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by

Sanne Glastra

Rachel Hall-Clifford
Co-Adviser

Seunghwa Rho
Co-Adviser

Quantitative Sciences

Rachel Hall-Clifford

Co-Adviser

Seunghwa Rho

Co-Adviser

George Luber

Committee Member

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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
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Abstract

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In Guatemala, malnutrition prevalence rates are among the highest in Latin America and the world. Malnutrition drivers are highly complex and intertwined, including socioeconomic, agricultural, and climatic factors. Though Guatemala is highly vulnerable to the effects of climate change, the connection between climate and malnutrition is thus far under-explored. In this thesis, we conduct an exploratory study of the relationship between climate and under-5 child malnutrition in Guatemala from 2000-2017 to better understand the importance of climate variables in determining malnutrition. To do so, regression and random forest analyses were performed to uncover the significance of the climate-malnutrition relationship and determine how climatic factors compare to non-climatic factors in determining malnutrition. Results demonstrate the most significant relationships are between climate and stunting malnutrition, especially in the highlands region, with a positive relationship between annual soil moisture (drought proxy) ($p<0.01$) and stunting. We also find a negative relationship between growing season temperature and stunting ($p<0.01$). Similar results were found for underweight malnutrition ($p<0.01$), though with lower effect size, indicating other non-climatic factors may be more important in predicting underweight malnutrition in Guatemala. Therefore, this thesis highlights the significance of some climate variables as contributing factors to malnutrition prevalence in Guatemala.

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INTRODUCTION

Malnutrition is a worldwide problem, with more than 30% of the world affected by one form of malnutrition (International Food Policy Research Institute (IFPRI), 2016). Guatemala, specifically, has among the highest rates of malnutrition in the world; the most severe effects are felt in young children under 4 years of age, when the most notable developmental delays occur (Marini & Gragnolati, 2003; Martorell, 2010). Chronic malnutrition rates in Guatemala are especially high, with the highest rate of stunting (low height-for-age) and underweight (low weight-for-age) malnutrition among under-5 children in Latin America; stunting prevalence reaches around 70% in some, predominantly indigenous departments in the highlands: Totonicapán, Quiche, and Huehuetenango (Ministerio de Salud Pública y Asistencia Social - MSPAS/Guatemala et al., 2017). Within Guatemala, high malnutrition prevalence has far-reaching consequences both on an individual level and societal level. Examples include overall lower quality of life, increased risks during pregnancy, working limitations due to stunting (leading to lower income), stigmas surrounding stunting leading to hindered academic performance, etc. (Martorell, 2010). Within society, individual-level eductions in intellectual performance and occupational capacity consequently result in lower overall productivity (Martorell, 2010). General contexts leading to and resulting from malnutrition have furthermore coincided with increased rates of out-migration to the United States, which has been demonstrated to have some positive influence on child nutrition in Guatemala (Carte et al., 2019; Carletto et al., 2011). Nevertheless, child malnutrition rates remain high, speaking to other existing driving factors that override the potential positive influences of migration.

Drivers of malnutrition in Guatemala are complicated and interwoven. It is important to note Guatemala is among the most ethnically diverse countries in Latin America, and 45% of the population is indigenous, located mostly in the highland region of Guatemala (Cerón et al., 2016; 12). Many malnutrition driving factors are often exacerbated for indigenous populations due to historical discrimination and marginalization against these groups (Mazariegos et al., 2019; Marini & Gragnolati, 2003; U.S. Agency for International Development (USAID), 2021; Cerón et al., 2016), further highlighted in chronic malnutrition incidence in Guatemala being almost double among indigenous groups (69.7%) as opposed to non-indigenous groups (35.7%) (Pan American Health Organization (PAHO), 2007). Other social contexts particularly important in determining chronic malnutrition outcomes in Guatemala include poor sanitation practices, low maternal education, low wealth index / poverty, and maternal short stature (12% more prevalent among indigenous women), to name a few (Marini & Gragnolati, 2003; U.S. Agency for International Development (USAID), 2021; Martorell, 2010). Lack of proper health care access furthermore magnifies food security issues, which is often the case in rural, poor, indigenous parts of Guatemala (Pan American Health Organization (PAHO), 2007). It is important to note ethnicity and the indicated social contexts are often intertwined, and rural indigenous populations have generally lower socioeconomic status and resources (U.S. Agency for International Development (USAID), 2021).

Rural sectors of Guatemala, where 70% of people live in poverty, are highly dependent on agricultural production for income and food (Lopez-Ridaura et al., 2019). As a result, agricultural factors furthermore play a major role in driving food insecurity and ultimately malnutrition outcomes. Sufficient arable land availability, for example, is hugely significant for food security and remains a significant issue in Guatemala. The Pan American Health Organization (PAHO) describes how, in Guatemala, children coming from households with less than 1.4 hectares of land are three times more at risk for malnutrition than those with greater than

3.5 hectares (2007). The issue particularly affects indigenous groups, who despite comprising half of agricultural workers in Guatemala, own only a ¼ of the land (Pan American Health Organization (PAHO), 2007). Dependence on agriculture income is also significantly associated with severe food insecurity (Beveridge, 2019). In Guatemala, income variability due to agricultural cycles often leave insufficient funds for food (Webb, 2018), and it is estimated more than half of Guatemalan families have monthly incomes too low to meet necessary dietary intake (Pan American Health Organization (PAHO), 2007). In Guatemala, though maize and beans (grown primarily in the rainy season) are the primary subsistence crops (Beveridge, 2019), there have been recent shifts towards production of export crops --particularly coffee-- in the Guatemalan highlands (Webb, 2018). Increased coffee cash cropping, however, comes with increased risks, given the high investment needed, difficulty of frequent droughts, as well as the problems with coffee rust common in Guatemala (Beveridge, 2019). Even more so, cash cropping has been found to correspond to intensified severe food insecurity, when degree of production sold is low (2019).

A final potential important driver of malnutrition in Guatemala to consider is climate. The country has experienced changing precipitation and temperature patterns in recent years, and Guatemala has been cited as highly vulnerable to the effects of climate change (Ruano & Milan, 2014). Historically, the primary season for growing crops in Guatemala is the rainy season, occurring roughly from May to October; it is typical for maximum rainfall to occur in the beginning and end of the season, with a drier period referred to as the mid-summer drought (MSD) of about 30 days in between (Beveridge, 2019). The length and intensity of the MSD varies based on El Niño-Southern Oscillation (ENSO) cycles, which are the main drivers of climate variability in the region (Beveridge, 2019; Ruano & Milan, 2014); when ENSO cycles are in an El Niño phase, rainy seasons are often drier, and MSD is more intense (Beveridge, 2019). In recent years, there has been an increased frequency of El Niño events; the amount of El Niño events occurring from 1991-2010 were twice as many (6 events) as in the twenty-year periods before that (3 events) (Ruano & Milan, 2014). The result has sometimes been consecutive dry growing seasons in Guatemala and severe drought events at times, often leading to widespread crop failure, thereby affecting locals' harvest reliability (Ruano & Milan, 2014) and overall food security (Beveridge, 2019). For example, the 2014 extended and intensified mid-summer drought (due to El Niño) resulted in 70-80% loss of harvests (UN Country Team in Guatemala, 2015). Similarly, drought has hindered coffee cash cropping success in Guatemala, exacerbating the risks already present in coffee growing (Beveridge, 2019). The resulting crop losses due to climate change have direct effects on food insecurity and ultimately malnutrition through less food availability, increased food prices (altering food stability and access), and reduced income (altering ability to afford food) (FAO et al., 2018; 19).

The connection between climate change and malnutrition has been documented by studies worldwide. For example, spatial analysis of the relationship between drought and child malnutrition in India showed a significant positive relationship between drought and stunting (Shaw et al., 2020). A longitudinal study in Ethiopia investigating the relationship between climate change and child malnutrition found that there is a significant partial effect of both rainfall and temperature on stunting and underweight prevalence (Hagos et al., 2014). Another study examining climate (through temperature and precipitation), livelihood, and malnutrition in Mali found a significant relationship between climate and stunting (Jankowska et al., 2012). In Nigeria, investigations of the effect of climate change on child underweight and stunting found an association between rising temperature and stunting (van der Merwe et al., 2022).

Though there is evidence of a climate change-malnutrition pathway in Guatemala, at this stage, there are few studies dedicated to exploring the indicated connection over time. As a result, this thesis hopes to explore a connection between climate change and under-5 child malnutrition from 2000 to 2017 in Guatemala, with aggregation at the department-level to account for spatial variability. We acknowledge malnutrition is highly complicated with a multitude of driving factors; we furthermore acknowledge the connection between climate and malnutrition is not direct. However, given the severity of the nutrition profile of under-5 children in Guatemala, the seriousness of how climate change is affecting the region now and in future projections (Climate Change Team of the Environment Department of the World Bank & Global Facility for Disaster Reduction and Recovery (GFDRR), 2011), as well as the plausible connection between the two indicators, we believe an exploratory study is warranted. To do so, we aimed to answer the following research questions:

1. Are climate indicators a relevant predictor for malnutrition in Guatemala?
2. Is there a differential impact of climate on malnutrition between the highlands and the lowlands in Guatemala?
3. What are the most important climatic and non-climatic factors predicting malnutrition in Guatemala?

To capture climate changes occurring in Guatemala and model overall mid-summer drought, soil moisture was selected as a proxy. Soil moisture has consistently shown to be an excellent variable for drought monitoring (Zeri et al., 2021; Tramblay & Quintana Seguí, 2022) and has been demonstrated to be a more effective proxy than climate indicators to assess how droughts affects agriculture (19). Considering reductions in soil moisture have strong negative consequences for rainfed and subsistence crops in particular (Zeri et al., 2021), soil moisture is the ideal indicator to capture drought in Guatemala and its effects on agriculture. Though temperature is less frequently cited as drought as a major food insecurity concern in Guatemala, temperatures have been rising steadily in Guatemala in recent years (Climate Change Team of the Environment Department of the World Bank & Global Facility for Disaster Reduction and Recovery (GFDRR), 2011). In addition, many studies worldwide have found connections between temperature and malnutrition, due to crop failures associated with extreme temperature (van der Merwe et al., 2022; Mark et al., 2017; Hagos et al., 2014). As a result, temperature (max, min, and mean) was selected as an additional climate variable for exploratory purposes and to create a more holistic picture of how climate change may be affecting malnutrition in the region. For both soil moisture and temperature, we captured early growing season, growing season, and annual indicators. We selected growing season with the purpose of capturing mid-summer drought through detection of soil moisture levels during that time. Early growing season and annual climate variables were also included for a more well-rounded analysis.

We use the following variables to define malnutrition: stunting, underweight, and wasting, with stunting being a proxy for chronic malnutrition, wasting for acute malnutrition, and underweight a combination of both (de Onis & Blössner, 2003). We include stunting and underweight, given the high prevalence of both indicators in Guatemala. Though wasting prevalence is generally low in Guatemala (U.S. Agency for International Development (USAID), 2021), we still include wasting to create a holistic analysis of the relationship between climate and malnutrition.

METHODS

Climate Data

Temperature timeseries data were obtained from the World Bank Climate Change Knowledge Portal (World Bank Group, Climate Change Knowledge Portal, n.d.). Annual maximum, minimum, and mean temperature data (in °C) were retrieved for each of the 22 departments in Guatemala from 2000-2017 (coinciding with the available years of malnutrition data) to create annual temperature indicators. The same was done for monthly maximum, minimum, and mean temperature data (°C), which was then used to create early growing season and growing season temperature indicators.

Soil moisture data (m^3 / m^3) was collected from the U.S. Geological Survey, specifically the Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System (FLDAS) data portal (2018). 0 – 10 cm monthly soil moisture data (0.25-degree spatial resolution) was extracted in geoTIFF file format for all months across 2000-2017 for the Central American region. Soil moisture data was processed in ArcGIS Pro: all raster data was downloaded, properly projected (UTM 15N), and clipped to just include the country of Guatemala (OCHA Field Information Services Section (FISS) & Coordinadora Nacional Para La Reducción De Desastres, 2021). Annual soil moisture data was created using cell statistics to find the mean of all monthly raster data for each year. Zonal statistics as table was then utilized to convert all annual and monthly spatial data to tables of soil moisture values by department and year; these tables were exported in CSV format to R for analysis. Within R, monthly soil moisture values were converted to early growing season and growing season soil moisture indicators.

We define early growing season as the weather events occurring directly before the rainy/growing season beginning in May; therefore, we select the last three months of the dry season (categorized as November to April according to (Depsky & Pons, 2020; Climate Change Team of the Environment Department of the World Bank & Global Facility for Disaster Reduction and Recovery (GFDRR), 2011): February, March, and April. Growing season for Guatemala was represented by the months of May, June, July, August, and September (Food and Agriculture Organization of the United Nations, 2022; Tay & Nelson, 2020). All climate data was summarized across the 22 departments and 18-year-period to create 396 (22 x 18) observations for each of the following climate indicators: annual soil moisture, annual temperature (min, max and mean), early growing season soil moisture, early growing season temperature (min, max, and mean), growing season soil moisture, and growing season temperature (min, max, and mean).

Malnutrition Data

Stunting, wasting, and underweight prevalence data for under-5 children were obtained from the Institute for Health Metrics and Evaluation (IHME) at 5 x 5 km spatial resolution from 2000 to 2017 (2018). The data combines Demographic Health Survey (DHS) and UNICEF Multiple Indicator Cluster Survey (MICS), in addition to Guatemala-specific surveys, to produce country-level, department-level, and municipality-level GeoTIFF and CSV data across the period. Given the spatial resolution of climate data (only available at the department level), department-level GeoTIFF and CSV data was extracted across the 18-year period (resulting in 396 observations).

The indicated malnutrition data was selected due the importance of temporal resolution in this study. Data was validated by comparing Global Health Data Exchange malnutrition data for

2014-2015 to Demographic Health Survey stunting, wasting, and underweight data for 2014-2015 (Ministry of Public Health and Social Assistance - MSPAS/Guatemala et al., 2017). Results show very high correlations between GHDE data and DHS data for stunting (ρ: 0.95) and underweight (ρ: 0.91); therefore, we concluded both stunting and underweight data for the Global Health Data Exchange were accurate. Correlation between GHDE data and DHS data for wasting was quite low (ρ: 0.34); though we continued with analysis for wasting data, we encourage repetition of our analysis for wasting with other datasets to ensure accuracy.

Control Variable Data

The following socioeconomic variables have been demonstrated to be associated with malnutrition indicators and were therefore selected as controls for this study, aggregated at the department level: proportion of rural households, proportion of indigenous mothers, proportion of children with low birth weight, proportion of low birth interval incidents, proportion of mothers with no education, proportion of mothers with low height, proportion of households with poor wealth index, mean maternal age, proportion of households with unimproved sanitation, and proportion of households with unimproved drinking water (Nshimyiryo et al., 2019; Fagbamigbe et al., 2020; U.S. Agency for International Development (USAID), 2021). By controlling for the indicated factors at the department level, general socioeconomic differences among departments were controlled for in analyses.

The 2014-2015 DHS survey for Guatemala was used to acquire all control variable data (Ministry of Public Health and Social Assistance - MSPAS/Guatemala et al., 2017). To decode the DHS survey responses for Guatemala and obtain all controls indicators, the following methods were used. For the indigenous categorization, Maya, Garifuna, and Xinxa ethnic groups were included, while Ladina / Mestizo was categorized as non-indigenous (U.S. Agency for

International Development, 2022). Low birth weight and low birth interval were defined per the WHO definition: birth weight of less than 2500 grams (World Health Organization, Nutrition Landscape Information System (NLiS), n.d.) and birth interval of less than 33 months (Wakeyo et al., 2022). No maternal education was defined as “no education/pre-primary” (Shaw et al., 2020). Low maternal height was defined using 145 cm as a cutoff, where anything below 145 cm is considered low maternal height (Bisai, 2011). Poor and poorest wealth index categories were grouped to create a “poor health index” indicator (Shaw et al., 2020). Mean maternal age was obtained by subtracting mother’s current age from child age. Unimproved sanitation included the following responses: "flush to somewhere else", "no facility", "latrine", and "open latrine"; not included in unimproved sanitation was “flush toilet", "flush to piped sewer system", "flush to septic tank", "flush, don't know where", "pit toilet latrine", and "ventilated improved pit latrine (vip)" (Croft et al., 2018). Unimproved drinking water included the following responses: "unprotected spring” , "mechanical or manual well", "river/irrigation channel", "lake or stream”, and “other”; not included in unimproved drink water was "piped into dwelling", "piped to yard/plot", "public tap/standpipe", "other piped", "public fountain/tank", "protected spring", "rainwater", "tanker truck", and "bottled water" (Croft et al., 2018).

All data were averaged across department to control for department-level socioeconomic differences that may influence malnutrition. Since controls were used to account for differences across Guatemala departments, this study assumed that 2014-2015 controls remained constant over time for each department and control data was applied for all years.

Descriptive Analysis

The descriptive table showing summary statistics for all malnutrition and climate variables was created with the table1 package in R. Since climate trends were generally consistent across department, country-level time series plots were created to summarize changes in climate indicators across the 18-year period; malnutrition indicators sometimes varied across department, so time series plots faceted by department were created. All plots were created using ggplot2 package in R. Maps representing annual prevalence rates of stunting, wasting, and underweight over time were drafted using ArcGIS Pro, categorized by prevalence level (World Health Organization, 1995).

Regression Analysis

Modeling methods used by previous studies examining the relationship between climate change and malnutrition (Bauer & Mburu, 2017; Grace et al., 2012; Shaw et al., 2020), a multiple linear regression model was utilized to examine the relationship between climate variables and child malnutrition prevalence, using malnutrition as the response variable and accounting for variation across departments using socioeconomic controls.

Figure 1. *Correlation of plots of climate indicators and socioeconomic indicators.*

A. Climate Indicators **B. Socioeconomic Indicators**

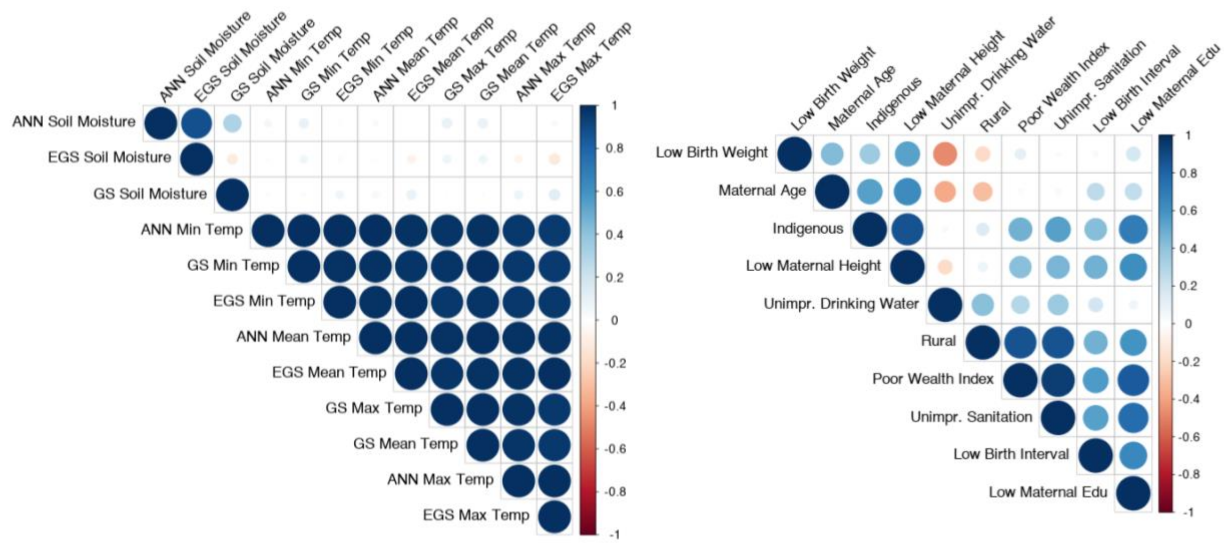


Figure 1A demonstrates correlation among all climate variables of interest, which demonstrates no correlation among soil moisture indicators and temperature indicators; however, we see very high correlation among all temperature indicators. As a result, all regression models included only one soil moisture indicator and one temperature indicator to ensure correlation among multiple temperature indicators would not affect value accuracy. As a result, the following models were used:

$$y^{s_{t+1},w,u_{t+1}} = \alpha + \beta_1 SoilMoisture + \beta_2 MinTemperature + \ \beta_3 Controls + \ \varepsilon \qquad (1)$$

$$y^{s_{t+1},w,u_{t+1}} = \alpha + \beta_1 SoilMoisture + \beta_2 MaxTemperature + \ \beta_3 Controls + \ \varepsilon \qquad (2)$$

$$y^{s_{t+1},w,u_{t+1}} = \alpha + \beta_1 SoilMoisture + \beta_2 MeanTemperature + \ \beta_3 Controls \ + \ \varepsilon \qquad (3)$$

All three models were completed for annual climate indicators, early growing season climate indicators, and growing season climate indicators, resulting in a total of nine regression models. Stunting and underweight were lagged by one year to account for the delayed effect of climate on such malnutrition indicators; Gonzalez Romero, et al. uses similar methods (2020). Controls included all previously discussed socioeconomic control variables; in addition, for wasting and underweight models, year was included as a control variable to account for the significant trending behavior seen for wasting and underweight in Figure 4 and Figure 5.

Figures 6 and 8 highlight a spatial aggregation of malnutrition indicators in the Guatemala highlands region for stunting and underweight, and Table 1 shows that stunting and underweight prevalence is 6-16% higher in the highlands than in the lowlands. Therefore, to explore differential effects of climate on child malnutrition in the Guatemala highlands versus lowlands, a multiple linear regression model accounting for the interaction of climate and highland variables was run.

$$y^{s_{t+1}, w, u_{t+1}} = \alpha + \beta_1 Climate + \beta_2 Highlands + \beta_3 Climate{:}Highlands \; + \; \varepsilon \tag{4}$$

Here, we remove all socioeconomic control variables to assess the sole impact of highlands alone on the relationship between climate and malnutrition. For wasting and underweight, a year control variable was added to account for trending behavior as was done in models 1, 2, and 3.

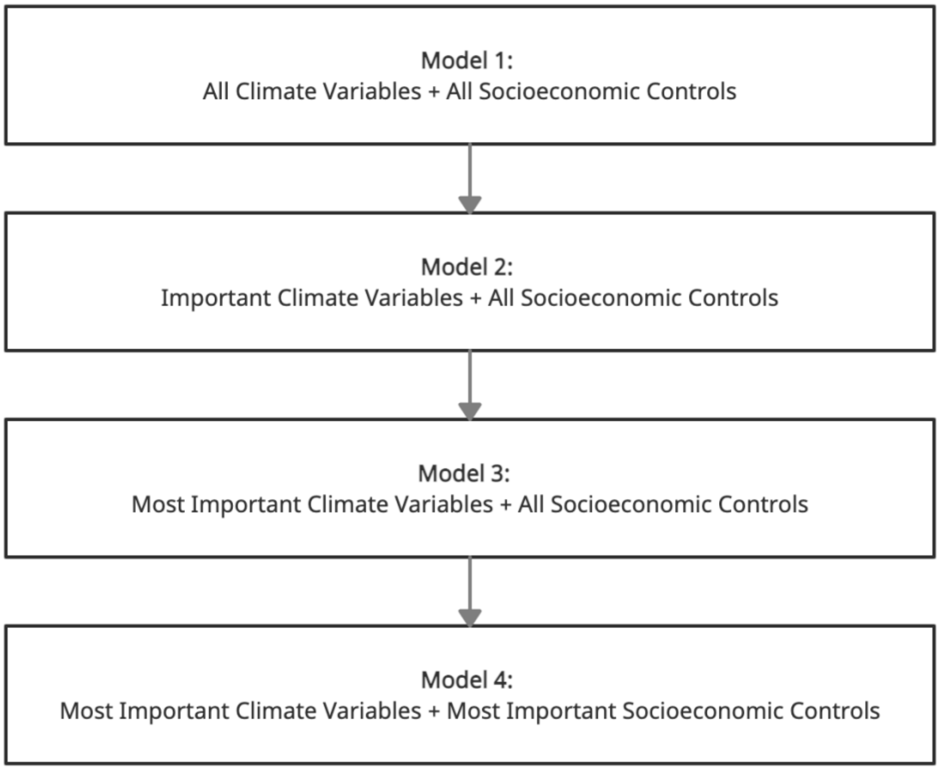
Benchmarks for practical significance for all regressions were determined by considering both variance and overall real-world practicality. Considering the standard deviations for stunting, wasting, and underweight are 10, 0.87, and 4.2 respectively (Table 1), we define a practically significant change in stunting to be 1% and a practically significant change in underweight to be 0.5%. We also choose 0.5% as the practical significance benchmark for wasting, since anything significantly below 0.5% would be too small of a change for real-world scenarios.

Random Forest Machine Learning Models

To understand how climate variables and socioeconomic variables compare in explaining child malnutrition in Guatemala, a random forest machine learning model was utilized. Random forest was selected as a favorable model to use considering its excellent predictive ability (Fernandez-Delgado et al., 2014) and its tolerance of data with much interaction among variables (Loef et al., 2022). The ability to rank variables in terms of importance allowed for easy insight into which variables are most significant in predicting malnutrition.

To run the random forest model, the R package randomForest was used in R software to run a random forest regression. We chose to use 500 trees, as this was large enough to minimize error in the model. Variable importance was defined by %MSE, which measures how much each individual variable decreases the model's overall predictive accuracy when it is removed (Boehmke, 2018). Variance importance plots were created using the ggplot2 package in R. To identify which variables are most important, the methodology shown in Figure 2 was used, in which stunting, wasting, and underweight were regressed onto Model 1, 2, 3, and 4.

Figure 2. *Process towards identification and selection of final Random Forest regression model.*



To ensure model accuracy, all variables included in Model 4 (the final model used in analysis) were uncorrelated with one another. Specifically, the most important climate variables in Model 4 consisted of one soil moisture indicator and one temperature indicator, since soil moisture and temperature are uncorrelated as shown in Figure 1A. In addition, if the most important socioeconomic controls were correlated with one another (shown in Figure 1B), the lesser important of the indicators was dropped. For both wasting and underweight, year was controlled for to account for trending behavior.

In our interpretation of results, we view the most important soil moisture indicator and the most important temperature indicator as proxies for general soil moisture and general temperature. Ultimately, the goal is to see how climate variables, such as soil moisture and temperature, predict malnutrition in comparison to socioeconomic variables.

RESULTS

Descriptive Analysis

Table 1. *Descriptive Characteristics of All Malnutrition and Climate Variables.*

	Lowlands (N=270)	Highlands (N=126)	Overall (N=396)
Stunting (%)			
Mean (SD)	45 (7.5)	61 (5.0)	50 (10)
Wasting (%)			
Mean (SD)	2.2 (0.86)	1.9 (0.87)	2.1 (0.87)
Underweight (%)			
Mean (SD)	13 (3.5)	19 (3.5)	15 (4.2)
Annual Soil Moisture (%)			
Mean (SD)	34 (1.9)	35 (1.1)	34 (1.7)
Annual Min Temp (°C)			
Mean (SD)	18 (2.1)	13 (1.4)	17 (3.1)
Annual Max Temp (°C)			
Mean (SD)	29 (2.1)	25 (1.5)	28 (2.6)
Annual Mean Temp (°C)			
Mean (SD)	24 (2.1)	19 (1.4)	22 (2.8)
Growing Season Soil Moisture (%)			
Mean (SD)	39 (1.5)	39 (1.7)	39 (1.6)
Growing Season Min Temp (°C)			
Mean (SD)	20 (2.1)	15 (1.3)	18 (2.9)
Growing Season Max Temp (°C)			
Mean (SD)	30 (2.2)	26 (1.5)	28 (2.7)
Growing Season Mean Temp (°C)			
Mean (SD)	25 (2.1)	20 (1.4)	23 (2.8)
Early Growing Season Soil Moisture (%)			
Mean (SD)	23 (4.4)	25 (1.8)	24 (3.8)
Early Growing Season Min Temp (°C)			
Mean (SD)	18 (2.2)	12 (1.5)	16 (3.3)
Early Growing Season Max Temp (°C)			
Mean (SD)	30 (2.0)	26 (1.5)	29 (2.6)
Early Growing Season Mean Temp (°C)			
Mean (SD)	24 (2.1)	19 (1.5)	22 (2.9)

Table 1 shows the prevalence of malnutrition indicators (stunting, wasting, and underweight) and values of climate indicators on average from 2000 to 2017. The results demonstrate that for Guatemala, across the 18-year time period, under-5 Stunting was in the "very high" prevalence category (World Health Organization, 1995) with an overall value of 50%; stunting prevalence was especially high in the highlands at 61% on average. For wasting, we see an overall low prevalence rate of 2.1% (World Health Organization, 1995), with no major difference between highlands and lowlands. Underweight prevalence was on average 15%, placing it in the "medium" prevalence category (World Health Organization, 1995); underweight prevalence was greater in highlands than lowlands by about 6%.

Table 1 furthermore highlights average climate markers for the 18-year period. Generally, we observe minimum temperature ranging from 17° C - 24° C at the early growing season, growing season, and annual level; in comparison, maximum temperature ranges from 28° C - 29° C and mean temperature ranges from 22° C - 23° C. Standard deviation does not vary much across all temperature indicators. Also noteworthy is that temperature is about 4-6° C low in the highlands than in the lowlands. In terms of soil moisture, we see much lower levels in the early growing season (24%) than in the growing season (39%) and at the annual level (34%); these values make sense as the early growing season takes place during the dry season while the growing season is part of the wet season (Climate Change Team of the Environment Department of the World Bank & Global Facility for Disaster Reduction and Recovery (GFDRR), 2011). Furthermore, early growing soil moisture has a much higher standard deviation (3.8) than growing season and annual soil moisture (1.6 and 1.7 respectively); soil moisture has comparable values between the lowlands and highlands.

Figure 3. *Time series analysis of mean stunting prevalence rate from 2000 to 2017 by department.*

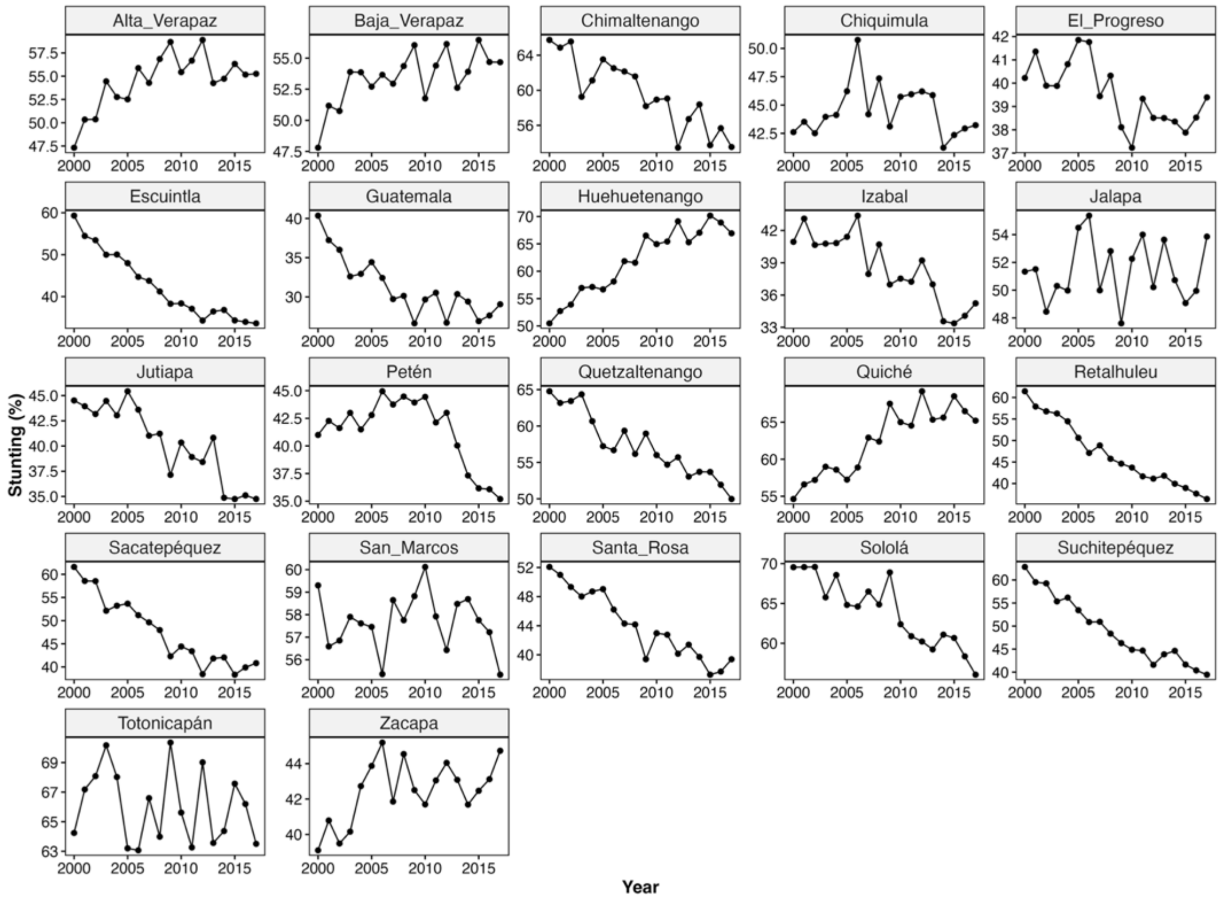


Figure 3 highlights the mean stunting prevalence rate by year and department, and the figure shows stunting trends vastly differed across department. Departments of Huehuetenango and Quiché experienced a ~10-20% increase in stunting prevalence from 2000-2017, while departments of Escuintla, Quetzaltenango, Retalhuleu, Sacatepéquez, Santa Rosa, Sololá, and Suchitepéquez experienced notable decline.

Figure 4. *Time series analysis of wasting prevalence rate from 2000 to 2017 by department.*

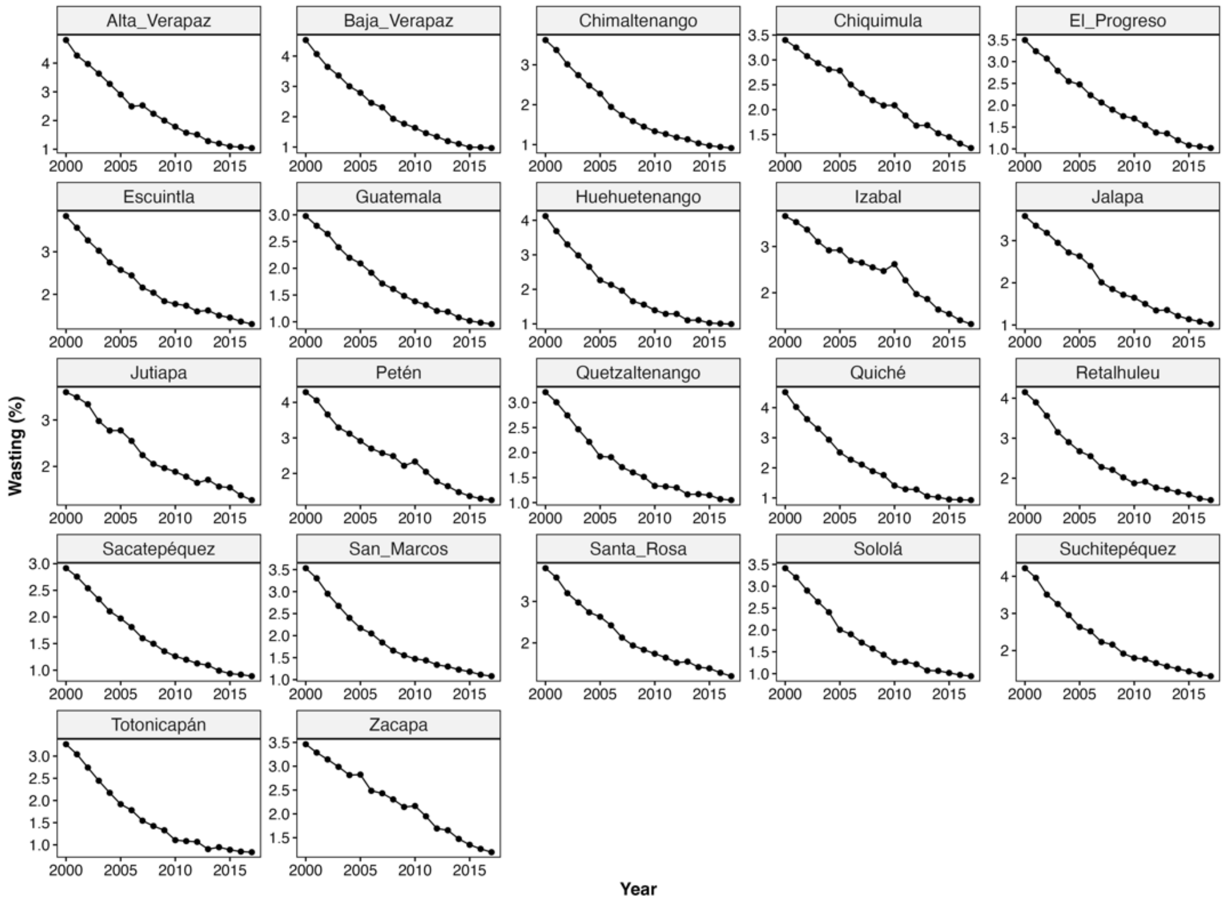


Figure 4 shows the percent of mean wasting prevalence across 2000-2017 aggregated by department. Here, it is evident that wasting has decreased sharply and in highly similar trends across all departments by ~2-4%.

Figure 5. *Time series analysis of underweight prevalence rate from 2000 to 2017 by department.*

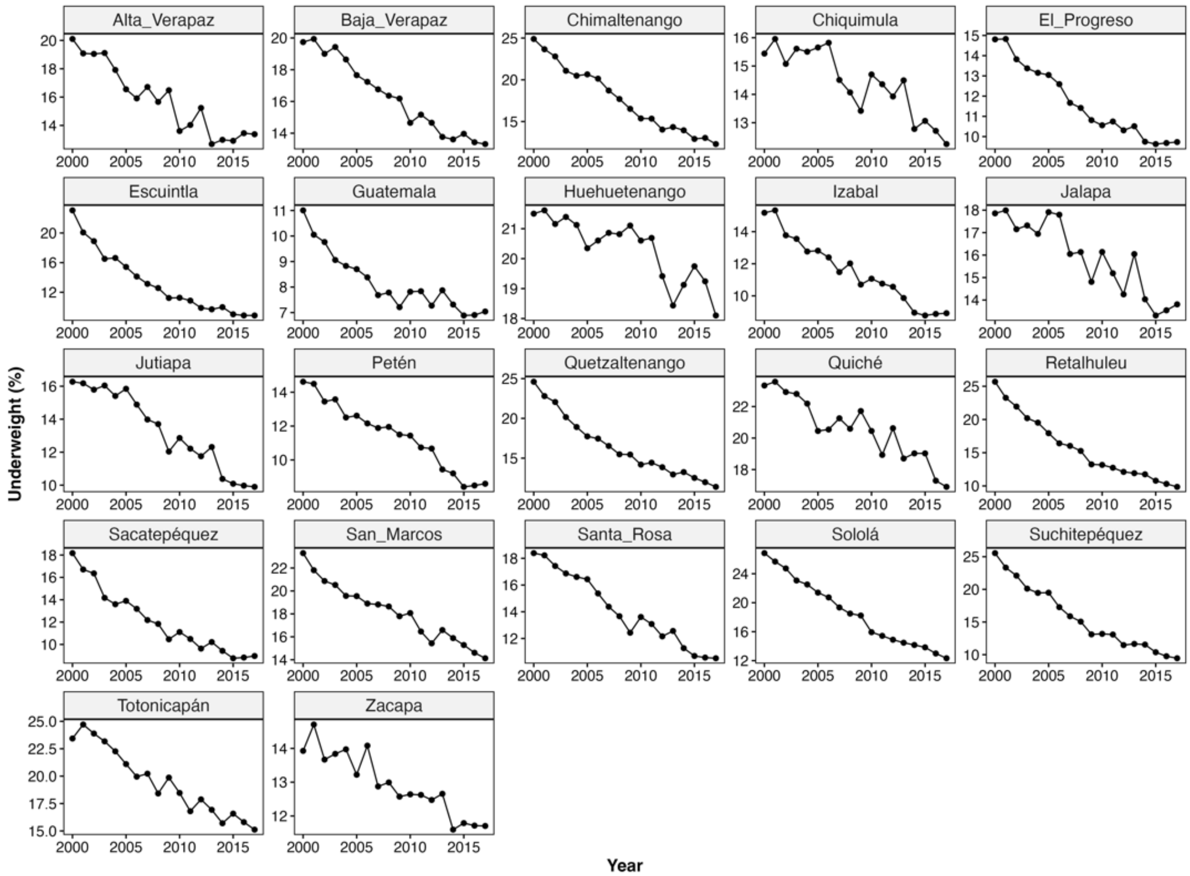


Figure 5 displays prevalence rate for undernutrition by year and department; underweight prevalence rate decreased across all departments, though at varying intensities. Escuintla, Quetzaltenango, Retalhuleu, Sololá, and Suchitepéquez all demonstrate steep declines (~10-15%), as opposed to departments such as Zacapa who declined more slowly across the period (~4%).

Figure 6. *Stunting prevalence rate in Guatemala from 2000 to 2017.*

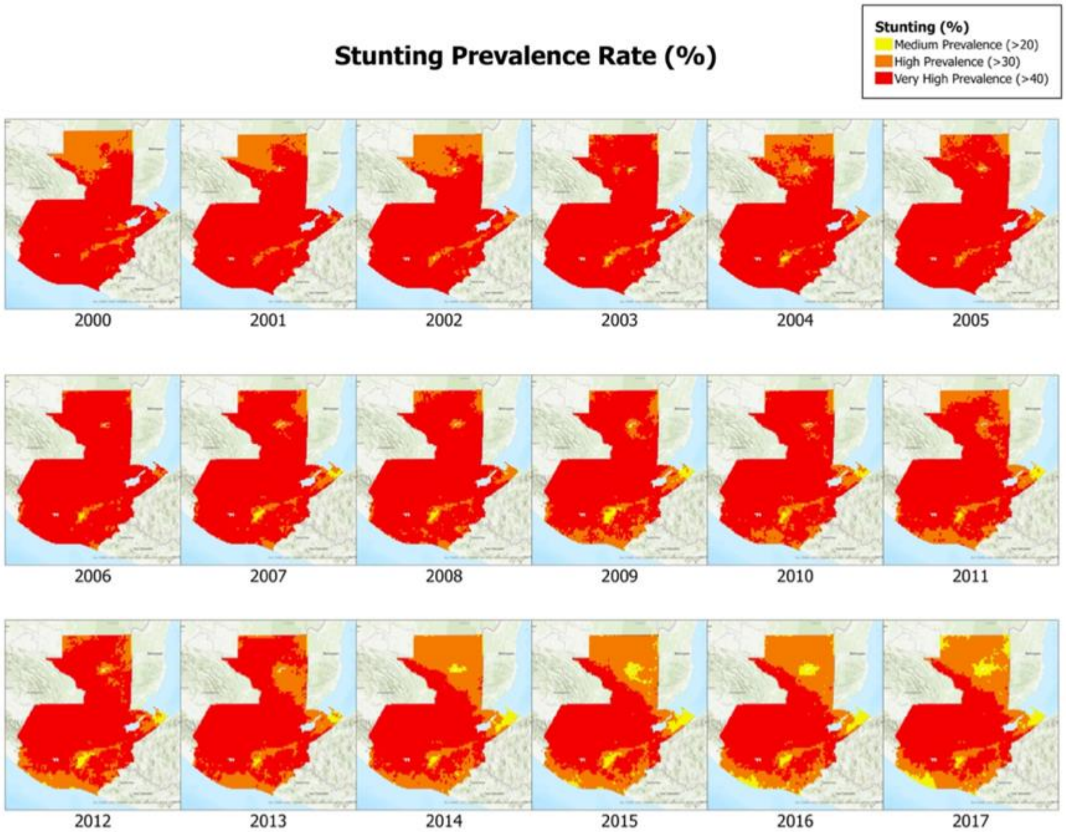


Figure 6 demonstrates the notoriously very high prevalence of stunting endemic to a majority of Guatemala. Though prevalence rates were uniformly very high across all of Guatemala for most of the period, around the year 2014, we start to see reduced prevalence in Northern and Pacific Lowlands of Guatemala, while the Guatemalan highlands retained a very high prevalence of stunting.

Figure 7. *Wasting prevalence rate in Guatemala from 2000 to 2017.*

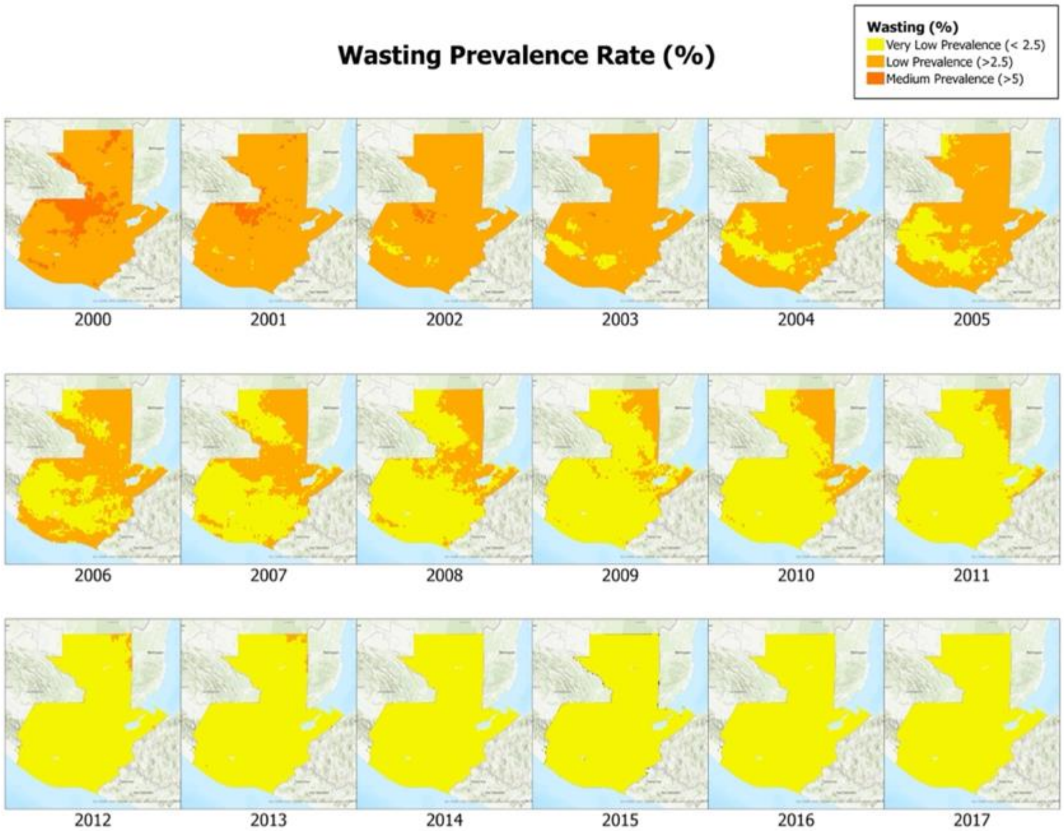


Figure 7 highlights that wasting has reach uniformly very low prevalence rates across Guatemala; until about 2006/2007, the country had mostly low prevalence rates, with the Western Highlands having lowest prevalence rates. From 2012 to 2017, Guatemala had very low wasting prevalence rates throughout.

Figure 8. *Underweight prevalence rate in Guatemala from 2000 to 2017.*

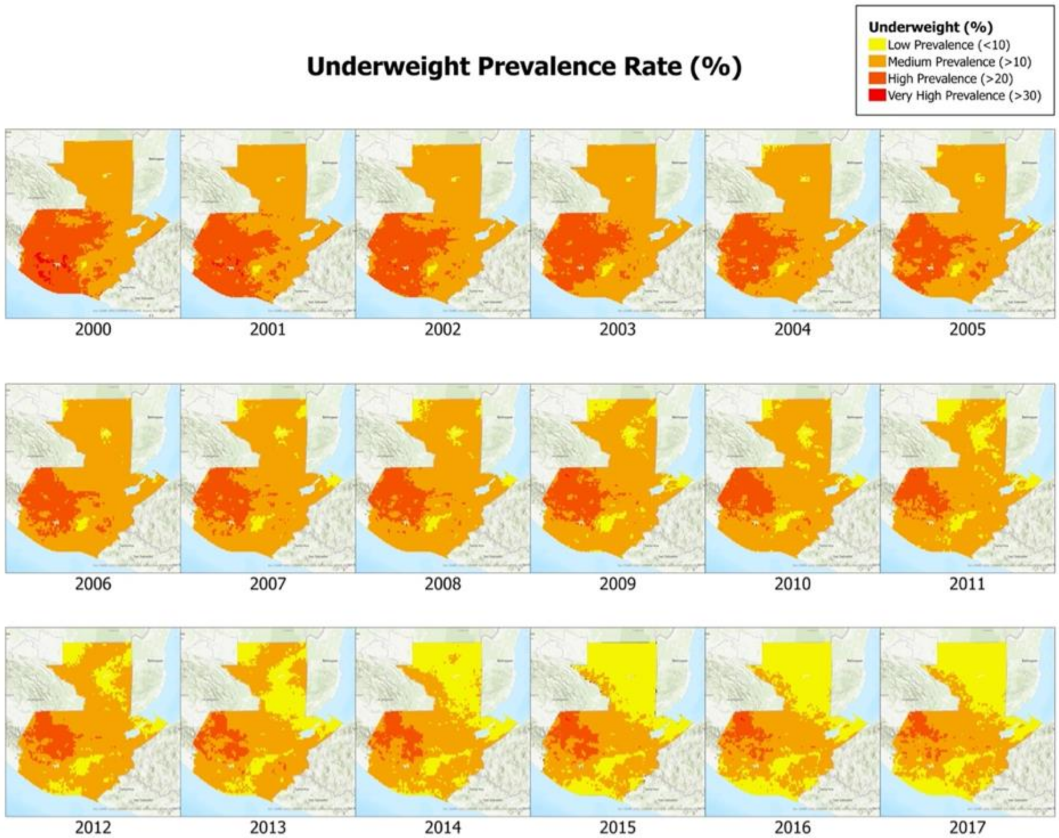


Figure 8 demonstrates that historically the highest underweight prevalence rates have concentrated in the Western Highlands region of Guatemala. However, across the period from 2000 to 2017, prevalence rates have generally declined. Specifically, the Northern and Pacific Lowlands drop from very high, high, and medium Prevalence to mostly low prevalence across the time period. Furthermore, there is a clear reduction in underweight prevalence in the highlands region also, though levels generally remain at medium prevalence, with some part of the Western highlands retaining high level underweight prevalence.

Figure 9. *Time series analysis of climate variables from 2000 to 2017 for Guatemala.*

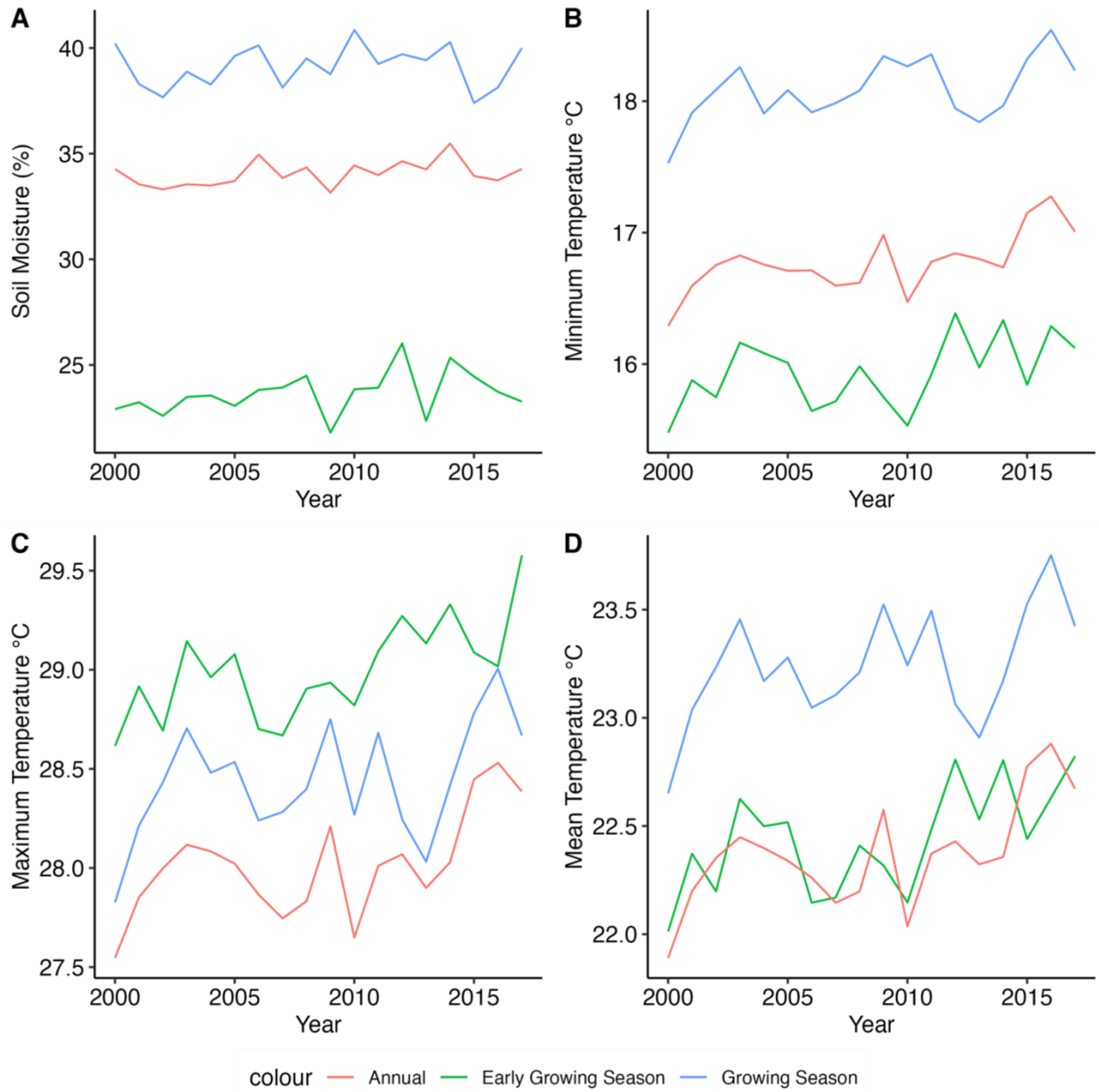


Figure 9 visualizes soil moisture, minimum temperature, maximum temperature, and mean temperature from 2000 to 2017 by department at all following levels: early growing season, growing season, and annual. Figure 9A demonstrates soil moisture values do not show clear increasing or decreasing trends over time. However, there are some notable valleys and peaks in soil moisture that coincide with known El-Niño drought episodes in Guatemala. For instance, early growing season, growing season, and annual soil moisture trends show a dip in soil moisture (most significant for annual soil moisture) in 2009; the indicated drop in soil moisture coincides with the 2009 El Niño drought episode resulting in 50% maize and beans crop losses (Beveridge, 2019). Furthermore, all soil moisture indicators demonstrate a drop in soil moisture from roughly 2014-2016, which matches the large El Niño event occurring from 2014-2015 which is estimated to have resulted in agricultural losses of about 80% (Climate Change Team of the Environment Department of the World Bank & Global Facility for Disaster Reduction and Recovery (GFDRR), 2011).

Figure 9B, 9C, and 9D show temperature in Guatemala shows some variation over the years; since 2010, temperature levels seem to be showing a gradually increasing trending behavior, most notable for mean and max temperature. We furthermore see a long period of higher temperatures from 2000 to 2006 and sharp drops in temperature in 2010 and 2013. Also clear are peaks in temperature during El Niño years; this is relevant, as we know El Niño events correspond to heatwaves (Food Security Information Network (FSIN), 2019). For example, we see a peak in maximum, mean, and to some degree minimum temperature in 2010, coinciding with the 2009 El Niño event. Also, there is a huge jump in most temperature indicators in 2015-2016, accompanying the 2015-2016 El Niño event.

Regression Analysis

Figure 10. *Regression Analysis of Marginal Effect of Annual Climate Indicators on Malnutrition.*

Marginal Effect of Annual Climate Indicators on Malnutrition

	Dependent variable:								
	Stunting Prevalence (%)			Wasting Prevalence (%)			Underweight Prevalence (%)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Annual Soil Moisture (%)	-1.228***	-1.361***	-1.281***	0.005	0.015	0.008	-0.413***	-0.476***	-0.444***
	(-1.523, -0.932)	(-1.647, -1.074)	(-1.572, -0.990)	(-0.013, 0.022)	(-0.002, 0.032)	(-0.009, 0.026)	(-0.516, -0.311)	(-0.577, -0.375)	(-0.545, -0.342)
Annual Min Temp (C)	-0.761***			0.066***			-0.260***		
	(-1.039, -0.483)			(0.049, 0.082)			(-0.355, -0.165)		
Annual Max Temp (C)		-0.921***			0.095***			-0.177**	
		(-1.301, -0.541)			(0.072, 0.117)			(-0.309, -0.044)	
Annual Mean Temp (C)			-0.864***			0.080***			-0.244***
			(-1.190, -0.538)			(0.061, 0.100)			(-0.357, -0.131)
Observations	374	374	374	396	396	396	374	374	374
R^2	0.831	0.829	0.831	0.911	0.912	0.912	0.871	0.865	0.868
Adjusted R^2	0.826	0.824	0.825	0.908	0.909	0.909	0.866	0.860	0.863
Note:							*p<0.1; **p<0.05; ***p<0.01		

At the annual level, results show a highly significant, negative relationship between soil moisture and both stunting and underweight malnutrition. At a practical level, soil moisture is significant for stunting, for with β values of -1.2286, -1.361, and -1.281, it is larger than the 1% set benchmark for practical significance for stunting. In addition, the relationship between soil moisture and underweight is marginally practically significant, with β values just below the 0.5% practical significance benchmark for underweight (-0.413, -0.476, and -0.444). Therefore, the relationship between annual soil moisture and stunting prevalence is statistically and practically significant; with a 1% increase in annual soil moisture, there is a ~1.3% decrease in stunting prevalence in the following year. The relationship between annual soil moisture and underweight is statistically significant and practically marginally significant; a 1% increase in annual soil moisture corresponds to a ~0.45% decrease in underweight prevalence in the following year.

Results also show a highly significant, negative relationship between all annual temperatures and all types of malnutrition. However, none of the relationship are significant at the practical level; β is less than 1% for stunting, and β is less than 0.5% for wasting and underweight. Therefore, there is not a statistically and practically significant relationship between annual temperature and any type of malnutrition.

Figure 11. *Regression Analysis of Marginal Effect of Early Growing Season Climate Indicators on Malnutrition.*

Marginal Effect of Early Growing Season Climate Indicators on Malnutrition

	Dependent variable:								
	Stunting Prevalence (%)			Wasting Prevalence (%)			Underweight Prevalence (%)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Early Growing Season Soil Moisture (%)	-0.771^{***}	-0.828^{***}	-0.790^{***}	-0.003	0.005	-0.0001	-0.304^{***}	-0.324^{***}	-0.313^{***}
	(-0.922, -0.620)	(-0.971, -0.685)	(-0.937, -0.643)	(-0.013, 0.006)	(-0.004, 0.014)	(-0.009, 0.009)	(-0.354, -0.253)	(-0.373, -0.276)	(-0.363, -0.264)
Early Growing Season Min Temp (C)	-0.494^{***}			0.065^{***}			-0.135^{**}		
	(-0.759, -0.229)			(0.049, 0.081)			(-0.223, -0.047)		
Early Growing Season Max Temp (C)		-0.788^{***}			0.092^{***}			-0.111	
		(-1.157, -0.418)			(0.070, 0.115)			(-0.236, 0.013)	
Early Growing Season Mean Temp (C)			-0.629^{***}			0.078^{***}			-0.135^{**}
			(-0.942, -0.316)			(0.060, 0.097)			(-0.239, -0.030)
Observations	374	374	374	396	396	396	374	374	374
R^2	0.836	0.837	0.837	0.911	0.911	0.911	0.882	0.881	0.881
Adjusted R^2	0.831	0.832	0.831	0.908	0.908	0.908	0.878	0.876	0.877

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Results show that early growing season soil moisture has a highly significant, negative relationship with both stunting and underweight prevalence; the relationship with wasting is not significant. On a practical level, the marginal effect of early growing season soil moisture on stunting is not significant with β values less than 1% (β: -0.771, -0.828, -0.790); similarly, the marginal effect of early growing season soil moisture on underweight is not significant with β values less than 0.5% (β: -0.304, -0.324, -0.313). Therefore, the effect of early growing soil moisture on any malnutrition type is not significant.

The effect of early growing season temperature is statistically very significant for stunting and wasting. The relationship between early growing season temperature is also significant for min and mean values, though not for maximum values. At a practical level, the change in stunting, wasting, and underweight prevalence is not significant due to β not meeting the previously mentioned benchmark for practical significance. Therefore, the relationship between early growing season temperature and malnutrition is not significant.

Figure 12. *Regression Analysis of Marginal Effect of Growing Season Climate Indicators on Malnutrition.*

Marginal Effect of Growing Season Climate Indicators on Malnutrition

	Dependent variable:								
	Stunting Prevalence (%)			Wasting Prevalence (%)			Underweight Prevalence (%)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Growing Season Soil Moisture (%)	-0.013	-0.023	-0.018	-0.004	-0.004	-0.004	0.036	0.033	0.034
	(-0.283, 0.257)	(-0.294, 0.249)	(-0.288, 0.252)	(-0.020, 0.011)	(-0.019, 0.012)	(-0.019, 0.011)	(-0.056, 0.127)	(-0.060, 0.126)	(-0.058, 0.126)
Growing Season Min Temp (C)	-1.234^{***}			0.064^{***}			-0.446^{***}		
	(-1.528, -0.939)			(0.048, 0.081)			(-0.546, -0.347)		
Growing Season Max Temp (C)		-1.468^{***}			0.080^{***}			-0.473^{***}	
		(-1.835, -1.101)			(0.059, 0.101)			(-0.599, -0.346)	
Growing Season Mean Temp (C)			-1.361^{***}			0.072^{***}			-0.468^{***}
			(-1.690, -1.032)			(0.054, 0.091)			(-0.581, -0.356)
Observations	374	374	374	396	396	396	374	374	374
R^2	0.812	0.810	0.811	0.909	0.909	0.909	0.860	0.854	0.857
Adjusted R^2	0.805	0.803	0.805	0.906	0.906	0.906	0.855	0.849	0.852
Note:							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Growing season soil moisture is not statistically significant for any of the malnutrition indicators. Growing season temperature, in contrast, was highly statistically significant for all malnutrition indicators. Though the relationship between growing season temperature and both wasting prevalence was not significant at the practical level with β values considerably less than 0.5%, stunting was practically significant with β values all above the 1% benchmark for practical significance for stunting. Specifically, as growing season min, max, and mean temperature increases by 1°C, stunting prevalence in the following year decreases by 1.234%, 1.468%, and 1.361% respectively. The relationship between growing temperature and underweight prevalence was marginally significant at the practical level, with β values just below 0.5% (-0.446, -0.473, -

0.468). Therefore, as growing season min, max, and mean temperature increases by 1°C, underweight prevalence in the following year decreases by -0.446%, -0.473%, and -0.468% respectively.

Figure 13. *Regression Analysis of Differential Effect of Annual Climate Indicators on Malnutrition: Highlands vs. Lowlands.*

Differential Marginal Effect of Annual Climate Indicators on Malnutrition: Highlands vs. Lowlands

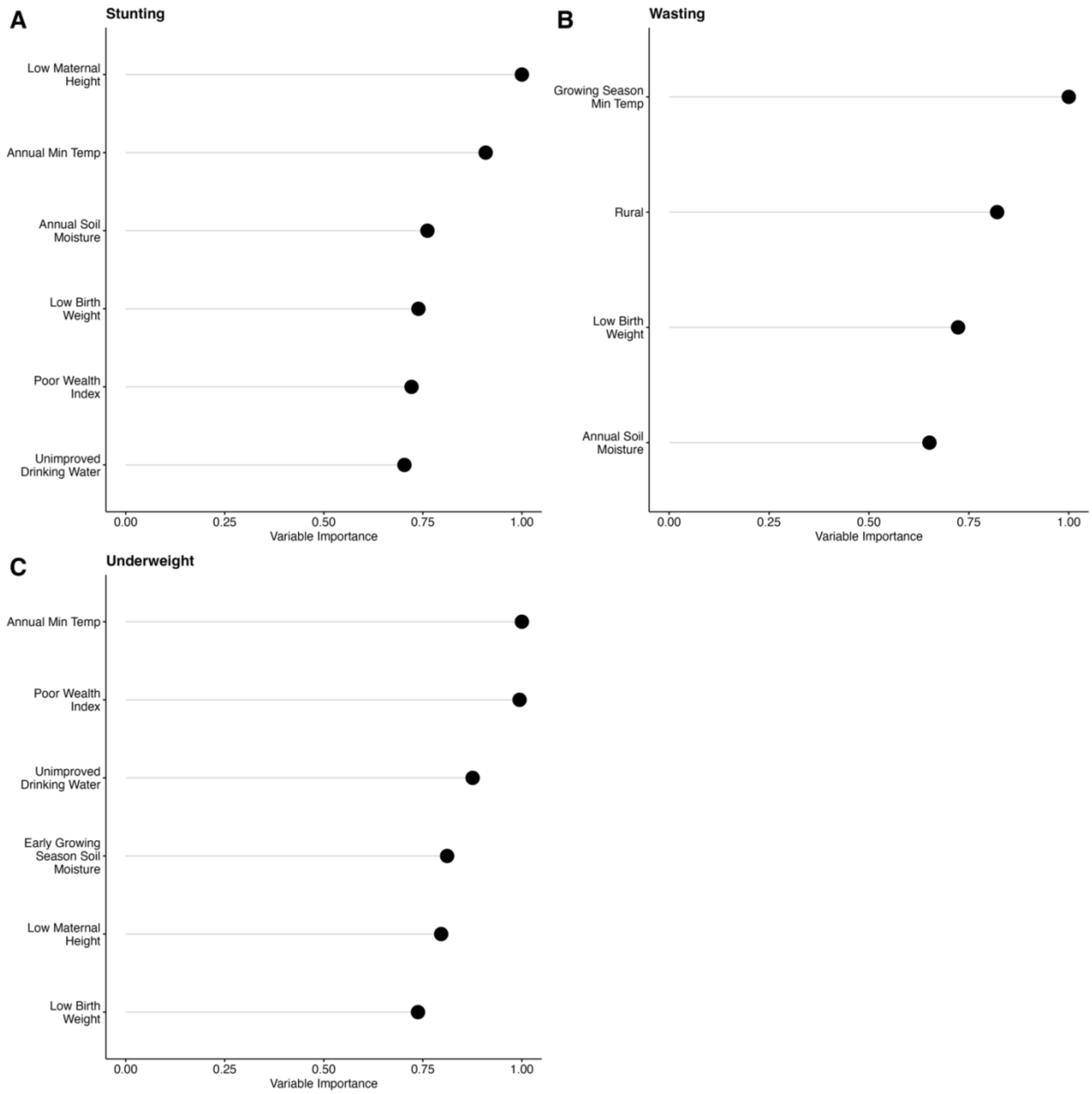
	Dependent variable:											
	Stunting Prevalence (%)				Wasting Prevalence (%)				Underweight Prevalence (%)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Annual Soil Moisture (%)	-0.336				0.054***				-0.190**			
	(-0.695, 0.024)				(0.036, 0.071)				(-0.315, -0.065)			
Annual Min Temp (°C)		-0.438**				0.088***				0.078		
		(-0.759, -0.116)				(0.074, 0.103)				(-0.035, 0.192)		
Annual Max Temp (°C)			-0.298				0.081***				0.149**	
			(-0.615, 0.019)				(0.067, 0.095)				(0.038, 0.260)	
Annual Mean Temp (°C)				-0.374*				0.087***				0.117*
				(-0.696, -0.051)				(0.072, 0.101)				(0.004, 0.231)
Annual Soil Moisture (%): Highlands1	-1.175*				0.003				-0.265			
	(-2.163, -0.187)				(-0.043, 0.050)				(-0.605, 0.075)			
Annual Min Temp (°C): Highlands1		-1.461***				-0.032				-0.519***		
		(-2.239, -0.683)				(-0.067, 0.002)				(-0.793, -0.244)		
Annual Max Temp (°C): Highlands1			-1.410***				-0.028				-0.455***	
			(-2.126, -0.694)				(-0.060, 0.004)				(-0.706, -0.204)	
Annual Mean Temp (°C): Highlands1				-1.492***				-0.030				-0.498***
				(-2.250, -0.735)				(-0.064, 0.003)				(-0.765, -0.231)
Observations	374	374	374	374	396	396	396	396	374	374	374	374
R^2	0.595	0.610	0.607	0.609	0.865	0.887	0.883	0.886	0.686	0.684	0.684	0.684
Adjusted R^2	0.591	0.607	0.604	0.606	0.863	0.886	0.882	0.885	0.682	0.681	0.681	0.681
Note:												*p<0.1; **p<0.05; ***p<0.01

Figure 13 regression results demonstrate that the absolute value of the effect of annual soil moisture for stunting (though not wasting or underweight) is significantly greater in the highlands region in comparison to the lowlands region, both statistically and practically. More specifically, regression results demonstrate that the effect of soil moisture on stunting in the lowlands is -0.336, in comparison to -1.511 (-0.336 – 1.175) in the highlands. The differential effect of soil moisture between highlands and lowlands was not statistically significant for wasting or underweight malnutrition.

Figure 13 furthermore highlands the significant difference between highlands and lowlands in the absolute effect of annual min, max, and mean temperature on stunting. The effect size of annual min, max, and mean temperatures on stunting in the lowlands is -0.438, -0.298, and -0.374 respectively, while the effect in the highlands is -1.899, -1.708, and -1.866 for annual min, max, and mean temperature. Therefore, the effect of temperature on stunting is much greater in the highlands than the lowlands region. In addition, the differential effect of min, max, and mean temperature between highlands and lowlands on underweight was highly statistically significant. At a practical level, results were marginally significant with β values of the interaction terms roughly at the 0.5% level (-0.519, -0.455, -0.498). Specifically, the effect of min, max, and mean temperature on underweight is 0.078, 0.149, and 0.117 in the lowlands in comparison to -0.441, -0.306, and -0.381 in the highlands. Therefore, with high statistical significance and marginal practical significance, the effect of annual temperature on underweight is greater in the highland region than the lowland region.

Random Forest Machine Learning Models

Figure 14. *Random Forest Variable Importance Plots for Stunting, Wasting, and Underweight.*



For Figure 14A, which identifies predictors of stunting, maternal height is more important than any climate variable or any other socioeconomic variable in predicting stunting a year later. Closely following maternal height as important indicators are climate variables (specifically annual min temperature and annual soil moisture), both of which are more important than other socioeconomic indicators in predicting stunting (except for maternal height). Temperature is slightly more important in predicting stunting a year later than soil moisture. Other socioeconomic variables important in predicting stunting are low birth weight, poor wealth index, and unimproved drinking water. Indigenous was also identified as important but was dropped because of its correlation with low maternal height.

Figure 14B showed the most important predictors of wasting. Results show that temperature is the most important predictor for wasting and is more important than soil moisture and all socioeconomic indicators. The following socioeconomic indicators followed temperature as very important predictors of wasting: rural (% in department) and low birth weight. Soil moisture, though more important than all other socioeconomic indicators, was less important than temperature, rural, and low birth weight. Poor wealth index, though identified as an important indicator, was dropped due to its high correlation with rural.

In Figure 14C, we see the most important predictor of underweight is temperature and poor wealth index. Following poor wealth index and temperature is unimproved drinking water. Temperature is more predictive of underweight malnutrition in the following year than soil moisture; though soil moisture is important, and more important than most socioeconomic indicators (including low maternal height and low birth weight), it is not as important as temperature, poor wealth index, and improved drinking water. Low maternal height and low birth weight are furthermore important socioeconomic variables predicting underweight.

DISCUSSION

All climate indicators, except for growing season soil moisture, were highly statistically significant for stunting. Of these, only annual soil moisture and growing season temperature were practically significant, and we observe a negative relationship between both annual soil moisture and growing season temperature and stunting. Similarly, for underweight malnutrition, apart from growing season soil moisture, all climate indicators were statistically significant for underweight. Of these, only annual soil moisture and growing season temperature were marginally significant for underweight at the practical level, with both annual soil moisture and growing season temperature values having a negative relationship with underweight. Wasting, in contrast, did not have a statistically significant relationship with any soil moisture indicator. Though all temperature indicators were highly statistically significant for wasting, no temperature indicator had a large enough effect size to be significant for wasting at the practical level. In comparing the effect of climate on malnutrition between the highlands and lowlands, the absolute effect of all annual climate indicators on stunting are significantly greater in the highlands than the lowlands. Even more so, all annual climate variables for stunting are highly significant in the highlands, but not in the lowlands. In addition, absolute effect of temperature on underweight is marginally significantly greater in the highlands than the lowlands. Results from random forest models highlight that some socioeconomic indicators (such as maternal height for stunting, rural for wasting, poor wealth index for underweight) are highly important in predicting malnutrition; yet, climate variables may be almost equally as important in predicting malnutrition, with temperature being universally more important than soil moisture.

Decreases in annual soil moisture, used as a proxy for drought, coincide with increases in stunting and underweight malnutrition in Guatemala; for stunting, the relationship is especially significant in the highlands (marginal statistical significance). The indicated inverse relationship is expected, as drought (which can be represented by a reduction in soil moisture) affects food insecurity through many pathways, one important one being agricultural production, which in turn can lead to malnutrition (Beveridge, 2019).

The highly significant, negative relationship between annual soil moisture (as an indicator for drought) and stunting is consistent with findings in the literature Most relevantly, Beveridge finds a positive association between mid-summer drought duration and stunting prevalence in Guatemala (2019). Furthermore, in India, Shaw et al. demonstrate a highly significant, positive relationship between drought (measured by a remote sensing retrieved Scaled Drought Condition Index) and stunting (2020). In addition, in a study by Jankowska et al. examining drought, livelihoods, and malnutrition in Mali, results demonstrate a positive relationship between arid climate and district-level stunting prevalence (2012). Cooper et al., conducting a study examining the effect of drought (measured by anomalies in precipitation) on stunting across 53 LMIC countries, finds significant positive relationships between all severities of drought and stunting (2019). The study furthermore highlights longer-term drought indicators (as opposed to growing season drought indicators) are best at predicting stunting prevalence (Cooper et al., 2019); this is consistent with our results that annual soil moisture was significant for stunting, but early growing season and growing season soil moisture was not. It is possible that since annual soil moisture includes conditions in both the primary and secondary growing seasons (Beveridge, 2019), it best captures the longer-term, compounded soil conditions ultimately leading to crop failure. Additional research is recommended to explore temporal relationships between drought and stunting in Guatemala, particularly in the highlands where the relationship is most strong.

Results from our random forest model confirm the relevance of soil moisture to stunting prevalence, considering it is the third most important indicator in predicting stunting (apart from maternal height and temperature). It is important to note, however, that some socioeconomic indicators are more important than soil moisture (maternal height) and some are almost equally as important as soil moisture in predicting stunting in Guatemala: low birth weight, poor wealth index, and unimproved drinking water. It is furthermore important to highlight that the intermediate in the connection between drought and stunting prevalence are regional socioeconomic trends such as food prices, income, etc. (Lloyd et al., 2018). Therefore, we conclude that of the different complex players that drive stunting prevalence in Guatemala, soil moisture (as a drought proxy) is one important one; this is consistent with conclusions from Jankowska et al. (2012).

Lieber et al., a meta-analysis of 22 studies investigating the impact of drought (among other climate change indicators) on malnutrition, finds that overall, there is a significant positive relationship between drought and wasting/underweight malnutrition (2020). Results for wasting in our study contradict these results, as we find no significant statistical relationship between any soil moisture indicator and wasting; it is important to keep in mind that our wasting data was inconsistent with DHS data and could not be validated. Therefore, it will be important to repeat methods with other wasting data to ensure there is indeed no relationship between wasting and drought in Guatemala (using indicators such as soil moisture).

Although our results for the relationship between annual soil moisture (drought) and underweight malnutrition align with those of Lieber et al. (2022) in terms of statistical significance, we find only a marginally significant practical effect size of annual soil moisture on underweight malnutrition in Guatemala. We know from previous research that, in Guatemala, the link between drought and acute food insecurity is complicated (Müller et al., 2020), and that the effect of drought on food insecurity may be mitigated or heightened by socioeconomic contexts (Beveridge, 2019). It is possible, therefore, that even though the effect of drought on underweight is highly statistically significant in Guatemala, it is not as significant in practice as other contextual factors and therefore the practical effect size is lower. From our random forest analysis, we know that some socioeconomic indicators, specifically poor wealth index and unimproved drinking water, are more important in predicting undernutrition than soil moisture. The indicated results are furthermore confirmed by our descriptive analysis showing that underweight malnutrition has overtime concentrated in the Western Highlands region, where social determinants of health are generally poor due to historical discrimination of indigenous groups in the area (Cerón et al., 2016). Therefore, though we can conclude drought partially contributes to underweight malnutrition prevalence in Guatemala, it will be important in the future to further investigate the relationship among drought, socioeconomic, and underweight indicators, particularly in the highland region, to better understand the significance of the role of drought in predicting undernutrition. It will also be important to examine the relationship between drought and malnutrition using indicators other than soil moisture to validate our results.

Increases in min, max, and mean growing season temperature corresponds to decreases in stunting in Guatemala. Though some studies concur with our results and find inverse relationships between seasonal temperature and stunting (Randell et al., 2020), most studies contradict our results and find a positive (not negative) relationship with temperature and malnutrition (van der Merwe et al., 2022; Mark et al., 2017), given the consensus that higher than average temperatures ultimately reduce crop yields (Nelson et al., 2009). However, when considering our analysis of the differential effects of annual temperature on stunting between the highlands and lowlands, perhaps our results are more plausible. More specifically, our analysis shows the negative relationship between temperature and stunting is highly significant in the highlands only (not the lowlands), consistent with findings from studies citing the same negative relationship between temperature and stunting in other highland regions, specifically the Mexican and Ethiopian highlands (Randell et al., 2020; Skoufias & Vinha, 2012)**.** Both indicated studies cite frost, which occurs in greater frequency with climate change (IPCC, 2018), as a potential mechanism for how low temperatures in highland regions correspond with increased stunting; considering temperatures are generally lower in the high altitudes, temperatures in these regions are more likely to reach freezing thresholds. In Guatemala, some literature suggests that deforestation has reduced insulation often created by forests, and as a result, higher altitudes in Guatemala are experiencing greater frost on immature crops (Ford, 1992). Climate Change Team of the Environment Department of the World Bank and Global Facility for Disaster Reduction and Recovery (GFDRR) also suggests that the increased temperatures in Guatemala have been more prominent in the lowlands than highlands (2011). However, beyond that, there is not much in the literature to suggest that frequent frost episodes are occurring in the Guatemalan highlands. As a result, though the inverse relationship between temperature and stunting is plausible, we recommend future research investigating how reduced temperature events (such as frost) in the Guatemalan highlands are affecting crop yield.

Though wasting did not have a practically significant association with growing season temperature, underweight did at the marginal level. The low effect size of growing season temperature on underweight can perhaps once again be explained by the greater significance of other socioeconomic factors on influencing underweight outcomes. Our random forest analysis demonstrates, for example, that poor wealth index was almost equally as significant in explaining underweight as temperature. Therefore, though temperature may be very important in predicting undernutrition, other socioeconomic factors may in practice have a greater effect; it will be important to further explore the relationship between temperature, socioeconomic indicators, and underweight malnutrition in the future, particularly in the Western Highlands.

It is important to acknowledge limitations in our study due to constrains in our methodology. Due to the limitations in practical knowledge, we were unable to model mid-summer drought as a drought indicator in Guatemala and instead used soil moisture as a general drought proxy; early growing season, growing season, and annual soil moisture may not represent drought in Guatemala as well as an MSD-specific drought indicator would. Furthermore, due to remote sensing and spatial epidemiology knowledge constraints, we did not run spatial autocorrelation and autoregressive models; therefore, granular spatial dependence of the climate-malnutrition relationship was not accounted for. Finally, due to the difficulty of retrieving reliable agricultural yield data for Guatemala overtime at the department-level, crop yield was not accounted for in our analysis or in our controls, which is a limitation considering the importance of crop yield as an intermediary in the relationship of climate and malnutrition.

Limitations furthermore exist in this thesis due to the lack of granularity in our data. Due to our interest in the time aspect of the climate-malnutrition relationship, our analysis had a relatively low amount of data points (396) with limited degrees of freedom; this may have affected the accuracy of our results. Data was furthermore summarized at the department-level due to data limitations; we therefore assumed that socioeconomic indicators, climate variables, and malnutrition prevalence are uniform within departments, which does not reflect reality. Malnutrition data was furthermore available at the annual level, and as a result, stunting and underweight were lagged by one year while wasting was not lagged; it would have been ideal to have monthly malnutrition data to better capture the nuances in the temporal relationship between climate and each of the malnutrition indicators. There are some notable limitations in the accuracy of our data as well. First and foremost, our wasting data did not align with validation data, and therefore, it is difficult to ensure wasting data utilized in this study was wholly accurate. Furthermore, Demographic Health Survey data was used to capture control variables in our study, one of which is the indigenous indicator; it is important to note that indigenous data is not always representative in Guatemala, as surveyors sometimes make assumptions about ethnicities of respondents and/or respondents sometimes are dishonest about their true ethnicity.

The indicated study is one of the few, to our knowledge, to examine the effect of climate indicators such as soil moisture and temperature on malnutrition over time in Guatemala. Factors leading to malnutrition are incredibly complex and the pathway of climate to malnutrition is not direct; yet this study highlights the significance of particular climate-malnutrition relationships, such as drought and stunting in the highlands, as contributing factors to overall malnutrition prevalence rates in Guatemala. As the effects of climate change are increasingly felt in future decades, it will be imperative to continue the indicated research to better understand the relationship between climate and malnutrition to drive climate-adaptation policy protecting vulnerable populations.

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