EVALUATION OF DRY BEAN YIELD RESPONSE TO EL NIÑO SOUTHERN OSCILLATION (ENSO) IN HAITI WITH THE SIMPLE MODEL. CASE STUDY: DUVIER

By

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To my lovely wife, my mom, my brother, my sister, and my dad for their endless love, support, and encouragement

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
ARID	Agricultural Refeference Index for Drought
CFSR	Climate Forescast System Reanalysis
CHIRPS	Climate Hazards Infrared Precipitation with Stations
CLLJ	Caribbean Low-Level Jet
DSSAT	Decision Support System for Agrotechnology Transfer
ENSO	El Niño-Southern Oscillation
FAO	Food and Agriculture Organization
GIS	Geographic Information Systems
GDP	Gross Domestic Product
MSD	Mid-Summer Drought
NAO	North Atlantic Oceanic
NOAA	National Oceanic and Atmospheric Administration
ONI	Oceanic Niño Index
PAW	Plant- Available Water
SOI	Southern Oscillation Index
SST	Sea Surface Temperature
UN	United Nations

Abstract of Thesis Presented to the Graduate School
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Dry beans are the sixth most grown crop in Haiti and represent an excellent and affordable source of protein for low-income families. However, according to a study conducted by Michigan State University in 2010, an annual decrease of 1.1% is observed in the yield of dry beans cultivated in Haiti during the decade 1994-2004. In this study, the potential impact of the annual climate cycle known as El Niño- Southern Oscillation (ENSO) on dry beans grown at Duvier, in Haiti, was investigated. The SIMPLE crop model was used to simulate yields for 37 years of weather data and three main growing seasons: November, April, and July. The ANOVA of the model simulated yields showed there were no significant dry bean yield responses to ENSO phases during the November and April seasons. However, in the case of dry beans planted in July, yields were significantly lower in El Niño years than La Niña and Neutral years. A plausible explanation for this was that a more complicated climate pattern generally dominates July seasons. Known as the mid-summer drought, since the Caribbean low-level jet peaks during that time, ENSO phases tend to be amplified during this season, as are its effects on bean yield in the study region. Simulation results also showed that sowing early during the November season leads to a 60% probability for above-average

yields. Whereas, planting late during the other two seasons was more beneficial with a chance of up to 60% to result in higher yields.

CHAPTER 1
INTRODUCTION

Ridding the world of hunger is the second sustainable development goal set by the United Nations (UN) for 2030 (Johnston, 2016). Consequently, current agriculture production worldwide should double to meet expected growth in human population and associated demand for food (Iglesias et al., 2011). However, due to the sensitivity of agriculture to climate variability, a slower increase in food production is expected in the future (Iglesias et al., 2011). This sensitivity to climate variation, has drastic implications for the economy worldwide, as agriculture holds a significant share in the Gross Domestic Product (GDP) of many countries (Byerlee et al. 2011). Given the importance of agriculture as an economic sector and food supplier, the links between climate variability with agricultural productivity have broad economic implications. Crops productions, climatic shocks, and food prices are interrelated (Bellemare, 2015). According to Bellemare (2015), an increase in food price during the world food crisis in 2007 and 2008, as a result of climatic shocks, led to several unrests in many developing countries. Therefore, farmers must consider climate information when making decisions about which crop to grow, when they should sow or harvest to earn a maximum profit or decrease losses.

Since the industrial revolution, the amount of greenhouse gases emitted into the atmosphere has significantly increased. The continued emission of these gases, which include carbon dioxide (CO2), methane (CH4), and nitrogen dioxide (NO2), have exacerbated the greenhouse effect. More energy trapped in the system has increased weather extremes around the globe (Kreft & Eckstein, 2014). Thus, extreme weather events, including droughts and excess rainfall, have severe consequences on economies worldwide, and particularly on a weather-sensitive sector like agriculture.

Numerous studies indicate that severe weather conditions, like droughts, extreme temperatures, and flooding, are bound to occur more frequently under the ongoing climate change and will affect the agricultural activities more severely (Bates, Kundzewicz, Wu, Palutikof, & Eds., 2008; G. Wang & Hendon, 2007). El Niño Southern Oscillation (ENSO), as part of a global set of climatic anomalies, is the most intense, most robust, and well-explained pattern of inter-annual climate variability (Hammer et al., 2001). Moreover, this phenomenon is related to cycles of droughts and flooding events and describes between 15% and 35% of worldwide yield fluctuation of staple crops (Iglesias et al., 2011). Agriculture can be affected by ENSO cycles in multiple ways, including changes in crop yield because of associated changes in precipitation and temperature (Roberts, Dawe, Falcon, & Naylor, 2009) or effects on the development of fungi diseases and pest damage (Iglesias et al., 2011). Therefore, climate variability related to El Niño Southern Oscillation (ENSO) represents a severe threat to crop yields including that of major staples such as maize, rice, dry beans and other legumes (Legler et al. 1999).

Researchers use crop models to understand how climate variability affects yields and develop strategies to adapt crop system production to the changes. Crop modeling is one of many fundamental approaches to manage the impacts of ENSO on crops, as they can help us detect the effect of this phenomenon on biomass accumulation. Indeed, the effects of climate variability on yields have been extensively discussed in research for some time. However, the use of crop models for seasonal yield forecasts has become increasingly popular recently. One reason for this is the ability for modelers to help guide agricultural decisions in light of climate risks (Asseng et al., 2013; Gelcer et al., 2018; Lobell & Asseng, 2017; Royce et al., 2011). Indeed, the use of such models to predict yield and support decision-making during favorable and non-favorable years has increased in recent years (Niyogi et al., 2015).

Agricultural Production at Risk in Haiti

As is the case for many countries in the Caribbean, agricultural activities are a significant component of the Haitian economy. Agriculture employs more than half the Haitian population and represents the primary source of income in rural areas. According to the World Bank, Haiti's population is over 10 million and is growing fast (world bank, 2015). The annual demand for food surpasses local production, which in turn results in a heavy dependency on imports and rampant food insecurity. Agricultural productivity, and especially the production of legumes like dry beans, highly depends on the climate. Since most of the land reserved for dry beans production have low to no access to irrigation, the ENSO cycles impact this legume severely.Without accounting for ENSO-added variability, the rugged topography increases the number of micro-climates on the territory. Moreover, ENSO signals are often masked by quick variations in altitude due to the ruggedness of the land. Climate variability and other factors related to seed quality, soil fertility, agriculture credit, and government subsidies are the fundamental causes of low crop yield.

Among all the other crops grown in Haiti, dry bean (Phaseolus vulgaris L.) has the second-highest demand after rice for direct human consumption in Haiti. In terms of harvested area, it is the sixth most important crop grown in the country (Beebe, Rao, Blair, & Acosta-Gallegos, 2013). Dry beans are the cheapest source of protein, thereby constituting an essential component of people's diet and represent the cheapest source of protein. Nicknamed the 'the meat of the poor,' beans are affordable regardless of household income. Dry beans are cultivated in highlands as well as in low lands throughout the country. Although this crop is easy to grow, it faces many biotic and abiotic threats that can cause yields to decrease by more than 50% (Porch et al., 2013). Common abiotic risks include soil salinity as well as heat and water stress induced by a lack of rainfall and high temperatures (Porch et al., 2013). These conditions can significantly affect the yield of dry beans depending on the phenological stage during which they affect the crop. According to a study conducted by Michigan State University in 2010, dry beans yield was decreasing at an annual rate of 1.1 % in Haiti (Michigan State University, 2010). Whether this decreasing trend is related to ENSO has not been established.

Crop modeling-based approaches are used in many tropical countries in Africa and Latin America to help detect climate impacts on crop production but not in Haiti (Abdolrahimi, 2016; Singh & Cohen, 2014). To the author's knowledge, there is no evidence of previous research or crop modeling efforts investigating the relationship between interannual variability of climate and dry beans yield in Haiti. In this study, the SIMPLE crop model was used to evaluate the yield of dry beans under varying climate conditions in Duvier, a town located in the mountain range of Port-au-Prince.

This research hypothesizes that the El Niño Southern Oscillation has a significant influence on the variability in dry bean yield during all dry beans growing seasons in Duvier.

Objectives

The overall objective of this study is to quantify the response of dry beans yields to weather conditions associated with ENSO and discuss the impacts of the phenomenon during the main dry beans growing seasons in Duvier, Haiti. Specifically, this research aimed :

- To evaluate the effects of ENSO on dry beans simulated yields with the SIMPLE crop model (Zhao et al.,2019);
- To determine which dry beans growing seasons and sowing dates are more likely to be affected by ENSO phases;
- To identify potential benefits from application of ENSO-based climate forecast for dry beans production in Haiti.

CHAPTER 2
LITERATURE REVIEW

History of ENSO

Early during the sixteenth century, fisher people from the coast of Peru and Ecuador noticed a yearly cycle of unusual warming of the sea surface water during winter (Abdolrahimi 2016). Yearly during the onset of the season, a stream of warm water heading south would disrupt the cold waters. However, this atypical warming would come earlier than anticipated every five to seven years, prolong into early summer and lasted over a year (Giralt et al., 2007). The southward-flowing of abnormally warm waters augmented the sea-surface temperature significantly and affected the fishery industry due to unfavorable heat and nutrient scarcity (Giralt et al. 2007). Besides, Peruvian geographers noticed the warm phase would persist for several years (Turner, 2004). The phenomenon was named after “the Christ Child” since it happened during Christmas, hence the term El Niño devised by the fishermen (Mjelde et al. 2006). The documentation of ENSO started in the scientific community with the collaboration between Peruvian researchers and researchers from abroad at the dawn of the 20th century (Lobell & Burke, 2008). Subsequently, they acknowledged El Niño as a wide-ranging event linked to the warming of the tropical Pacific Ocean (Turner 2004) with a cycle of 3.8 years.

Usually, the sea level pressure (SLP) in the south-central Pacific is comparatively higher than the Northern Australia and the Indian Ocean region combined. During ENSO neutral conditions, surface trade winds blow westward across the equatorial Pacific Ocean. These winds generate westward current. During El Niño conditions, the winds decrease in intensity and the current reverse. The decrease in strength of the sea level pressure difference among the eastern and western side produced calm trade winds every couple of years and causing drought in the west of the Pacific Ocean. The Southern Oscillation Index (SOI) was devised by Walker to measure these fluctuations. Bjerknes confirmed, through the analysis of El Niño and Southern Oscillation data collected during the periods 1957-1958, 1963-1964, 1965-1966, the interactions between the ocean and the atmosphere in the tropical Pacific (C. Wang & Fiedler, 2006). Succeeding Bjerknes, Wyrtki (Bjerknes, 1964, 2012) devised an original structural description of El Niño inception. Bjerknes utilized evidence of wave measurements to observe the level of the sea in the tropical Pacific (Bjerknes, 1964).

Before the intense episode El Niño of 1982-83, ENSO research was not envisioned. The insufficient knowledge about the intensity of the warm phase and the full progression of the phenomenon sparked the interest of researchers from tropical countries to look into the description of ENSO and its forecast (G. Wang & Hendon, 2007).

ENSO Worldwide Climate Impacts

The verifiable recorded events such as scriptural dry seasons in Egypt are proof that The ENSO cycle has been an element of Earth's atmosphere for a long time (Eltahir, 1996; Lu et al., 2018). El Niño impacts on the climate of Peru goes back to the year 1525 (Abdolrahimi 2016b). The associations among sea and climate in the tropical Pacific region have been connected to atmosphere fluctuations on the planet (Ropelewski & Halpert, 1996). Several studies research the connection between ENSO and precipitation. Ropelewski and Halpert (1996) directed the most comprehensive research that collected overall information from 2000 precipitation stations.

El Niño-Southern Oscillation episodes can alter the climate pattern in more than two-thirds of all countries in the world (Verchot et al., 2007). Compelling evidence demonstrates that precipitation and temperature difference patterns are related to ENSO index signals (Wang and Fiedler, 2006). The ENSO impacts on the tropics are immediate and extreme, particularly in storm influenced nations in Asia, Australia, and Africa. Also, ENSO represents a considerable extent of precipitation and temperature changes in many countries in America (Hammer et al. 2001). The significant worldwide El Niño fluctuation is surpassing the mean temperature inconsistencies over the pattern (Salinger, 2005). It has been demonstrated that precipitation on the planet is influenced by ENSO events, although the degree of the impact varies with the area (Crasswell & Simpson, 1993). Hsiang and Meng (Hsiang, Meng, & Cane, 2011) show +1°C increment in Niño3.4 record results in +0.27°C rise in tropics nearby temperature and -4.6cm precipitation reduction. ENSO quality and the severity of impacts are connected, it is generally flimsier for La Niña events (Lyon B. & Barnston A. G., 2005). El Niño causes an eastbound move in tropical rainstorm pattern, so that, abnormal climatic conditions emerge over northern Australia and Indonesia. Besides, researchers observed drier winters in southeastern Africa and northwestern India. Contemporary, in the central and eastern Pacific and west bank of South America precipitation level unreasonably raise (Salinger 2005). Usually, dry seasons in the western Pacific, above-average rains over the tropical coast of South America and the event of thunderstorms and blizzards in the Pacific region are an El Niño-instigated worldwide atmosphere variety (Cashin et al. 2017). Practically inverse scenarios occur during La Niña episode

(Salinger 2005). The global climatological impacts of an El Niño and La Niña episode are condensed.

Influence of ENSO in the American Continents

Grimm et al. (1998) were the first to demonstrate the ENSO-induced temperature and precipitation variety in southeastern South America (Argentina, Brazil, Uruguay). The warm episode of ENSO presents positive precipitation irregularities during November– February, and cold event causes atypical precipitation during June-December. Grimm et al. (1998) express the inconsistency level is bigger in Uruguay than Argentina and Brazil. There is proof that ENSO influences precipitation during November– February, a lower degree, and during October– December in southern Brazil and Uruguay (Diaz et al. 1998).

Podesta et al. (2002) claim Argentina experiences more than average precipitation during El Niño events, while it is the opposite during La Niña. Wet summer during El Niño years that results in flooded fields in Argentina and incredibly dry summer causes dry season during La Niña years (Pol & Binyamin, 2014). According to Grimm (Grimm, 2003) during El Niño, within the period starting from January through March, Northeast Brazil receives above-average precipitation whereas it tends to decrease drastically over the Amazonian region for the same period. However, during the summer, El Niño events tend to cause drought in both Northeast of Brazil and the Amazon (Grimm 2003). El Niño events are related to lower temperature in the southeast U.S. winter.

Izaurralde et al. (1999) demonstrate the air temperature and precipitation deviation of a moderate and strong El Niño episode from the ordinary condition in North America. They conclude that winters are hotter during the two instances of El Niño;

aside from the eastern U.S. (in moderate El Niño) and tropical Mexico location. More torrid spring and Summer seasons occur during a mild and strong El Niño episode, however not in subtropical Mexico and the U.S. (during Spring strong El Niño). Except for Canada and Mexico (under moderate El Niño event), air temperature diminishes in northern America during harvest time in winter. There is abnormal precipitation in summer in the U.S or pre-winter in Canada during the El Niño episode. Winter precipitation diminishes in Canada, subtropical Mexico and the U.S. Corn Belt in moderate El Niño episode. In Spring of a moderate El Niño, precipitation increments in Mexico and diminishes in other areas. During strong El Niño, spring is wetter than typical years, except for Canada. Phillips et al. (1999) demonstrated that summer temperature and precipitation in the U.S. Corn Belt are contrarily connected with Niño3 record, separately.

Influence of ENSO in the Caribbean

In most of the regions of the Caribbean, precipitation is bimodal with a rainy season that ranges from April to June and another one that spans the period from August to November (Giannini et al. 2000). The first season has a peak in May and the second in August. This general trend is different for the southern part of the Caribbean, closer to the coast of Venezuela where the primary rainy season occurs during winter (November-January). The precipitation in the Caribbean is influenced by both the eastern Pacific and the North Atlantic oceanic (NAO) and atmospheric pattern (Jury et al. 2007). According to Georges and Saunders (George & Saunders, 2001), the NAO positive phase, amplified by the North Atlantic trade winds, is accompanied by lower than average rainfall. The ENSO influence on rainfall is related to the subtropical jet stream change of direction toward the equator during the warm phase, which exacerbates the late -and early summer drought. Therefore, warm ENSO events are associated with anomalously dry conditions during the later Caribbean rainfall season. There is also a delayed impact with declining warm ENSO events in boreal spring related to anomalously wet conditions over the Caribbean (Chen & Taylor, 2002). The intensity of the relationship between the tropical Pacific and Caribbean basin may also be modulated by central and eastern Pacific ENSO events (Gouirand, Moron, Hu, & Jha, 2014). During La Niña or the cold phase, weather conditions are wetter than average during the rainfall season of August-November. This season is associated with hurricane season that starts in June to end in November.

Therefore, this rainfall season can be exacerbated during La Niña. According to Giannini et al. (2001), the Caribbean low-level jet (CLLJ) influence significantly the way ENSO affects rainfall in the Caribbean. The CLLJ is a strong wind blowing from the North Atlantic toward Central America, following the pressure gradient of the North Atlantic Subtropical High (NASH). In February and July, these winds intensify creating conditions drier than usual during El Niño.

Evidence of the Relationship between ENSO and Food Security

Despite significant achievements in new farming techniques and technologies around the world, agriculture is still strongly dependent on atmosphere and climate as a significant factor in deciding profitability. Since this sector requires specific levels of solar radiation, temperature, and rainfall to enable crop development, it is particularly sensitive to ENSO (Iglesias et al. 2000). In 1972 abnormal atmospheric conditions drastically affected agriculture worldwide causing a humanitarian crisis.

A further consequence of the intense El Niño episode of 1972-73 was the disruption of the fishery industry along the west coast of South America. As an alternative to cope with the shortage of fish, farmers switch to the use of soybean as a source of protein to feed their hens. This situation appealed U.S. ranchers to grow soybean as a trade for wheat. It was done at a time when wheat was a highly needed crop, and worldwide food crisis was grave (McPhaden et al. 2006).

The El Niño of 1982– 83 was one of the most powerful episodes of the twentieth century. In Peru, several crops, including staples and legumes, were completely ravaged (Iglesias et al. 2000). As a result, food prices significantly increased, and millions of farmers became food insecure (Cavledes, 1985, Iglesias et al.,2000).

The 1997– 98 El Niño events, again, stunned mainstream researchers due to their abrupt beginning and amplitude (McPhaden et al. 2006). The worldwide financial expense of this was about US$100 billion, and 110 million people touched with famine (FAO, 2007). In the southeast of South America, rich soil dampness identified with a typical wet El Niño was beneficial a record in Brazil and Argentina for soybean crop, though in Central America trade vegetable production was affected during the dry season.

Crop Modelling

Crop models are simulation models that are designed to replicate crop growth and development as a function of management and environmental conditions. Simulation models are available for many important crops such as wheat (Asseng et al. 2013), maize (Bassu et al., 2014), rice (Li et al., 2015) and potato (Fleisher et al., 2017). Only a few models have been developed for oil and fiber yields, vegetables, and organic products, limiting research, policy, and decision-making (Zhao et al., 2019). The parameterization, calibration, and evaluation of a full-scale process-based model often requires a lot of data on the characteristics of the crop, environmental conditions and management strategies, which may limit their application (Jones et al., 2003; Keating et al., 2003). For instance, DSSAT stands out amongst the most broadly utilized yield models, requires many genotype-specific parameters, which are not always available (Zhao et al., 2019). In an attempt to compensate for missing data, many functions or models have subsequently been developed. These include Expolinear development functions (Monteith & Ross, 2006), the EPIC model (Izaurralde, Williams, McGill, Rosenberg, & Jakas, 2006), the AquaCrop model (Steduto, Hsiao, Raes, & Fereres, 2009) and the LINTUL (Haverkort et al., 2015). These models often still require many parameters, similar to 22 for EPIC and 29 for AquaCrop (Zhao et al. 2019).

Statistical models represent an alternative to dynamic harvest models (Lobell & Asner, 2003). These have been used to investigate the effect of environmental change on yields, for which crop-specific models are not yet available (Lobell & Asseng, 2017). However, statistical models are generally ineffective in characterizing the biophysical processes of the system when taking into account the relationship between the atmosphere, genetic features, and crop management (Lobell & Burke, 2008). As such, statistical models are frequently limited to surveying past atmosphere effects and are less pertinent for future situations. A deterministic approach, instead of a stochastic approach, can restrict our conclusion on the impact of atmospheric conditions on crop development because they are continually changing. It is necessary to try random values of the variables to constitute what-if scenarios, and thus determining the sensitivity of the model to the evolving conditions (Gelcer et al., 2018; Zhao et al., 2019).

CHAPTER 3
METHOD AND DATA

Study Area

This study was conducted for a location in Duvier, a rural town located at 18° 29' 44 N of latitude and 72° 15' 24 W of longitude, about 7 kilometers away from the commune of Port-au-Prince to the south-east direction, in Haiti (Figure 3-1). The location is almost 887 m above sea level and is part of one of the numerous mount regions of the mountain range "Chaine de la Selle" in the west area of Haiti. The mean annual air temperature is lower than in the city of Port-au-Prince and during winter months, and it can be cold relative to other parts of the country. Duvier is classified as tropical savanna or tropical wet and dry climate. This type of weather corresponds to the Köppen climate classification categories "Aw" and "As." Tropical savanna climates have monthly mean temperatures above 18 °C in every month of the year and a typically pronounced dry season. The driest month has less than 60 mm of precipitation. The dry season at Duvier generally starts in late November through early March. The driest months are necessarily December and January. The rainfall season can be divided into two, one that begins in April and ends in June and the other starts in August. Figure 3-3 shows a peak in rainfall during the first season in May and the second peak in September-October. July is sometimes considered as a transition between rainy seasons, and it is referred to as the term mid-summer drought (C. Wang, 2007).

The main crops grown in this locality are vegetables such as pepper, tomatoes, cabbage, and beans, the latter being the most important crop in terms of nutritional value. This crop is cultivated everywhere in the country with some areas growing a higher acreage than others. Figure 3-2 shows the spatial distribution of dry beans production in the country where the dark green areas are locations with a yearly harvested area of 1416 ha or more.

Weather Data

The model requires daily weather data to simulate crop development and growth, including minimum and maximum air temperature, solar radiation, and precipitation. Historical weather data for Duvier is limited and sometimes inexistent. As the model requires continuous weather data records over at least 30 years, gridded weather data were used. The minimum and maximum daily total air temperature in Celsius, and daily solar radiation in MJ/m^2 data for the period starting from 1987 to 2017 were acquired from the Climate Forecast System Reanalysis (CFSR) (Saha et al., 2010). The spatial resolution of this dataset was 0.25^o and offers a reliable interpolation of temperature and solar radiation observations (Saha et al. 2010). The daily rainfall totals in millimeters for the same period were obtained from the Climate Hazards Infrared Precipitation with Stations (CHIRPS) dataset. CHIRPS combines satellite data, at a spatial resolution of 0.05°, with on-site weather stations to generate gridded rainfall time series (Funk et al., 2015).

Classification of ENSO Phases

The Oceanic Niño Index (ONI) is the index used by NOAA to classify El Niño (warm) and La Niña (cold) episodes in the tropical Pacific (Dahkman, 2009). It reflects the running 3-month mean SST anomaly for the Niño 3.4 region (i.e., 5^o N-5^o S, 120^o - 170^o W). Events are defined as five consecutive overlapping 3-month periods at or above the $+0.5^o$ anomaly for warm (El Niño) events and at or below the -0.5 anomaly for cold (La Niña) events. The threshold is further broken down into Weak (with a 0.5 to 0.9 SST anomaly), Moderate (1.0 to 1.4), Strong (1.5 to 1.9) and Very Strong (≥ 2.0) events. For an event to be categorized as weak, moderate, strong or very strong in this study, it must have equaled or exceeded the threshold for at least three consecutive overlapping 3-month periods (APPENDIX). Given the short season duration simulated in this research, a crop season was classified as El Niño if the sowing date falls within a month triplet for which the anomaly is greater or equal to the +0.5 ^{o}C. The same rule applied for La Niña years for a corresponding anomaly of 0.50 ^{o}C or less Classification of ENSO Phases (Dahkman, 2009) (Figure 3-4).

Crop Model Simulations

The SIMPLE crop model (Zhao et al. 2019) was selected to simulate common bean yield in the region of study. The SIMPLE model has 13 parameters, of which four are cultivar-specific. The model was developed in R and DSSAT and calibrated for 14 crops, including green bean and dry bean (Zhao et al. 2019).

Many of the parameters were derived from all established literatures. These include RUE (radiation use efficiency), the existing CROPGRO DSSAT (Jones et al. 2003) and model parameters for dry bean (such as the base temperature, the optimal temperature for crop development, harvest index (HI) and CO2 or computed harvest indices found in DSSAT outputs). Other coefficients were calibrated (e.g., Tsum) for the specific data sets of aboveground dry matter accumulation, percent light interception, and final economic yield (dry grain, fresh tomato, fresh bean, fresh banana).

The SIMPLE model runs at a daily time-step, and requires the following inputs:

- Rainfall and irrigation;
- Temperature;
- Solar radiation;
- Elevated atmospheric CO2 concentration;
- Cultivar differences;
- Soil water-holding characteristics.

A SIMPLE water budget routine simulates water stress without detailed soil profiles. The Priestley and Taylor equation (Stannard, 1993) is used to simulate crop evapotranspiration demand and the ARID (Woli et al. 2012a) water stress index model, based on rainfall/irrigation and a SIMPLE soil-water balance based on a single soil computational layer. The SIMPLE model does not take into consideration the fertilization input, like N, or vernalization requirements and photoperiod sensitivity, frost, pest and disease impacts. The subroutines in the SIMPLE model have been tested in the US under different conditions (Zhao et al. 2019) including temperature and heat stress (wheat), and delayed sowing dates or different seasons (wheat, soybean, potatoes, tomato), water balance (wheat, maize, soybean, dry bean) and CO2 (wheat, cotton). The SIMPLE model has not yet been tested in Haiti.

Single treatment data were available for extensive model testing and calibration for rice, green bean, sweet corn, peanuts, carrots, cassava, banana. Besides, a sensitivity analysis with increments of temperature change and atmospheric CO2 was carried out for different growing conditions for wheat, maize and soybean showing expected responses to these factor changes for crop production in the US (Zhao et al. 2019).

SIMPLE Model Description

Equations used in the SIMPLE model account for the impact of heat stress, water stress, daily temperature, and CO2 concentration.

SIMPLE uses daily air temperature to define phenological development based on degree days accumulation as follows:

$$\Delta TT = T - Tbase,\ T > Tbase;\ \Delta TT = 0,\ T \leq Tbase \quad (3\text{-}1)$$

$$TT_{i+1} = TT_i + \Delta TT \quad (3\text{-}2)$$

Where, TTi is the aggregate mean air temperature for a particular day number, and ΔTT is the mean air temperature to be augmented daily. T is the daily mean temperature, and Tbase is the base temperature for phenological development and also, for crop growth. For simplicity, the model starts to accumulate the temperature required to achieve maturity when it surpasses the base temperature of the crop, regardless of an optimal threshold for the temperature (Zhao et al. 2019). However, canopy degeneration is quickened with heat stress causing the model to speed up crop development by reducing the time to maturity. A cumulative temperature requirement from sowing to maturity (Tsum) is used to reach physiological maturity in the model.

SIMPLE relies on the concept of radiation use efficiency (RUE) concerning photosynthesis. RUE is the actual fraction of radiation that is captured by the plant canopy and converted into crop biomass. The growth here refers to the amount of biomass produced by the plant that does not include non-harvested parts like usually the roots. The final yield is obtained by multiplying the biomass by the harvest index of the crop. The daily biomass is affected by the variation of daily temperature, heat, water stress, and the amount of CO2 available in the atmosphere.

$$Biomass\_rate = Radiation \times fsolar \times RUE \times fCO2 \times fTemp \times \min(f(Heat), f(water)) \quad (3\text{-}3)$$

$$Biomass\_cum_{i+1} = Biomass\_cum_i + Biomass\_rate \quad (3\text{-}4)$$

$$\text{Yield} = \text{Biomass\_cum}_{maturity} \times \text{HI} \tag{3-5}$$

The biomass rate is the rate at which the crop grows every day, while Biomass_cum is the aggregate of the biomass for a particular day number. RUE stands for radiation use efficiency. fCO2, fHeat, fTemp, fWater, are respectively CO2 impact, heat stress, temperature impact, and water stress on biomass accumulation. All of these factors penalize the growth accumulation of the crop. fSolar is the fraction of solar radiation that is captured by the plant canopy. The fSolar is based on Beer-Lambert' law of light tempering (Ross 2012) and solar radiation capture. However, it does not rely on leaf area index. The leaf growth and senescence period obtain from the fSolar are calculated as follows:

$$\text{Solar} = \begin{cases} \dfrac{fSolar\_max}{1 + e^{-0.01x(TT - I50A)}} & \text{Leaf growth period} \quad (3\text{-}6) \\[2ex] \dfrac{fSolar\_max}{1 + e^{-0.01x(TT - (Tsum - I50B)}} & \text{Leaf senescence period} \quad (3\text{-}7) \end{cases}$$

I_{50A} is the required cumulative temperature to enable the leaf area to intercept 50% of solar radiation in canopy final event, whereas I_{50B} is the accumulation of temperature that the crop requires after reaching maturity until the interception of 50% radiation during canopy senescence (Zhao et al. 2019). This model, however, has some limitations due to its simplicity. For instance, it does not account for fertilization, photoperiodicity, and vernalization and the effect of disease on biomass accumulation.

The impact of temperature on biomass growth rate (Zhao et al., 2019) is calculated as described in the following formula:

$$f(\text{Temp}) = \begin{cases} 0 & T < Tbase \quad (3\text{-}8) \\ \dfrac{T - Tbase}{Topt - Tbase} & Tbase \leq T < Topt \quad (3\text{-}9) \\ 1 & T \geq Topt \quad (3\text{-}10) \end{cases}$$

T is the daily mean temperature, and Tbase and Topt are the base and optimal temperature for biomass growth, respectively, for a given crop species.

The heat stress on biomass production takes the following form:

$$f(\text{heat}) = \begin{cases} 1 & Tmax \leq Theat \quad (3\text{-}11) \\ 1 - \dfrac{Tmax - Theat}{Textreme - Theat} & Theat \leq Tmax < Textreme \quad (3\text{-}12) \\ 0 & Tmax > Textreme \quad (3\text{-}13) \end{cases}$$

Where Tmax is the daily maximum temperature, Theat is the temperature limit when the biomass growth rate is penalized by heat stress, and Textreme is the extreme temperature threshold when the biomass growth rate reaches 0 due to heat stress.

The water budget subroutine used for the water balance simulation and to define water stress without including too much detail on soil characteristics, especially the water holding capacity. The impact of water stress is evaluated with the Agricultural Reference Index for Drought (ARID) index by the following formula:

$$f(water) = 1 - Swater \times ARID \quad (3\text{-}14)$$

$$ARID = 1 - \frac{\min(ET0, 0.096 * PAW)}{ET0} \quad (3\text{-}15)$$

PAW is plant-available water content in the soil profile for the rooting depth, while 0.096 is a generic daily root water uptake constant (Woli et al., 2012) representing the maximum fraction of available water extracted in a day. ET_0 is the Priestley-Taylor's reference evapotranspiration. Swater is the sensitivity of RUE to the ARID index.

$$\lambda E_a = \alpha \frac{S}{S+\gamma} (R_n - G) \quad (3\text{-}16)$$

Ea :actual evapotranspiration, R_n: net radiation

λ: latent heat of vaporization, G: soil heat flux

γ: psychrometric constant α: model coefficient

Dry Beans Growing Season in Haiti

The growing season is defined in this study as starting on the planting date and ending on the day of harvest for a given year. Dry beans take at least 60-70 days to reach maturity, especially for the early varieties (Porch et al., 2013). Crop growth simulations were conducted using model parameters for the black bean variety Salagnac 90'(Dorcinvil et al. 2010), which is the most common variety of black beans in Haiti's mountain areas. The Salagnac 90 dry bean variety was developed and released in 1990 by the Salagnac Experimental Station of Haiti and had an indeterminate type III growth habit. With the right edaphic and weather conditions, meaning that the soil is not P and N deficient and relatively mild weather, the Salagnac 90' can reach maturity as early as 60 days after planting.

However, the maximum days to reach maturity for this variety is around 70 days (Clermont-Dauphin 2003). This variety can yield up to 2500 kg/ha at the optimal condition (Clermont-Dauphin 2003).

In Haiti, there are three major growing seasons for dry beans, and black beans variety Salagnac 90 has the most share of the land assigned, accounting for 70% of common bean grown (Clermont-Dauphin 2003). The dry black beans are produced from April through June and July through September across the country on the mountain range, and from November through March in irrigated lowlands. In this study, the November season was divided into October-December and January-March. The first half consisted of four planting dates starting from October 1st to October 22nd, while for the second half dates were used in the simulation starting from January 1st to February 12th. All the planting dates are one week apart. In April, the sowing dates were from March 11th to April 22nd. For the July season, the sowing dates were from June 10th to July 22nd.

Data Analysis

The model simulated yields for 37 years and started from 1981 to 2017. An analysis of Variance (ANOVA) was performed on both the simulated yields of the model and the amount of rainfall during the season, to determine whether there was a significant difference in mean across seasons and ENSO phases. The results of the ANOVA were further analyzed with the Tukey HSD test to define which planting dates showed substantial differences in yield compared under any given ENSO phase. The simulated yields were ranked in descending order during each growing season. The new sorted datasets were then split into four quartiles, and the probabilities of the sowing dates were calculated.

The first quartile was calculated for low yields; the median-low and median-high were for the second and third quartiles. Finally, high yields fell in the fourth quartile. The number of times a specific sowing date appears in one of the categories mentioned above is counted and divided by the 37 years to calculate the probability. These calculations were performed for all years.

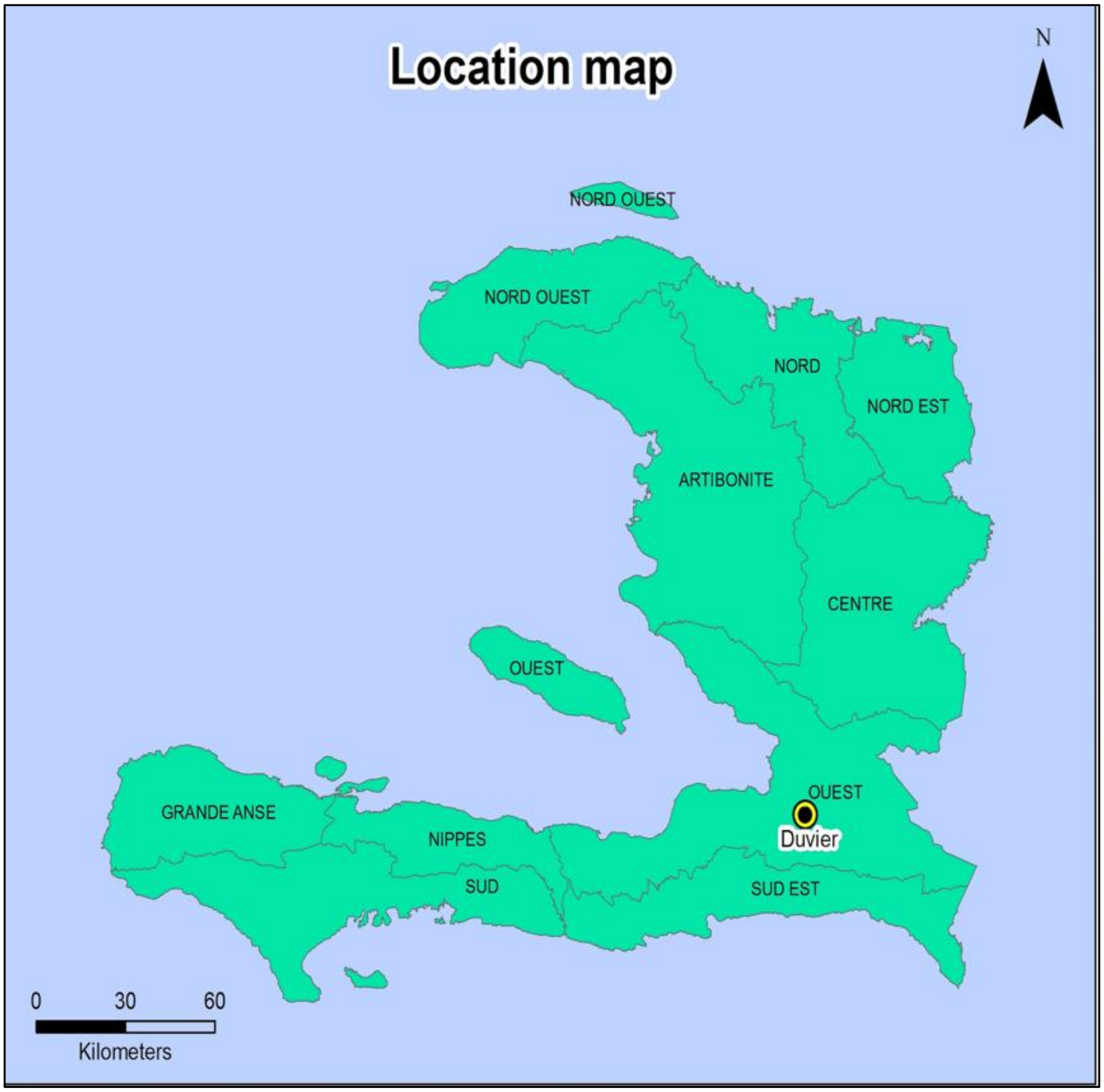

Figure 3-1. Experiment site for the case study. The model simulated the yields using weather characteristics of that location.

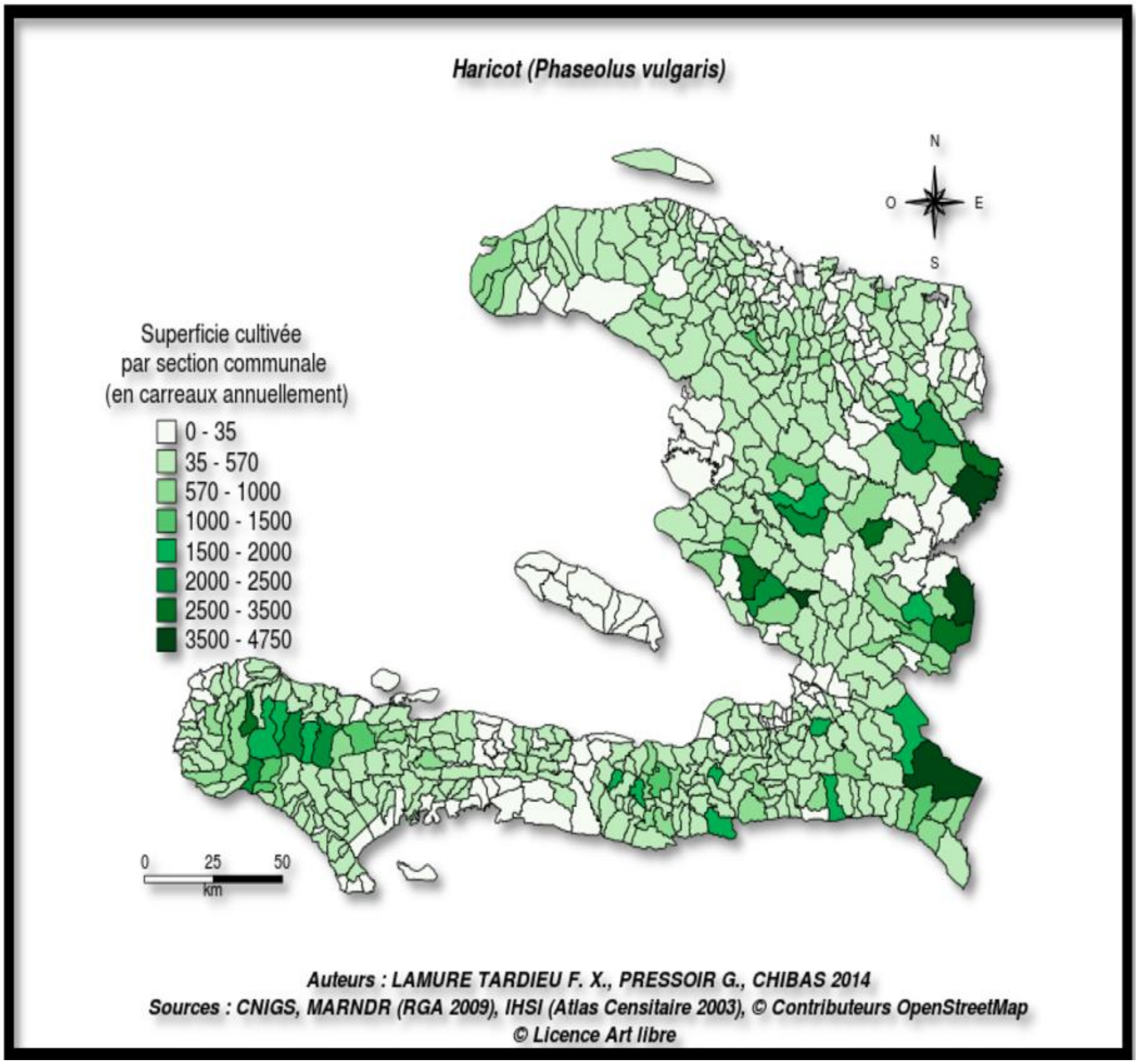

Figure 3-2. Harvested area in hectare for dry beans in Haiti. The areas from white to green varied from zero to 6128 ha. The greener the polygons are in this map, the denser the beans production is in that area.

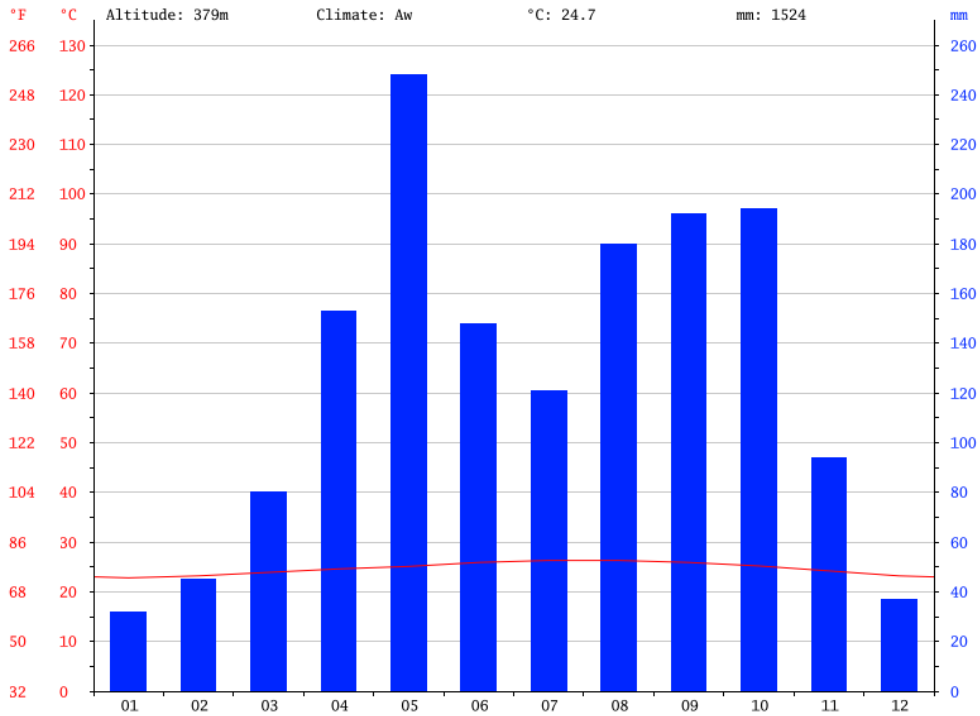

Figure 3-3. Monthly average precipitations in millimeters and temperatures in in Port-au-Prince. This follows the common precipitation trend of the whole country.

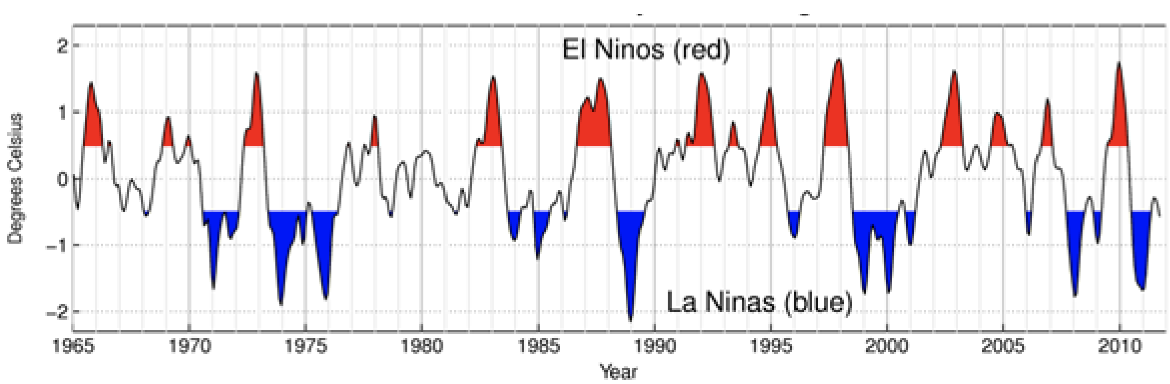

Figure 3-4. Oceanic Niño Index for the period 1985 to 2010

CHAPTER 4
RESULTS AND DISCUSSION

The results presented in this chapter were obtained from the simulations of the SIMPLE model. This model used weather variables such as daily minimum and maximum temperature, the solar radiation, and the daily total rainfall to output total biomass for each of the growing season and planting dates for dry beans. The yields were calculated by multiplying the total biomass by a harvest index. The daily total rainfall during each season has undergone analysis of variance to determine the significant difference in the means during a typical ENSO phase. Another analysis of variance was performed on the simulated yields to determine whether there was a considerable difference in the yields during a particular ENSO phase. Lastly, the simulated yields were ranked in descending order and according to the planting dates and were categorized with the quartiles to calculate the probability of particular planting date to fall in a category of yield (low, median, high).

Anova of Rainfall for All Growing Seasons during ENSO

The period considered for this analysis spanned from 1981 to 2017. During this period, 11 years fell into the category of the neutral ENSO phase, 12 as El Niño and 14 as La Niña. Among the 12 episodes of El Niño recorded, 3 of them namely 1982,1997 and 2015 were significant events. As for La Niña, there were five extreme events among the 14 episodes,1988,1998,1999, 2007, and 2010. Giannini et al. (2000) associated the warm ENSO phase (El Niño) with significantly dry conditions during the later Caribbean rainfall season, namely in August through November. However, the analysis of variance of the rainfall during the growing season that spanned the sowing dates from October 1st to October 22nd revealed no significant differences between

ENSO phases (Figure 4-12). A plausible explanation for that is the decline in the intensity of the Caribbean Low-Level Jet (CLLJ) (Schumacher et al. 2011).

For the sowing dates spanning the period of January 1st to January 12, there were 11 episodes of El Niño, among which four were considered very strong (1993,1998, 2015, 2016), nine for La Niña with one extreme event (1999) and 17 for Neutral. From January 29th to February 12th there were nine El Niño, seven La Niña and 21 Neutral. The rainfall was significantly lower during La Niña on January 1st, but not during the other planting dates (P-value>0.05) (Figure 4-11). According to Giannini et al. (2000) and Torres-Valcarcel (2018), the high intensity of the CLLJ dominated this period, which creates drier than normal conditions in late January and February. The influence of the CLLJ masked ENSO impact because the sample size for the ANOVA was too small.

During April season, there were nine episodes of El Niño (with five extreme events in 1982,1983,1998, 2015, 2016), six La Niña (one intense episode in 1999) and 22 Neutral for sowing dates of March 11th to March 25th. From April 1st to April 22nd there were eight episodes of El Niño, six La Niña and 23 Neutral events. The ANOVA indicated that La Niña rainfalls during the sowing dates of April 15 and 22 were significantly lower than the other ENSO phases (P-value<= 0.05) (Figure 4-13) (Giannini et al.,2000, Torres-Valcarcel 2018, Schumacher et al., 2011).

During the season of July, there were nine El Niño events (three were very strong,1982,1997, 2015), five La Niña (all of them were strong) and 23 Neutral for sowing dates of June 10th to June 24th. From July 1st to July 22nd eight El Niño events and nine La Niña were identified. El Niño years were significantly drier than La Niña years, especially on June 24th (P-value <= 0.05) (Figure 4-14). Usually, the July rainfall pattern, also known as the mid-summer drought, is typically exacerbated during El Niño or La Niña episodes according to Giannini et al. (2000), Schumacher et al. (2011) and Torres-Valcarcel (2018). A possible explanation for this is during July the combining effect of sea level pressure and the Caribbean Sea surface temperature anomalies result in low rainfall (C. Wang, 2007). Due to the small number of El Niño or La Niña events identified from 1981 to 2017 for this particular season, there were no significant differences in the mean of rainfall during the other planting dates.

Anova of Simulated Yields for the November Season

November season accounted for 12% of all the area harvested for dry black beans (Salagnac 90) grown in the country, in the lowland under irrigation management. However, in some locations in the highlands, farmers still grow dry beans to take advantage of the late rain season (August-November). It spans the period from November to March of the next year. Due to its length, this season was divided into two halves: October to December and January to March. For the first half of this season, yields were simulated for four planting dates: October 1^{st}, 8^{th},15^{th}, 22^{nd} starting from 1981 to 2017 (Figure 4-3 & 4-4).

Simulated planting dates were one week apart because weather conditions can vary rapidly and have a significant impact on the yield from one week to another. The dry beans yield simulation for the October 1st planting date started every time on the same date for the whole period of 1981-2017 (37 years). The analysis of variance of the simulated yields revealed no statistically significant differences in the yield

(P-value=0.49) during different ENSO phases. The long-term simulated average yield was 2070 kg/ha, with 54% of the yields surpassing that value.

The standard deviation from that mean was 253 kg/ha. Therefore the coefficient of variation (CV) is 0.12; which means that there was not much variation in simulated yields among years. The season that started on October 8th of every year did not differ much from the previous one. Although it consisted of the same number of Niño, Niña, and Neutral years, the long-term simulated average was 1876 kg/ha, which was not significantly different from the season that started on October 1st. Again, no particular ENSO phase was associated with statistically significant differences in the yield (P-value=0.26). The standard deviation of the yield was 339 kg/ha, which also shows there was not much variation among simulated yields (CV=0.18). The long-term simulated average yields for October 15th and 22nd were respectively 1614 and 1304 kg/ha. These two last planting dates displayed more variation between yields with a coefficient of variation 0.25 and 0.30 for October 15th and October 22nd planting dates, respectively. Although there was no statistically significant difference in the yields between ENSO phases (p-value=0.22) for October 15th and 22nd, a lot more variations in the yields from year to year could be seen in comparison to the other two previous planting dates (Figure 4-3 to 4-19). Even though there were no significant differences in yield during the October season for ENSO years, the long-term average decreased when the planting date starts at the beginning of November.

Anova of Simulated Yields for the January Season

Farmers growing dry beans during the second half of the long November through March season, usually have irrigation. It is almost impossible to grow dry beans in the mountainous regions during early January and February due to the dry climate that prevails (Torres-Valcarcel 2018, Schumacher et al.,2011). The simulation for planting date of January 1st resulted in lower yields when compared to the previous season.

The long-term simulated average of the yield was 626 kg/ha and coefficient of variation 0.55, which depicted a substantial change from year to year. There were no significant differences in the yield across ENSO phases (p-value=0.26) (Figures 4-5 to 4-6).

Anova of Simulated Yields for the April Season

Planting carried out during this season shared the 44% of the area harvested for dry beans with July season. This season is called "Spring season" or "Spring campaign." The SIMPLE model was run for seven planting dates with three of them starting before April 1st and three later than this date. The sowing dates for the simulations were March 11th, 18th, 25th, April 1st, 8th,15th, 22nd. There were no significant differences in the yields between the phases of ENSO and across the sowing dates (P-value>0.05), notwithstanding a difference from one year to another was noticed (Figure 4-7 to 4-8).

Anova of Simulated Yields for the July Season

This season is the second most prevalent season after April in terms of dry beans production in Haiti's mountainous regions. As rainfall in the summer can be highly unpredictable, starting the season early in June was not the right choice (Torres-Valcàrcel,2018). There were significant differences between simulated yields beginning on June 10th through July 22nd for different ENSO phases (P-value=0.05). During this season, simulated yields were lower during El Niño (Figure 4-9 to 4-10).

Yield Probability for All Years during the November Season

The simulated yields were divided into four quartiles. The first and the fourth quartile were respectively denominated as low and high; the second and third quartiles were denominated as median-low and median high respectively. The range of the simulated yields was 500 to 2700 kg/ha. Therefore simulated yields of 500 to less than 1000 kg/ha were considered as low yield, whereas 2000 to 2700 kg/ha were deemed to be high. These values were overestimated in the model when compared to the average actual yield observed in Haiti for dry beans, which is within the range of 600 kg/ha to 800 kg/ha. A season that started on October 1st had a 51% chance to result in the high yield category, and 35 % to be in median-high yield. Whereas, waiting until October 22nd to start the season is very risky since there was a 59% chance for the expected yield to fall in the low yield category, and a 30% chance to observe a median-low. The chances of high yield for that particular planting date were of only 3% (Figure 4-15).

Yield Probability for All Years during the January Season

The January season had the lowest simulated yields during the study. The simulated yields varied from 200 kg/ha to 2000 kg/ha. Therefore, low yields were within the range of 100 to 500, and high yields were between 1500 to 2000 kg/ha. Some sowing dates during the period of January to March were less favorable than others in terms of expected yields. For instance, January 1st is a risky date to start the season as there was a 43% chance to obtain a low yield and 38% to fall in the median low yield category. Thus, there was a combined 81% chance of below-median for this season when the season started on that particular date. Whereas, when the simulation started later, on February 12th, the combined likelihood for above-median yield was of 81% with

57% probability to harvest high yield and 24% to be in the median high yield category. Consequently, the favorable period to start the season and expect a somewhat high probability for higher yield was between January 29 and February 12th (Figure 4-16).

Yield Probability for All Years during the April Season

During the April season, simulated yields varied from 500 kg/ha to 3500 kg/ha. Low yields were within the range of 500 kg/ha to 800 kg/ha, and high yields were between 2000 to 3500 kg/ha. The categorization of simulated yields revealed that planting early in April was associated with a low probability of high yield. For instance, March 11th and 18th were the riskiest dates to start the season of dry beans. The chances of getting a low or median-low yield for March 11th were respectively 49 and 30%. During March 18th the odds for low yields or median-low yields were 38 and 28 %. If instead of starting the season on April 1st as it is customary, farmers wait until April 22nd, they might improve their odds and expect a 45% probability of high yield, and 22% probability of median-high yields (Figure 4-17).

Yield Probability for All Years during the July Season

The simulated yields varied from 75 kg/ha to 2700 kg/ha. Simulated yields during the strong El Niño in 2015 for all the planting dates were Meager. When it comes to deciding which sowing dates were riskiest, those that showed a significant response to ENSO phases had the highest probability for low and median low-yield. For instance, June 10th,17th, 24th and July 1st all had a chance greater or equal to 30 % to be in the small yield category, and 20% or above to be in the median-low group. Delaying the planting dates increased the probability to obtain a higher yield. Even on July 22nd, the likelihood for simulated yields to fall in the top category was above 50%. There was also a 28% chance for yields to fall in the low-median yield category (Figure 4-18).

Limitations of the Study

All the analyses in this study were conducted using the simulated yields of the SIMPLE model. Although the model helped to incorporate the effects of ENSO on the dry bean's yields, especially during the July season, there are several levels of uncertainty related to the input data, the model itself, and preset soil and crop parameters. Besides, the applicability of the results in Haiti socio-economic paradigm issues needs to be addressed to ensure reproducibility of the research. The first angle analyzed is the input data for the model. For this study, gridded temperature and solar radiation data at a spatial resolution of 0.25º from the CFSR, which roughly covers 27 km served as inputs for the model. The use of CFSR can pose a problem given Haiti's topography. Within a grid cell of size 27 km by 27 km, minimum temperature can vary rapidly as the mountain range tends to be cooler due to a higher elevation. Although a better spatial resolution for rainfall was used (CHIRPS (0.05º)), in a square of 5 km by 5 km, significant variability can occur in rains due to the ruggedness of the terrain and convective rainfall. The lack of actual data from on-site weather stations makes it impossible to test the accuracy of the gridded data.

Furthermore, climate, and especially rainfall, is not stationary (Milly et al., 2005). Previous atmospheric conditions do not necessarily; that is another source of uncertainty. Moreover, the choice of the ENSO index to associate with the growing season can lead to different results (Royce et al. 2011). In this study, the ONI index considered the tri-monthly anomalies of sea surface temperature (APPENDIX & Figure 3-4). Since the simulated growing seasons do not exceed three months, it was appropriate to select the ONI index as ENSO phase indicator for this research.

The SIMPLE model was calibrated for 14 crops using preset values of parameters obtained from the literature (Zhao et al., 2019). As mentioned earlier in chapter 3, the SIMPLE model has limitations. It does not consider the effect of fertilization (N, P), photoperiodicity, and diseases impact. Therefore, the model can significantly overestimate the yield. Besides, in Haiti and especially at the studied location (Duvier), the fertility of the soil is questionable since erosion episodes washed away a large part of the arable layer. Besides, bean golden mosaic virus (BGMV), rust and other fungi and bacterial diseases are ubiquitous in this zone and known to decrease the yield every season, especially in the absence of control measures. Other potential limitations are related to the water balance equations that the model uses to evaluate drought. The first issue pertains to the use of the equation of Priestley-Taylor to estimate the evapotranspiration (Sumner & Jacobs, 2005). For the sake of simplicity, and because lesser weather variables for calculation, the Priestley-Taylor equation fit in this context, but it can underestimate the actual evapotranspiration (Sumner & Jacobs, 2005). In this region, due to deforestation and slash-and-burn for agriculture, and low soil cover, evapotranspiration tends to be high. Other uncertainties are related to the use of the agricultural reference index for drought (ARID). ARID is a SIMPLE drought index used to evaluate agrarian drought (Woli et al., 2012). Since it uses the Priestley-Taylor equation for the evapotranspiration, the model might have underestimated the water stress impact. Another limitation of the model is that it does not take into consideration previous atmospheric conditions and soil moisture before the date the simulation starts. Lastly, due to the inexistence of yield records for dry beans in this region, the performance of the model could not be adequately evaluated.

Regardless of its limitations, the model has proven useful in providing information about ENSO impacts on the growing seasons, and also about which planting windows are riskiest to start the season for dry beans. Notwithstanding, crop model simulations can only help with climate impact. In Haiti socio-economic context, the climate is not the only potential limitation to dry beans production. Also, planting recommendations based on the model outputs will have to face socio-cultural challenges to be accepted by farmers. Haitian farmers are very conservative and traditional about agricultural practices. The best way to convince them that the model works is through demonstration parcels. The extension agent would have to conduct field experiments and show evidence that yield improvements are due to the application of model outputs. Aside from climate impacts, farmers in Haiti have to deal with poor seed quality, low soil fertility, lack of adapted cultivar, limited access to irrigation water and subsidies or microloans. According to Shields (2002), the most impoverished farmer would make an effort to acquire improved seeds, if they were available on the market, to enhance dry beans production. Even though the model effectiveness convinced them, government policy would have to be set in motion to help them with the acquisition of improved seeds, with irrigation and fertilizers. That way, a significant amelioration in dry beans production and a decrease in food insecurity would be expected. Further research that would take into consideration all the limitations about data input, stationarity, the model core subroutines, and the socio-economic aspect for applicability of findings are advised to develop practical tools and help Haitian farmers adapt to climate variability.

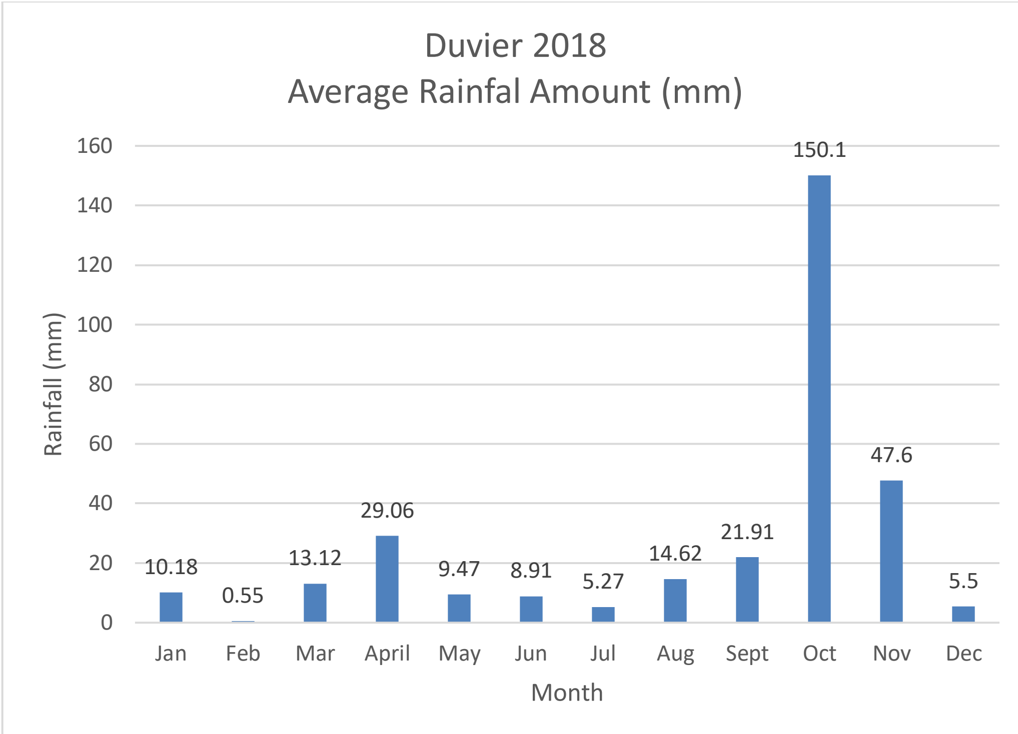

Figure 4-1. Monthly precipitation for Duvier in 2018

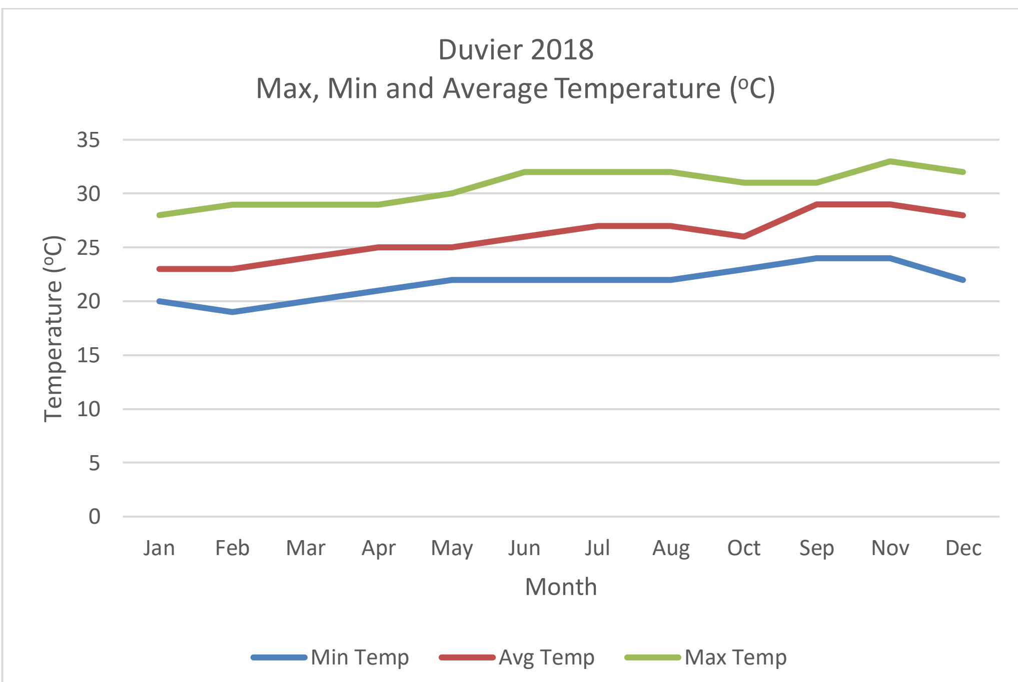

Figure 4-2. Monthly temperature in Celsius for Duvier in 2018

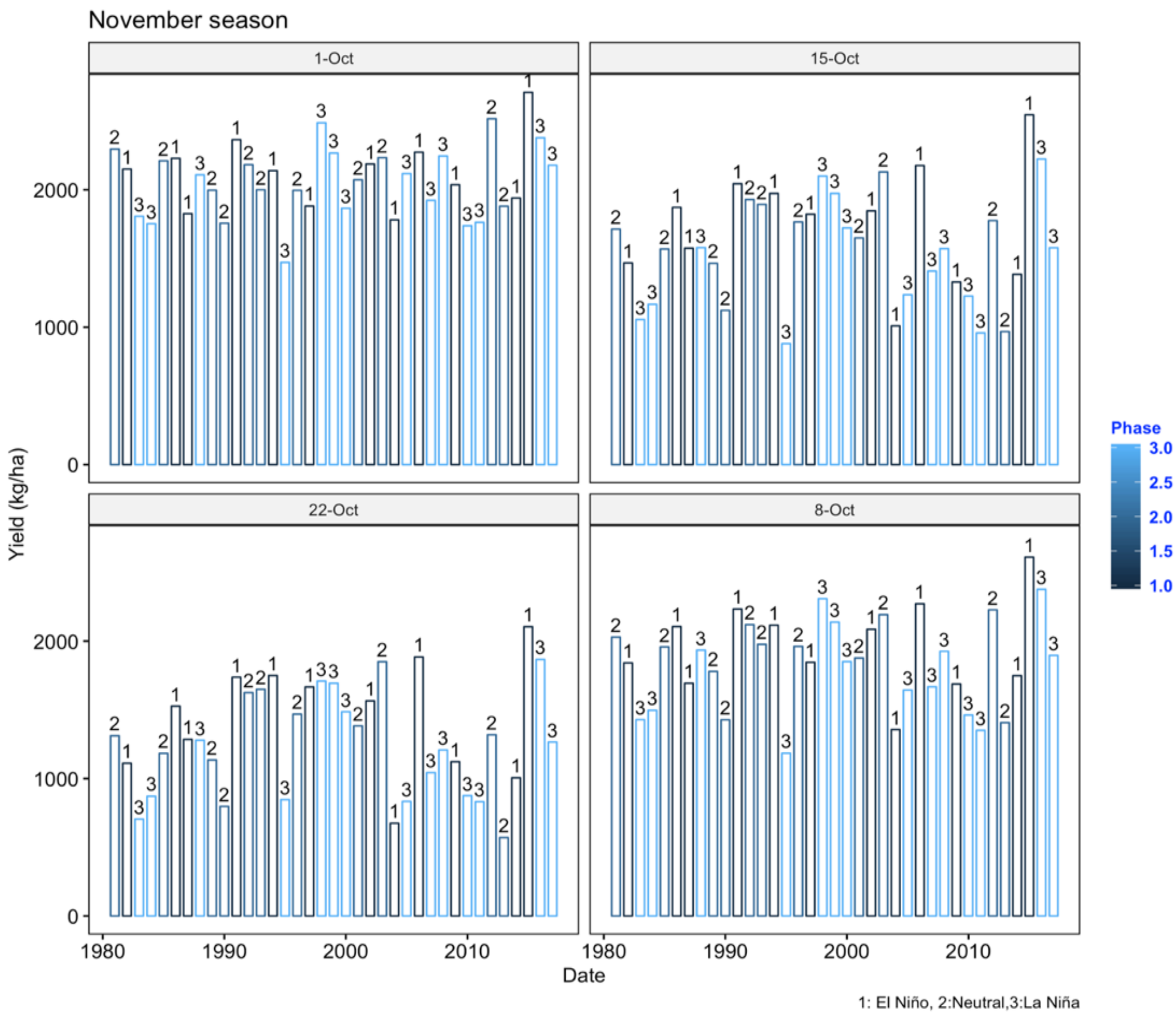

Figure 4-3. Simulated yields for October/November season during El Niño (1), La Niña (3), and Neutral years (2)

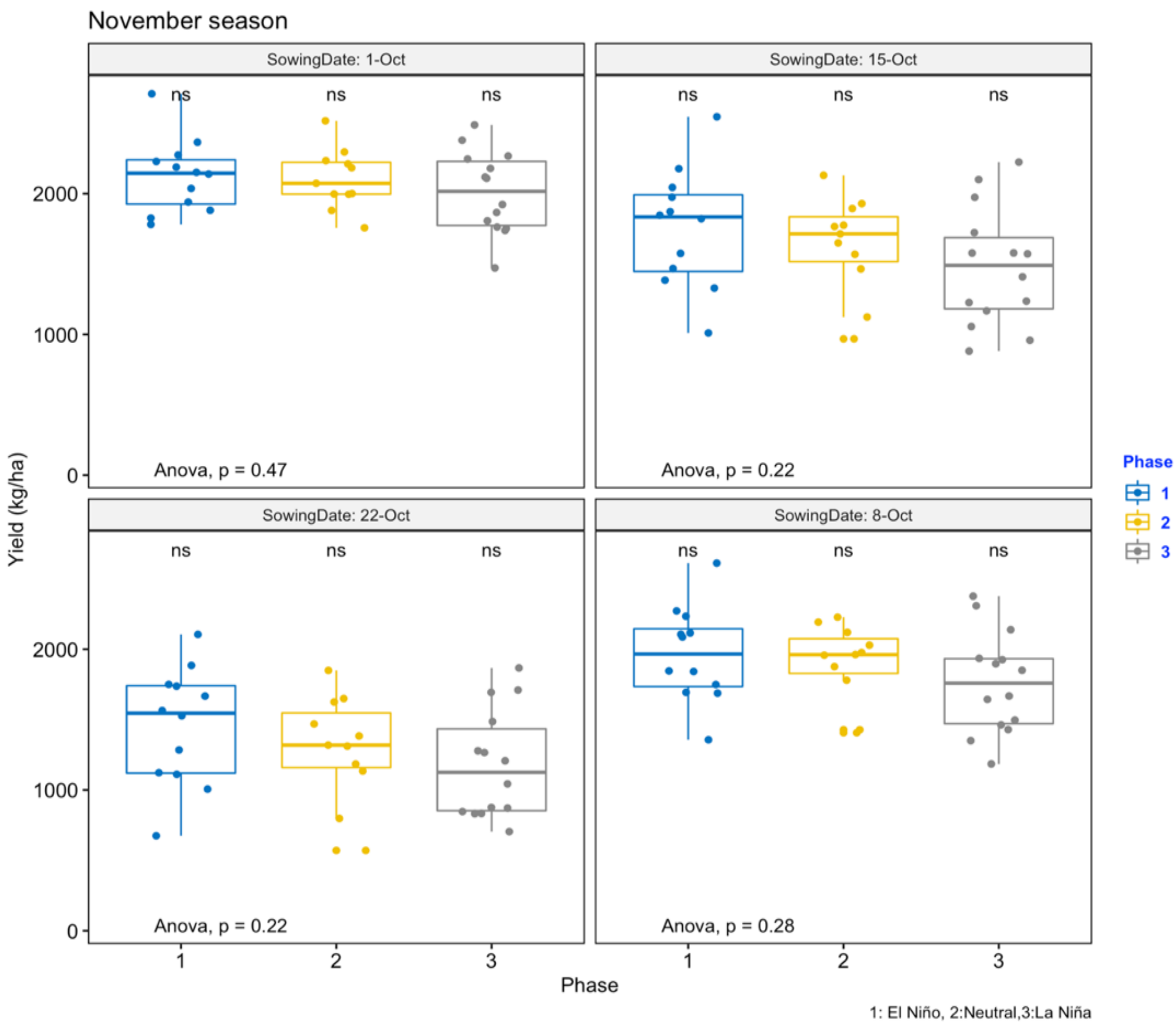

Figure 4-4. Anova of the simulated yields during October/November season during El Niño (1), La Niña (3), and Neutral years (2)

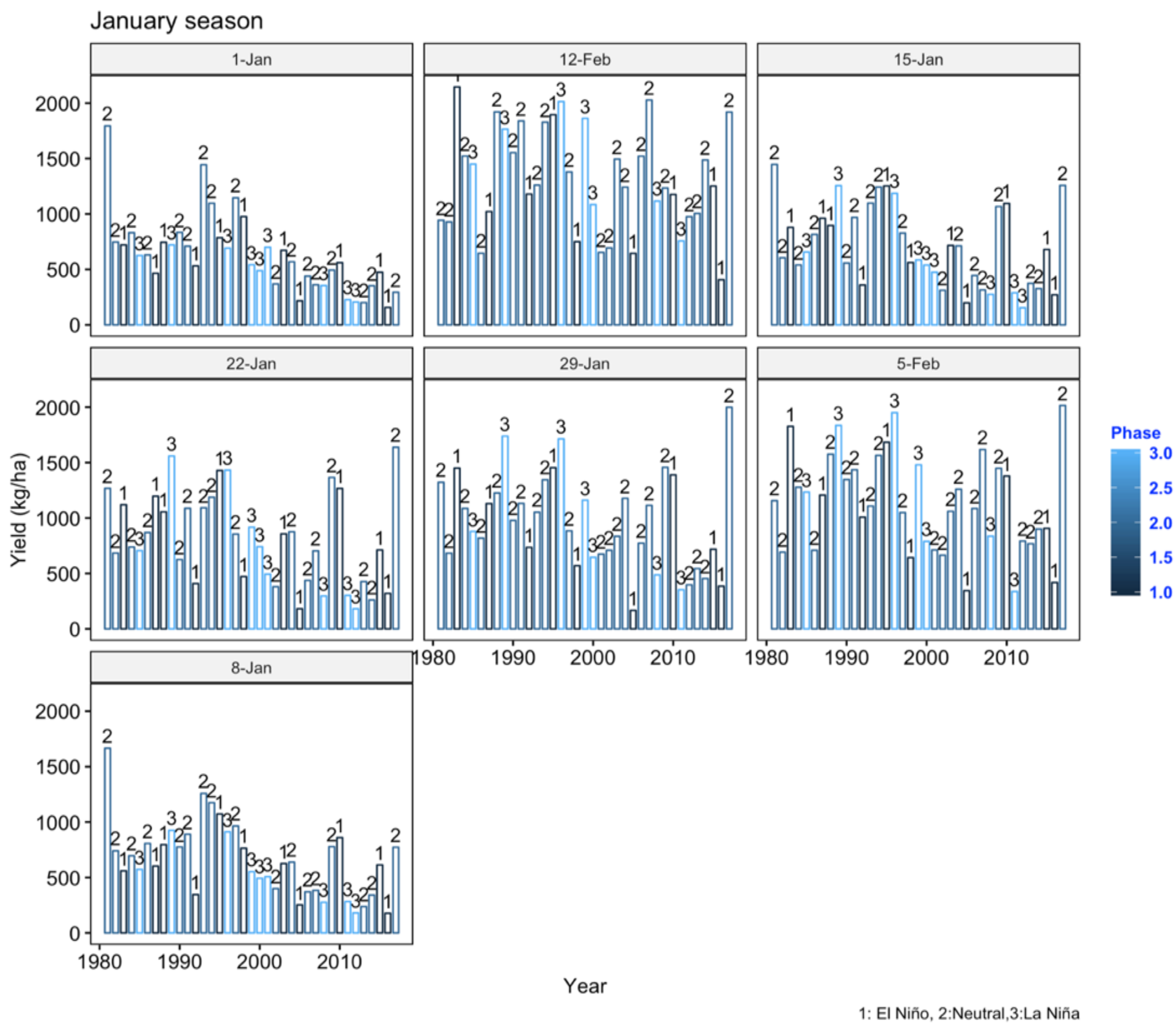

Figure 4-5. Simulated yields for January season during El Niño (1), La Niña (3), and Neutral years (2)

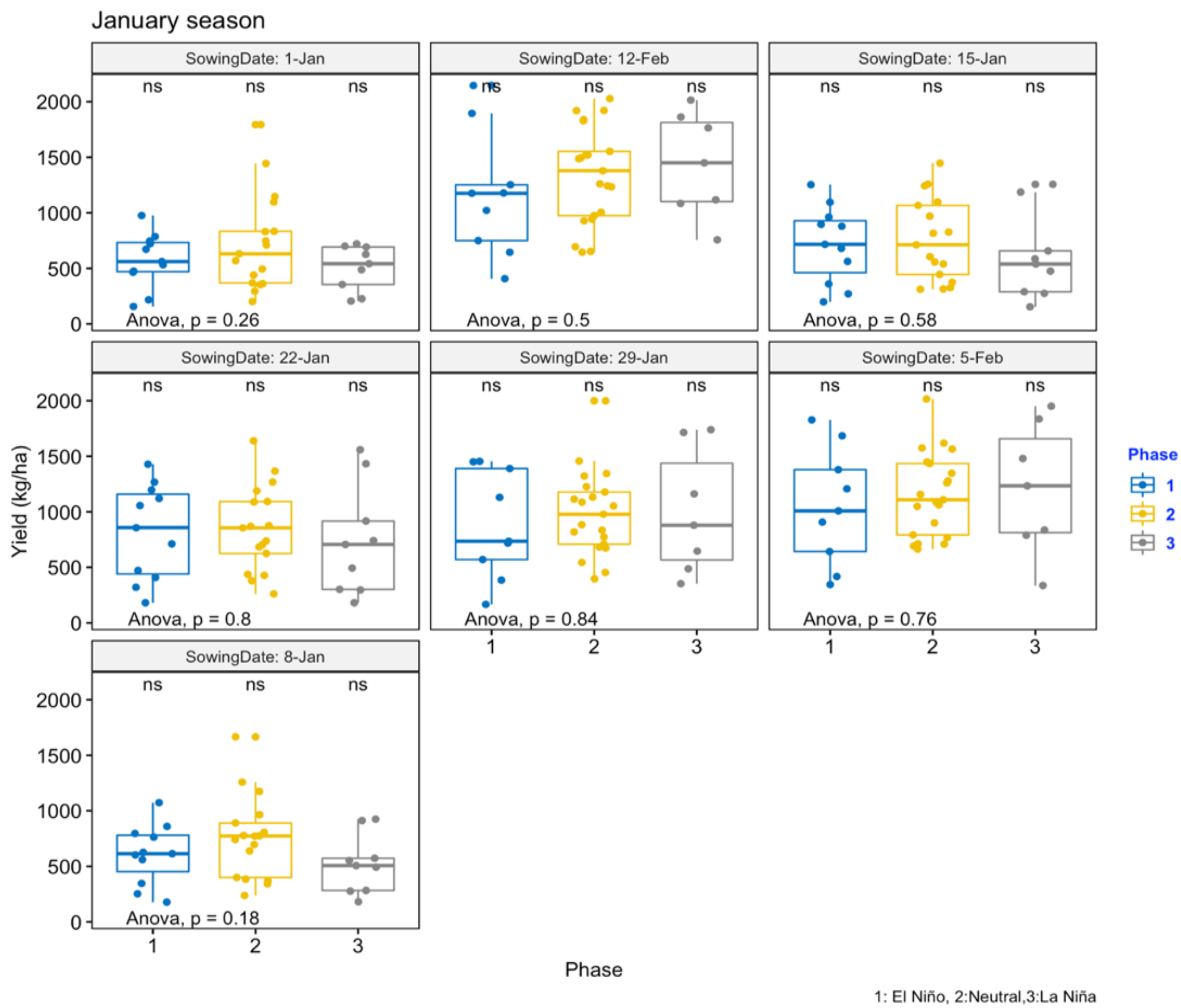

Figure 4-6. Anova for simulated yields for January season during El Niño (1), La Niña (3), and Neutral years (2)

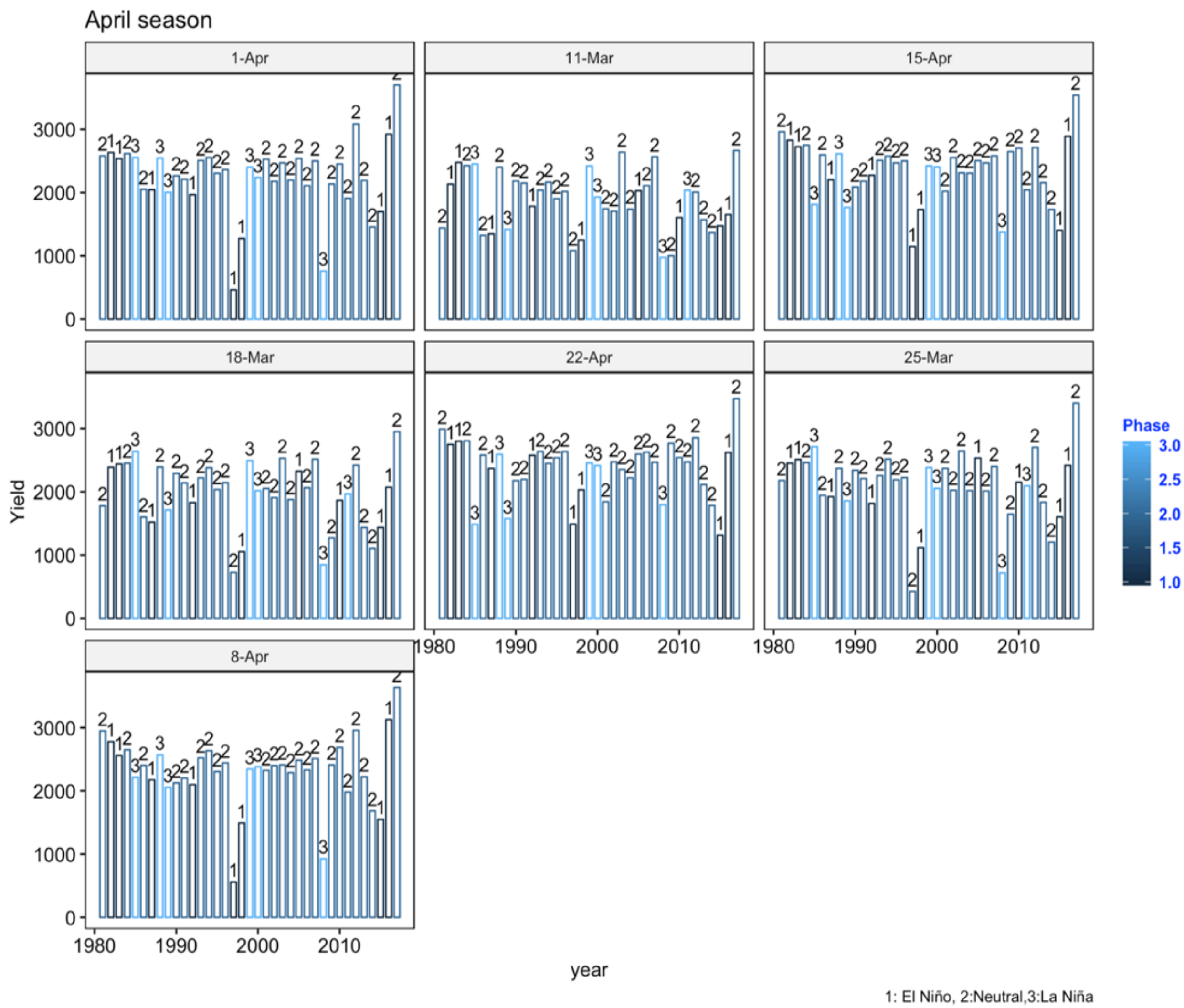

Figure 4-7. Simulated yields for April season during El Niño (1), La Niña (3), and Neutral years (2)

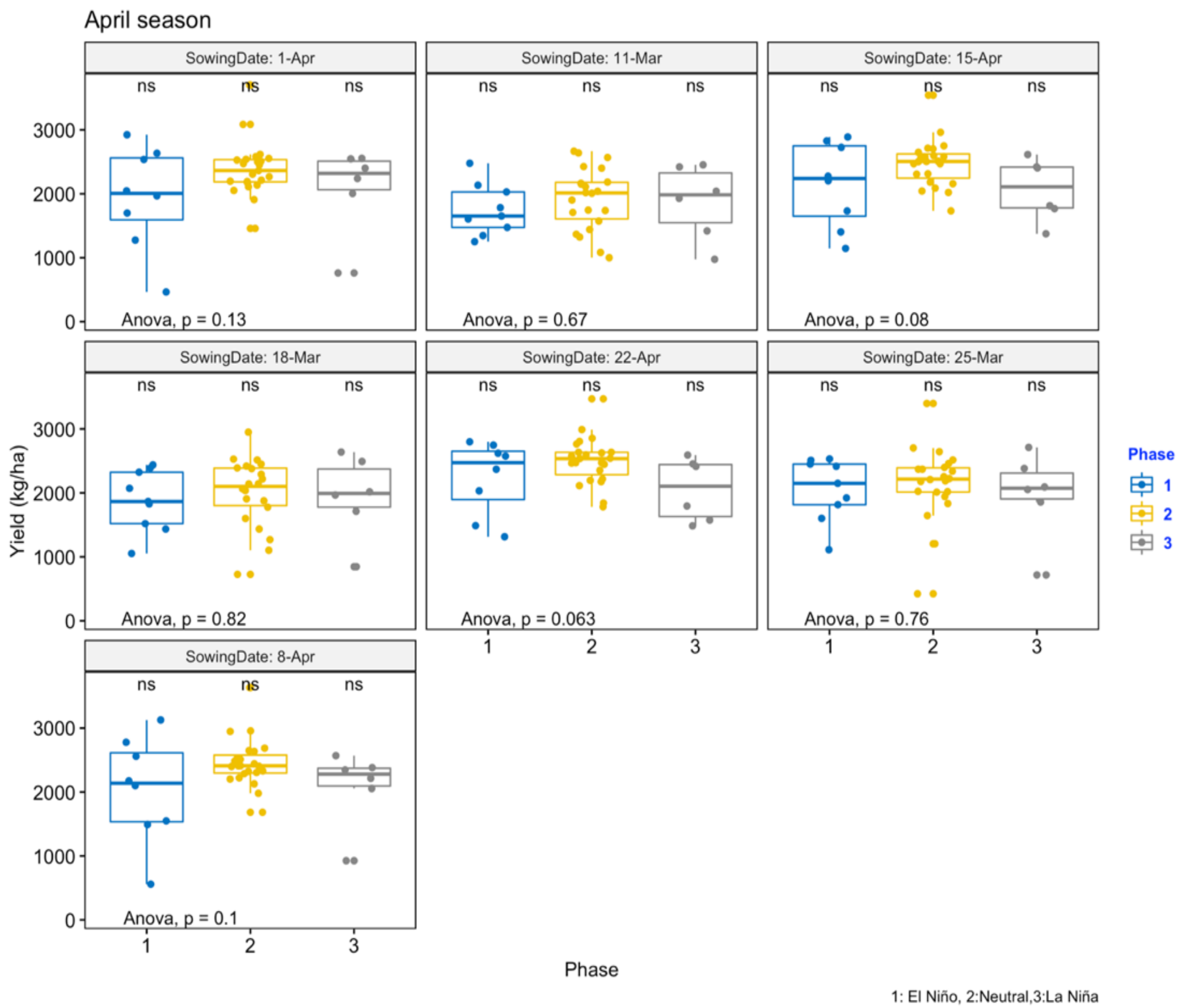

Figure 4-8. Anova of simulated yields for April season during El Niño (1), La Niña (3), and Neutral years (2)

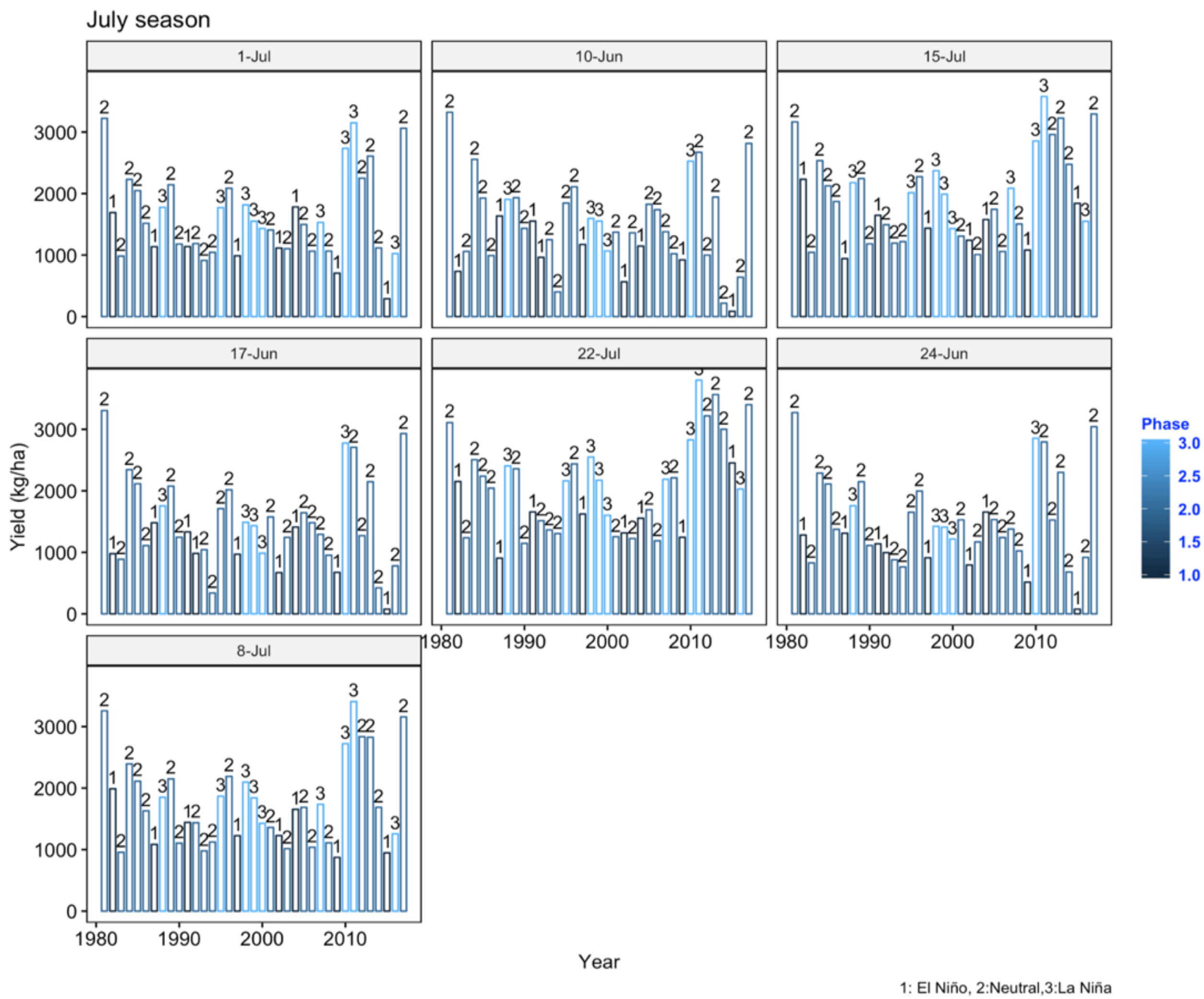

Figure 4-9. Simulated yields for July season during El Niño (1), La Niña (3), and Neutral years (2)

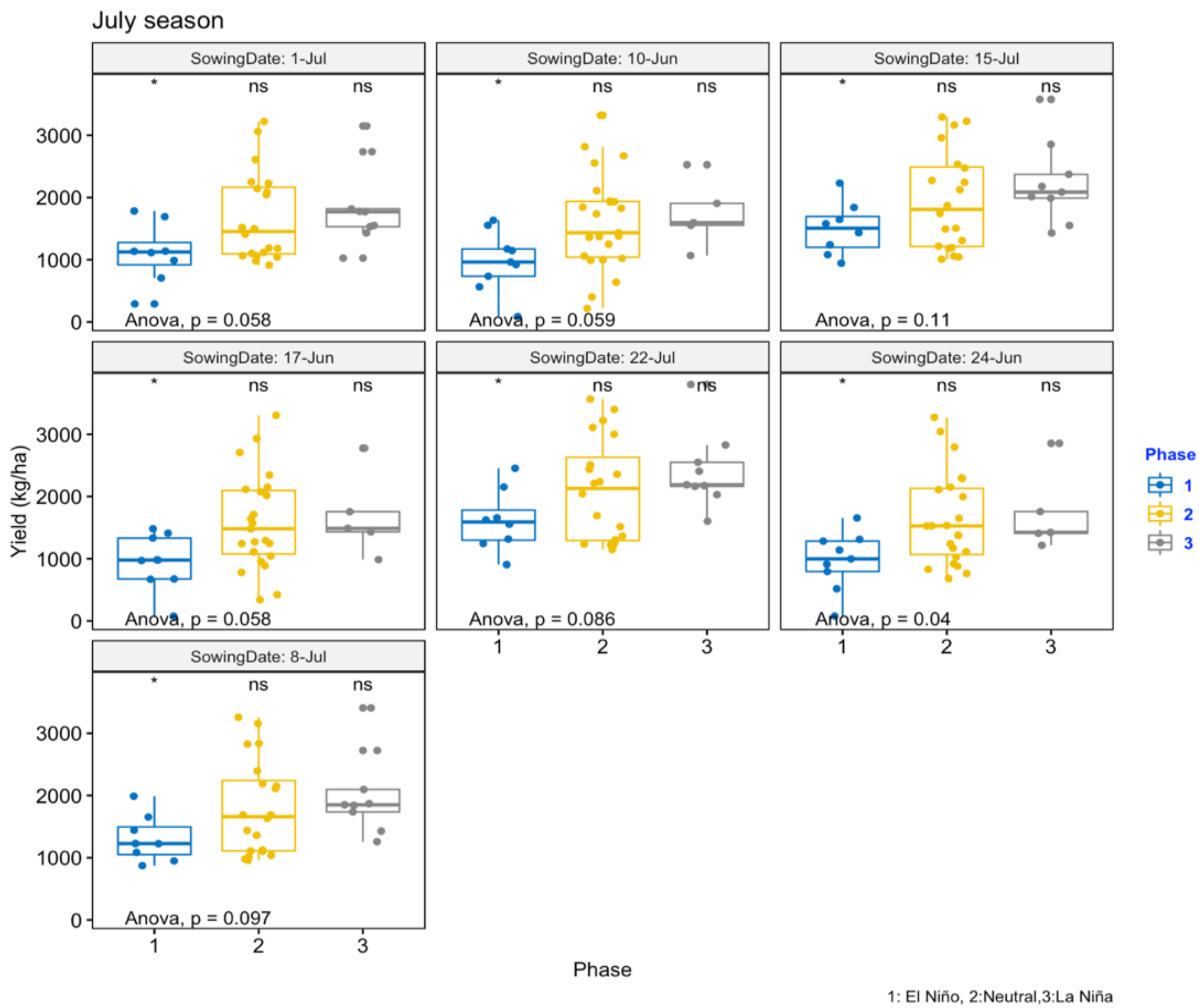

Figure 4-10. Anova of the simulated yields for July during El Niño (1), La Niña (3), and Neutral years (2)

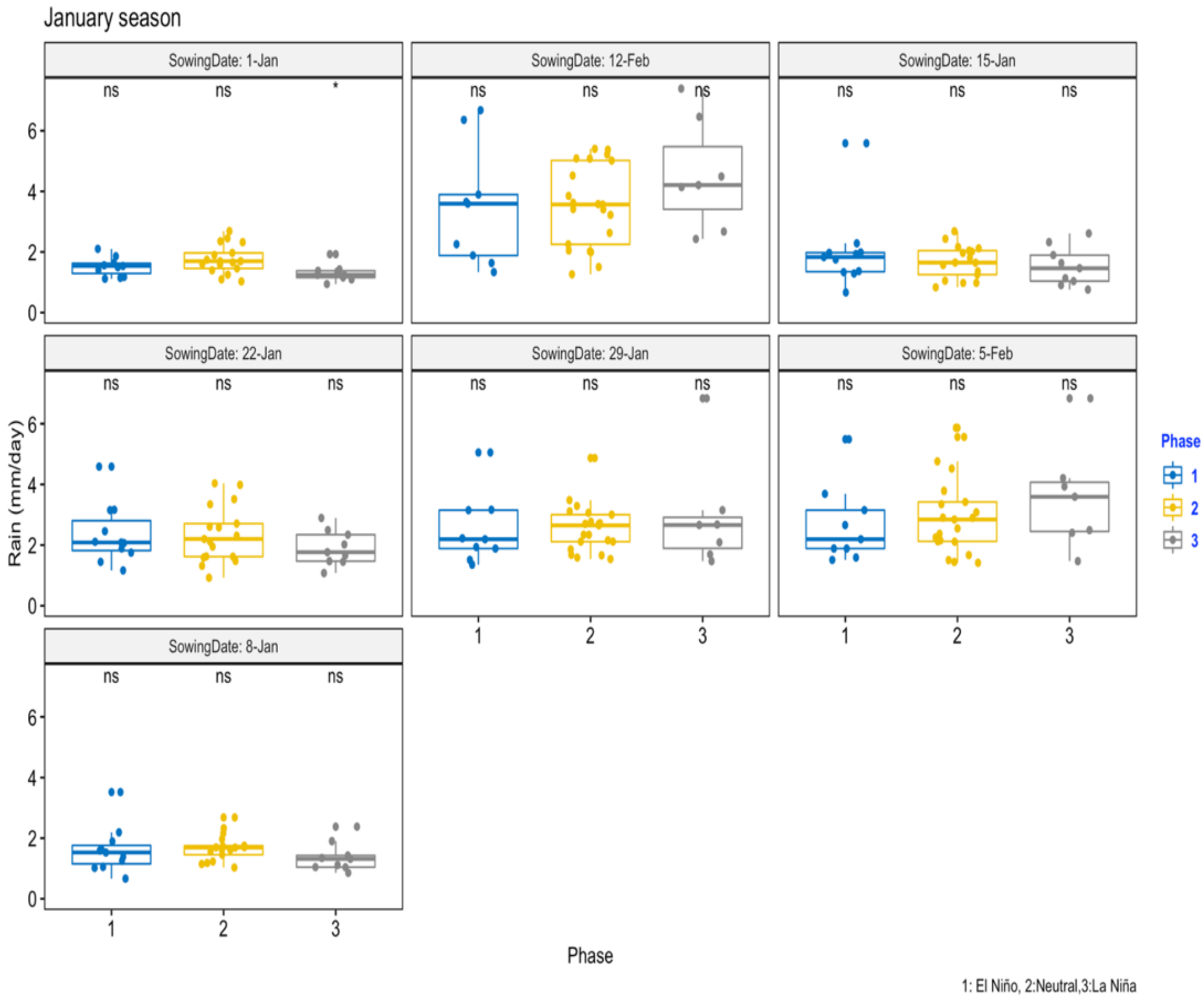

Figure 4-11. Anova of rainfall during January season for El Niño (1), La Niña (3), and Neutral years (2)

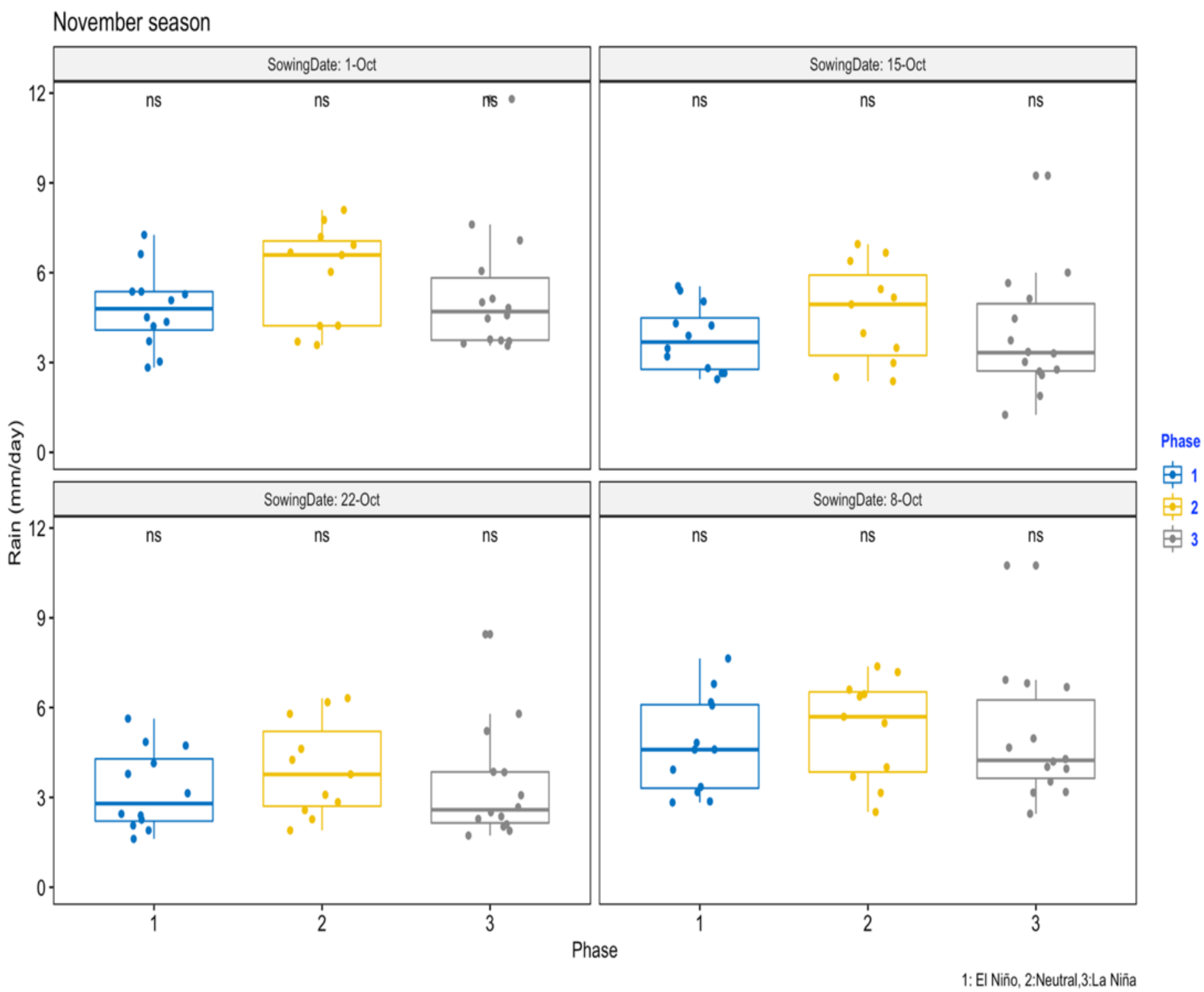

Figure 4-12. Anova of rainfall during October/November season for El Niño (1), Neutral (2), La Niña (3) phases

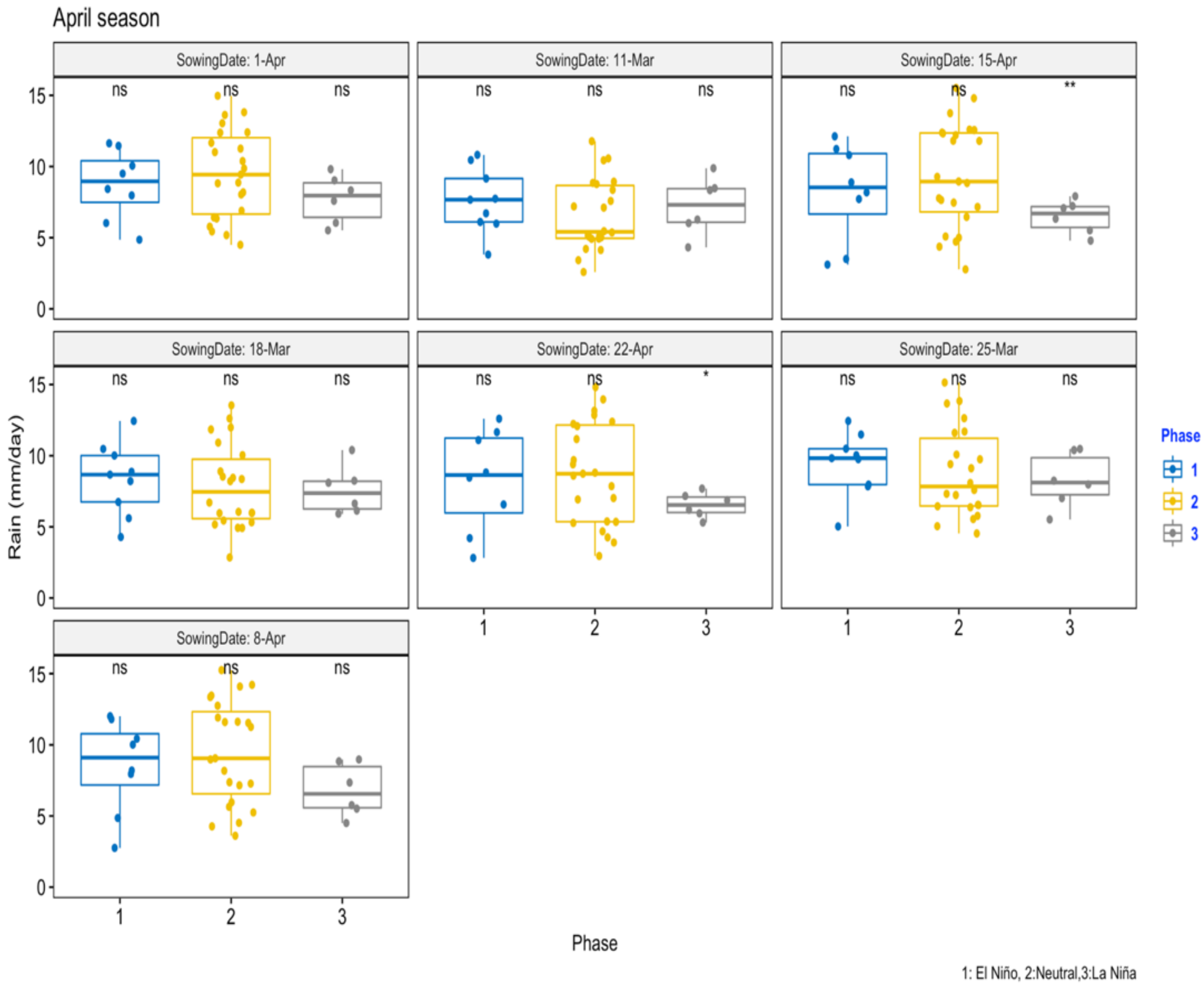

Figure 4-13. Anova of rainfall during April season for El Niño (1), La Niña (3), and Neutral phases (2)

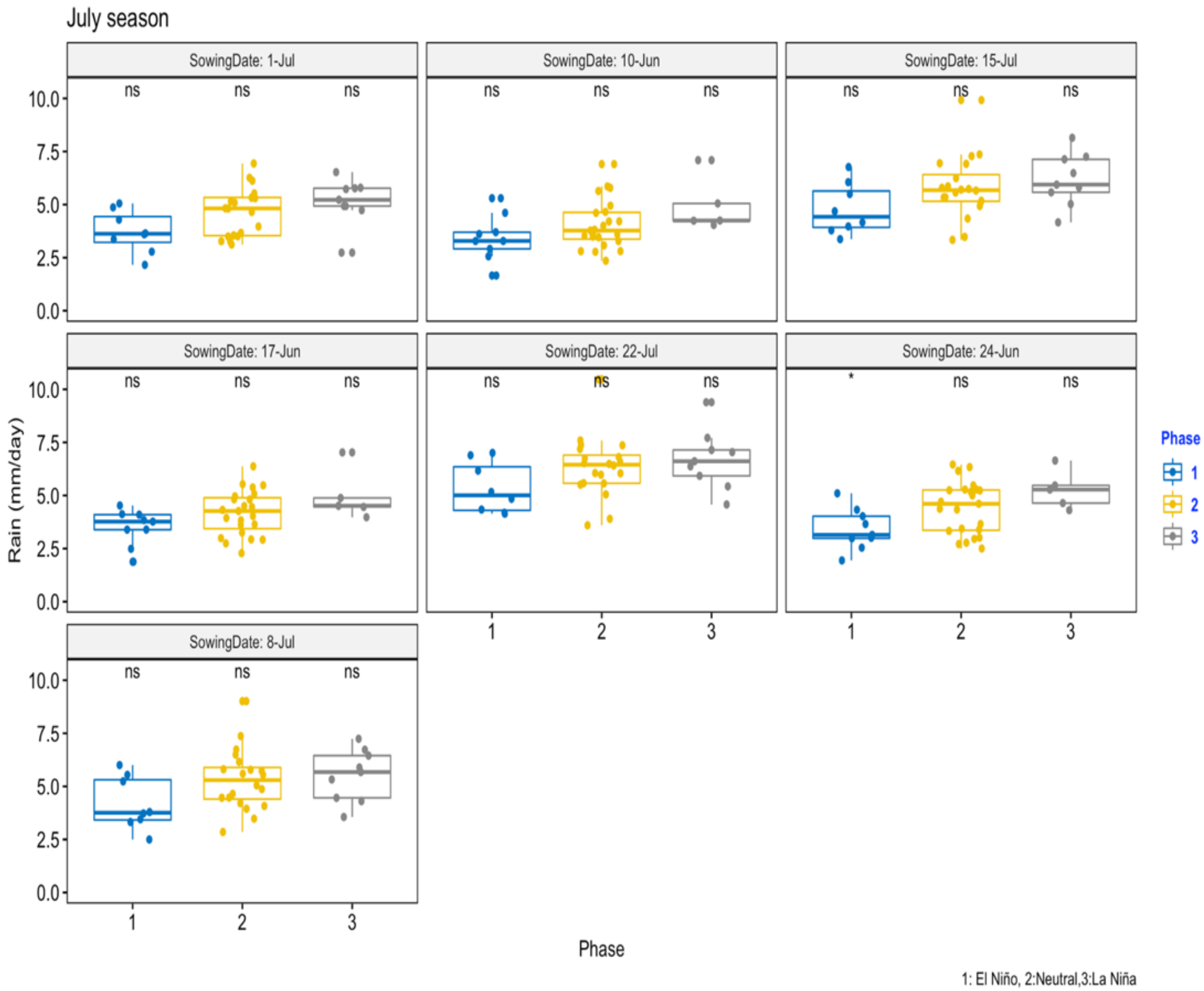

Figure 4-14. Anova of rainfall during July season for El Niño (1), La Niña (3), and Neutral (2) phases

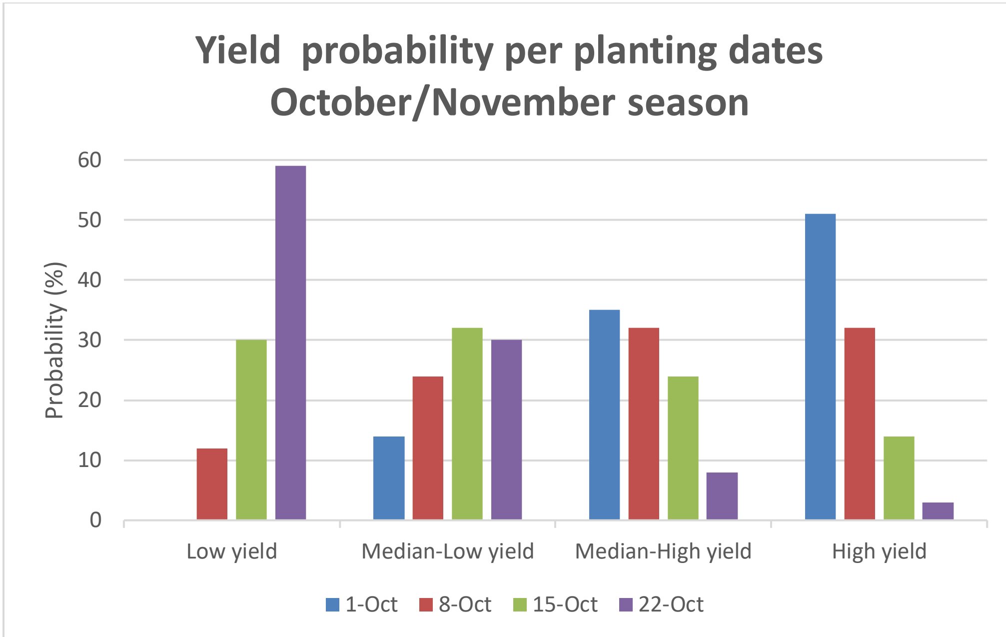

Figure 4-15. Yield Probability per category with respect to planting dates in October/ November season from October 1 to October 22. The probabilities are calculated using ranked simulated yields and categorized according to the quartiles

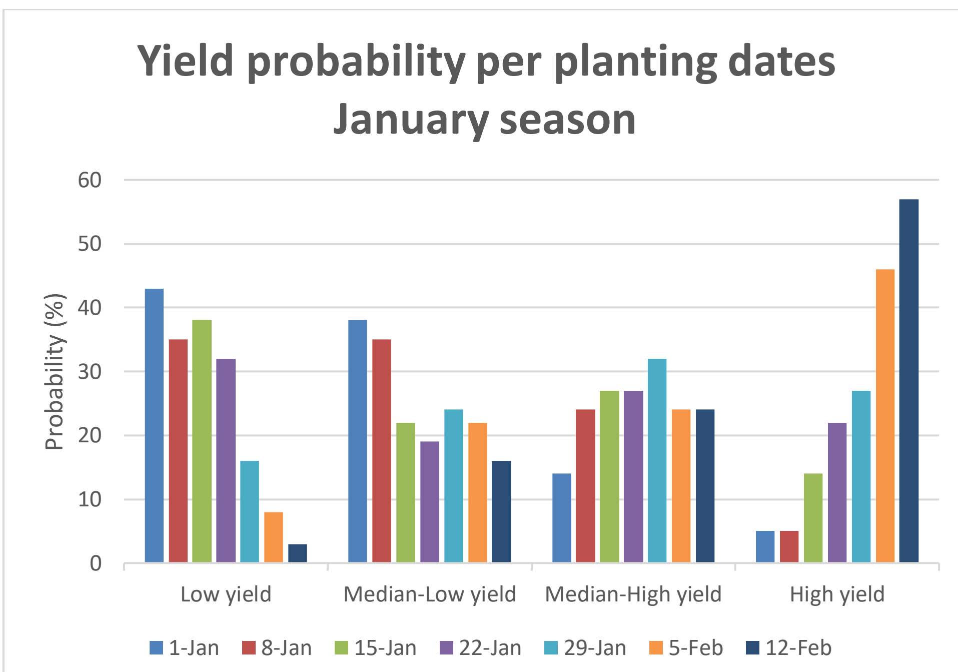

Figure 4-16. Yield Probability per category with respect to planting dates in January season from January 1 to February 12

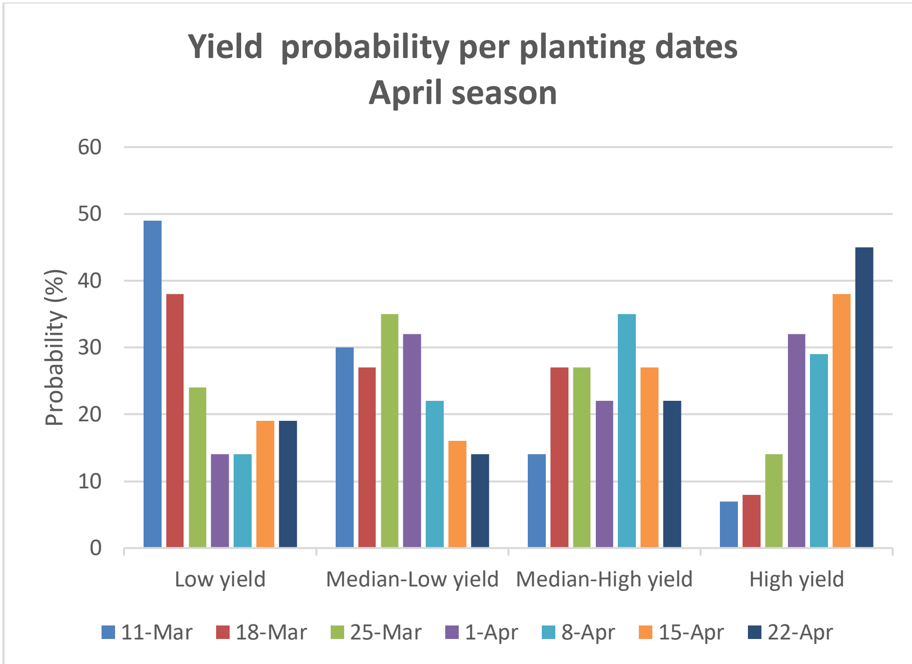

Figure 4-17. Yield Probability per category with respect to planting dates in April from March 11 to April 22

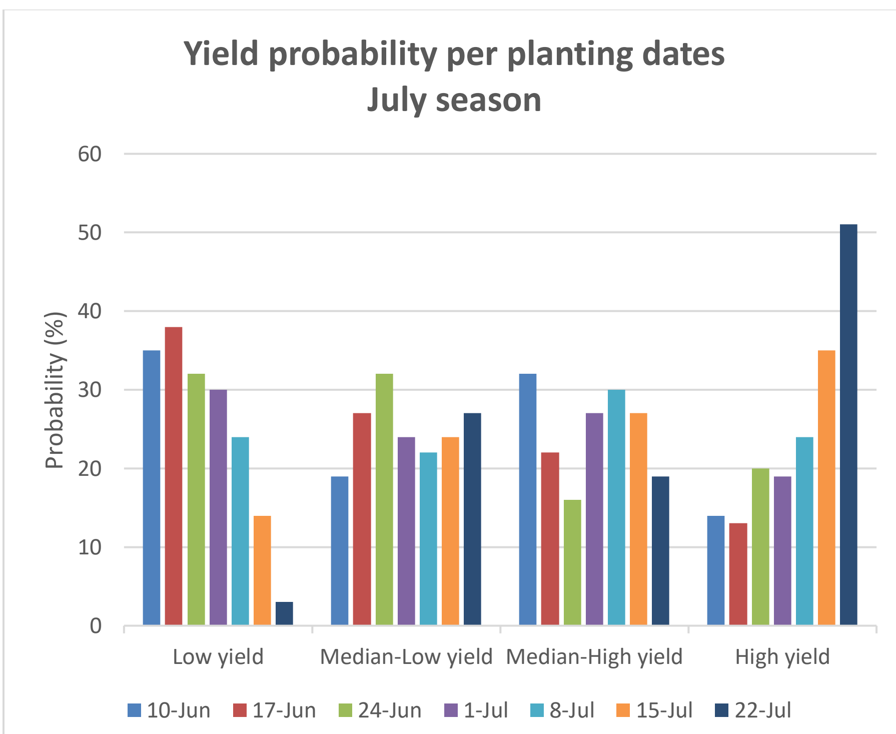

Figure 4-18. Yield Probability per category with respect the planting dates in July season

El Niño				La Niña		
Weak - 11	Moderate - 7	Strong - 5	Very Strong - 3	Weak - 10	Moderate - 4	Strong - 7
1952-53	1951-52	1957-58	1982-83	1954-55	1955-56	1973-74
1953-54	1963-64	1965-66	1997-98	1964-65	1970-71	1975-76
1958-59	1968-69	1972-73	2015-16	1971-72	1995-96	1988-89
1969-70	1986-87	1987-88		1974-75	2011-12	1998-99
1976-77	1994-95	1991-92		1983-84		1999-00
1977-78	2002-03			1984-85		2007-08
1979-80	2009-10			2000-01		2010-11
2004-05				2005-06		
2006-07				2008-09		
2014-15				2016-17		
2018-19				2017-18		

Figure 4-19. Intensity of ENSO phases from 1952 to 2018 according to the classification of NOAA

CHAPTER 5
CONCLUSION

Crop models are essential tools to capture the impact of climate variability and change on farming. They are sometimes an alternative for on-field experiments which can be tedious, and cost-ineffective when detecting climate effects over a long period. Therefore, with the proper calibration and enough historic data, models can predict with an acceptable level of accuracy the yields of crops under different climate scenarios. SIMPLE has been calibrated and tested for several plants in the United States but was not for Haiti due to a lack of actual historical yield records for dry beans, especially for specific growing seasons. Consequently, the performance of the model could not be tested against observed yields.

Moreover, since the model does not take into account the impact of pests and diseases and fertilizers intake, it is bound to overestimate crop yield in a given season. Nevertheless, it provided valuable insight regarding the response of dry bean yields to the ENSO cycle based on the planting dates of a particular growing season. The hypothesis, stated at the beginning, that all seasons for dry beans production in Haiti are affected by the ENSO cycle was rejected. In fact, among the four seasons, namely January, April, July and November, only July showed a significant impact of the phases of ENSO on dry bean yield. However, the effect decays when the simulations run during later sowing dates. During the other seasons, although there are visible differences between simulated yields from one phase to another, they are not statistically significant, and it is difficult to know whether it was mere luck. The simulation results have revealed that planting early during the July season, during the first three weeks in June, would dramatically impact the expected yield. The same scenario is also noticed for January and April, in which simulated yields drop for early planting dates. Whereas, planting early during November is much more beneficial as simulated yields are more likely to be in the high category.

These are valuable information that a farmer and decision-makers in Haiti can benefit from, given the fact that sowing date is a crucial decision in farming. Knowing which season can be affected by ENSO is highly advantageous in developing adaptation strategies to cope with climate variability and devise policies that are effective and efficient to increase the probability for higher yield over the seasons. Moreover, when farmers know ahead of time which sowing window can offer an increased likelihood for higher yields, they can decrease chances for low yields and increase profits by investing more and optimizing operations during the favorable seasons. This study is a first milestone to help farmers in Haiti better strategize their dry beans growing seasons. Previous research focused more on the effect of ENSO on rainfall in the Caribbean, but not on its impact on crop yields. More research is needed on the effects of ENSO on dry beans, to help foster better agricultural practices, and curtail food insecurity.

APPENDIX
RUNNING 3-MONTH MEAN ONI VALUES

ENSO Type	Season			JJA	JAS	ASO	SON	OND	NDJ	DJF	JFM	FMA	MAM	AMJ	MJJ
	1981	-	1982	-0.3	-0.2	-0.2	-0.4	-0.6	-0.8	-0.8	-0.5	-0.2	0.2	0.4	0.6
VSE	1982	-	1983	0.8	1.1	1.6	1.2	1.0	0.8	0.5	0.4	0.3	0.3	0.2	0.0
WL	1983	-	1984	0.3	-0.1	-0.5	0.1	0.0	0.1	0.4	0.6	0.6	0.7	0.8	0.8
WL	1984	-	1985	-0.3	-0.2	-0.2	0.8	0.8	0.8	0.8	0.5	0.0	-0.4	-0.5	-0.5
	1985	-	1986	-0.5	-0.5	-0.4	-0.8	-0.7	-0.7	-0.7	-0.6	-0.7	-0.8	-0.8	-0.7
ME	1986	-	1987	0.2	0.4	0.7	-1.4	-1.7	-1.5	-1.1	-0.8	-0.6	-0.5	-0.5	-0.5
SE	1987	-	1988	1.5	1.7	1.6	-0.4	-0.4	-0.4	-0.2	0.1	0.4	0.7	0.9	1.1
SL	1988	-	1989	-1.3	-1.1	-1.2	1.4	1.5	1.7	1.8	1.7	1.3	0.9	0.7	0.6
	1989	-	1990	-0.3	-0.3	-0.2	0.4	0.5	0.6	0.6	0.6	0.5	0.3	0.2	-0.1
	1990	-	1991	0.3	0.4	0.4	0.0	0.0	0.0	-0.1	-0.1	-0.1	0.0	0.0	0.0
SE	1991	-	1992	0.7	0.6	0.6	0.2	0.1	0.1	0.0	0.0	0.0	0.1	0.2	0.3
	1992	-	1993	0.4	0.1	-0.1	-0.3	-0.2	-0.2	-0.2	-0.2	-0.2	-0.3	-0.3	-0.2
	1993	-	1994	0.3	0.3	0.2	-0.2	-0.3	-0.4	-0.4	-0.2	0.2	0.3	0.3	0.5
ME	1994	-	1995	0.4	0.4	0.6	1.3	1.4	1.3	1.1	0.6	0.1	-0.3	-0.6	-0.6
ML	1995	-	1996	-0.2	-0.5	-0.8	-0.8	-0.8	-0.8	-0.6	-0.3	-0.1	0.2	0.5	0.8
	1996	-	1997	-0.3	-0.3	-0.4	2.0	2.0	1.7	1.4	1.2	1.0	0.7	0.4	0.2
VSE	1997	-	1998	1.6	1.9	2.1	-0.1	-0.2	-0.3	-0.4	-0.5	-0.5	-0.4	-0.2	0.0
SL	1998	-	1999	-0.8	-1.1	-1.3	-0.4	-0.3	-0.4	-0.6	-0.7	-0.6	-0.4	0.0	0.3
SL	1999	-	2000	-1.1	-1.1	-1.2	0.5	0.7	1.0	1.1	1.1	0.9	0.8	0.6	0.4
WL	2000	-	2001	-0.6	-0.5	-0.5	0.9	0.8	0.6	0.5	0.3	0.3	0.2	0.0	-0.3
	2001	-	2002	-0.1	-0.1	-0.2	-0.7	-0.9	-1.1	-1.4	-1.4	-1.1	-0.8	-0.7	-0.7
ME	2002	-	2003	0.8	0.9	1.0	-0.9	-1.0	-0.9	-0.7	-0.4	0.1	0.4	0.7	0.9
	2003	-	2004	0.1	0.2	0.3	1.8	2.1	2.1	1.8	1.2	0.5	-0.1	-0.5	-0.9
WE	2004	-	2005	0.5	0.6	0.7	-1.7	-1.9	-2.0	-1.8	-1.6	-1.2	-1.0	-0.9	-0.8
WL	2005	-	2006	-0.1	-0.1	-0.1	-0.6	-0.8	-0.6	-0.5	-0.6	-0.7	-0.7	-0.8	-1.0
WE	2006	-	2007	0.1	0.3	0.5	-1.4	-1.6	-1.7	-1.6	-1.2	-0.7	-0.5	-0.3	0.0
SL	2007	-	2008	-0.5	-0.8	-1.1	0.8	0.9	0.8	0.7	0.6	0.3	0.2	0.2	0.3
WL	2008	-	2009	-0.4	-0.3	-0.3	0.7	0.8	0.8	0.7	0.4	0.1	-0.2	-0.3	-0.3
ME	2009	-	2010	0.5	0.5	0.7	-0.3	-0.1	0.0	0.0	0.1	0.2	0.3	0.2	0.0
SL	2010	-	2011	-1.0	-1.4	-1.6	0.5	0.5	0.6	0.6	0.5	0.3	0.4	0.5	0.5
ML	2011	-	2012	-0.5	-0.7	-0.9	0.0	0.1	0.0	-0.3	-0.5	-0.5	-0.4	-0.3	-0.3
	2012	-	2013	0.3	0.3	0.3	-0.1	-0.2	-0.1	0.0	0.1	0.2	0.5	0.7	0.7
	2013	-	2014	-0.4	-0.4	-0.3	2.0	2.2	2.2	2.2	1.9	1.5	1.3	1.1	0.7
WE	2014	-	2015	0.1	0.0	0.2	-0.8	-1.0	-0.9	-0.6	-0.4	-0.3	-0.4	-0.5	-0.4
VSE	2015	-	2016	1.5	1.8	2.1	-0.6	-0.9	-1.1	-1.0	-0.8	-0.8	-0.8	-0.8	-0.6
WL	2016	-	2017	-0.3	-0.6	-0.7	-0.3	-0.3	-0.4	-0.5	-0.5	-0.3	-0.2	-0.1	0.0
WL	2017	-	2018	0.2	-0.1	-0.4	0.9	1.1	1.2	1.2	1.2	1.1	0.9	1.0	1.2
WE	2018	-	2019	0.1	0.2	0.4	1.5	1.3	1.1	0.8	0.5	0.1	-0.3	-0.9	-1.3

WE=Weak El Niño, ME=Moderate El Niño, SE=Strong El Niño, VSE=Very Strong El Niño
WL=Weak La Niña, ML=Moderate La Niña, SL=Strong La Niña

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BIOGRAPHICAL SKETCH

Josue St Fort was born in 1989, in Port-au-Prince, Haiti. He earned a bachelor's degree at the State University of Haiti, from the college of agriculture and veterinary medicine in 2015. After his graduation, Josue worked for two years at the ministry of agriculture as a rural engineer. He was responsible for the construction of dams across several ravines to reduce erosion on the watersheds. In 2017, he got a scholarship to pursue a master's degree in agricultural and biological engineering, with a focus on geographic information systems (GIS) and climatology.