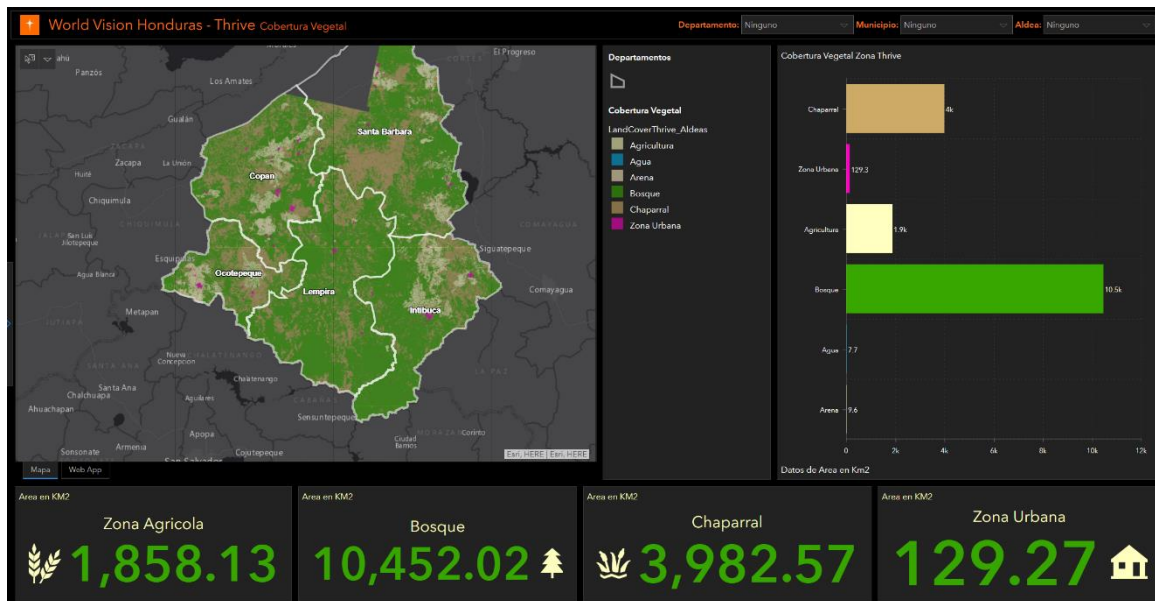
Figure 79. Land cover dashboard and web app
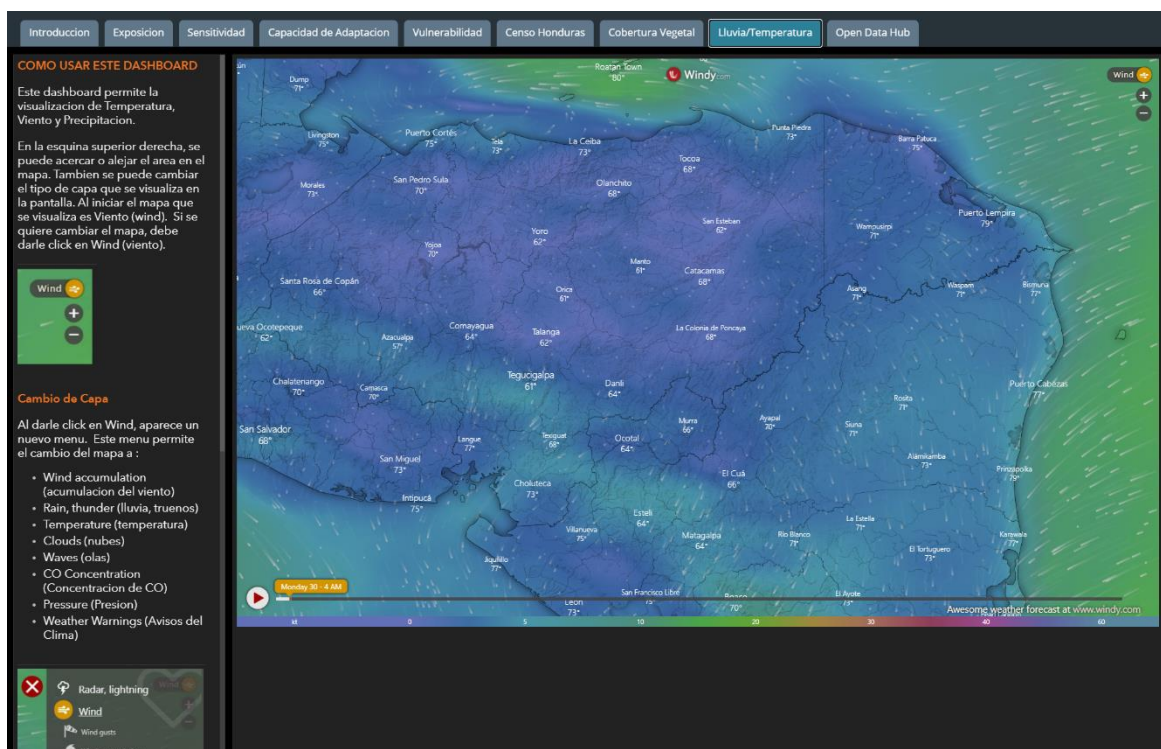
Figure 80. Climate visualization tool
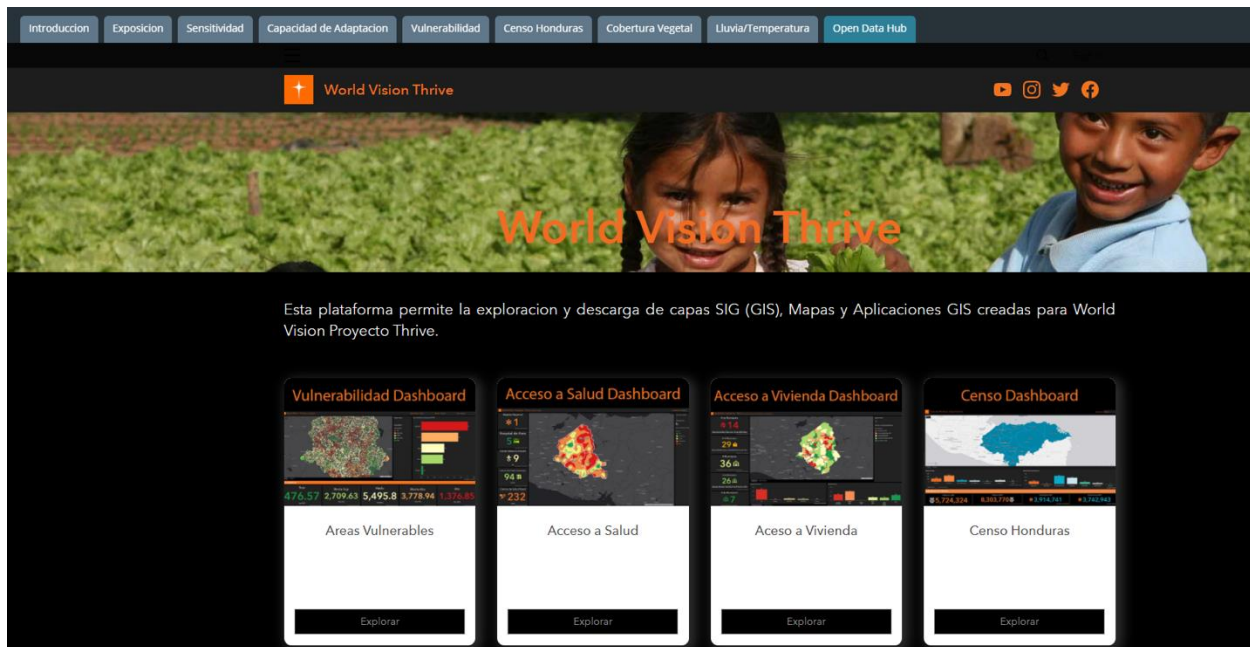
Figure 81. World Vision THRIVE Open Data Hub

And finally, the web app includes an Open Data Hub (figure 79) allowing the users to use and download the data, apps and dashboards developed in this research.

5.8 Evaluation

The evaluation of the Thrive app partnered with World Vision Honduras Project THRIVE (Transforming Household Resilience in Vulnerable Environments) which works in three pillars to equip small farmers, End-To-End Business of Farming, Natural Resources Management, and Emergency and Situational Awareness. The app covers the Departments of Intibucá, Lempira, Ocotepeque, Copan, and Santa Barbara with a total area of 17,303.13 km^2 and 114 municipalities. All departments are in Western Honduras having corn, sorghum, and beans as their population's main agricultural products, with harvest time between May and October (Ben-Davies et al., 2014). The THRIVE Web App was evaluated through a qualitative approach understand the utility of the app, focusing on its usefulness and ease of use. The qualitative method used semi-structured interviews as data collection methods and were conducted through Zoom and Teams.

An initial interview was conducted with the WV Development Officer, followed by six additional interviews with professionals outside World Vision, one located in Honduras and the rest located in the

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US but able to speak and read Spanish. This initial meeting was extremely important as this person

oversees the project's data for monitoring and evaluation purposes. Afterwards, two focus groups of

twelve persons each were conducted with the THRIVE team in Honduras including the THRIVE National

Director and the WV Regional Strategy Coordinator. All the interviews were conducted through zoom.

The semi-structured interviews were guided by the following questions:

1. How does the THRIVE Web App improve your job performance?

2. How can the THRIVE Web App support critical aspects of your job?

3. How can the THRIVE Web App enhance your effort in identifying and analyzing vulnerability

   areas and understanding the different reasons for these vulnerabilities?

4. How can your rate your experience using the THRIVE Web App?

5. What components of the THRIVE Web App would you consider confusing?

6. What components of the THRIVE Web App would you consider easy to use?

After transcribing the interviews, theme identification analysis was performed identifying the

following themes:

5.8.1 Usefulness

This evaluation tried to measure the Perceived Usefulness as defined by (Davis, 1989) to identify

the "degree to which a person believes that using a particular system would enhance his or her job

performance". Both group of participants, professionals outside World Vision and World Vision staff,

considered the Web-based app as innovative and useful.

Participant 1, professional outside World Vision identified a possible user:

"If I were a local government or authority in the region, would see this tool as extremely useful to

identify where the population is living, under what conditions, and providing useful insights for

decision making."

Participant 2, World Vision staff identified possible uses:

"This tool will be extremely useful, for example in a project design, very soon we will start the

process for the 2021 – 2026 strategy planning, and I believe this tool will play an important role

during this process. I see us using it for the climate change transverse axis in our projects, specifically with climate change adaptation processes."

Participant 3, World Vision staff mentioned:

"This tool will easily provide data and maps for our reports."

Participant 4, World Vision staff identified possible uses:

"This tool is a clear sample of how GIS can be used in our projects not only to map points but for deeper analysis processes. I see us using this tool in planning processes. It will be extremely helpful providing data and easily accessing it through filters."

Participant 5, Professional outside World Vision mentioned:

"I find this tool extremely interesting and innovative. I think this tool can be used for decision making among local authorities and by anyone who has access to internet. Developing this type of data requires a lot of work and you should consider copyright all your data and processes."

Participant 6, Professional outside World Vision mentioned:

"I am not a geography professional, but I think this is a useful tool to be used to get data from the region under study. I believe the tools for printing and exporting the information seem to be very useful and I could see myself using them in the case I would need to get data from the region. In general, I think this is an innovative and useful tool."

Participant 7, Professional outside World Vision mentioned:

"This tool provides very useful information and I find the additional tools for printing, measuring and the possibility of exporting the layer table as extremely useful."

5.8.2 Ease of Use

This evaluation tried to measure the Perceived Ease of Use is defined by " (Davis, 1989) to identify "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989). In general, most of the participants agreed the tool is easy to use with some exceptions from professionals who mentioned they were initially not sure where to start or what to do.

Participant 1, Professional outside World Vision mentioned:

"Initially I was very confused, and I didn't know what to do. But once I got into the guide, it was

very easy to use."

Participant 2, World Vision staff mentioned:

"Something I like about this tool, is that it is very easy to use. And if needed the help sections in

the left panels provide additional support on how to use it."

Participant 8, World Vision staff mentioned:

"I consider this tool very user-friendly."

Participant 7, Professional outside World Vision mentioned:

"I find the how-to guide in the side panel, very useful and once I read it, it was very easy to use

the tool."

Participant 9, Professional outside World Vision found the how-to guide useful:

"Initially, I didn't know what to do or where to go. Once I saw the guide it was easy to use"

5.8.3 Change or Edit Recommendations

During the evaluation, one of most common themes was the recommendations from the

participants to edit or change sections from the web-app. All the recommendations provided were used to

improve the web-app.

Participant 1, professional outside World Vision focused on the organization of the app:

"I think it is a little bit disorganized, and if you could maybe organize it better maybe using the

determinants used for the analysis. I think the Census tab seems a little bit outside the topic and I

think should not be the first maybe change it in order."

Participant 2, World Vision staff identified possible additional layers to use:

"I think this tool will be very useful, but if we could have additional information it would be

better. We generally use the watersheds as a unit. Is there a possibility of adding the watersheds

to the maps and make the analysis based on the watersheds? Additionally, the forest fire topic is

extremely important, and it is recurrent more if compared to flooding for example. But the

government does not really provide a good fire management except giving statistics of how much

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forest cover was lost. The effects of forest loss due to fires will only sharpen in the coming years and I think a tool that allows us to monitor forest fire will be needed."

Participant 7, Professional outside World Vision recommended using other variables for health access:

"I have seen similar analysis for health access. Have you consider also including the type of roads and maybe the time it could take someone to reach a health center?"

Participant 10, World Vision staff requested a summary of the vulnerability values in the region:

"This tool is usable and digestible, but is there a possibility of creating something like a guide that depending on the vulnerability values in the map and specifically the areas where World Vision is working, identify the situation that is causing that vulnerability, for example, if this area has high forest fire risk and maybe identify the factors that need to be attacked so we can take preventive measures?"

Participant 11, World Vision staff requested adding the climatic stations:

"I find the weather tool very useful and it gives a very good idea of what is happening. But I consider if we could also add the climatic stations managed by the project, we could have near real-time data."

Participant 12, World Vision staff requested near real-time forest fire data:

"I think the tool is very useful and it can help us for post event situations, if we could have the 26 climatic stations it will provide us a better picture of the current situation. Is there a possibility of adding near real-time forest fire data? Having fire data could help us incredibly. "

Participant 13, World Vision staff requested adding landslides data:

"I find this tool very innovative and useful and saw how you included the soil moisture data. Is there a possibility of adding landslide vulnerability to the analysis? We could easily get this with precipitation data and slopes."

5.8.4 Future work

During the interview, a recurring topic was the possibility of extending this tool to include additional departments and the possibility to extend it to the Central American region.

Participant 2, World Vision staff with the possibility of creating a regional tool:

> "This type of tool can also be used by the region; it is just of obtaining the information from the local authorities and then update it. We should think if making a macro project but also not forgetting the micro as well."

Participant 14, World Vision staff requested adding other departments to the analysis:

> "The tool is extremely useful for my work, but I want to know if there is possibility to add El Paraiso to this analysis?"

Participant 15, World Vision staff requested the possibility of making a regional tool:

> "I think this tool has a lot of potential and could bring a dialogue for a second phase. Maybe create a sub-regional tool, we could start identifying the owners of the projects in each of the countries in the region to start working with Claudia. There should also be further discussion if the answers given by the tool, for example the option of identifying what is making an area vulnerable, as mentioned by a colleague are applicable to our reality. We should identify if the actions can be validated somehow."

Participant 16, World Vision staff, requested possible costs to update data:

> "This tool is very useful, but I want to know what the costs we would incur to be able to update this data and how much time it will require to be able to have this tool updated?"

CHAPTER 6: CONCLUSION AND FUTURE RESEARCH

Climate change is expected to slow the economic growth of nations and regions (World Bank, 2013) and is now affecting every known society. Disadvantaged people, such as rural poor and smallholder producers in developing countries, are at a higher risk as the changes in climate patterns will impact crop yields and undermine food security, especially among subsistence farmers who generally produce low yields and are least able to cope with their effects (Altieri et al., 2015; Antle, 1995; FAO, 2017; IPCC, 2014; P. Jones & Thornton, 2003; Kang et al., 2009; Misra, 2014; Schmidhuber & Tubiello, 2007; UN, 2018; World Bank, 2013). To help build climate change resilient communities among rural farmers, the first step is to understand the impact of climate change on the population.

This study proposes a Climate Change Vulnerability Assessment Framework (CCVAF) (See Figure 6) to better evaluate the different indicators for vulnerability assessment. The framework not only allows the assessment of the overall climate change vulnerability but also the understanding of how different vulnerability indicators would impact the overall vulnerability to support decision making in building climate change resilient communities. The framework was demonstrated using a case study in Honduras, partnering with the World Vision THRIVE team. Further, a GIS-based web application, named THRIVE, was designed as a visualization and knowledge platform to support decision-makers in assessing climate change vulnerabilities among rural farming communities. Although the THRIVE app is built specifically for Western Honduras, it is an instantiation of the CCVAF framework and can be easily extended to different areas around the world. The qualitative evaluation of the THRIVE app shows that it is an innovative and useful tool for vulnerability assessment.

This dissertation makes both knowledge and practical contributions. From the knowledge perspective, the CCVAF provides a comprehensive set of the indicators for climate change vulnerability assessment focusing on small famers. Additionally, it includes related measurements and data sources for these indicators. The framework thus contributes to the knowledge base of the vulnerability assessment. It also

contributes to the design science literature by providing guidelines to design a class of climate change vulnerability assessment solutions. While the THRIVE app is a highly organization-specific solution focusing on the western Honduras, its design and the principles it is based on (i.e. the CCVAF framework), can be easily reused by adding any additional indicators and layers in other similar context. To the best of our knowledge, the CCVAF is the first generalizable artifact that can be used to build a group of ICT-based climate change vulnerability assessment solutions. Another knowledge contribution of this dissertation is its reproducibility by making the input and output data available to the research and practitioner community through a GeoHub. The dissertation also makes practical contributions to both the research and practitioner communities. Researchers and practitioners can easily follow the framework to consistently design a vulnerability assessment tool, starting with the set of indictors organized by the three-level determinants and following specific spatial data analysis and models. Such an ICT-based tool adds practical values to tackle climate change challenges.

Future Research

Further research is needed to examine the exposure and sensitivity determinants along with adaptive capacity. For exposure determinant, several components should be analyzed using extreme climate events, change in climate and soil carbon. For the sensitivity determinant, future research should include the percentage of irrigated land, crop diversification and land degradation. For the adaptive capacity, future research should include measurements of economic capacity and access to basic sanitary service at a household level, financial access, market access, and improved health access. Previous analysis should be validated especially the land cover layer, the access to health, access to house a basic sanitary service. Additionally, a research plan would be developed to include the expansion of THRIVE app to other areas of Honduras and in the Central American region.

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