EHESP

Master of Public Health

Master de Santé Publique

The impact of environmental factors on child malnutrition in districts and communes of the South of Madagascar: a time series (2015-2022) and stratified analysis (2018 and 2021).

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Table of Contents

List of acronyms

- CRENAS: Centres de Récupération et Education Nutritionnelle Ambulatoire pour la Malnutrition Aiguë Sévère or Ambulatory Nutritional Rehabilitation and Education Center for severe acute malnutrition
- ENA: Emergency Nutrition Assessment software
- GAM: Global Acute Malnutrition
- LAI: Leaf Area Index
- MAM: Moderate Acute Malnutrition
- MSWEP Multi-source Weighted Ensemble Precipitation
- SAM: Severe Acute Malnutrition
- SMART: Standardized Monitoring and Assessment of Relief and Transitions”
- MUAC: Mid-upper arm circumference

Abstract in English

Introduction: Malnutrition is a critical health issue in Madagascar, affecting around 2 million individuals, especially children. This thesis explores the relation between malnutrition forms in relation to precipitation, vegetation, climate, as well as their inter-annual rhythmicity.

Methods: Malnutrition prevalence data was collected for 2018 and 2021 at the commune level and data from 2015-2022 focuses on admissions to CRENAS centers and incidence in Malagasy districts. Descriptive and univariate analyses were performed, in relation to vegetation and precipitation indicators. These were then analyzed via multi-level multivariate zero-inflated beta regression models and multivariate quasi-poisson model considering seasonality, respectively.

Results: Commune data shows that communes with semi-arid climate are more likely to develop Severe acute malnutrition(SAM) in 2018 and 2021, while moderate and global acute malnutrition(MAM/GAM) exhibit this relation only for 2021. Vegetation was negatively associated with GAM and MAM in 2021, while no association was found between precipitation and any malnutrition type. Trimesters 2, 3 (dry season), and 4 (start rainy season) were negatively associated with all malnutrition forms, showing the protective effect of the dry season and harvested crops. District-level analysis exhibited contradictory results, with a positive relationship between 1-month-lagged vegetation and malnutrition incidence in Ampanihy and Betioky-Atsimo and not in Amboasary-Atsimo. Once more, precipitation was not associated with malnutrition.

Conclusion: While our study is limited by data quality and quantity, it demonstrates the deep impact of semi-arid climate on SAM, MAM and GAM. Vegetation acts as a protective factor of MAM and GAM, and dry and harvest season are protective of all malnutrition forms. Our district-level analysis presents contradicting results, explained by unreliable data. This thesis emphasizes the importance of this topic in Madagascar. Further studies are needed and would allow local public health systems to increase surveillance of environmental predictors of malnutrition to prevent and attend to malnutrition cases.

Keywords: Malnutrition, Precipitation, Vegetation, Climate, South Madagascar

Abstract in French

Introduction : La malnutrition est un problème de santé critique à Madagascar, affectant environ 2 millions d'individus, en particulier les enfants. Cette thèse explore la relation entre toutes les formes de malnutrition en relation avec la précipitation, la végétation et le climat, ainsi que leur rythmicité interannuelle.

Méthodes : Les données de prévalence de la malnutrition ont été collectées en 2018 et 2021 au niveau des communes et les données de 2015-2022 portent sur les admissions dans les centres CRENAS et l'incidence dans les districts de Madagascar. Des analyses descriptives et univariées ont été réalisées, en relation avec les indicateurs de végétation et précipitation. Ceux-ci ont ensuite été analysés via des modèles multivariés de régression bêta avec excès des zéros multi-niveaux et un modèle quasi-poisson multivarié tenant compte de la saisonnalité.

Résultats : Les données des communes montrent que les communes au climat semi-aride sont plus susceptibles de développer de la malnutrition aigüe sévère (SAM) en 2018 et 2021, tandis que les malnutritions aiguës modérée et globale (MAM, MAG) ne présentent cette relation que pour 2021. L'indice de végétation est négativement associé à la MAG et à la MAM en 2021, tandis qu'aucune association n'a été trouvée entre la précipitation et tout type de malnutrition. Les trimestres 2, 3 (saison sèche) et 4 (début saison humide) étaient négativement associés à toutes les formes de malnutrition, ce qui montre l'effet protecteur de la saison sèche et des récoltes. L'analyse au niveau du district a montré des résultats contradictoires, avec une relation positive entre la végétation décalée d'un mois et l'incidence de la malnutrition à Ampanihy et Betioky-Atsimo, mais pas à Amboasary-Atsimo. Une fois de plus, la précipitation n'a pas été associée à la malnutrition.

Conclusion : Bien que notre étude soit limitée par la qualité et la quantité des données, elle démontre l'impact significatif du climat semi-aride sur MAS, MAM et MAG. La végétation agit comme un facteur de protection de la MAM et de la MAG, et la saison sèche et la saison des récoltes protègent de toutes les formes de malnutrition. Notre analyse au niveau du district présente des résultats contradictoires, qui s'expliquent par le manque de fiabilité des données. Cette thèse souligne l'importance de ce sujet à Madagascar. D'autres études sont nécessaires et permettraient aux systèmes de santé publique locaux d'augmenter la surveillance des prédicteurs environnementaux de la malnutrition afin de prévenir et de traiter les cas de malnutrition.

Mots-clés : Malnutrition, Précipitation, Végétation, Climat, Sud de Madagascar

Introduction

Background and context

Malnutrition can be defined by deficiencies, excesses, and imbalances in a person's intake of energy or nutrients. It can be classified into 2 groups: one being 'undernutrition' and the other being overweight, obesity and diet-related non-communicable diseases. Undernutrition includes stunting, meaning low height for age, wasting, meaning low weight for height, and finally underweight, meaning low weight for age (WHO team, 2023). Malnutrition can also be categorized as severe acute malnutrition and moderate acute malnutrition, respectively SAM and MAM. MAM, corresponding to wasting, is defined by a -3 to -2 z-score (standard deviation), which uses both the child's height and weight with regards to a reference population, and a mid-upper arm circumference (MUAC) between 11.5cm and 12.5.cm SAM on the other hand, is the most dangerous form of acute malnutrition and is defined by (weight for height z-score/weight for length z-score)<-3 standard deviation or a mid-upper arm circumference inferior to 11.5cm. Diagnosis of SAM includes severe wasting, with a loss of fat and muscle tissue, as well as the presence of oedema on the limbs, skin lesions, enlarged liver and hair thinning. Global Acute malnutrition refers to MAM and SAM together, often used as nutritional status measurement at population level and to assess situation severity. Malnutrition in children, even if treated, can still have an impact on the physical and mental development of the child in the long term (Prost et al, 2019; Lenters et al, 2016).

Acute malnutrition is particularly serious as it is one of the principal causes of morbidity and mortality in children under the age of 5 years old in the world. As previously mentioned, malnutrition can be caused by an inadequate dietary intake due to social or environmental factors, however, it can be the result of diseases. Indeed, malnourished children are more likely to fall ill due to their diminished resistance, which will cause them to lose their appetite, furthering their state of malnourishment, in a vicious circle (Nassur et al, 2022). Furthermore, a study conducted in Malawi showed that SAM survivors have poorer physical strength and physical capacity as well as lower school achievements. If they are exposed to unhealthy lifestyles, as seen in changes in dietary trends in many African countries, they may face increasing weight gain and be at greater risk of non-communicable diseases (Lelijveld et al, 2016). Moreover, severe malnutrition can have severe long-lasting impacts on health. Indeed, this exposure can lead to an increased risk of cardiometabolic non-communicable diseases, as well as impaired glucose metabolism (Grey et al, 2021). Children impacted by either MAM or SAM have respectively a 3- and 9-fold increased mortality rates according to a longitudinal study from Asia, Africa and South America (Prost et al, 2019). Generally, the WHO estimates that 10% and 20% of malnourished children die

within 2 to 3 months without treatment (Prost et al, 2019). Stunting has also been reported to affect and increase the risk of chronic diseases. In addition, some evidence exists exhibiting that stunted children earn on average 20% less as adults than non stunted children, and can thus have an economical impact (De Onis et al, 2016).In Sub-Saharan African countries stunting diminishes the likelihood of completing secondary school and obtaining wage-earning employment, and women that have experienced stunting and malnutrition as children are more likely to face complications during delivery (Grace et la, 2012).

Many areas in the world, including Sub-Saharan Africa are severely affected by undernutrition. Madagascar is one of them. According to the United Nations International Children's Emergency Fund (UNICEF), the percentage of children under 5 years old that are stunted is very high, higher than 47%. In comparison, the percentage of overweight children is between 2.5% and 5%, which is considered low. Furthermore, Global acute malnutrition (GAM) affects more than 6% and SAM affects 1% of children under 5 years of age. (Nassur et al, 2022). In addition, the COVID-19 pandemic has accentuated this situation and increased the risk regarding all forms of malnutrition, leading to serious repercussions. Indeed, it has undermined food and nutrition security, by limiting access to fields and markets in many areas, and the ability to purchase food for vulnerable populations; as well as reducing income-earning opportunities (Conti et al, 2021). Moreover, the adult population of Madagascar also faces malnutrition, with, for example, 37% of women suffering from iron deficiency. It is important to note that, in Madagascar, rural areas are marginally more prone to food insecurity than urban areas (Conti et al, 2021) (Rakotosamimanana, et al. 2014).

The presence of food insecurity in Madagascar is partly led by seasonality. Madagascar is an island located 400km fom the Southeast African coast, organized into 6 provinces, 22 regions, and 1549 communes (Ministere de l’interieur et de la decentralization, 2015). It has a highly varied topography, winds, and climates. The south of Madagascar experiences three types of climates. The South-East faces a humid climate, the South-West a semi-arid climate, and the south of the highlands face a tropical climate. It experiences two main seasons: a dry one from May to October and a rainy one from November to April (Rakotoarison et al, 2018). The seasonal reductions in food consumption during the lean season (a period of time between planting and harvesting where food harvested from the previous year is starting to run low and is not yet replenished by the crops of the new harvest; and where job opportunities are scarce and income plummets) can put one million Malagasy below the poverty line, joining 9 million more who remain chronically malnourished throughout the year (Harrington et al, 2022). This food insecurity coincides with diseases present during the rainy season, worsening the health of Malagasies (Dostie et al, 2022). In Madagascar, the rainy season occurs mainly from November to April and is a critical period

for agriculture. December to March also coincides with the lean season (Harrington et al, 2022; Dostie et al, 2002).

Over the years, heat has increased in all regions of the island, and is combined with the rise of minimum and maximum temperatures. The atmosphere warming leads the entire island to experience modifications in the hydrological cycle with fluctuating rainfall patterns that impact the quality and quantity of available water resources (Nematchoua et al, 2018)

The impact of droughts is also dependent on the region and geographical location, as arid and semi-arid regions tend to be more vulnerable to such events, thus impacting the South of Madagascar more (Salvador et al, 2020). In the South of Madagascar, 90% of the population lives below the poverty line, compared to 77% for the rest of the country; and many face famine-like conditions. Regions like Androy are severely hit especially when drought induced reduction in rain fall affects the region during the rainy season, leading to crop failures. Regions located in the highlands and the East of Madagascar can also be affected by droughts, especially when the rainy season onset is delayed, reducing precipitation below normal levels along with surface and groundwater, thus having a negative impact on agricultural and food production. It is also important to note that factors other than droughts also play a role in aggravating food insecurity, such as demographics, infrastructures, and policy stresses. (Harrington et al, 2022; Norohasina Rakotoarison et al; 2018)

Over the years, droughts and political crises in Madagascar have negatively impacted the population, its economic capacity, and their resilience. Furthermore, agricultural productivity has been lowered and water sources depleted (Nassur et al, 2022). A recent example are the droughts triggered by the El Nino phenomenon in September 2015, which created a nutritional crisis in the South of Madagascar (Rakotoarison et al, 2018).

Droughts do not have a clear definition and are complex environmental events. They cannot be quantified due to the fact that it is difficult to establish their beginning and end, as defined by Gillette in 1950, they are a “creeping phenomena” developing slowly over long periods of time (Wall et Hayes, 2016). Therefore, several types of droughts have been distinguished. Meteorological droughts are due to a prolonged deficit of precipitation or acute shortages and affects large areas. It is usually defined by its severity and duration. In comparison, hydrological droughts are associated with surface water and groundwater supplies and their relationship with precipitation. Agricultural droughts refer to soil moisture and crops, while socio-economic droughts are based on excess demand of a good following water shortage. These are all interrelated, and a drought should be seen as an inter-

disciplinary event. In short, droughts are a consequence of a deficit of rainfall over long periods of time (Salvador et al, 2020).

In general, droughts lead to a reduction in water availability and quality as well as food production diminution. Such a decrease in good quality water can lead to chemical and microbiological contamination and increase the risk of diseases. Diminution of food production will lead to food insecurity, via reduction of quantity and stability of food, leading to malnutrition, mortality and morbidity (Salvador et al, 2020). For example, in Brazil, half of natural disasters are related to droughts. There, droughts lead to unsafe water consumption and sanitation issues, displacement of population and disruption of local health services and impact vulnerable populations more prominently. It impacts malnutrition, increases risk of communicable and respiratory diseases and can additionally lead to mental health disorders and psycho-social stress (Sena et al, 2014).

On another note, droughts and stresses on water availability can lead to the reutilisation of wastewater, lowering its quality and furthering sanitation and hygiene issues. Indeed, waterborne infectious diseases cause 801 000 children worldwide to die annually due to diarrheal diseases of microbial or viral origin and from infectious diseases like intestinal parasites which impact the digestive system and its function and are direct causes of malnutrition and undernutrition (Shahira et al, 2018; Ravaoarisoa et al, 2018).

Additionally, droughts can lead to food insecurity and malnutrition by reducing food production and crops, thus limiting food access (Coughan de Perez et al, 2019). Reduced agricultural production is likely to happen in many African countries, due to climate change, reducing per capita harvested areas, and reducing per capita calorie availability; inevitably leading to undernutrition. In addition, “micro-nutrient” deficiencies can increase the risk of acquiring infectious diseases, which themselves can lead to and worsen undernutrition (Phalkey et al, 2015). A study conducted in Madagascar demonstrated that most mothers with malnourished children had limited access to food, with limited food variety (Asgary et al, 2015). Finally, a study conducted in Burkina Faso showed that children are especially more vulnerable to reductions in crop yield by using the Normalized Difference Vegetation Index (Belesova et al, 2023).

While several studies exist studying anthropocentric variables affecting malnutrition in Madagascar and elsewhere, such as dietary diversity, socio-economic status, social profile and economics etc; very few studies were conducted on modeling and quantifying the impact of precipitation, vegetation, climate, and environmental indicators on malnutrition (Nassur et al, 2022; Ravaoarisoa et al, 2018). A review conducted on the impacts of climate change on undernutrition demonstrated that climate and weather variables can play as much of a role in

childhood malnutrition as anthropocentric and household variables (Phalkey et al, 2015). Some studies in other African countries like Mali, Kenya and Nigeria have shown that changes and reduction in precipitation and increase in temperatures can have an impact on the prevalence of stunting and undernutrition of children in these countries (Van der Merwe et al, 2022; Iankowska et al, 2012; Niles et al, 2021). Even fewer studies are available focusing on the impact of the presence of vegetation on malnutrition. One study performed in the Democratic Republic of Congo showed that the state of vegetation can be associated with childhood stunting, especially in rural areas (Bangelesa et al, 2023). Even fewer studies have investigated the effect of the temporal evolution and time series of these indicators.

Being able to understand the relation between climates, seasonal patterns, environmental indicators of Madagascar and malnutrition will allow researchers to better understand, prevent, and anticipate malnutrition tendencies. If we manage to establish the presence of a relation this would potentially permit us to anticipate malnutrition based on predictions of precipitations of the affected districts and could possibly allow help systems, Governmental agencies and non-governmental organizations to tailor their actions.

There are little to no attribution studies examining individual weather events over Madagascar, and projection studies conclude on the reduction of mean rainfall under moderate and high emission scenarios (Shared Socioeconomic Pathway 2-4.5 & 5-8.5), which further stresses the importance of studying the impact of droughts, precipitation and environmental indicators on health and malnutrition to understand and potentially adapt to such future events (Harrington et al, 2022). This issue is particularly pressing as Madagascar, especially the South is a barely documented area and has a high poverty rate and a highly vulnerable population of approximately 2 000 000 people, which will face, as do many other countries in the world, worsening environmental events and droughts due to climate change (World Bank, 2020; Semenza, 2020).

Context of the project

This practicum and Master's thesis consist of a preliminary database construction, data description and research work which fall under a future ANR project (National Research Agency) led by Simon Carriere, PhD. This "Drought impact on groundwater and population health in Madagascar" (DIGAP) project aims to elucidate the link between groundwater dynamics at a regional scale in the poorly documented area of the South of Madagascar and study how environmental factors, especially groundwater, can be used as warning signs of deteriorating health situations. This practicum was overseen by Dr. Jacques Gardon at Hydrosciences Montpellier, where I performed the aforementioned data management and exploratory analysis.

Aim and rationale

- General objective

The aim of this research is to understand if the local hydrological dynamics of precipitation and water availability impact malnutrition in districts in the South of Madagascar. This will be done by studying the relationship between environmental and malnutrition indicators in the South of Madagascar and performing a stratified analysis of the communes of the years 2018 and 2021, as well as exploring the seasonal patterns and trends of districts from 2016 to 2022.

- Specific objective

The specific objectives include: i) Creation of a database following data gathering that is usable for future research, ii) understanding the relation of the various climates of Madagascar on malnutrition, iii) determining the role of inter-annual rhythmicity on malnutrition, and finally iv) quantifying the association between vegetation and precipitation indicators and malnutrition prevalence and incidence among children under 5 years old in the South of Madagascar.

- Hypothesis

We expect to observe a negative relation between precipitation and vegetation indicators and malnutrition prevalence and incidence. Similarly, according to the literature, we expect semi-arid districts to be more severely impacted by malnutrition than humid and semi-humid ones.

Methods

- **Data collection**

For the environment, we used an indicator for vegetation cover, as well as a rainfall indicator. For malnutrition, we used three prevalence indicators: severe acute malnutrition (SAM), moderate acute malnutrition (MAM), and global acute malnutrition (GAM), as well as an incidence indicator: number of admissions to “Centres de Récupération et Education Nutritionnelle Ambulatoire pour la Malnutrition Aiguë Sévère” (CRENAS) or “Ambulatory Nutritional Rehabilitation and Education Center for severe acute malnutrition”. Malnutrition, vegetation, and precipitation data were all collected at two distinct and complementary scales. One at the level of districts, and the other at the commune level, where communes are aggregated under districts. This decision was made as malnutrition data was acquired for these two scales but with a sub-sample of districts at the commune level. Both levels of analysis are relevant providing both spatial and temporal approaches to our analysis.

Vegetation and Precipitation data

Data regarding vegetation was obtained from the Copernicus Global Land Monitoring Service website, which used Remote Sensing data from the Vegetation, PROBA-V sensor, at a spatial resolution of 300 meters to 1 kilometer. The Leaf-Area Index (LAI) indicator is often used as a measure in studies on forests, crops and climate. It is estimated as “half the total area of green elements of the canopy per unit horizontal ground area” or “half the area of all leaves per unit of ground”, or “leaf area(m^2) per ground area (m^2)” and thus does not have units (Trimble. S, 2022) (Copernicus, 2022). The former definition was used throughout this work. This indicator is reliable for assessing plant growth and is therefore often used in agronomy and horticulture. It is important to note that the LAI estimated by the satellite takes into consideration the canopy of all layers of the plant, including the understory, which is a significant contribution, especially in forests. In other words, LAI can be used to measure not only plant growth, but also vegetation cover and thickness (Copernicus, 2022). Studies assessing the quality of various vegetation indicators demonstrated that the LAI indicator had the best agreement with their reference data (Brown et al, 2020). Similarly, a study conducted in 2020 demonstrated that the LAI estimated by the Copernicus Global Land Service agreed best with available human-based ground observations in forests in Europe and the United States (Bornez et al, 2020).

Other studies assessing the quality of this indicator among others provided by the Copernicus Global Land Monitoring Service established it to be consistent with guidelines from the Land Product Validation (Fuster et al, 2020). LAI provided by Copernicus is recognized as an Essential Climate Variable, which is a “physical, chemical or biological

variable […] that critically contributes to the characterization of Earth's climate" by the Global Climate Observing System (Copernicus, 2020; GCOS, 2023). All these factors contributed to the decision to use this indicator for our study.

Precipitation data was obtained from the GloH20 website (https://www.gloh2o.org/). The Multi-source Weighted Ensemble Precipitation (MSWEP) indicator was used. This global-gridded precipitation indicator was developed by including, in the most optimal manner, several data sources consisting of gauges, satellites, and reanalysis data. This was done in order to obtain reliable precipitation estimates on a global scale. Gauge data is retrieved from a large set of 13 762 stations across the world. Furthermore, MSWEP is collected at a 3-hourly timescale, daily, as well as monthly temporal resolutions, with a spatial resolution of 0.25°, which corresponds to approximately 25km at the equator. The performance of this indicator was estimated using data from 125 meteorological tower stations around the world and was compared to several other precipitation datasets. The MSWEP dataset obtained the best score for 60% of the stations compared to the other datasets. It obtained the highest daily correlation coefficient (*R*) amongst all the datasets, with a median *R* of 0.67 compared to 0.44 to 0.59 for the other datasets (Beck et al, 2017).

Studies performed in Iran and China compared different precipitation datasets and demonstrated that MSWEP's performance was the best with a high correlation with in situ observations at monthly time scales and was particularly good at distinguishing rainfall from no-rainfall conditions (Alijanian et al, 2017; Xu et al, 2019). Furthermore, another study exhibited the consistency of the MSWEP indicator with small biases found in the satellite products compared to gauge-based and reanalysis products for MSWEP. The study suggests that MSWEP better represents rainfall over Madagascar than other indicators or datasets (Hundilida Randriatsara, et al. 2022).

Both of these indicators (LAI and MSWEP) were extracted from the aforementioned websites into a shapefile (.shp file) on a monthly basis, from 2015 until 2023, both at the level of communes and districts (Figure 1). The MSWEP indicator is measured in millimeters of rainfall per month.

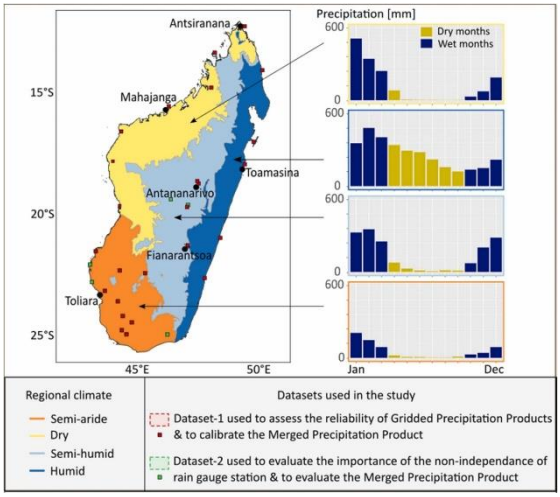

Figure 1: Average monthly precipitation totals based on all rain gauges for each climatic region for the period 2011-2018 (Ollivier et al, 2023)

Malnutrition and demographic data

The following two types of malnutrition data were collected by the National Office of Nutrition and the Ministry of Public Health through the

various regional public health departments with the technical and financial support of UNICEF.

Malnutrition data at the district level (incident cases) were obtained on a monthly basis from the website Response Relief Web[1]. This database regroups the new admissions for severe acute malnutrition in the “Centre de Recuperation Nutritionnelle pour la Malnutrition Aigue Severe” (CRENAS) or “Ambulatory Nutritional Rehabilitation and Education Center for severe acute malnutrition”. These centers are healthcare infrastructures managed by doctors and nurses. This data has been collected for 21 districts. Among districts, three have data ranging from 2015 until 2022, six have data starting in 2016, and twelve starting in 2019. The data collected will focus on districts located in the South of Madagascar, for which complete time series data is available.

Data collected at the commune level (prevalence data) comes from screenings implemented by the National Nutrition office and the Ministry of Public Health and performed in each commune each trimester. This malnutrition data is available for 245 communes at the time interval of trimesters, from 2018 until 2021. The municipalities do not cover the entire territory of the 21 aforementioned districts (Appendix 1). For each commune, the number of screened children, the exhaustivity rate of the screening, the percent of children diagnosed with GAM, MAM, and SAM were reported. These last three indicators were determined using MUAC, where MUAC inferior to 125mm and/or oedema presence meant GAM, MUAC between 115mm and 125mm meant MAM, and finally MUAC under 115mm and/or presence of oedema meant SAM.

Both malnutrition databases quality was assessed using the ENA software following “Standardized Monitoring and Assessment of Relief and Transitions” (SMART) criterias by the Nutrition Cluster of Madagascar (Unicef bulletin d’information cluster nutrition, 2022). This data is readily available online under the format of quarterly reports[2].

The SMART methodology was developed during the early 2000s and incorporates the Emergency Nutrition Assessment (ENA) software. ENA is an easy-to-use software to enter, analyze and check the quality of the data collected every day through questionnaires. The ENA software comprises of a verification system for the rapid identification of measurement errors for them to be corrected in the most efficient and swift manner (Baille et al, 2020), It includes automated functions for sample size calculation, sample selection, quality checks, standardization for anthropometry measurements and report generation (SMART, 2022).

[1] https://response.reliefweb.int/madagascar/nutrition

[2] https://www.unicef.org/madagascar/rapports/bulletin-dinformation-du-cluster-nutrition-2021

The SMART methodology was created to assess nutritional status in emergency situations. It includes several steps from defining objectives, geographic areas and population group, to meeting community leaders and selecting time and sampling methods, obtaining the equipment and training the teams. The final step entails enhancing data accuracy and report redaction. This methodology includes how to measure and define malnutrition types in children, whether it is considered Severe, Moderate, or Global Acute malnutrition. While this methodology pushes forward the use of z scores, it also proposes a protocol to assess the state malnutrition using mid-upper arm circumference (Emergency Nutrition Network, 2022).

CRENAS admission data, and malnutrition screening data, are published online and are non-nominative aggregated data, therefore, their use does not present an ethical problem, as tracing the individual would not be possible. However, because the data being used is sourced from Madagascar and will be exploited in a larger ANR project (National Research Agency), a request for a data transfer agreement between the Ministry of Health of Madagascar and Sorbonne University is in the process of being signed.

Additional data was collected to assess the population size at the district level. Data regarding the population of the districts was obtained from the INSTAT ("Institut National de la Statistique – Madagascar" or National Institute of Statistics – Madagascar). We used data from the third general census of the population and habitation performed in 2018, as well as the census performed in 2013 (INSTAT, 2020).

- **<u>Data Management</u>**

Firstly, two relational databases were created using Microsoft Access from the various data collected, and data management was performed to ensure data quality by cross-checking sources. One database was created using prevalence data at the commune level while the other was created using the number of incident cases data at the district level.

For data at the level of districts, data about the yearly population size was established by determining the district population growth rate from the census of 2013 and 2018 and the following equation:

$$Population\ Growth\ Rate = \frac{Population_{time\ 2} - Population_{time\ 1}}{Population_{time\ 1}} * 100$$

<=>

$$Population_{time\ 2} = (Population\ Growth\ Rate + 1) * Population_{time\ 1}$$

This equation allowed us to determine the evolution of the population over time. Our data focuses on the population that are under 5 years old, therefore we took the proportion of children under 5 for each region established in the "Recensement General de la Population

et de l'Habitat of 2018" or "General population and habitat census of 2018" and applied it to each yearly population under the assumption that this proportion remains unchanged over time. This gave us the yearly population of children that are under 5 years old for each district, leading to the estimation of the monthly incidence per 1000 children under 5 years old.

We excluded all districts with data starting in 2019 as the time series duration would be too short to perform a significant analysis. We excluded the districts of "Nosy-Varika" and "Ikongo" due to a large proportion of missing values.

For both levels (Districts and communes), MSWEP precipitation data was converted from mm/month to m/month.

For data at the level of communes, some communes had to be aggregated to ensure correspondence with precipitation and vegetation data. To do so, from the percentages of GAM, SAM, MAM, and number of children screened, we estimated the number of children with SAM, MAM, GAM. We summed them up and re-determined the percentage of SAM, MAM, GAM for the aggregated communes (see following equation).

$$Number\ of\ MAG\ children = Number\ of\ screened\ children * \%MAG$$

$$\%MAG_{aggregated\ commune} = \frac{\sum Number\ of\ MAG\ children}{\sum Number\ of\ screened\ children} * 100$$

We excluded years where only data for one or two trimesters were available, leaving us with data for the years 2018 and 2021. Similarly, we excluded districts where no commune data was available. We then imputed GAM, MAM, SAM data for communes using the median for each trimester and each district.

We removed outliers, and communes with prevalence superior to 100% which were not interpretable values. Moreover, we divided malnutrition prevalence by 100 in order to have values between 0 and 1 to perform a beta regression. Finally, for LAI and MSWEP data, which had been collected at a monthly interval, the mean of 3 months was taken for the trimester value (for example, mean LAI for January to March 2018, will be that value for trimester 1 for 2018).

- **Statistical model**

For the analysis at the district level, we followed the methodology developed by Bhaskaran, et al. in "Time series regression studies in environmental epidemiology". This includes performing a time series decomposition using one of three methods: time stratified models, periodic functions (fourier terms), or flexible spline functions. The latter was used. In

our analysis, we decided to focus on a couple of districts individually and apply the flexible spline function method (Bhaskaran et al, 2013). These districts were favored based on the length of their time series. This allows us to account for the seasonality in our model, as well as remove autocorrelation. We performed descriptive statistics to understand the distribution and evolution over time of our indicators by districts, as well as performing lag analysis to verify the presence of lagged relationships. We then performed a quasi-poisson regression due to the wide variance present in the model. This type of regression was favored as we are working with admission counts and a relatively small sample size (Hayat, et al, 2014).

For the analysis at the commune level, descriptive analysis was performed. Then univariate analyses were performed with a 0.25 level of significance to determine which covariates outside of our variables of interest were to be included in the final model. Then multivariate beta regression was performed. Beta regression was favored as it is a regression model which can accommodate continuous data that are restricted on the interval (0,1) (Figueroa Zuniga et al, 2013). This type of regression is adapted to our outcome data (SAM, MAM, GAM) that is expressed in percentages (de Azevedo Souza et al, 2018). In addition, our beta regression was a zero-inflated model. Indeed, our data presented many entries with values at zero, which could cause issues in the analysis. Thus, performing the analysis with a zero-inflated model allows us to take into consideration these values (Liu et al, 2015). Finally, we decided to perform a multi-level regression, as the communes are grouped within districts. In addition, a likelihood-ratio test and the AIC showed the multi-level model to be more appropriate than the non-multi-level model.

All the multivariate statistical analysis was performed using the R software using the level of significance alpha=0.05.

Results

- **Communes: Description of the study population**

For the years 2018 and 2021, data from communes has been collected. For both years, 80.2% of the communes had a Semi-arid climate compared to 19.7% with a humid climate. Similarly, for both years, similar proportions of communes were found in each district with approximately 12%, 13.5%, 12%, 13%-14%, 4.5%, 20%, 20%, and 5% for the districts of Amboasary-Atsimo, Ambovombe-Androy, Ampanihy, Bekily, Beloha, Betioky-Atsimo, Taolagnaro, and Tsihombe respectively. Moreover, for 2018, each 24-25% of communes were present for each of the four trimesters, while for 2021, 33.33% of communes were present for each of the three trimesters (Table 1).

Regarding our prevalence outcomes of interest, the communes mean and median SAM, MAM and GAM for 2018 were 0.82% (SD:1.22) and 0.50% (IQR: 0.90-0.20), 7.52% (SD: 7.74) and 5.50% (IQR: 9.70-2.40), and 8.49% (SD: 9.29%) and 6.20% (IQR: 10.60-2.90). For the year 2021, SAM's, MAM's, and GAM's median and mean were of 1.77% (SD:1.94) and 1.10 (IQR: 2.40-0.40), 11.18% (SD:7.43) and 10.40% (IQR: 15.70-5.25), and finally 12.95% (SD: 8.93) and 11.34 (IQR: 18.40-5.98) (Table 1).

For the environmental indicators LAI and MSWEP in 2018, the mean and median were respectively of 0.92 (SD: 1.02) and 0.51 (IQR: 0.98-0.29), and 0.045 m/month (SD: 0.04) and 0.047m/month (IQR: 0.056-0.005), For the year 2021 for LAI and MSWEP, the mean and median are 0.93 (SD: 1.01) and 0.57 (IQR: 0.99-0.30), and 0.043m/month (SD: 0.043) and 0.025m/month (IQR:0.071-0.005) (Table 1).

Table 1: Descriptive characteristic of communes of the South of Madagascar in 2018 and 2021

	2018	2021
Variables	**Nb (%) N=542 communes**	**Nb (%) N=542 communes**
SAM	Mean: 0.82 (+/- SD=1.22) Median: 0.50 (IQR: 0.90-0.20)	Mean:1.77(+/- SD=1.94) Median: 1.10 (IQR:2,40-0.40)
MAM	Mean: 7.52 (+/- SD=7.74) Median: 5.50 (IQR: 9.70-2.40)	Mean: 11.18 (+/- SD=7.43) Median: 10.40(IQR:15.70-5.25)
GAM	Mean: 8.49 (+/- SD=9.29) Median: 6.20 (IQR: 10.60-2.90)	Mean: 12.95 (+/- SD=8.93) Median: 11.34(IQR:18.40-5.98)
Climate Semi-arid Humid	 435 (80.26) 107 (19.74)	 330 (80.29) 81 (19.71)
District Amboasary-Atsimo Ambovombe-Androy Ampanihy Bekily Beloha Betioky-Atsimo Taolagnaro Tsihombe	 64 (11.81) 74 (13.65) 64(11.81) 73(13.47) 24(4.43) 108(19.93) 107(19.74) 28(5.17)	 48 (11.68) 57(13.87) 48(11.68) 57(13.87) 18(4.38) 81(19.71) 81(19.71) 21(5.11)
Trimester T1 T2 T3 T4	 137 (25.28) 134 (24.72) 134(24.72) 137(25.28)	 137(33.33) 137(33.33) 137(33.33) -
LAI	Mean: 0.92 (+/- SD=1.02) Median:0.51 (IQR:0.98-0.29)	Mean: 0.93 (+/- SD=1.01) Median: 0.57 (IQR: 0.99-0.30)
MSWEP	Mean: 0.045 (+/-SD=0.04) Median:0.047 (IQR: 0.056-0.005)	Mean:0.043 (+/-SD:0.043) Median:0.025 (IQR: 0.071-0.005)

The distribution of our outcomes of interest (SAM, MAM, and GAM) by communes for both years 2018 and 2021 present a strong proportion of values at 0, as well as have a distribution very indicative of a beta distribution (Figure 2, Appendix 2 and Appendix 3), as previously mentioned in the Methods section, this corroborates our choice in performing a zero-inflated beta regression model. Furthermore, the boxplot presented in Appendix 4 and Appendix 5 provide a visual representation of the changes in distribution and range of the indicators in each district, which has comforted our choice of performing a multi-level regression, as mentioned in the Methods section. Indeed, for the year 2018, for all three indictors, the district of Ampanihy appears to have a wider range and an increased median compared to other districts. Similarly, the District of Taolagnaro presents a smaller median and smaller range compared to the other districts (Appendix 4).

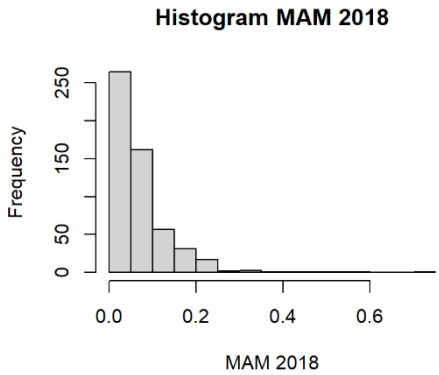

Figure 2: Distribution of MAM in 2018 in the South of Madagascar

For the year 2021, the district of Taolgnaro presents similar trends as in 2018, while Ampanihy's is less definite as in 2018, especially for SAM (Appendix 5).

- **Municipality: Relation between environmental indicators and Malnutrition prevalence during 2018 and 2021**

Three sets of univariate analyses were performed for each of the malnutrition indicators (SAM, MAM, GAM). For SAM in both 2018 and 2021, Climate, Trimesters and LAI had p-value inferior to 0.25, while this was only the case for MSWEP in 2021. The p-value for MSWEP in 2018 was 0.69 and was still included in the multivariate analysis. Similar observations can be made for both MAM and GAM, with only the p-value for the second trimester of 2018, changing and becoming less significant (Appendix 6,7,8).

The results of our multi-level multivariate regression analysis are presented in tables 2 to 4. The results in Table 2 showed that for MAM in 2018, only Trimesters 3 and 4 compared to Trimester 1 provided statistically significant results (p=0.026 and 0.044 respectively) with coefficients of -0.26 [-0.48- -0.03] and 0.83 [–0.036- -0.00]. For the year 2021, more variables appear to be significant. Indeed, communes located in the semi-arid climate are significantly associated with MAM (p=0.009), as well as LAI with a p-value of 0.026, with coefficients of 1.02 [0.25-1.79] and -0.15 [-0.29- -0.02] respectively. Moreover, both trimesters 2 and 3 were significantly related to MAM (p=0.039 and p<0.001). For both years, MSWEP does not appear to be significant. For this model the conditional R^2 for 2018 is 0.367 and for 2021: 0.742, while the marginal R^2 0.179 and 0.563(Table 2).

Table 2: Association between environmental indicators and moderate acute malnutrition in communes of the South of Madagascar in 2018 and 2021.

	MAM 2018			MAM 2021		
Predictors	β	*CI*	*p*	β	*CI*	*p*
Climate						
Semi-arid	0.64	-0.16 – 1.43	0.118	1.02	0.25 – 1.79	**0.009**
Trimester						
T2	-0.13	-0.34 – 0.07	0.199	-0.26	-0.50 – -0.01	**0.039**
T3	-0.26	-0.48 – -0.03	**0.026**	-0.58	-0.85 – -0.32	**<0.001**
T4	-0.18	-0.36 – -0.00	**0.044**			
LAI	-0.04	-0.18 – 0.11	0.639	-0.15	-0.29 – -0.02	**0.026**
MSWEP	-1.44	-4.65 – 1.76	0.377	0.12	-2.95 – 3.20	0.938

Significant results: p<0.05
Marginal R^2 / Conditional R^2 2018: 0.179 / 0.367
Marginal R^2 / Conditional R^2 2021: 0.563 / 0.742

For GAM in 2018, similar results to MAM can be observed. Indeed, both Trimesters 3 and 4 appear to have a significant relation to GAM (p=0.026 and p=0.038). For 2021, once

more we observe a similar pattern as in MAM, where Climate and LAI are both significantly associated with GAM (p=0.009 and p=0.033), as well as both trimesters 2 and 3 (p=0.01 and p<0.001). For Climate semi-arid, the coefficient is 1.03 [0.26- -1.81], while for LAI it is -0.15 [-0.28- -0.01]. For both years, MSWEP does not appear to be significant (Table 3). For this model the conditional R^2 for 2018 is 0.360 and for 2021: 0.762, while the marginal R^2 is 0.192 and 0.581 respectively.

Table 3: Association between environmental indicators and global acute malnutrition in communes of the South of Madagascar in 2018 and 2021.

	GAM 2018			GAM 2021		
Predictors	β	*CI*	*p*	β	*CI*	*p*
Climate						
Semi-arid	0.67	-0.09 – 1.44	0.084	1.03	0.26 – 1.81	**0.009**
Trimester						
T2	-0.09	-0.30 – 0.11	0.377	-0.33	-0.57 – -0.08	**0.01**
T3	-0.26	-0.49 – -0.03	**0.026**	-0.69	-0.96 – -0.43	**<0.001**
T4	-0.19	-0.38 – -0.01	**0.038**			
LAI	-0.04	-0.19 – 0.11	0.606	-0.15	-0.28 – -0.01	**0.033**
MSWEP	-1	-4.26 – 2.26	0.548	0.29	-2.79 – 3.37	0.853

Significant results: p<0.05
Marginal R^2 / Conditional R^2 2018: 0.192 / 0.360
Marginal R^2 / Conditional R^2 2021: 0.581 / 0.762

Finally, for SAM, the results appear to differ compared to the other two indicators. Indeed, in 2018 the Semi-arid Climate is significantly related to SAM with a p-value of 0.017 and a coefficient of 0.61 [0.11-1.11]. Then both trimesters 3 and 4 are significant with p-values of <0.001 and 0.006. The other variables: MSWEP, LAI, and trimester 2 are not significant. For the year 2021, Climate semi-arid once more appears to be significantly related to SAM with a p-value of 0.036, and a coefficient of 0.82 [0.05-1.58]. This time, trimesters 2 and 3 are significantly related to SAM compared to trimesters 3 and 4 with both p-values inferior to 0.001. This again, LAI and MSWEP do not appear to be significantly related to SAM (Table 4). For this model the conditional R^2 for 2018 is of 0.179 and for 2021: 0.590, while the marginal R^2 is of 0.141 and 0.457 respectively.

Table 4: Association between environmental indicators and severe acute malnutrition in communes of the South of Madagascar in 2018 and 2021.

	SAM 2018			SAM 2021		
Predictors	β	*CI*	*p*	β	*CI*	*p*
Climate						
Semi-arid	0.61	0.11 – 1.11	**0.017**	0.82	0.05 – 1.58	**0.036**
Trimester						
T2	-0.17	-0.38 – 0.04	0.107	-0.59	-0.87 – -0.31	**<0.001**
T3	-0.42	-0.66 – -0.19	**<0.001**	-1.13	-1.43 – -0.82	**<0.001**
T4	-0.26	-0.45 – -0.07	**0.006**			
LAI	0.01	-0.14 – 0.17	0.857	-0.06	-0.20 – 0.08	0.407
MSWEP	-1.46	-4.96 – 2.04	0.413	0.67	-2.81 – 4.15	0.706

Significant results: p<0.05
Marginal R^2 / Conditional R^2 2018: 0.141 / 0.179
Marginal R^2 / Conditional R^2 2021: 0.457 / 0.590

- **District: Description of the study population**

For the dataset at the district level, 3 stratified analyses were performed on the districts of Amboasary-Atsimo, Ampanihy, and Betioky-Atsimo. For the CRENAS admissions, the mean incidence per 1000 children under 5 years old were of 7.26 (SD:7.12),8.64 (SD:7.87), and 4.54 (SD: 3.14) for Amboasary-Atsimo, Ampanihy, and Betioky-Atsimo respectively. A significant monthly seasonal pattern was observed (Figure 3, Appendix 9).

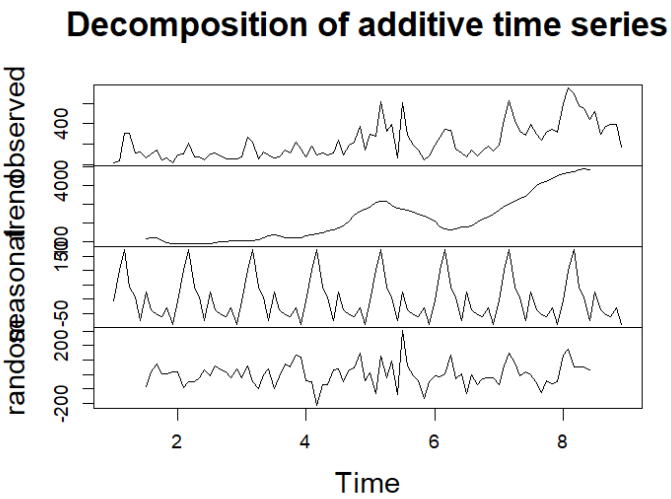

Figure 3: Decomposition of CRENAS admission time series between 2015-2022 in Betioky-Atsimo

For LAI, the mean was of 0.71 (SD: 0.34), 0.53 (SD: 0.32) and 0.62 (SD: 0.39) for Amboasary-Atsimo, Ampanihy, and Betioky-Atsimo respectively with a significant monthly seasonal pattern. Finally, for MSWEP the mean was of 0.059 (SD: 0.059), 0.034 (SD: 0.044), and0.044 (SD: 0.057) for Amboasary-Atsimo, Ampanihy, and Betioky-Atsimo respectively. MSWEP did also present a significant seasonal pattern on a monthly basis (Table 5).

Table 5: Demographics table for incidence for severe acute malnutrition in the districts: Betioky-Atsimo, Amboasary-Atsimo, and Ampanihy, in the South of Madagascar between 2015/2016 and 2022

District	Betioky-Atsimo	Amboasary-Atsimo	Ampanihy
Time period	January 2015- December 2022	January 2016- December 2022	January 2015- December 2022
Frequency	Monthly	Monthly	Monthly
CRENAS Incidence			
Nb observations	96	84	96
Summary Statistics	Mean=4.54 SD=3.14 Min=0.37	Mean=7.26 SD=7.12 Min=0.73	Mean=8.64 SD=7.87 Min=0.18
Autocorrelation	No Significant lag correlation	No Significant lag correlation	No Significant lag correlation
Outliers	10	4	2
Missing data	None	None	None
Trend and seasonality	Significant seasonal pattern (monthly)	Significant seasonal pattern (monthly)	Significant seasonal pattern (monthly)
LAI			
Nb observations	96	84	96
Summary Statistics	Mean= 0.62 SD=0.39 Min=0.19	Mean=071 SD=0.34 Min= 0.31	Mean=0.53 SD=0.32 Min=0.18
Autocorrelation	Significant correlation at lags: 6,10	Significant correlation at lags:1,6	Significant correlation at lags: 12
Outliers	0	4	1
Missing data	None	None	None
Trend and seasonality	Significant seasonal pattern (monthly)	Significant seasonal pattern (monthly)	Significant seasonal pattern (monthly)
MSWEP			
Nb observations	96	84	96
Summary Statistics	Mean=0.044 SD=0.057 Min=4.74 e-05	Mean=0.059 SD=0.059 Min=0.001	Mean=0.034 SD=0.044 Min=0.001
Autocorrelation	No Significant lag correlation	Significant correlation at lags:4	No Significant lag correlation
Outliers	3	6	5
Missing data	None	None	None
Trend and seasonality	Significant seasonal pattern (monthly)	Significant seasonal pattern (monthly)	Significant seasonal pattern (monthly)

- **District: Relation between environmental indicators and severe acute malnutrition incidence in time series from 2015 to 2022.**

Here, the multivariate quasi-poisson regression was performed using both MSWEP and LAI with a lag of one month. The results demonstrate that MSWEP does not appear to be significantly related to CRENAS incidence for any of the districts. On the other hand, LAI with a lag of one month (LAI Lag 1) appears to be significantly related to CRENAS incidence for the districts of Betioky-Atsimo and Ampanihy, but not for Amboasary-Atsimo, with p-values of 0.015, <0.001, and 0.352 respectively. Moreover, for Betioky-Atsimo and Ampanihy, the Incidence Rate Ratios for LAI Lag1 are of 3.44 (CI:[1.28-9.29]) and 31.64 (CI:[11.38-90.39])

respectively (Table 6). The autocorrelation plots do not present significant autocorrelation within the time series of the residuals of our models, as the autocorrelation residuals are within the two dashed lines (Appendix 10). The distribution of the residuals of the models appears normally distributed (Appendix 11)

Table 6: Multivariate analysis for incidence for severe acute malnutrition in the districts: Betioky-Atsimo, Amboasary-Atsimo, and Ampanihy, in the South of Madagascar between 2015/2016 and 2022.

	CRENAS admission - Betioky-Atsimo			**CRENAS admission - Amboasary-Atsimo**			**CRENAS admission - Ampanihy**		
Predictors	*Incidence Rate Ratios*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*	*Incidence Rate Ratios*	*CI*	*p*
LAI - Lag1	3.44	1.28 – 9.29	**0.015**	2.22	0.42 – 11.87	0.352	31.64	11.38 – 90.39	**<0.001**
MSWEP	5.88	0.30 – 112.90	0.242	2.72	0.15 – 48.45	0.497	30.07	0.93 – 948.97	0.054

Discussion

- **Interpretation**

The compilation of data from various sources allowed us to create a database, which will be used for future studies and research projects (for example the DIGAP project). Via the analysis at the commune level, we have been able to establish and understand the presence of a significant positive relationship between the semi-arid cliamte with SAM in 2018, and all types of malnutrition in 2021. Both the analysis at the commune level and the district level have enabled us to understand and quantify the relation between environmental indicators (vegetation and precipitation) and malnutrition. While precipitation is not shown to be a predictor of malnutrition, vegetation is. The analysis at the district level remains unreliable, but commune level analysis exhibits a significant negative relationship with in 2021 for GAM and MAM (β =-0.15). Finally, this study and thesis aimed to determine the role of inter-annual rhythmicity on malnutrition. This was achieved, to some extent, by studying time series and the decomposition of the CRENAS incidence indicator, where the presence of a significant seasonal pattern and trend was observed. Additionally, inter-annual change was detected in the relation between semi-arid climate and vegetation for MAM and GAM between 2018 and 2021.

To my knowledge, this master's thesis represents one of the first papers looking at the impact of both precipitation and vegetation as well as climate on the various forms of malnutrition within the regions of the South of Madagascar.

- **Communes**

From table 1, we can see that between the years 2018 and 2021 there has been an increase in malnutrition prevalence in both the mean and median for all malnutrition indicators (SAM, MAM, GAM). For example, mean SAM goes from 0.82 to 1.77 in 2018 and 2021 respectively, and median SAM goes from 0.50 to 1.10. Similar increases are observed in MAM and GAM. While this increase is observed for malnutrition, there is no discernable increase in LAI or MSWEP over those two years.

Climate and Malnutrition

These results imply that communes located in a region with a semi-arid climate are more likely to develop SAM, which appears to hold true over time, a stable inter-annual trend. Although, while this relation appears to hold true, it appears to have increased, going from a 0.61 coefficient to a 0.82 one, approximately a 30% increase over time. On the other hand, this type of climate appears to affect MAM and GAM only in 2021. This sudden significance and increase in intensity of the relation between semi-arid climate and

MAM/GAM and SAM, respectively, could potentially be due to increases in droughts (for example, agricultural droughts) over time affecting more semi-arid areas which could be due to climate change, however there are no studies to verify this explanation (Salvador et al, 2020; Semenza, 2020). From these results, we can say that the semi-arid climate has had an increased role in the increment of malnutrition prevalence over time.

Environmental indicators and malnutrition

For the significant negative relation between LAI and GAM and MAM present only in 2021, this signifies that compared to 2018, in 2021 increases in LAI and increases in vegetation lead to decreases in GAM and MAM, and that over time vegetation has an increased role in MAM and GAM (where decreased vegetation would lead to increased malnutrition). In 2018, this relation did not seem to be present, which could mean that other environmental and/or anthropocentric factors were linked to MAM and GAM. In addition, vegetation does not appear to have an impact on SAM regardless of the year.

From these we can conclude that SAM does not appear to be affected by environmental indicators such as precipitation and vegetation, but only impacted by the semi-arid climate, while MAM and GAM's relation to environmental factors changed over time, with vegetation and semi-arid climate being respectively negatively and positively related to malnutrition.

Season and Malnutrition

Regarding the relation between the time of the year (the trimesters) and malnutrition, all three indicators of malnutrition exhibited the same pattern. In 2018, trimesters 3 and 4 were protective factors compared to trimester 1; while in 2021, trimesters 2 and 3 were protective factors compared to trimester 1. Trimesters 2 and 3 correspond to the months of April until September and coincide almost completely with the dry season, while trimester 4 (October to December) corresponds to the start of the rainy season. On the other hand, trimester one (January to March) overlaps with both the rainy season and the lean season (Harrington et al, 2022; Dostie et al, 2002). These results are coherent. Indeed, in Madagascar, the main crops, which include rice, maize, potatoes, and wheat are usually harvested between the months of March and June, during the dry season (FAO, 2022; Hartog et al, 2011). The harvest thus happens throughout the second trimester and could be consumed until the beginning of the fourth trimester. Results show in areas where smallholder livelihoods are undiversified, people rely on crop harvested during the year for sustenance to overcome food shortages (Rojas et al, 2010). Thusly, the protective effect of the dry season and harvested crop on malnutrition in comparison to the lean season present in trimester one is consistent. One point of concern would be the difference between 2018 and 2021, with trimester 2 becoming significant in the latter. The presence of this inter-

annual change is not clear. One potential explanation could be the fact that trimester 4 is lacking from the year 2021 in the database. Had it been present, there is a possibility that the obtained results could be altered.

- **District**

Our short analysis at the district level, shows that once more, MSWEP is not significantly related to malnutrition incidence. These results are dissimilar to the ones found at the commune level and go against the established literature. It is interesting to observe that during the analysis, a significant association between CRENAS incidence and LAI with a one-month lag was observed for the districts of Ampanihy and Betioky-Atsimo. However, there is a very large difference between the incidence rate ratios of these two districts (3.44 for Betioky-Atsimo and 31.64 for Ampanihy), which could be potentially explained by the smaller number of admissions in Ampanihy. These varying numbers of admissions could also vary depending on the number of CRENAS centers present in the district, a piece of information that would need to be included in later studies. In this incidence time series analysis, we find a positive relation between vegetation and CRENAS incidence, which goes against our analysis at the commune level. However, the time series analysis was done over only 3 districts, over short periods of time, which limits its reliability, despite the lack of autocorrelation and normal distribution of the residuals providing accuracy to our analysis (Appendix 10, 11).

Overall, our results partially comply with the literature. Indeed, we have mentionned in the introduction that studies conducted in the Democratic Republic of Congo have shown that vegetation is associated with childhood stunting notably in rural areas (Bangelesa et al, 2023), which has been observed in our analysis in 2021 for MAM and GAM. Furthermore, a study in Mali exhibited that locations with arid climate and semi-arid climate negatively impact stunting and malnutrition which is beyond adaptability and the coping mechanisms of livelihoods (Iankowska et al, 2012). Our analysis has demonstrated similar observations for all three of our malnutrition indicators. The change in significance between 2018 and 2021 for these variables is not clear and the inter-annual variability would benefit from further studies.

Regarding precipitation, our results are not in line with the literature, as studies conducted in Mali, Kenya and Nigeria have shown that reduction in precipitation coupled with increases in temperatures can impact the prevalence of stunting and undernutrition in children (Van der Merwe et al, 2022; Iankowska et al, 2012; Niles et al, 2021). Furthermore, one of the few studies conducted in Madagascar finds a similar association with low precipitation and high temperatures with child weight reductions and wasting risk (Thiede et

al, 2016). Thus, performing further analyses with other precipitation data could be useful. For example, including a variable presenting the number of days with no rainfall per month could provide another angle, as its increase would be linked to increased malnutrition. Additionally, comparing the remote sensing MSWEP data from GloH20 to local data from meteorological towers would allow us to compare and make note of any significant discrepancy between both.

Lastly, the explained variance of our models remains low. For the commune level for 2018, it lies between 17.9% to 36.7% of the variance being explained by our model, while for 2021 it lies between 59% and 76.2%. These relatively small variances, especially for 2018, imply that additional variables need to be taken into consideration in our models.

Our models at the commune level have allowed us to conclude that semi-arid climate and vegetation are respectively positively and negatively related to malnutrition prevalence, especially in recent years, while precipitation is not. The variation in significance of LAI and climate between 2018 and 2021 for MAM and GAM, and the increased relation between climate and SAM provide some evidence of inter-annual variation. The model analyzing incidence of new cases of malnutrition at the district level is less reliable, and provides answers contradictory to the literature; however, upon improvement, it could reveal some insight regarding the inter-annual rhythmicity of our indicators.

- **Limitations and perspectives**

It is important to keep in mind that this study presents a number of limitations. Firstly, in Madagascar, like in many sub-Saharan countries, data reporting and data quality can be difficult to ensure. For example, a study conducted in Antananarivo, the capital city, assessed the quality of death notification data. This study demonstrated that Madagascar has one of the weakest systems in terms of vital statistics among countries. Furthermore, it expressed the matter that all offices have a short supply of resources to store registers and encode them in a database. Finally, it expressed that most of the available data is based on epidemiological models estimated by UN agencies and academic groups (Masquelier et al, 2019). While that paper was focused on death registries, it exemplifies the difficulty to obtain health data with a secure quality, especially over long periods of time. With regards to our analysis, we cannot fully ensure that the data retrieved has a quality equivalent to the standard to which we would hold data acquired in developed countries, mostly due to the difference in resources available to the systems. In addition, having data regarding other variables over longer periods of time would have strengthened our analysis. Performing time series analysis over 8 years is a short time duration, and it is difficult to extract a precise and accurate temporal and seasonal patterns.

Moreover, having data over a wider selection of districts and communes, especially located in the Semi-Humid region, would have heightened our estimates regarding the implication of the climate variable on malnutrition.

Similarly, there are many other environmental factors which can come into play and modify the relation between precipitation, vegetation, climate and malnutrition, whether it be at the commune level or district level. Indeed, having indicators regarding cases of Malaria, diarrheal diseases could be valuable to further understand this relation. Malaria, among other diseases such as Dengue, and yellow fever, are climate sensitive vector-borne diseases. According to the World Health Organization, their number are expected to increase due to the increase in the average annual temperature of Madagascar (Rakotoarison et al, 2018). For malaria, areas with a semi-arid climate are more prone to peaks of incidence; however, clinical reporting data is quite poor as most rural areas have poor access to clinical care; rendering retrieval of this data quite difficult (Rice et al, 2021). In addition, with climate change *Anopheles fluviatilis* and *A. funestus*, the mosquito vectors transmitting malaria in Madagascar, have increased its multiplication (Nematchoua et al, 2018; Tedrow et al, 2019). Studies have shown that Malaria is linked to precipitation, as dry conditions limit the development of the vector, only for it to lead to an increase in malaria when rainfall returns (Dos santos et al, 2007). In a study, malaria was proposed as a mediator for the relation between precipitation and malnutrition, while another study conducted in Ethiopia demonstrated that children under five years old exposed to *Plasmodium* have increased odds of being malnourished (Liever et al, 2022; Gone et al, 2017). Furthermore, malnutrition can be caused by diseases, which themselves can be due to undernutrition related diminished resistance, a vicious cycle (Nassur et al, 2022).

Another variable which could be worth exploring is the amount of investment in the region. Investment could play a significant role in the relation between precipitation and malnutrition, as regions where investment is more prominent, for example bettering their water access, would suffer less from low precipitation than other areas. While some collection of all the projects and investments regarding water has started to be made by Programme Solidarite Eau (Water Solidarity Program/pS-Eau), this compilation however does not include every project and aid provided to Madagascar. The goal of this network between Ps-Eau and the Malagasi NGO Ran'Eau, is to better the quantity and quality of projects regarding water access and sanitation. To do so, it provides up-to-date information regarding stakeholders, and actions led in Madagascar, as well as supporting project leaders. The information provided there, however, is, as of May 2023, not sufficient to be included in the analysis without being considered as noise. While it includes the stakeholders, and duration and cost of a project, along with the description and location of

the project, there is little breakdown as to when the project was concluded, or how much money was spent on a monthly basis. Working more closely with the stakeholders of each project would be beneficial but time-consuming, yet it should still be considered (pS-Eau, 2023).

In addition, having indicators of temperature evolution would have added more depth to our study and would have allowed us to compare our results with the literature more precisely. Finally, another variable that should be taken into account is groundwater. Groundwater variables will be included in the future ANR project, as explained in the introduction. Having a deeper look at the presence and quality of groundwater will allow a more accurate representation of the access to water in the districts and communes. Indeed, when chronic droughts occur, many NGOs will dig boreholes in order to provide potable drinking water to the population, as an alternative water source. However, the complex hydrogeology of the region of the South of Madagascar can render this complicated. Drilling failure can occur due to low yield, high salinity of water, or lack of reliable groundwater data, or the weak capacity of drilling. Furthermore, groundwater availability is dependent on aquifer recharge. Aquifer recharge depends on many different factors including geological structures, topography, etc. Finally, the South of Madagascar has three types of aquifer systems (basement, sedimentary, and karstic), rendering more complex uses of groundwater in the region (Serele et al, 2020).

Thusly, future studies should include, as explained above, higher quality data across longer durations and including more districts/communes, indicators of groundwater availability and quality, indicators of malaria and other diarrheal diseases, indicators of investment as well as temperature.

Other limitations are present within our study, as the indicators used could pose some issues. First, our malnutrition data focuses on children under the age of five, however, malnutrition is not limited to this portion of the population, therefore our study does not fully depict the relation between environmental indicators and malnutrition, but only a snippet of it. Moreover, CRENAS data at the district level only provides new SAM admissions. Once again, here is omitted a significant portion of malnutrition cases: MAM and GAM. In future studies, obtaining data for the rest of the population would describe more precisely the relation. Secondly, over time, there may have been changes in the protocol for malnutrition diagnosis which have not been reported. It would be important to interview healthcare workers at those CRENAS centers to resolve this point of concern. In addition, while the website states that these are newly admitted SAM patients, some uncertainty remains as the cases could have already been registered some month prior, challenging the independence

of our data. Moreover, mapping the presence of CRENAS centers would be beneficial. Areas with a higher density of CRENAS centers would have higher SAM admission rates compared to others and would thus not accurately represent the incidence in the area. In addition, the use of Mid-upper arm circumference to diagnose SAM, MAM, and GAM is not precise. While it is easier to measure MUAC, it is more difficult to be precise as it is not standardized for age and the cut off is not universally accepted but used for screening to identify children in need of referral for further assessment (SMART, 2006).

The indicator for precipitation MSWEP, like many precipitation datasets, and datasets relying on satellites, can have temporal discontinuities introduced by satellite sensor degradation or instrument changes over time (Beck et al, 2017). Moreover, using more precise indicators of crop yield in addition to LAI would render the analysis stronger.

On a separate note, working with time series is quite a complicated process. Further studies are needed to assess and take into account seasonality, long-term and short-term trend and patterns. In addition, environmental events and epidemics need to be taken into consideration while carrying out future time studies. For example, obtaining additional data on the impact of the Measles outbreak in 2019, or the COVID-19 pandemic, or tornados could bring more insight onto this topic. Some of the preceding points raised will fall within the scope of the ANR DIGAP project.

Overall, the data used in this study can be considered quite fragile due to the field of study, thusly choices had to be made when conducting this study.

- **Strengths**

Despite these limitations, this master's thesis remains substantial as it is innovative in a still very exploratory field. Few studies look into the South of Madagascar and include vegetation when examining precipitation and climate on malnutrition. Furthermore, we have looked at different indicators of malnutrition (SAM, MAM, GAM), which includes wasting, an acute form of malnutrition which is often overlooked in research on the topic which focuses on chronic outcomes (Brown et al, 2021). The results obtained indicate that the semi-arid climate has a deep impact on SAM, and more recently an impact on MAM and GAM. In addition, vegetation was shown to be a protective factor of MAM and GAM. Moreover, our analysis is one of few studies to look at the evolution over time of these indicators in this region of the world, and which looks both at the communes and districts. Moreover, this study can be used to identify research gaps in Madagascar, as well as recommend and shed light to the importance of conducting further research on the impact of environmental indicators and malnutrition.

Conclusion, recommendations, implications

To conclude, through this Master's thesis it has been shown and demonstrated that communes with semi-arid climate tend to be more prone to severe acute malnutrition in children under 5 years of age than semi-humid communes in the South of Madagascar, which holds true in 2018 and 2021. It is also shown within the data that months during the dry period and beginning of the rainy period are negatively associated with all types of malnutrition, as well as an increase in vegetation correlated to a decrease in GAM and MAM, based off of data from 2021. Though our analysis of time series at the district level present contradicting results, the short extent of the data renders it unreliable.

Though this study is one of the first and few of its kind and presents an abundance of limitations, it still shows relevant association between undernutrition in relation to climate and vegetation within the South of Madagascar and presents a steppingstone to exhibit the importance of this topic in this poorly researched area and scarcely represented in studies. Further research and studies will need to be conducted to show these more effectively as well as more varied and reliable data will need to be collected to create and gain a better understanding of the correlations, causes, and effects.

Such a study would allow local public health systems to increase surveillance of vegetation, as well as pay close attention to semi-arid regions of Madagascar during the lean season in order to better prevent and attend to malnutrition cases in affected areas, which would hopefully limit the number of cases in malnourished children and better their health and quality of life. Madagascar is home to a large and vulnerable population of people and especially children. Children who would, will and have suffered the short and long-term effects of undernutrition. This thesis is also used to exhibit the primordial need to study this area comprehensively and adapt local systems to take into consideration markers and predictors of malnutrition to act more quickly and effectively (World Bank, 2020). For example, implementing a more local and malnutrition specific early warning system, similar to the one already implemented by the United States Agency for International Development could be a solution. It could provide decision and policymakers, along with healthcare services, evidence to monitor and evaluate the situation while building resilience and providing better care to the population by being prepared (Nhamo et al, 2018). Especially as acute forms of malnutrition can be avoided and mitigated with timely and tailored interventions, this entails that we could minimize the suffering and maximize the wellbeing of children of Southern Madagascar by directing resources to the most vulnerable areas (Brown et al, 2021).

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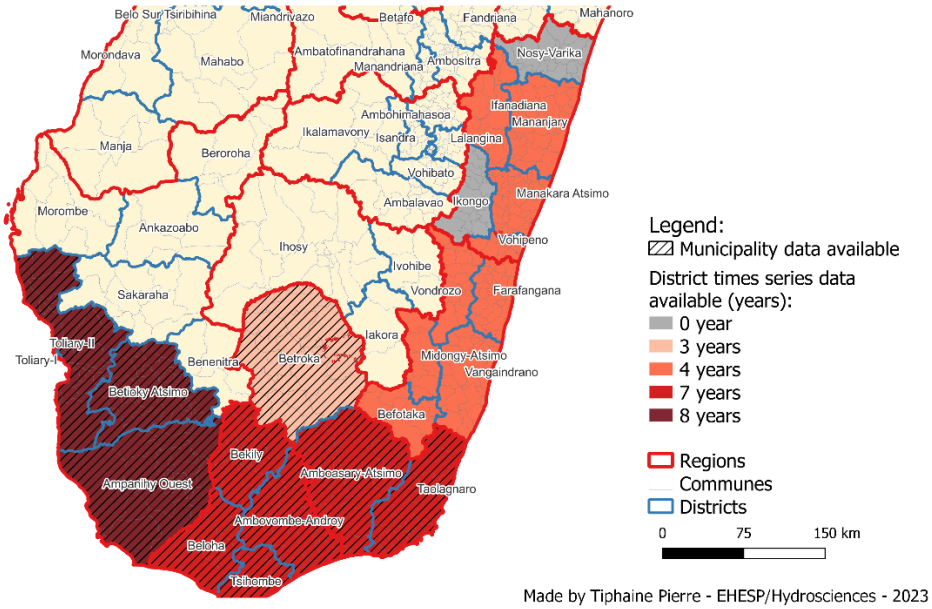
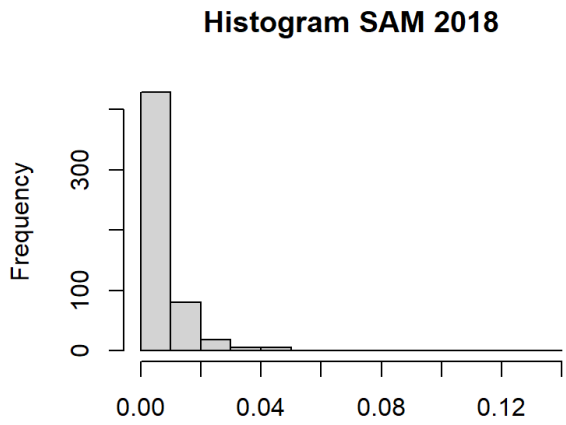
List of appendices

Data available for analysis at district and municipality level



<u>Appendix 1: Map representing the malnutrition data available in districts and communes of the South of Madagascar</u>

0 year : no data available, 3 years: 2020-2022, 4 years: 2019-2022, 7 years: 2016-2022, 8 years: 2015-2022



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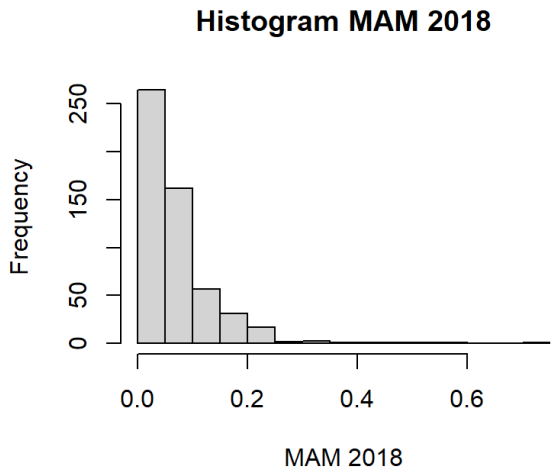

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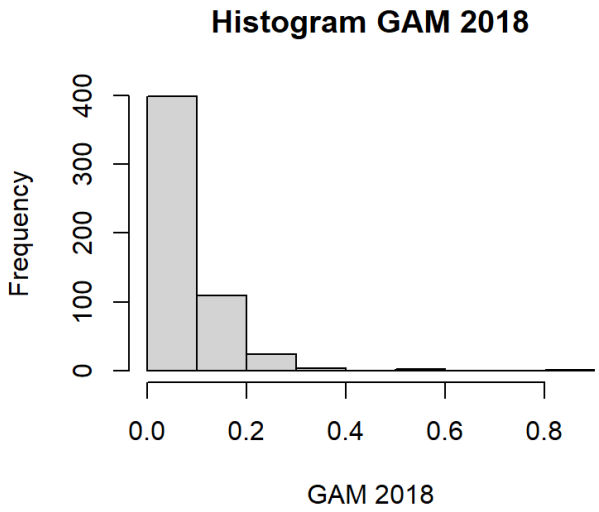
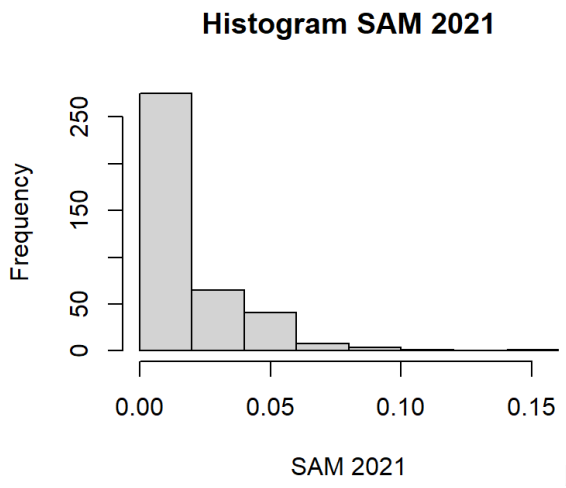


c)

<u>Appendix 2: Distribution of SAM, MAM, GAM in the South of Madagascar in 2018</u>.

a) SAM 2018, b) MAM 2018, c)GAM 2018



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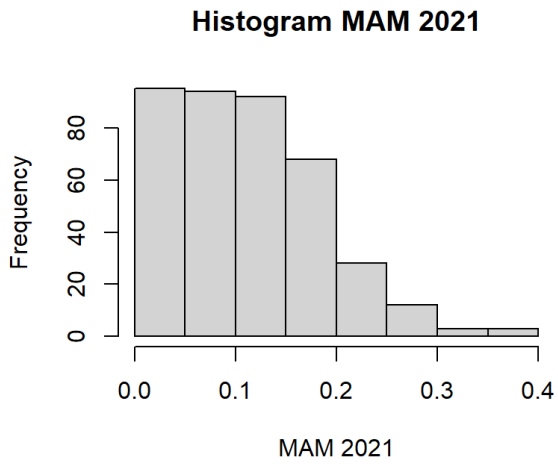

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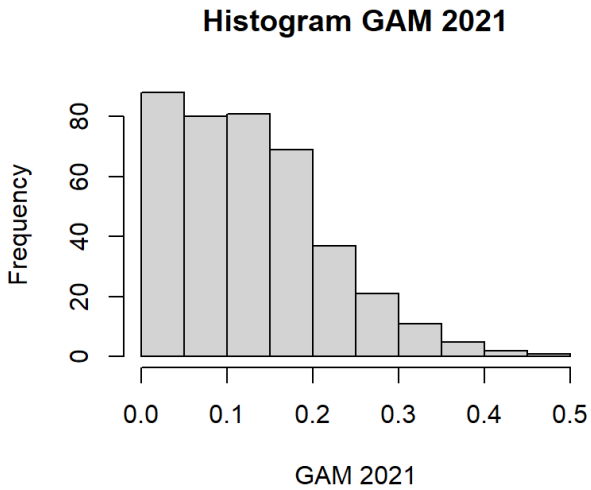
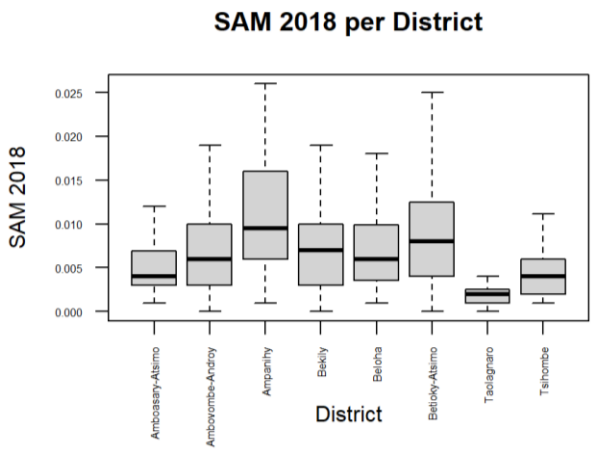


c)

<u>Appendix 3: Distribution of SAM, MAM, GAM in the South of Madagascar in 2021</u>.

a) SAM 2021, b) MAM 2021, c)GAM 2021



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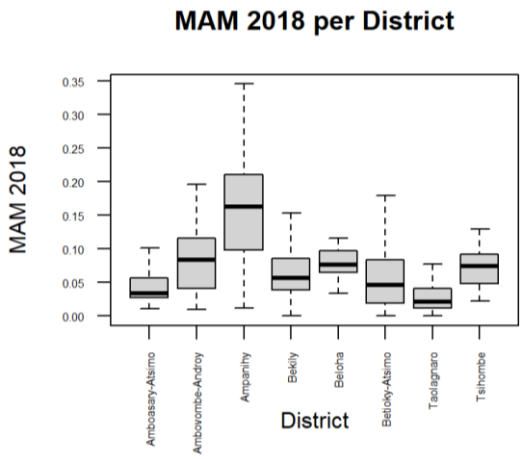

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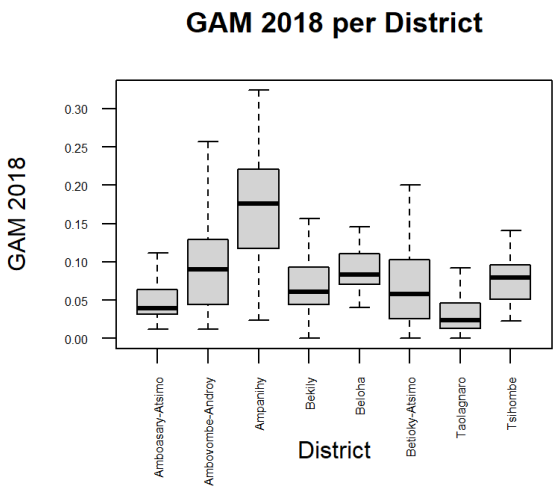
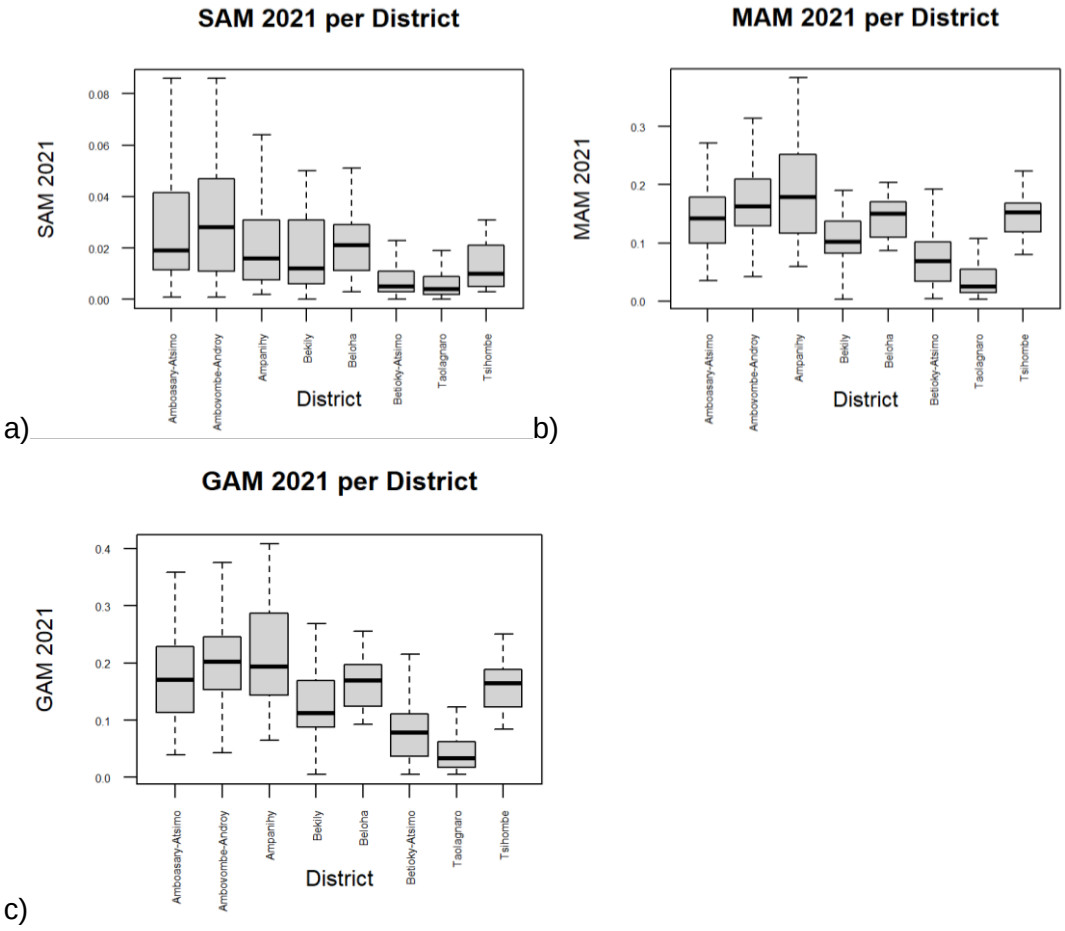


c)

<u>Appendix 4: Boxplot distribution of SAM, MAM, GAM per district in the South of Madagascar in 2018</u>.

a) SAM 2018, b) MAM 2018, c)GAM 2018



a) b)

c)

Appendix 5: Boxplot distribution of SAM, MAM, GAM per District in the South of Madagascar in 2021.

a) SAM 2021) MAM 2021, c) GAM 2021

Appendix 6: Univariate analysis for moderate acute malnutrition in the South of Madagascar in 2018 and 2021.

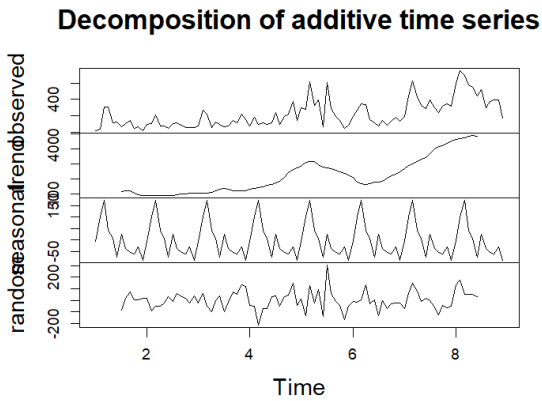
	MAM 2018			MAM 2021		
Predictors	β	*CI*	*p*	β	*CI*	*p*
Climate						
Semi-arid	0.81	0.06 – 1.55	**0.035**	1.29	0.59 – 1.98	**<0.001**
Trimester						
T2	-0.06	-0.23 – 0.10	0.433	-0.26	-0.38 – -0.13	**<0.001**
T3	-0.17	-0.33 – -0.01	**0.043**	-0.54	-0.66 – -0.42	**<0.001**
T4	-0.18	-0.35 – -0.02	**0.027**			
LAI	0	-0.13 – 0.13	0.997	0.01	-0.13 – 0.14	0.937
MSWEP	-0.58	-2.49 – 1.32	0.549	4.36	3.13 – 5.59	**<0.001**

Appendix 7: Univariate analysis for global acute malnutrition in the South of Madagascar in 2018 and 2021.

	GAM 2018			GAM 2021		
Predictors	β	*CI*	*p*	β	*CI*	*p*
Climate						
Semi-arid	0.83	0.12 – 1.53	**0.022**	1.24	0.55 – 1.93	**<0.001**
Trimester						
T2	-0.04	-0.21 – 0.13	0.635	-0.34	-0.46 – -0.21	**<0.001**
T3	-0.19	-0.36 – -0.03	**0.024**	-0.67	-0.79 – -0.54	**<0.001**
T4	-0.19	-0.35 – -0.02	**0.029**			
LAI	0	-0.13 – 0.13	0.972	0.04	-0.09 – 0.18	0.547
MSWEP	-0.4	-2.35 – 1.55	0.688	5.45	4.20 – 6.69	**<0.001**

Appendix 8: Univariate analysis for severe acute malnutrition in the South of Madagascar in 2018 and 2021.

	SAM 2018			SAM 2021		
Predictors	β	*CI*	*p*	β	*CI*	*p*
Climate						
Semi-arid	0.64	0.26 – 1.02	**0.001**	0.67	0.09 – 1.24	**0.023**
Trimester						
T2	-0.12	-0.28 – 0.04	0.152	-0.63	-0.78 – -0.49	**<0.001**
T3	-0.36	-0.53 – -0.19	**<0.001**	-1.16	-1.32 – -1.00	**<0.001**
T4	-0.28	-0.45 – -0.11	**0.001**			
LAI	0.08	-0.05 – 0.22	0.236	0.14	-0.01 – 0.29	0.064
MSWEP	0.41	-1.61 – 2.43	0.69	9.28	7.80 – 10.76	**<0.001**



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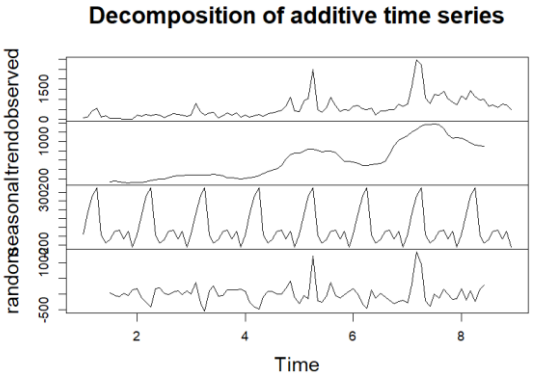

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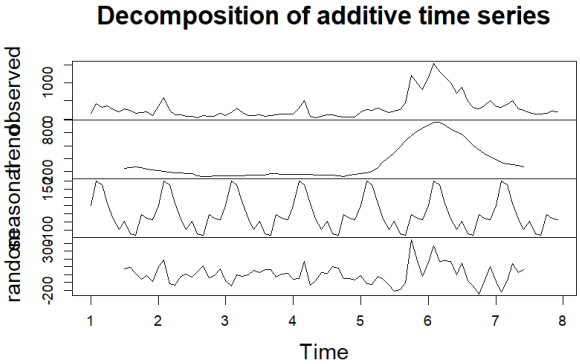
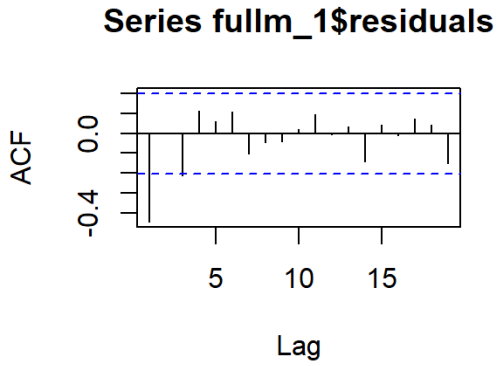


c)

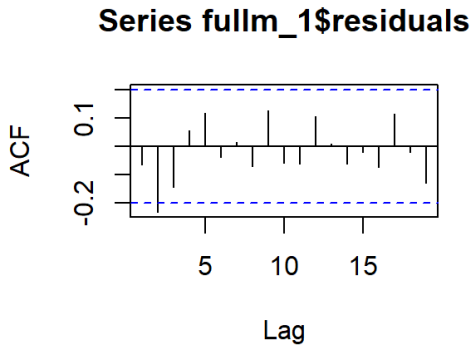
<u>Appendix 9: Decomposition of CRENAS admission time series between 2015-2022</u>

a) Betioky-Atsimo b) Ampanihy c) Amboasary-Atsimo

The first row represents the raw data. The second one represents the trend, the third one represents the seasonal pattern, while the fourth one represents the residuals.



a)



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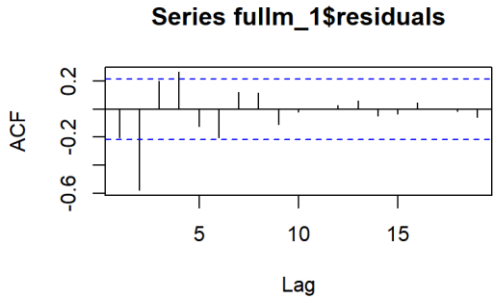
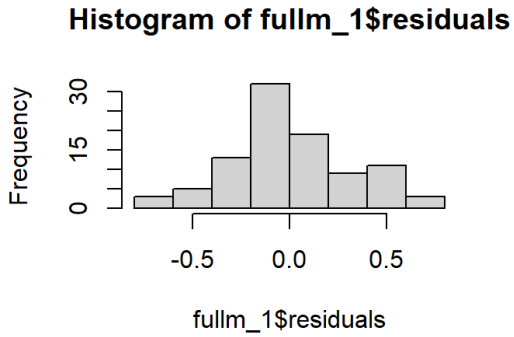


c)

Appendix 10: Autocorrelation function graph post-multivariate model between 2015-2022

a) Betioky-Atsimo b) Ampanihy c) Amboasary-Atsimo



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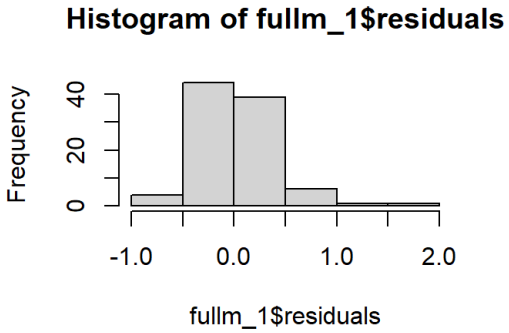

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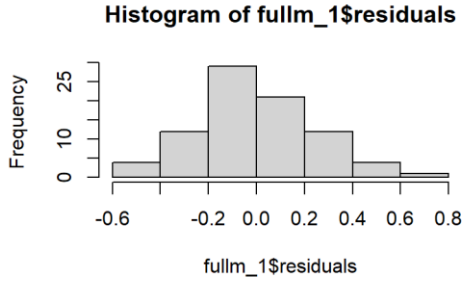

c)

Appendix 11: Histogram of the residuals of the multivariate model between 2015-2022

a) Betioky-Atsimo b) Ampanihy c) Amboasary-Atsimo