A Work Project, presented as part of the requirements for the Award of a Master's degree in Business Analytics from the Nova School of Business and Economics.

WEATHERING THE STORM: THE INFLUENCE OF TROPICAL CYCLONES ON MADAGASCAR'S TOURISM INDUSTRY

George Godfrey McGuigan

Work project carried out under the supervision of:

Alice Caeteno, Leid Zejnilovic, Lenia Mestrinho

NOVA SCHOOL OF BUSINESS & ECONOMICS

15/5/2024

Abstract

This thesis examines the impact of tropical cyclones on Madagascar's tourism industry through a detailed analysis of storm data from 1990 to 2024. Employing time-series forecasting and regression models for the politically stable period of 2010 to 2019, the study explores how cyclonic activity correlates with fluctuations in tourist arrivals. Results indicate that while cyclones reduce tourism in the short term, other meteorological and economic variables have greater predictive power in estimating tourist arrivals in the long term. This research provides valuable insights for policymakers and stakeholders in regions prone to similar climatic challenges.

Keywords

Tropical Cyclones, Tourism Impact, Madagascar, Time-Series Forecasting, Disaster Management, Climate Change, Predictive Modeling, Weather Patterns

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

Dedication

To my Granny, Maureen McGuigan, for her continual encouragement, devotion and love, and my Grandpa, George White, who taught me to never leave a job half done. Why? Because "Raiders Never Quit"!

1 Introduction

1.1 Madagascar Overview

Madagascar, the fourth largest island in the world and home to 30 million people, is renowned for its unique biodiversity and vibrant culture, making it a significant destination for eco-tourism. Located in the Indian Ocean off the southeast coast of Africa, the island is characterized by its diverse ecosystems, ranging from lush rainforests to arid deserts. However, Madagascar's geographical positioning also makes it prone to severe weather events, particularly tropical cyclones, which can have profound impacts on its environment and economy. According to the Disaster Risk Profile devised by the World Bank Group, the average annual loss from tropical cyclones is $87 million in total direct costs and $20 million in emergency costs [2]. This thesis explores the relationship between the severity of tropical cyclones that make landfall and fluctuations in international tourism arrivals, aiming to provide insights into how weather patterns influence Madagascar's tourism industry. Through a detailed analysis of storm data from the period of 1990 to 2024, this study seeks to understand the correlation between increased cyclonic activity and potential declines in tourism, thus offering valuable information for stakeholders in tourism planning and disaster management.

1.2 Tourism in Madagascar from 1990 to 2024

Madagascar's tourism industry has seen significant evolution since the 1990s, marked by growth, setbacks, and continuous adaptations to both internal and external challenges. In the early 1990s, Madagascar was just beginning to tap into its potential as a major ecotourism destination. The government and various international organizations started investing in tourism as a means to boost the economy and promote sustainable development. Efforts were made to highlight the island’s unique wildlife and landscapes, which are famed for their endemic species

[5]. The mid to late 1990s saw a rise in the number of visitors, encouraged by improvements in infrastructure such as better roads and expanded air connections. The country's profile was raised through its inclusion in international travel publications and global conservation initiatives, which drew tourists interested in nature and adventure [5].

However, political instability in the early 2000s, particularly the political crisis in 2002 and another in 2009, significantly affected the industry. These periods of turmoil resulted in travel advisories from several countries and a temporary decline in tourist arrivals. The sector suffered from cancellations, reduced investments, and a tarnished international image. Recovery was gradual following the resolution of political conflicts. The government and private sector re-commenced promotion efforts, focusing on stability, unique biodiversity, and cultural heritage as major draws. Over the years, Madagascar has increasingly emphasized sustainable and responsible tourism to protect its ecological assets while providing economic opportunities to local communities [5].

In recent years, prior to the global impact of COVID-19, Madagascar was experiencing a renewed increase in tourist numbers. In 2019, 383,000 international tourists visited the island nation with tourism amounting to a historic high of 10.4% of the country’s GDP [17]. The country continued to develop niche markets, including luxury eco-resorts and community-based tourism, which cater to both high-end tourists and those seeking authentic experiences. Efforts have also been made to diversify attractions beyond the main wildlife tours, incorporating cultural and beach tourism. Despite occasional setbacks from global economic downturns and health crises like the COVID-19 pandemic, Madagascar's tourism industry has shown resilience and capacity for recovery, aiming to balance economic benefits with environmental and cultural sustainability.

1.3 Cyclonic Activity in Madagascar from 1990 to 2024

Tropical cyclones are highly concentrated circular storms that form over warm tropical oceans and are distinguished by a decrease in air pressure, strong winds, and substantial precipitation. They are known by different names in different parts of the world — hurricanes in the Atlantic, typhoons in the Pacific, and cyclones in the Indian Ocean. The South West Indian Ocean is a hotbed for cyclone activity, particularly between November and April. This region's cyclone season aligns with the southern hemisphere's summer when sea surface temperatures are at their warmest, promoting the formation of cyclones.

In the South West Indian Ocean, tropical cyclones are categorized based on their intensity, which is determined by measurements of their ten minute sustained wind speeds. The regional meteorological organization responsible for this, the Météo-France's office in Réunion, uses a specific scale, featured in Table 1 below, to classify these storms by wind speed.

Scale	Storm Type	Description	Wind Speed (kts)
1	Tropical Disturbance	Storm is at the initial stage of any cyclonic activity	<28
2	Tropical Depression	System shows increased organization	28-33
3	Moderate Tropical Storm	Storm structure becomes more defined with clear cyclonic features	34-47
4	Severe Tropical Storm	Storm picks up more energy and potential for damage	48-63
5	Tropical Cyclone	Cyclone features a well-defined eye, and its impact potential is considerably higher	64-89
6	Intense Tropical Cyclone	Cyclone can cause significant damage due to their powerful winds and heavy rainfall	90-115
7	Very Intense Tropical Cyclone	Cyclone poses extreme threats and require urgent and comprehensive response measures	115>

Table 1: Classification of Tropical Storms in the South West Indian Ocean Basin

2 Data

2.1 Data Description

2.1.1 Meteorological Data

Data on historical tropical cyclone activity was sourced from the International Best Track Archive for Climate Stewardship (IBTrACs), a project under the National Centers for Environmental Information [11]. IBTrACs amalgamates recent and historical data from multiple agencies into a comprehensive, publicly accessible best-track dataset [10]. This dataset enhances inter-agency comparisons and offers the most robust and reliable information on the geographical and temporal magnitude of storms, which is crucial for the visualizations presented in Figure 1. Additionally, the Emergency Events Database (EM-DAT) was utilized for its detailed estimations regarding the economic impact of infrastructure damage, the number of people affected, and aid contributions following natural disasters [12].

Data on daily weather conditions such as temperature, humidity, precipitation, and windspeed were extracted from the Copernicus Climate Data Store (CDS) [13]. These data points were collected from the IVATO Airport Station located in the country's capital Antananarivo. It's worth mentioning that the weather in Antananarivo doesn't completely reflect the conditions across the entire island. By tapping into regional tourism data, one can better understand how local weather affects various areas, leading to more precise conclusions.

2.1.2 Tourism Data

Tourism data, specifically measured by inbound international arrivals, was sourced from the UNWTO Tourism Data Dashboard, which provides detailed monthly datapoints for Madagascar and other cyclone-affected countries in the region [14]. To ensure accuracy, these figures were cross verified with data from the annual Economic and Financial Reports published by

Madagascar's Ministry of Economy and Finances [15]. These reports offer a comprehensive view of the tourism sector, including additional metrics such as average duration of stay, tourism revenues, investments, employment generated in the tourism sector, and the evolution of the supply of hotels and other tourism service establishments. However, since these values were reported at the annual level, they were not fit to be used in the time-series forecasting model.

To enhance the predictive accuracy of the time-series forecasting model, two critical economic indicators that influence tourism were incorporated: Madagascar's inflation rate and the exchange rate between the Malagasy Ariary and the Euro. The Euro was chosen as in 2019, 75% of international tourists were from Europe, predominantly from France and Italy [8]. These variables, available as monthly datapoints from the website Trading Economics, play significant roles in shaping tourism dynamics [16]. As inflation rises, the cost of travel-related expenses like accommodation, food, local transport, and activities increases, potentially making Madagascar less appealing to cost-sensitive tourists, especially when other destinations remain more affordable. Conversely, a weakening Ariary against the Euro makes Madagascar more economical for Eurozone tourists, boosting its attractiveness as a budget-friendly destination. Tourists are able to obtain greater value in terms of accommodation, dining, activities, and shopping. However, should the Ariary strengthen, the resultant higher costs could discourage visits from Euro-based tourists.

2.2 Data Preprocessing

2.2.1 Meteorological Data

To focus specifically on the region around Madagascar, IBTrACS data was filtered to include only storms occurring within the latitude range of -30 to -10 and the longitude range of 40 to 60. Storm tracks lacking geographic coordinates were excluded from the analysis. Wind speeds, sourced from various agencies, were consolidated into a single measure based on the following priority order: WMO_WIND first, REUNION_WIND second, and USA_WIND third. These wind speeds were then transformed into a categorical variable using the South West Indian Ocean Scale, which ranks storms on a scale from 1 (weakest tropical disturbance) to 7 (very intense tropical cyclone). Storms with a minimum score of 5 qualify as a Tropical Cyclone. Landfall determination involved creating a geographical bounding box around Madagascar and verifying whether the storm tracks latitude and longitude fell within this range. Cyclone seasons were defined such that November and December of the previous year, along with January, February, March, and April of the current year, were grouped together.

Feature	**Description**	**Type**
SID	unique storm identifier	identifier
Season	season in which cyclone took place	numerical
Name	name of storm	nominal
LAT	position in latitude	numerical
LON	position longitude	numerical
ISO_TIME	time stamp for wind speed / position	datetime
Wind_Aggregated	10 minute avg wind speed in knots	numerical
SWIO Class	categorization of storm based on wind speed	categorical
Landfall	"Y" if storm made landfall on Madagascar	binary

Table 2: Features used to plot storm tracks from IBTrACS

Weather data including daily temperature (Celsius), precipitation (mm), humidity (%), and wind speed (kph) were obtained from the Climate Data Store and aggregated to monthly averages. For temperature, humidity, and wind speed, monthly values were calculated using the mean of daily measurements. For precipitation, monthly totals were computed by summing daily values.

2.2.2 Tourism Data

International arrivals data from the UNWTO was used without any alterations, assuming that all non-resident entries were categorized as tourists. Given the lack of more detailed data, this broad definition of tourists had to be used. This approach carries the risk that international arrival figures might be inflated following natural disasters, as humanitarian aid workers arriving to aid after a natural disaster will be counted alongside bona fide tourists. For instance, during the severe drought from October to December 2016, there was a notable surge in international arrivals, reaching up to 40,000 per month, at a time when approximately 850,000 people in Madagascar were on the brink of starvation. Efforts were made to contact Madagascar's Ministry of Tourism to acquire visitor surveys that could differentiate between tourists and other types of international arrivals, however no response was received.

2.3 Exploratory Data Analysis

2.3.1 Cyclone Data

Between 1980 and 2024, 310 storms appeared in the IBTrACS data of which 97 reached a high enough sustained wind speed to be classified as a tropical cyclone. Of the 97 tropical cyclones in the defined area surrounding Madagascar, 47 made landfall on the island country. Madagascar is ranked 27th out of 191 countries in the 2024 Tropical Cyclone INFORM Risk Index, which is a worldwide risk assessment tool based on exposure, vulnerability, and coping capacity indicators [6]. It is considered to be at very high risk.

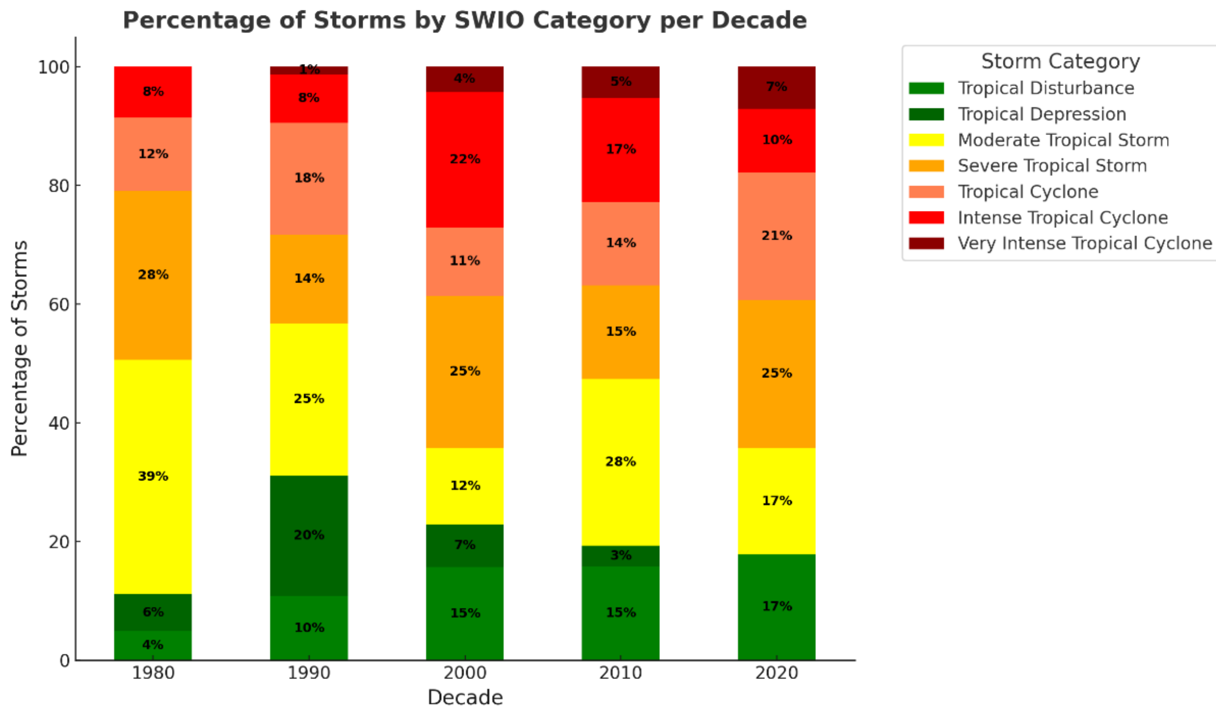


Figure 1: Distribution of Storm Intensities by Decade from the 1980's to 2020's

The chart illustrates the distribution of storm categories in the Southwest Indian Ocean (SWIO) by decade, from the 1980s to the 2020s. The data indicates a fluctuation in the frequency of storms reaching at least the Tropical Cyclone level. In the 1980's, 20% reached tropical cyclone levels, compared to 27% in the 1990's, 37% in the 2000's, 36% in the 2010's, and 38% in the 2020's. This supports the research performed by The World Bank which indicates that the effects of climate change, notably the increase in ocean temperatures, will cause more storms to reach cyclonic levels over time [4]. Madagascar, like other nations, is likely to experience heterogeneous effects due to climate change and increased cyclone activity. While some regions or sectors might adapt and find ways to mitigate the impacts, others could suffer significant economic setbacks. For instance, agriculture and tourism, which are crucial to Madagascar's economy, might be negatively impacted by more frequent and severe cyclones [1].

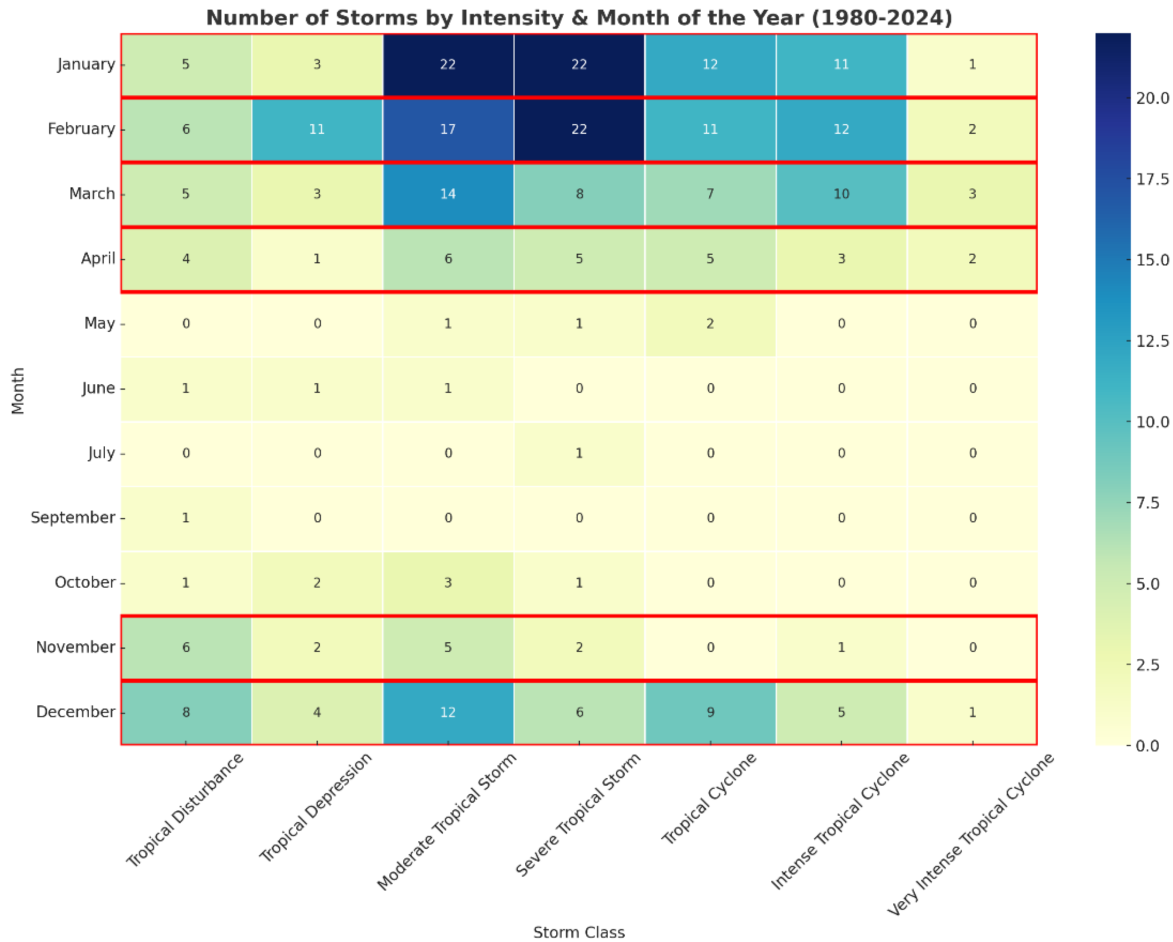


Figure 2: Heatmap of Storms by Month of Year and Storm Intensity

For this analysis, the cyclone season is defined as November to April given that it captures 95% of all storms and 98% of storms that reach cyclonic level. Peak storm activity occurs in the months of January (24%) and February (26%). This is consistent with travel advisories related to the cyclone season issued by Madagascar’s Ministry of Tourism [8].

2.3.2 Tourism Data

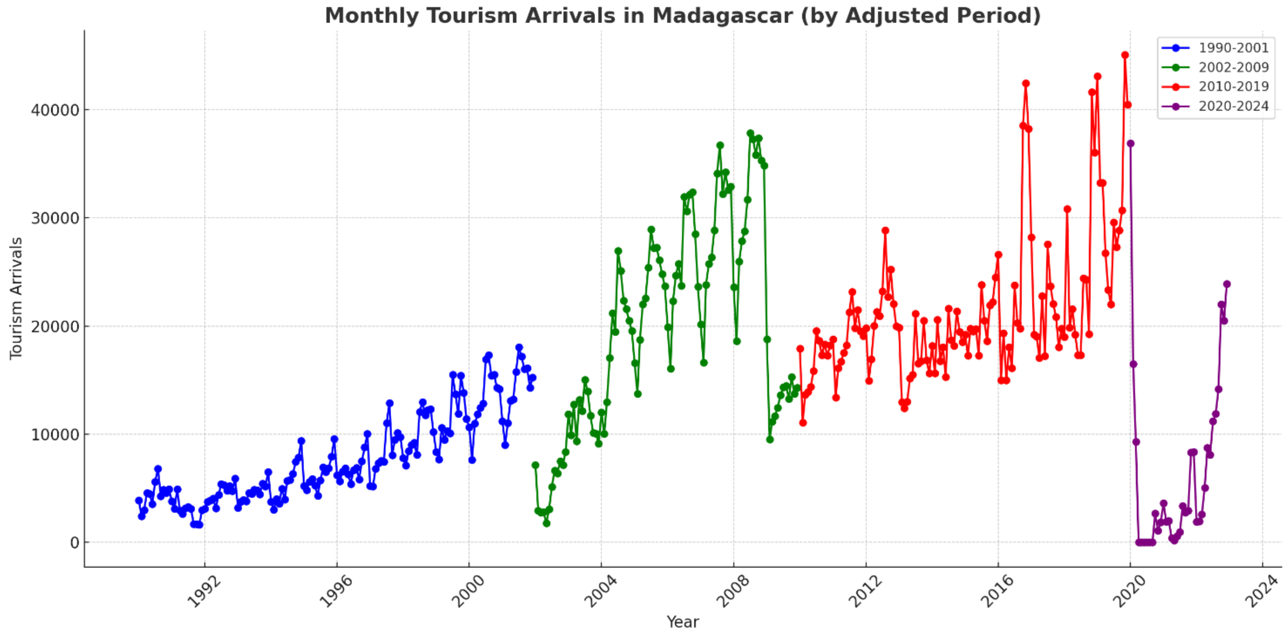


Figure 3: Monthly International Arrivals from 1990 to 2022

Annual international arrivals to Madagascar is featured in the chart above. The trend in Madagascar tourism can be defined in four periods of growth. The first being from 1990 to 2001 which was interrupted by a political crisis in 2002 stemming from a contested presidential election. The second being from 2003 to 2008 which was interrupted by another political crisis in 2009 in which a military-backed transitional government seized control over the country [3]. The third being from 2010 to 2019 which was interrupted by the COVID-19 pandemic in 2020. The fourth being post COVID-19 recovery from 2021 to present day. Since this analysis is focused on how weather patterns impact tourism, a period with relative political stability, period 3 from 2010 to 2019, was chosen for training our time-series forecasting models.

3 Methodology

3.1 Creating Data Visualizations of Storm Tracks using IBTrACs data

The methodology used for creating the storm track charts involves several steps, each designed to handle specific aspects of data visualization and analysis, leveraging Python's powerful libraries like Matplotlib and Basemap. The process begins with filtering the storm data for a specific season, ensuring that only relevant entries are considered for plotting. This is achieved by selecting rows from the dataset where the 'SEASON' column matches the specified season. This targeted approach helps in focusing the analysis and visualization on a per-season basis, which is crucial for understanding seasonal patterns and variations in storm activities. Two plots are prepared using a subplot configuration where the upper plot is dedicated to a geographical map and the lower plot to a tabular display.

The geographical map is set up with the Basemap library, which allows for detailed map projections. The map's boundaries are defined to focus on a specific region (in this case, latitudes -30 to -10 and longitudes 40 to 60), which is typical for viewing storm activities in the Southwest Indian Ocean. On the map, each storm is represented by coordinates plotting its path, with each storm assigned a unique marker from a predefined set. The colors of these markers are determined by the storm's intensity category. This visual differentiation helps in quickly assessing the severity and track of each storm within the season. A color bar is integrated into the map to provide a reference for the storm intensity categories, making it easier to understand the scale of storm severity at a glance. Additionally, a legend correlates storm names with their respective markers, further aiding in the identification of specific storms on the map.

Below the map, a table summarizes key data points for each storm, including names, start and end dates, maximum intensity, and whether the storm made landfall. This tabular data is generated by grouping the season's storm data by storm ID and aggregating relevant details. This provides a concise and informative overview of the storms for quick reference.

3.2 Regional Analysis of Storms Impact on Tourism

The first part of the study involved collecting data on tourist arrivals, number of storms, and storm intensity using the SWIO scale for Mauritius, Réunion, and Madagascar over the period from 2010 to 2019. The data were meticulously cleansed to ensure accuracy and then merged to create a comprehensive dataset that represents the region's tourism and meteorological conditions. To assess the immediate impact of storms on tourism, month-to-month changes in tourist arrivals were calculated. Statistical analysis was conducted using Welch's t-test to compare these changes during storm months versus non-storm months, aiming to determine if the observed differences were statistically significant.

3.3 Difference in Differences Analysis on Tropical Cyclones Effect on Madagascar Tourism

The second part of the study assessed whether tourism in Madagascar specifically declines in the month a cyclone makes landfall or in the month following, by employing a Difference-in-Differences analysis using historical data on cyclone occurrences and tourism arrivals. The dataset included monthly data from 1990 onwards, detailing tourism arrivals, cyclone landfall counts, and other relevant variables. First, I defined a treatment variable to represent the months directly affected by cyclones—either the month of a cyclone landfall or the subsequent month. This variable was derived by identifying months where the cyclone landfall count was greater than zero and marking these, as well as the following month, as treated.

Using this treatment definition, I conducted a regression analysis to estimate the impact of cyclone landfalls on tourism arrivals. The model included the treatment variable, a post-treatment indicator (representing periods from the year 2000 onwards, assumed to have different baseline tourism characteristics), and the interaction of these two variables, which is key to the Difference of Differences approach. This model isolates the effect of cyclones from other time-varying effects that could influence tourism numbers.

3.4 Constructing a Time-Series Model to Predict International Arrivals

The third part of the study aims to find the best performing model for predicting and forecasting international arrivals. The model was set up with the variables featured in Table 3.

Variable	Variable Type	Description
International Arrivals	Dependent	# of International Arrivals
Temperature	Independent	Avg Mean Temperature over Month
Precipitation	Independent	Total Precipitation over Month
Windspeed	Independent	Avg Windspeed over Month
Humidity	Independent	Avg Humidity over Month
# of Storms made Landfall	Independent	Count of Storms Making Landfall
# of Cyclones made Landfall	Independent	Count of Cyclones Making Landfall
Total Storm Intensity	Independent	Summed SWIO Scale of all storms in Month
Inflation	Independent	Inflation Rate of Madagascar
Exchange Rate	Independent	Exchange Rate between Ariary and Euro

Table 3: Description of Variables used in Time-Series Forecasting Models

The period of 2010 to 2019 was used to train the models, with 20% of the training set, specifically 24 months, randomly chosen (random_state = 42) to form the test set and evaluate the model's performance. The best performing model was then used to forecast the period of 2020 to 2024.

The following models and the reasoning behind choosing them are as follows:

1. Gradient Boosting Regressor: GBRs are built on decision trees, which are adept at handling complex, non-linear relationships between features. This makes them suitable

for tourism data, where arrivals could be influenced by a complex interplay of factors like weather conditions, economic indicators, and global events. Decision trees, the building blocks of GBRs, naturally segment data into smaller groups, making them less sensitive to outliers. This can be particularly useful in tourism forecasting, where anomalous events tropical cyclones might otherwise skew predictions.

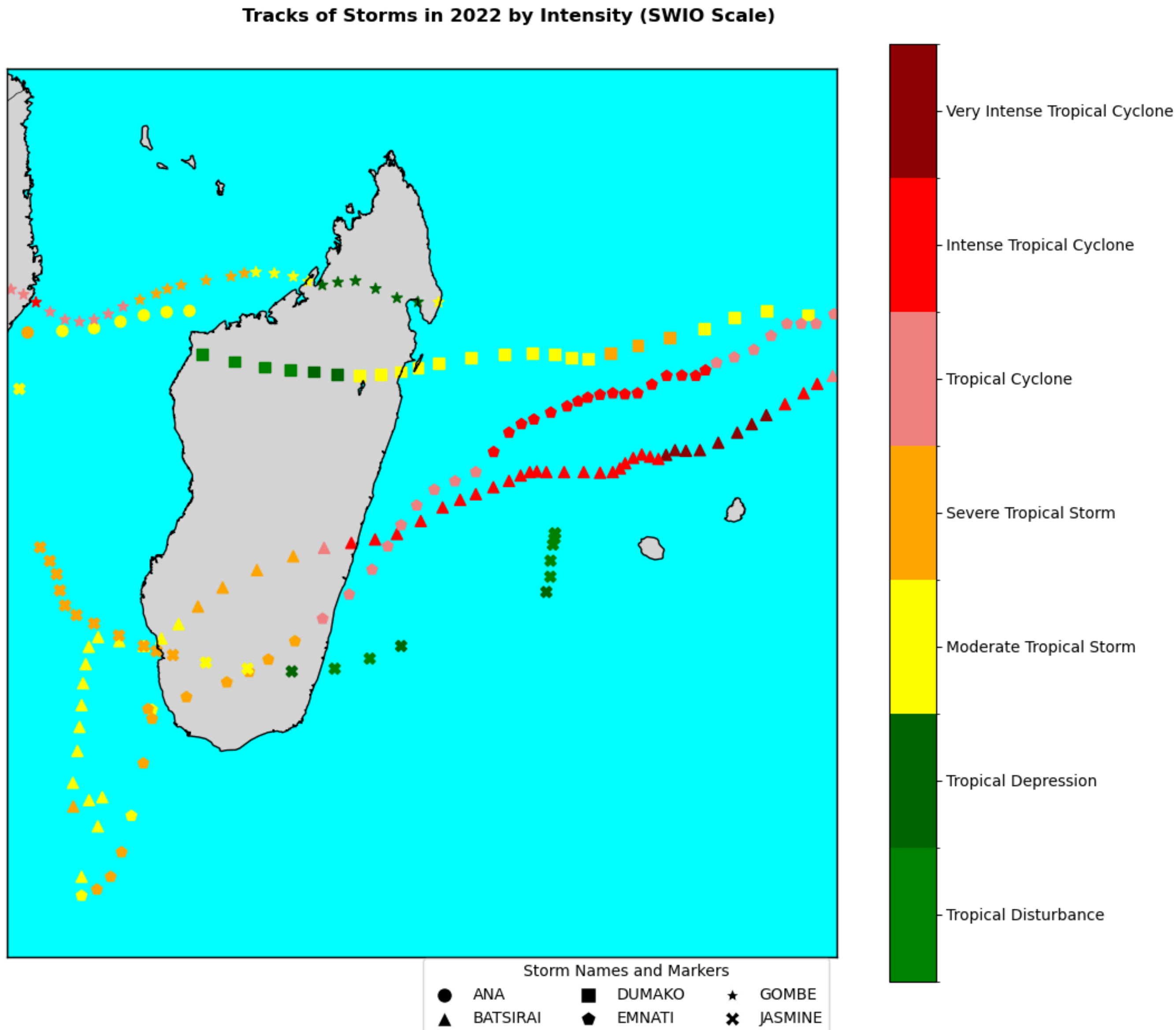
2. Random Forest Regressor: Random Forests utilize an ensemble method that aggregates the predictions from multiple decision trees to improve accuracy and reduce the risk of overfitting. This makes the model robust against noise and outliers in the data, which are common in dynamic industries like tourism.
3. SARIMAX: Seasonal AutoRegressive Integrated Moving Average with eXogenous variables model is tailored for time series forecasting. It can incorporate seasonal patterns and external variables, making it ideal for analyzing how specific weather events influence tourism over time. It accounts for trends, seasonality, and the influence of past values.
4. XG Boost: XGBoost is a highly flexible and powerful machine learning model that performs well on a variety of prediction tasks. It can handle different types of data features and capture complex nonlinear patterns effectively, potentially offering insights into intricate relationships between weather conditions and tourism arrivals.
5. Prophet: Prophet is specifically designed for time series data with strong seasonal effects and multiple seasonality, which is typical in tourism data. It's robust to missing data and shifts in trend, and can handle holiday effects, which could coincide with weather events (e.g., tropical cyclones during high tourist seasons).

The primary metric employed to evaluate and compare the performance of different models was the Root Mean Squared Error (RMSE). RMSE is calculated as the square root of the average of the squared differences between predicted values and actual values, providing a measure of the spread of residuals. Additionally, other evaluation metrics such as Mean Absolute Error (MAE) and R-Squared values were also presented in the results table to offer a comprehensive view of model performance. MAE measures the average magnitude of the errors in a set of predictions, without considering their direction (i.e., it averages the absolute differences between predicted and actual values). R-Squared, on the other hand, provides a statistical measure of how well the regression predictions approximate the real data points, expressed as a percentage, where a higher value indicates a better fit to the observed data.

4. Results

4.1 Creating Data Visualizations of Storm Tracks using IBTrACs data

Featured in Figure 4 on the next page is an example of the storm tracks data visualization created for the year 2022. These visualizations help determine in the regional analysis, what month of the year storm's made landfall and the intensity of the storm when it did so. The included range features storm's that made landfall on Madagascar, Mauritius, and the Réunion Islands. Data visualizations for all storm tracks spanning between 2010 and 2024 can be found in Exhibit B at the end of this paper.



Storm Name	Start Date	End Date	Max Strength	Made Landfall?
ANA	1/23/2022	1/24/2022	Severe Tropical Storm	N
BATSIRAI	2/1/2022	2/8/2022	Very Intense Tropical Cyclone	Y
DUMAKO	2/13/2022	2/16/2022	Severe Tropical Storm	Y
EMNATI	2/18/2022	2/24/2022	Intense Tropical Cyclone	Y
GOMBE	3/8/2022	3/11/2022	Intense Tropical Cyclone	Y
JASMINE	4/24/2022	4/29/2022	Severe Tropical Storm	Y

Figure 4: Storm Tracks for the Cyclone Season 2022

4.2 Regional Analysis of Storms Impact on Tourism

The combined dataset of Mauritius, Réunion, and Madagascar showed a significant decrease in tourist arrivals during storm months. This was supported by a p-value of 0.0196 from Welch's t-test, indicating a statistically significant reduction in tourist arrivals correlated with storm events. The results of the study suggest that storms have a tangible and negative impact on tourist arrivals in the studied regions. This impact is not uniform across all locations, highlighting the localized nature of storms' effects on tourism. This analysis is limited by the assumption of uniformity in data reporting across different countries and does not account for other potential factors that could influence tourism, such as economic conditions, political stability, and promotional activities. These limitations suggest the need for a cautious interpretation of the findings. Following this analysis, I checked to see whether the effects of a storm would carry over to the following month by introducing a lagged variable called post-storm month. However, no significant differences were found between post-storm months and non-storm months ($t = -1.371$, $p = 0.1804$), nor between storm months and post-storm months ($t = -0.416$, $p = 0.6793$). This suggests that while storms deter tourist arrivals, the recovery in the month following a storm is swift enough that it does not differ significantly from normal conditions.

4.3 Difference of Differences Analysis on Tropical Cyclones Effect on Madagascar Tourism

The regression analysis revealed that while the post-2000 period saw a significant increase in tourism arrivals, the impact of cyclone landfalls (as indicated by the interaction term) resulted in a decrease in tourism arrivals by approximately 2,572 tourists. However, this particular effect was not statistically significant ($p = 0.270$). When isolating for the impact of tourism in the month that the cyclone made landfall, a decrease of approximately -1,879 tourists was evident but was also found to not be statistically significant (p=0.478). This indicates that while there is a negative impact observed, it does not meet conventional levels of statistical confidence (p<=0.05) to assert the effect definitively as attributable to cyclones.

The findings suggest that cyclone landfalls potentially have a dampening effect on tourism, though the evidence is not strong enough to confirm this definitively. For policymakers and stakeholders in the tourism industry, this points to the need for further investigation with potentially more data or refined models. For regions prone to cyclonic activity, the results underscore the importance of considering the economic impact of cyclones on tourism and potentially investing in infrastructure and strategies to mitigate these impacts. More robust statistical evidence could further guide targeted interventions to support the tourism sector during and after cyclone events.

4.4 Constructing a Time-Series Model to Predict International Arrivals

4.4.1 Results of Tested Models

Of the five time-series forecasting model's tested in this analysis, the Random Forest Regressor model showed the best performance across all metrics. This model has the lowest RMSE and MAE, indicating that it generally has the smallest prediction errors and the highest R-Squared, meaning it explains the most variance (67%) in tourism arrivals. The summary of the five tested model's ranked by performance is featured in Table 4.

Model Type	RMSE	MAE	R-Squared
Random Forest Regressor	3869	2925	67%
Prophet	4826	3529	49%
Gradient Boosting Regressor	5069	3635	44%
SARIMAX	5156	4089	42%
XG Boost	5551	4007	33%

Table 4: Performance Summary of the Forecasting Models

4.3.2 Permutation Analysis for Feature Importance

The Random Forest Regressor was then passed through a permutation importance analysis assess the importance of each feature in predicting the target variable, international arrivals. Permutation importance was calculated for a Random Forest Regressor model using the sklearn.inspection.permutation_importance function. The model was trained and then tested on a set of features like exchange rates, humidity, temperature, and other climatic and economic factors. I used the test dataset and specified 10 repeats with a fixed random state to ensure consistency in the results.

Rank	Variable	Importance Mean	Importance St Dev
1	Exchange Rate (Mal to Euro)	0.559	0.141
2	humidity	0.158	0.076
3	temp	0.140	0.035
4	precipitation	0.065	0.019
5	windspeed	0.028	0.026
6	Inflation	0.003	0.018
7	# of Cyclones (Landfall)	0.000	0.000
8	Total Storm Intensity	-0.002	0.007
9	# of Storms (Landfall)	-0.008	0.004

Table 5: Permutation Importance of Predictor Variables

These results revealed that the Exchange Rate (Mal to Euro) was the most significant predictor, showing a high mean importance and considerable influence on the model's predictions. Humidity and temperature were also important, though less so than the exchange rate. Surprisingly, features directly related to cyclones, like the number of cyclones making landfall and their intensity, showed minimal or even negative importance, suggesting they do not significantly impact the model's predictions within the tested framework.

4.4.3 Forecasting using Random Forest Regressor

Using the Random Forest Regressor model, I set out to make predictions for 2020 to 2024. Since this analysis focuses on the effects of weather on tourism, I have considered the counterfactual to COVID-19, meaning what would tourism have looked like had COVID-19 not occurred. 2020 to 2022 actuals have been plotted for the purpose of illustrating that the number of international arrivals are returning to pre-pandemic levels.

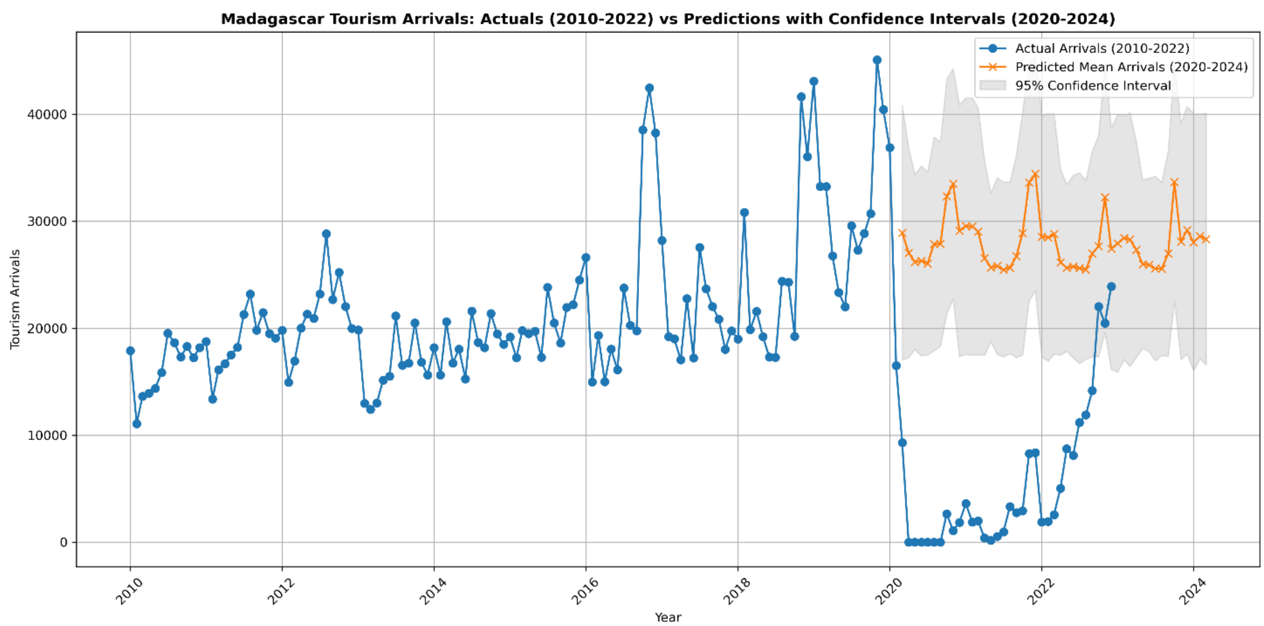


Figure 5: Random Forest Regression Forecast for 2020 to 2024

It will be crucial to test this model's effectiveness when the World Trade Organization posts the monthly international arrivals data for 2023 and 2024. This data will provide a true sense of the model's capabilities of predicting international arrivals without the disruption of COVID-19 pandemic or other political conflicts.

5. Implications of Results and Recommendations for Future Research

The observed decrease in tourist arrivals during storm months highlights the need for robust disaster management and preparedness strategies to mitigate economic losses. Governments and tourism boards should consider developing contingency plans that include insurance mechanisms to safeguard revenues and marketing strategies to boost tourism post-disaster. Furthermore, future research could explore long-term trends and incorporate additional variables such as economic indicators and marketing efforts to provide a more nuanced understanding of the relationship between weather events and tourism. Future studies would benefit from having access to regional tourism as Madagascar is a large country (584,000 km^2) and while a cyclone making landfall in one part of the country will effect regional tourism significantly, the effects are not being captured well at the national level.

This was evident when the difference of differences analysis found a drop in international arrivals of 1,879 but was determined to be statistically insignificant. Future studies examining the effects of tropical cyclones on tourism should focus on data that is more stationary year over year. Madagascar's tourism arrivals proved to be difficult as it featured many ebbs and flows, largely driven by periods of political instability, making it hard to compare international arrivals in years of high cyclone activity to years of low cyclone activity. Mauritius and the Réunion Islands are good candidates for future analysis as they both feature relatively stable monthly international arrivals across years. Plots of monthly international arrivals from 2010 to 2019 for these two countries are featured in Exhibit A at the end of this paper for reference.

Finally, of the five models tested in this analysis, the Random Forest Regressor proved to have the best predictive accuracy for international arrivals, largely in part to its ability to capture complex, non-linear relationships. Future studies could add additional predictive variables such as the inclusion of other extreme weather phenomena, such as droughts, as well as other economic variables, such as GDP per capita and the consumer confidence index. From the perspective of a potential tourist, it would be worthwhile to examine the amount of publications featured in France and Italy covering tropical cyclones in Madagascar. From the perspective of Madagascar's Ministry of Tourism, it would be beneficial for the model to analyze major events, like sports matches, cultural festivals, or international conferences, as well as tourism marketing spend. Since the primary focus of this paper is to understand how weather patterns impact tourism, these were not considered in the model.

6. Conclusion

This thesis has provided a comprehensive analysis of the impacts of tropical cyclones on Madagascar's tourism industry, using a multi-faceted approach to explore how these severe weather events affect tourist arrivals. Through detailed exploratory data analysis, time-series modeling, and regression techniques, this study has shed light on the complex dynamics between natural disasters and tourism dynamics.

The exploratory analysis of cyclone data revealed a noticeable fluctuation in storm intensity and frequency, corroborating global climate change predictions about increasing storm severity. This foundational understanding guided further investigation into the direct and lagged impacts of cyclones on tourism. The regional analysis incorporated data from Madagascar and neighboring countries, Mauritius and Réunion, highlighting the localized nature of cyclones' impacts and the varying degrees to which they influence tourism.

The Difference of Differences analysis was particularly insightful, revealing that while the immediate effects of cyclones reduce tourist numbers, the recovery is often swift, suggesting resilience in the tourism sector. However, the statistical significance of these findings was limited, indicating the need for further data to confirm these trends definitively.

The time-series forecasting models tested in this study, particularly the Random Forest Regressor, provided valuable predictions about future tourist arrivals. These models highlighted the importance of various predictors, including economic factors like the exchange rate and inflation, which interact with cyclone occurrences to influence tourism trends. This modeling approach not only forecasts future scenarios but also assists in understanding the relative importance of different variables in tourism dynamics. This model serves as a strong candidate for use in forecasting tourism arrivals for Mauritius and the Réunion Islands.

This thesis underscores the critical need for robust infrastructure and strategic planning to mitigate the impacts of tropical cyclones on tourism. It suggests that enhancing disaster preparedness, integrating comprehensive data analysis, and employing predictive modeling are essential for developing resilient tourism strategies in cyclone-prone regions.

For future research, it is recommended to incorporate additional predictive variables and explore the inclusion of other extreme weather phenomena. Further studies could benefit from a more detailed regional focus that would allow for a nuanced understanding of cyclones' impacts at a local level. Moreover, extending the analytical framework to include political and economic stability could provide deeper insights into the external factors influencing tourism beyond natural disasters. This thesis contributes to the broader discourse on sustainable tourism and climate change, offering insights that can help policymakers, stakeholders, and researchers in their efforts to fortify the tourism industry against the inevitable challenges posed by increasing cyclonic activity.

References

[1] Ahmadi, Maryam, Chiara Casoli, Matteo Manera, and Daniele Valenti. 2022. “Modelling the Effects of Climate Change on Economic Growth: A Bayesian Structural Global Vector Autoregressive Approach.” *Social Science Research Network*, January. https://doi.org/10.2139/ssrn.4307686.

[2] Alanna, Simpson, Emma Phillips, and Simone Balog. 2016. “Disaster Risk Profile Madagascar.” Washington D.C. 20433, USA: The World Bank, The International Bank for Reconstruction and Development.

[3] Bakker, Martine Hendrica Elize, Juliana Shu Tan Kua, Hannah R. Messerli, and Bradley Lawrence Weiss. 2013. “Indian Ocean Islands Tourism Sector Review : Madagascar.” *WorldBank.org*. Washington D.C. 20433, USA: World Bank Group. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/994701467992523618/indian-ocean-islands-tourism-sector-review-madagascar.

[4] World Bank Group. 2011. "Climate Risk and Adaptation Country Profile: Madagascar." April. Accessed April 20, 2024. http://countryadaptationprofiles.gfdrr.org.

[5] Iain, Christie, and Elizabeth Crompton. 2003. “Republic of Madagascar: Tourism Sector Study.” *Policycommons.net*. United States: The Africa Region Working Paper Series. https://policycommons.net/artifacts/1458141/republic-of-madagascar/2096305/.

[6] “INFORM Risk - Country Risk Profile.” 2024. Drmkc.jrc.ec.europa.eu. European Commission. 2024. https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Risk/Country-Risk-Profile.

[7] “Madagascar Cyclone Exposures and Vulnerabilities .” 2019. *Reliefweb.com*. acaps. https://reliefweb.int/report/madagascar/acaps-thematic-report-madagascar-cyclone-exposure-and-vulnerabilities-19-january-2024.

[8] “Ministère Du Tourisme de Madagascar.” n.d. Ministère Du Tourisme. Accessed April 8, 2024. https://www.tourisme.gov.mg/.

[9] “World Bank Climate Change Knowledge Portal.” n.d. Climateknowledgeportal.worldbank.org. https://climateknowledgeportal.worldbank.org/country/madagascar.

[10] Knapp, K. R., M. C. Kruk, D. H. Levinson, H. J. Diamond, and C. J. Neumann, 2010: The International Best Track Archive for Climate Stewardship (IBTrACS): Unifying tropical cyclone best track data. Bulletin of the American Meteorological Society, 91, 363-376. doi:10.1175/2009BAMS2755.1

[11] Knapp, K. R., H. J. Diamond, J. P. Kossin, M. C. Kruk, C. J. Schreck, 2018: International Best Track Archive for Climate Stewardship (IBTrACS) Project, Version 4. [indicate subset used]. NOAA National Centers for Environmental Information. doi:10.25921/82ty-9e16 April 24, 2024.

[12] Delforge, D. et al.: EM-DAT: The Emergency Events Database, Preprint, https://doi.org/10.21203/rs.3.rs-3807553/v1, 2023

[13] Copernicus Climate Change Service (C3S). "Climate Data Store." Accessed April 2nd 2024. https://cds.climate.copernicus.eu/.

[14] World Tourism Organization. "Global and Regional Tourism Performance." Accessed March 23rd 2024. https://www.unwto.org/tourism-data/global-and-regional-tourism-performance.

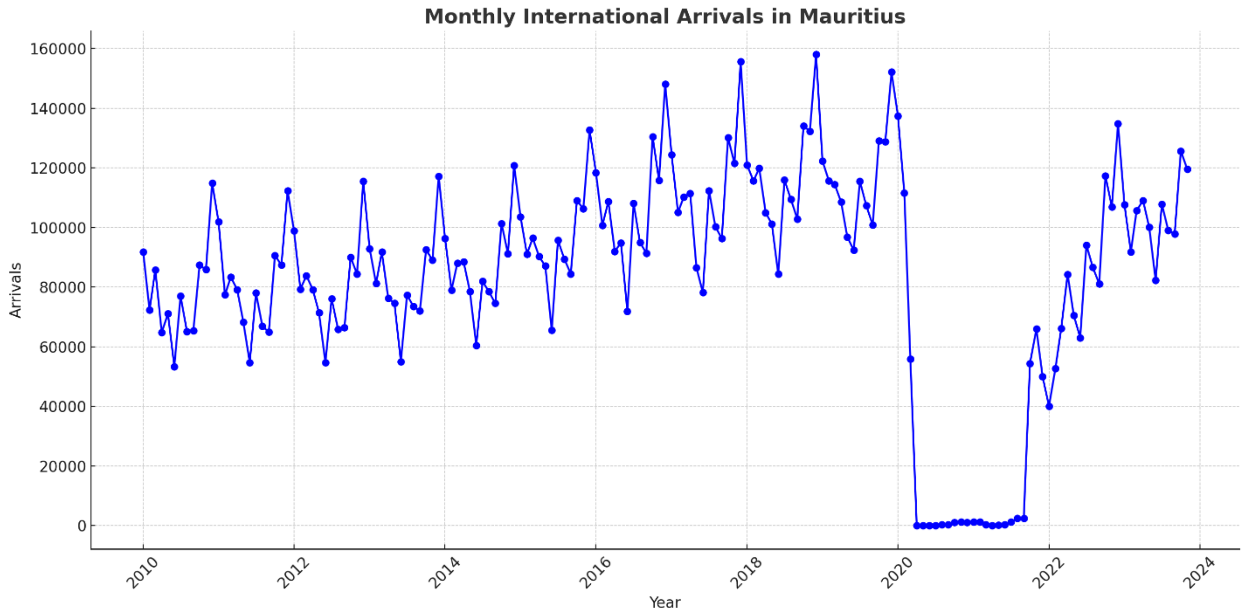
[15] Ministère de l'Économie et du Plan. Rapport Économique et Financier 2010-2017. Direction Générale de l'Économie. Accessed March 28th 2024.

[16] "Madagascar Inflation CPI." Trading Economics. Accessed April 5th 2024 https://tradingeconomics.com/madagascar/inflation-cpi.

[17] World Travel & Tourism Council. Madagascar 2024 Annual Research: Key Highlights. London: World Travel & Tourism Council, 2024. https://assets-global.website-files.com/6329bc97af73223b575983ac/662fa792532f5fcd637861d5_Madagascar2024_.pdf

Exhibits:

Exhibit A: Monthly International Arrivals from WTO Tourism Dashboard for Mauritius and Réunion Islands



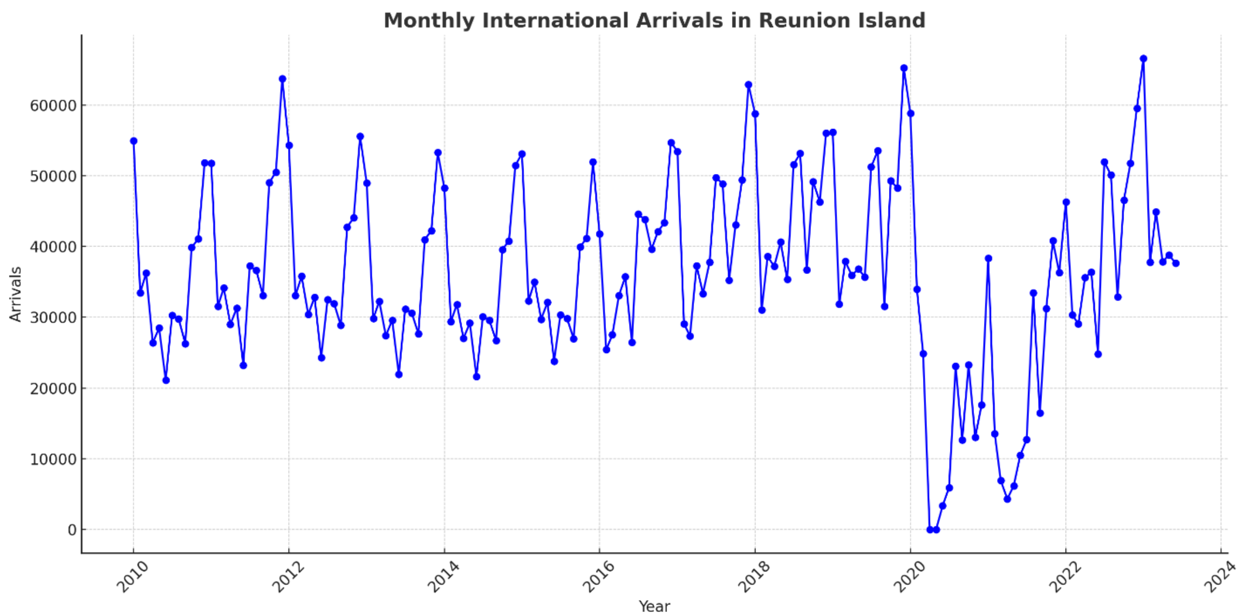
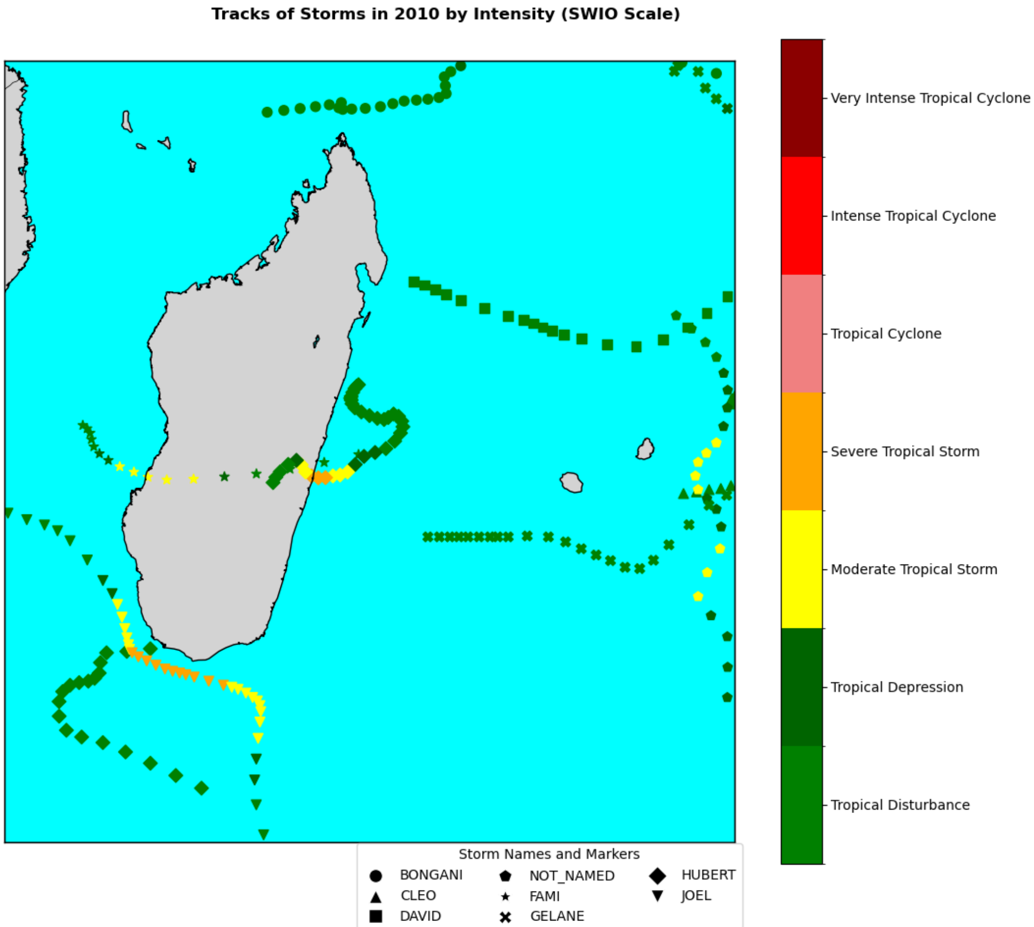
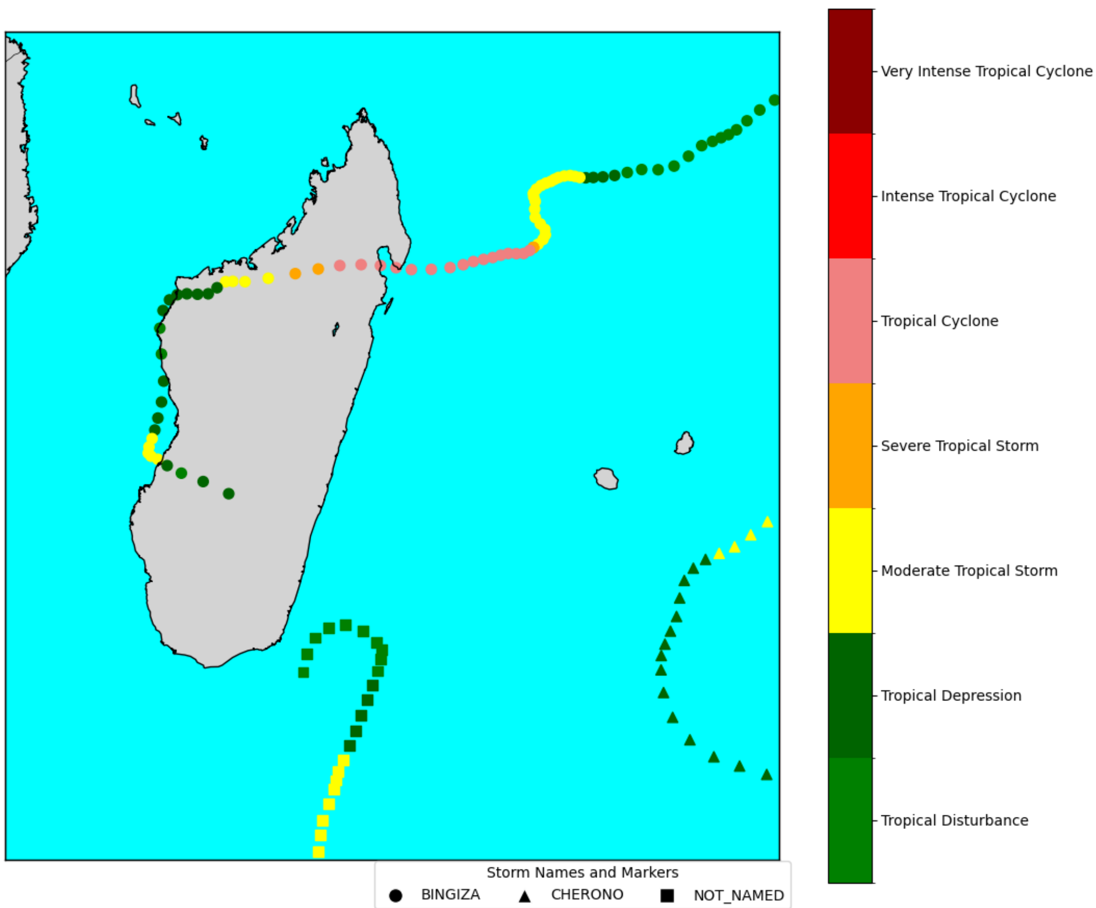


Exhibit B: *Storm Tracks developed from IBTrACs data for Cyclone Seasons 2010 to 2024*

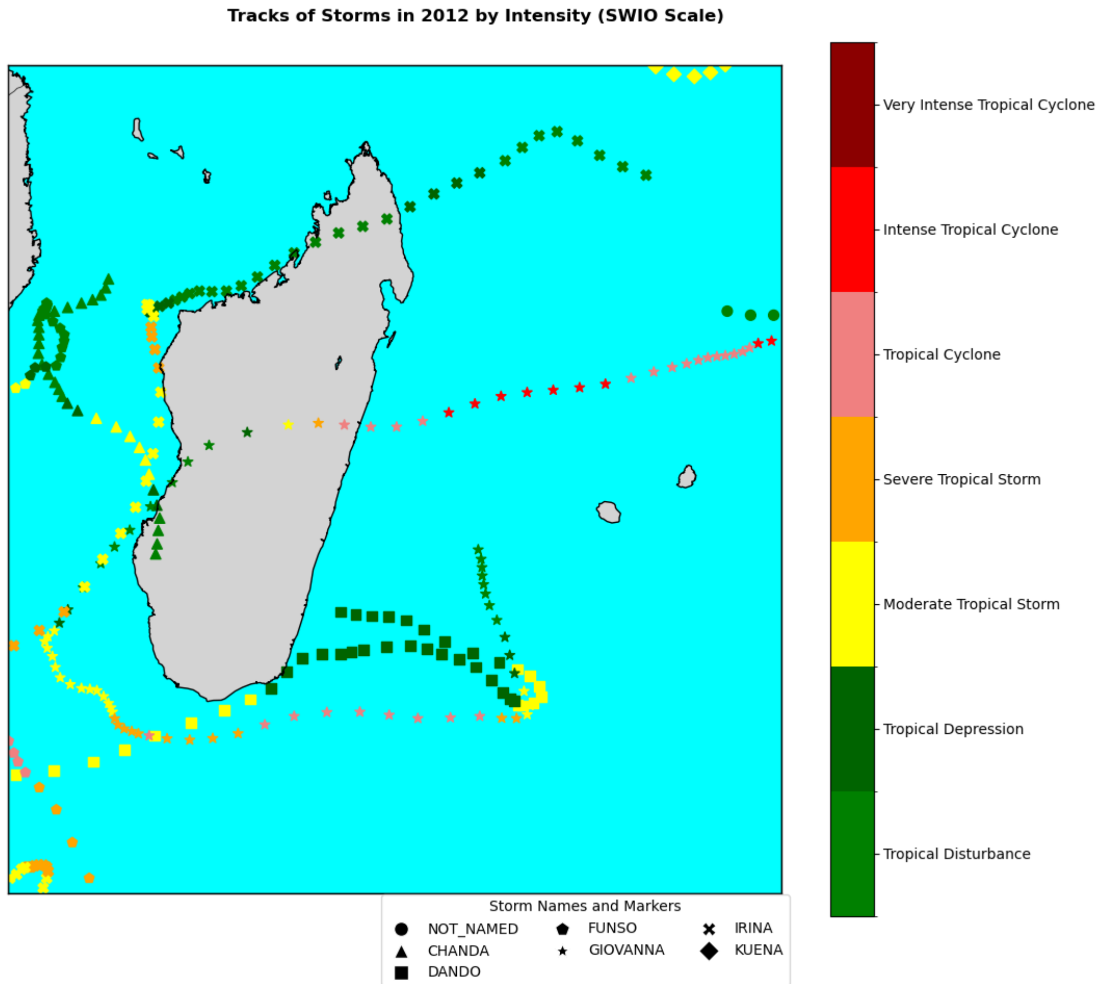


Storm Name	Start Date	End Date	Max Strength	Made Landfall?
BONGANI	11/21/2009	11/26/2009	Tropical Depression	N
CLEO	12/14/2009	12/17/2009	Tropical Disturbance	N
DAVID	12/29/2009	12/31/2009	Tropical Disturbance	N
NOT_NAMED	1/26/2010	1/29/2010	Moderate Tropical Storm	N
FAMI	2/1/2010	2/3/2010	Moderate Tropical Storm	Y
GELANE	2/15/2010	2/25/2010	Tropical Depression	N
HUBERT	3/7/2010	3/15/2010	Severe Tropical Storm	Y
JOEL	5/24/2010	5/29/2010	Severe Tropical Storm	N

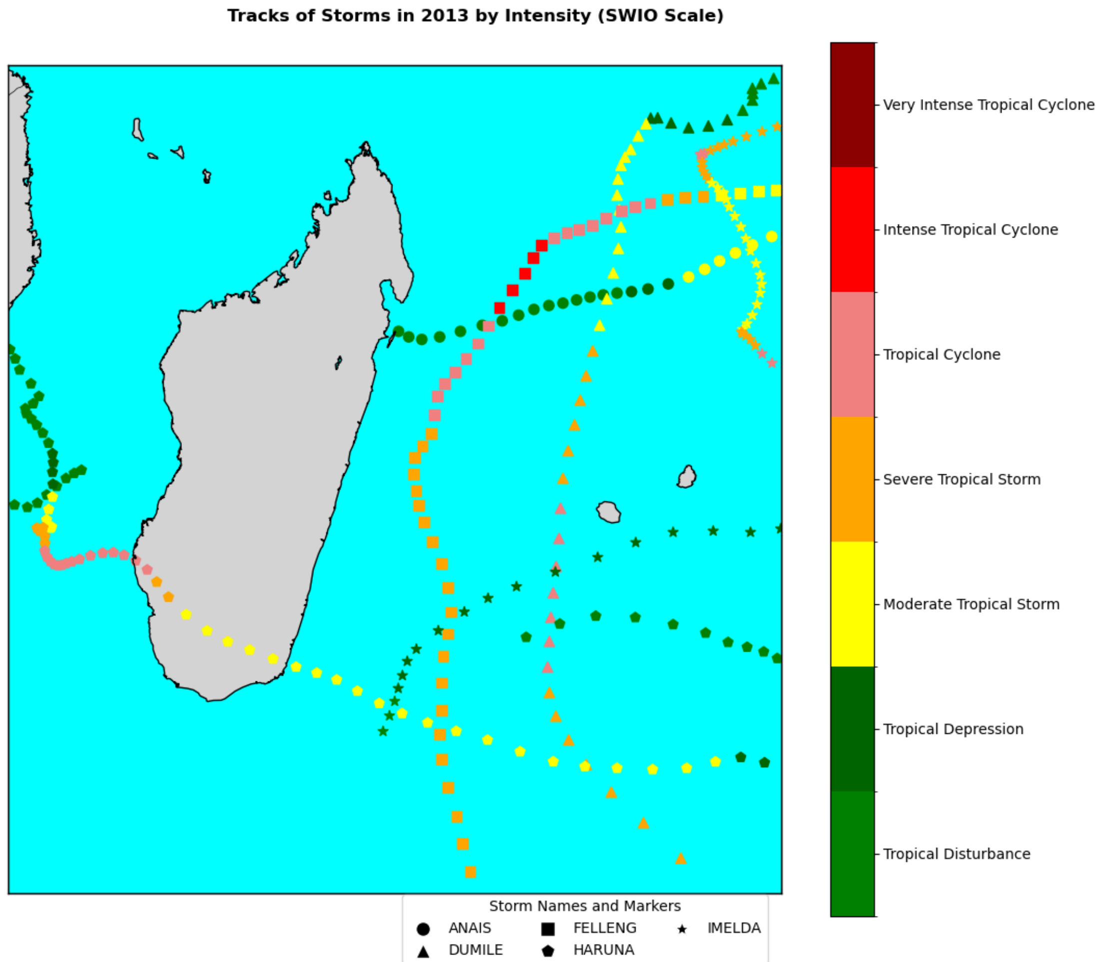
Tracks of Storms in 2011 by Intensity (SWIO Scale)



Storm Name	Start Date	End Date	Max Strength	Made Landfall?
BINGIZA	2/7/2011	2/21/2011	Tropical Cyclone	Y
CHERONO	3/20/2011	3/23/2011	Moderate Tropical Storm	N
NOT_NAMED	4/11/2011	4/14/2011	Moderate Tropical Storm	N

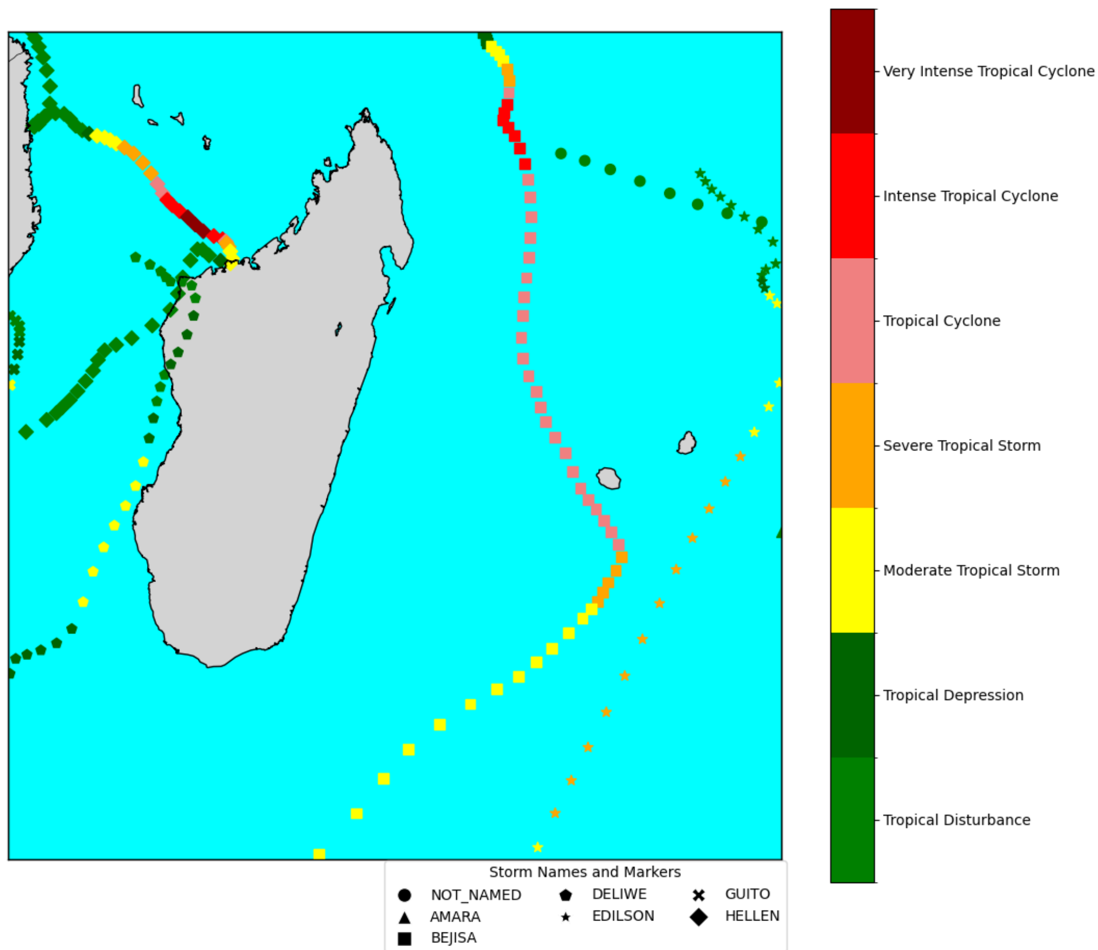


Storm Name	Start Date	End Date	Max Strength	Made Landfall?
NOT_NAMED	12/11/2011	12/11/2011	Tropical Disturbance	N
CHANDA	1/5/2012	1/10/2012	Moderate Tropical Storm	Y
DANDO	1/10/2012	1/15/2012	Moderate Tropical Storm	Y
FUNSO	1/17/2012	1/28/2012	Tropical Cyclone	N
GIOVANNA	2/11/2012	2/22/2012	Intense Tropical Cyclone	Y
IRINA	2/25/2012	3/8/2012	Severe Tropical Storm	Y
KUENA	6/6/2012	6/6/2012	Moderate Tropical Storm	N

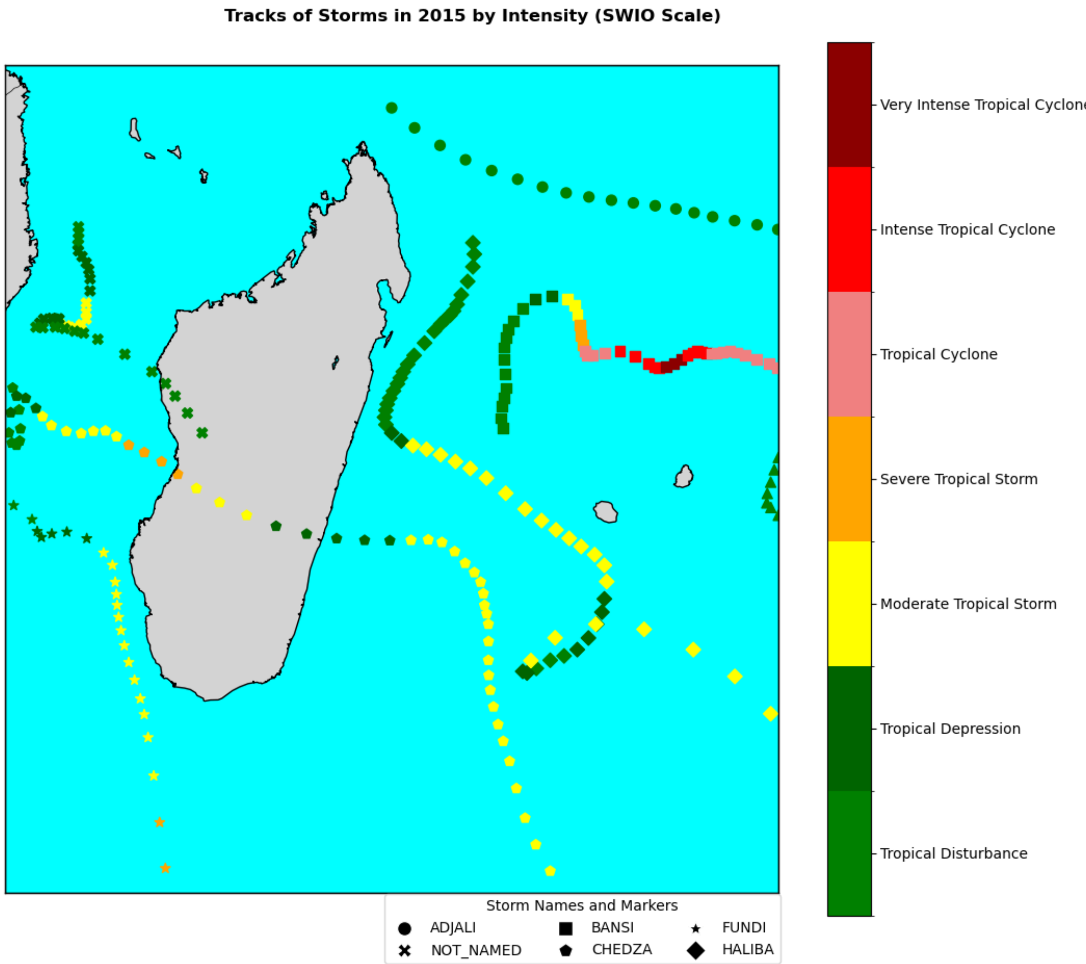


Storm Name	Start Date	End Date	Max Strength	Made Landfall?
ANAIS	10/16/2012	10/19/2012	Moderate Tropical Storm	N
DUMILE	12/30/2012	1/5/2013	Tropical Cyclone	N
FELLENG	1/28/2013	2/3/2013	Intense Tropical Cyclone	N
HARUNA	2/14/2013	2/28/2013	Tropical Cyclone	Y
IMELDA	4/9/2013	4/20/2013	Tropical Cyclone	N

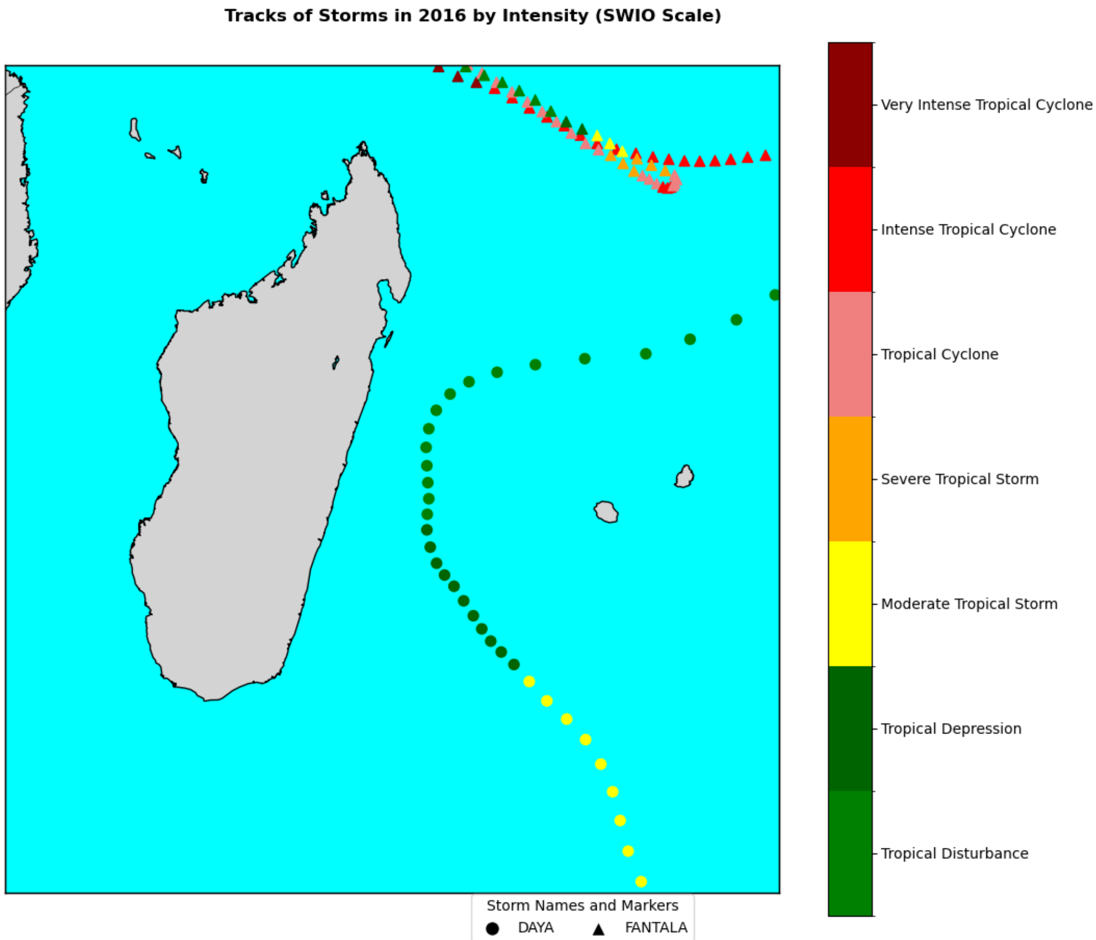
Tracks of Storms in 2014 by Intensity (SWIO Scale)



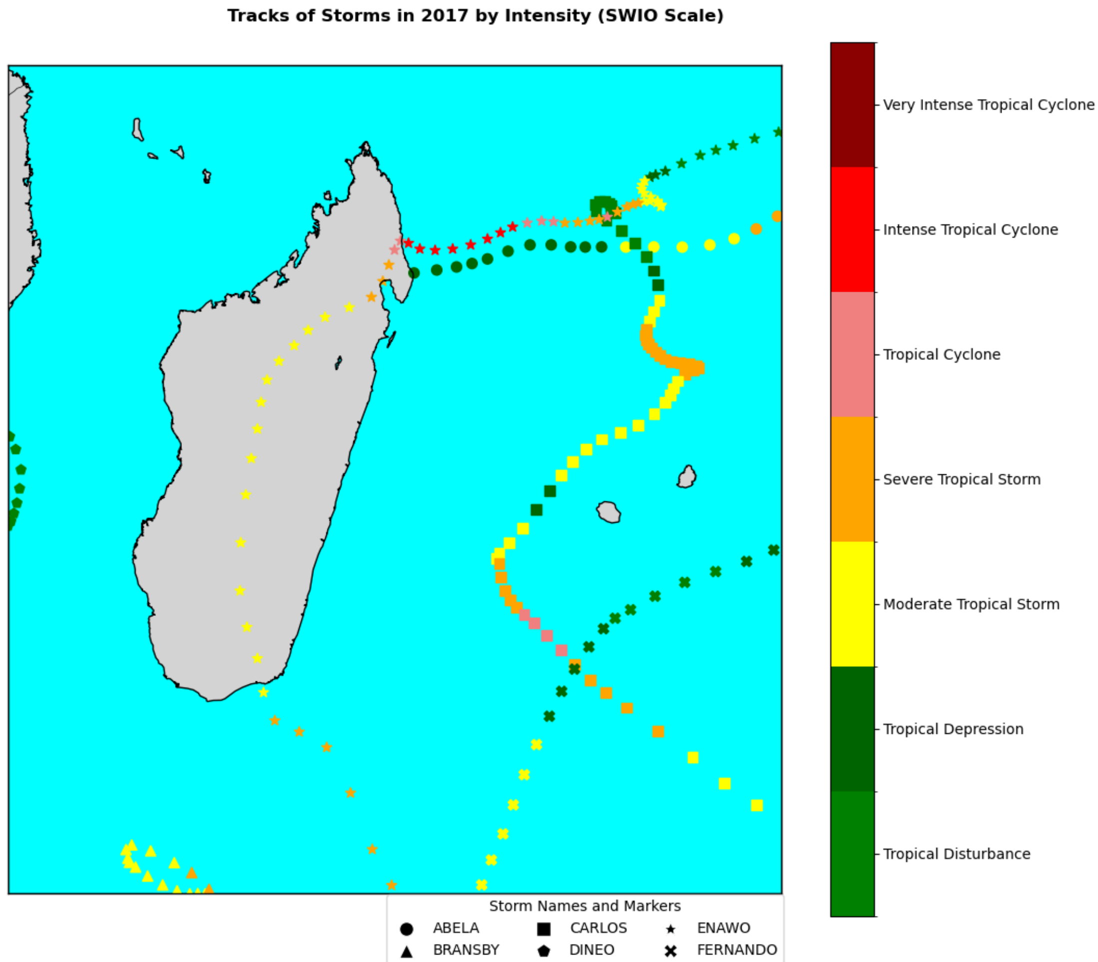
Storm Name	Start Date	End Date	Max Strength	Made Landfall?
NOT_NAMED	10/28/2013	10/29/2013	Tropical Disturbance	N
AMARA	12/28/2013	12/28/2013	Tropical Disturbance	N
BEJISA	12/29/2013	1/5/2014	Intense Tropical Cyclone	N
DELIWE	1/14/2014	1/18/2014	Moderate Tropical Storm	Y
EDILSON	2/3/2014	2/7/2014	Severe Tropical Storm	N
GUITO	2/17/2014	2/18/2014	Moderate Tropical Storm	N
HELLEN	3/26/2014	4/3/2014	Very Intense Tropical Cyclone	Y



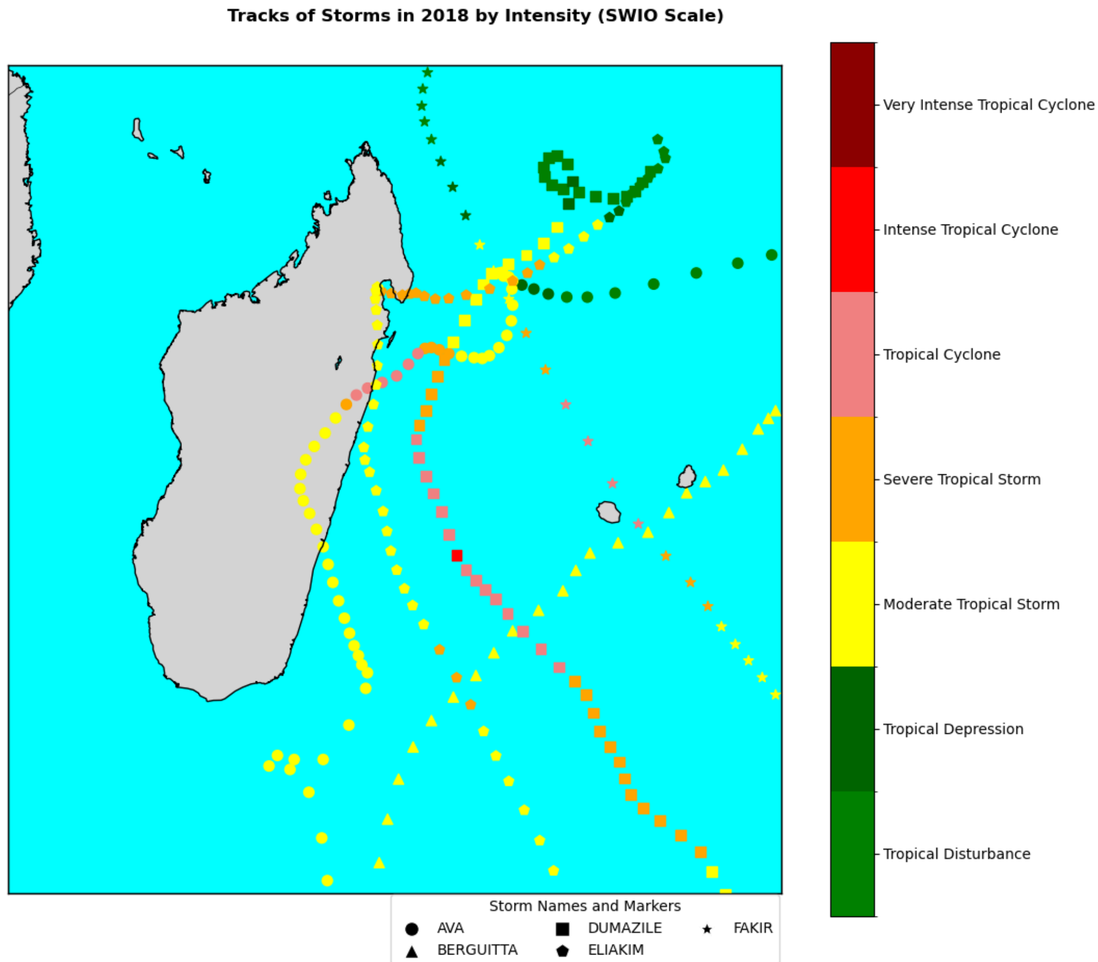
Storm Name	Start Date	End Date	Max Strength	Made Landfall?
ADJALI	11/22/2014	11/24/2014	Tropical Disturbance	N
NOT_NAMED	11/30/2014	12/1/2014	Tropical Disturbance	N
BANSI	1/8/2015	1/14/2015	Very Intense Tropical Cyclone	N
CHEDZA	1/14/2015	1/20/2015	Severe Tropical Storm	Y
FUNDI	2/5/2015	2/8/2015	Severe Tropical Storm	N
NOT_NAMED	3/4/2015	3/9/2015	Moderate Tropical Storm	Y
HALIBA	3/4/2015	3/12/2015	Moderate Tropical Storm	N



Storm Name	Start Date	End Date	Max Strength	Made Landfall?
DAYA	2/7/2016	2/12/2016	Moderate Tropical Storm	N
FANTALA	4/15/2016	4/24/2016	Very Intense Tropical Cyclone	N

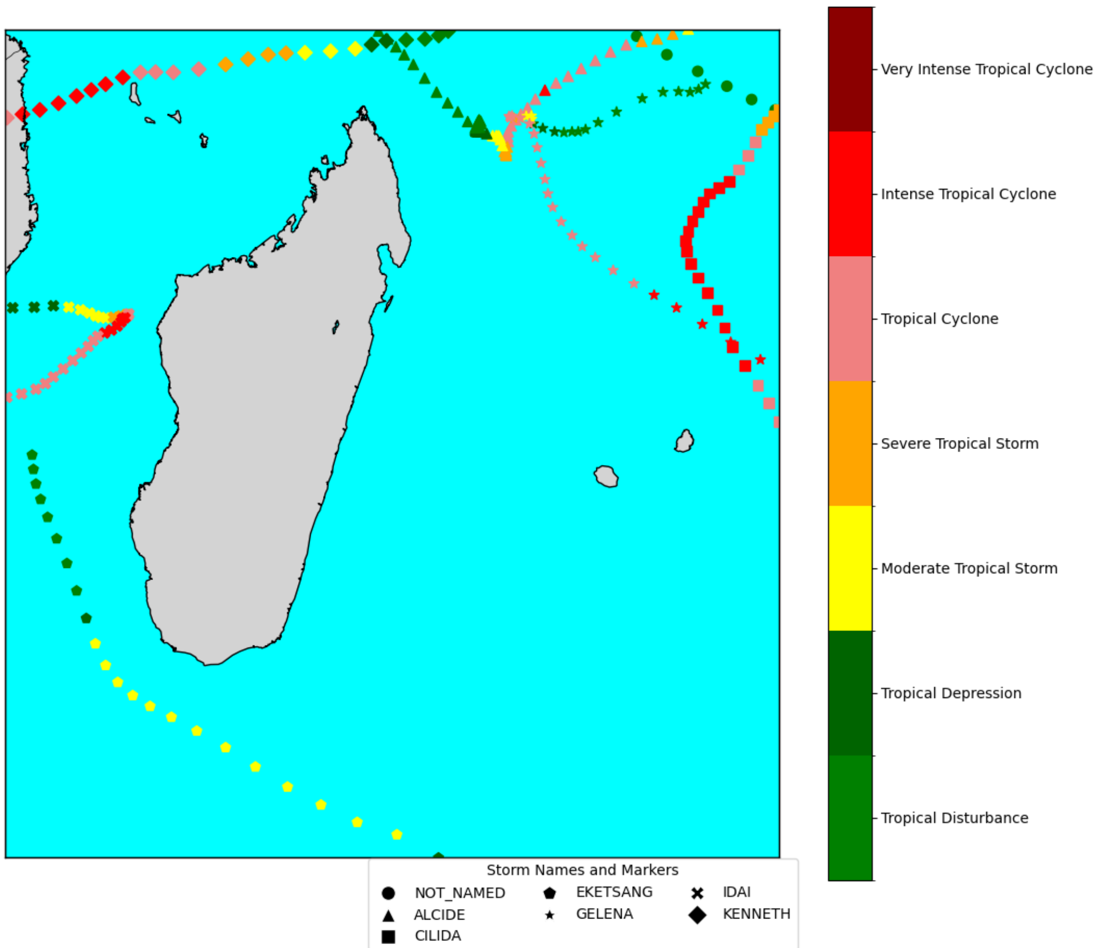


Storm Name	Start Date	End Date	Max Strength	Made Landfall?
ABELA	7/18/2016	7/20/2016	Severe Tropical Storm	N
BRANSBY	10/4/2016	10/6/2016	Severe Tropical Storm	N
CARLOS	2/2/2017	2/10/2017	Tropical Cyclone	N
DINEO	2/11/2017	2/12/2017	Tropical Disturbance	N
ENAWO	3/2/2017	3/10/2017	Intense Tropical Cyclone	Y
FERNANDO	3/12/2017	3/14/2017	Moderate Tropical Storm	N



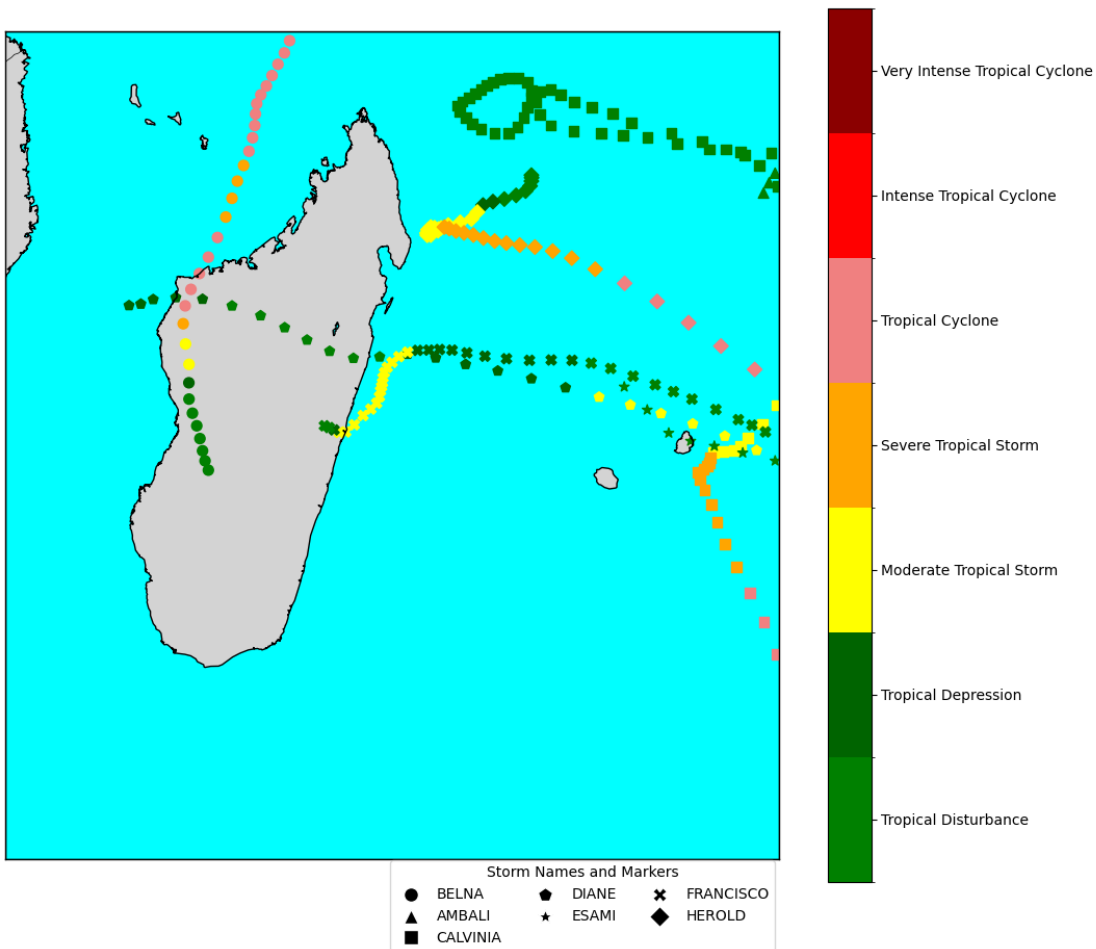
Storm Name	Start Date	End Date	Max Strength	Made Landfall?
AVA	1/1/2018	1/9/2018	Tropical Cyclone	Y
BERGUITTA	1/17/2018	1/20/2018	Moderate Tropical Storm	N
DUMAZILE	3/1/2018	3/8/2018	Intense Tropical Cyclone	N
ELIAKIM	3/13/2018	3/20/2018	Severe Tropical Storm	Y
FAKIR	4/22/2018	4/25/2018	Tropical Cyclone	N

Tracks of Storms in 2019 by Intensity (SWIO Scale)



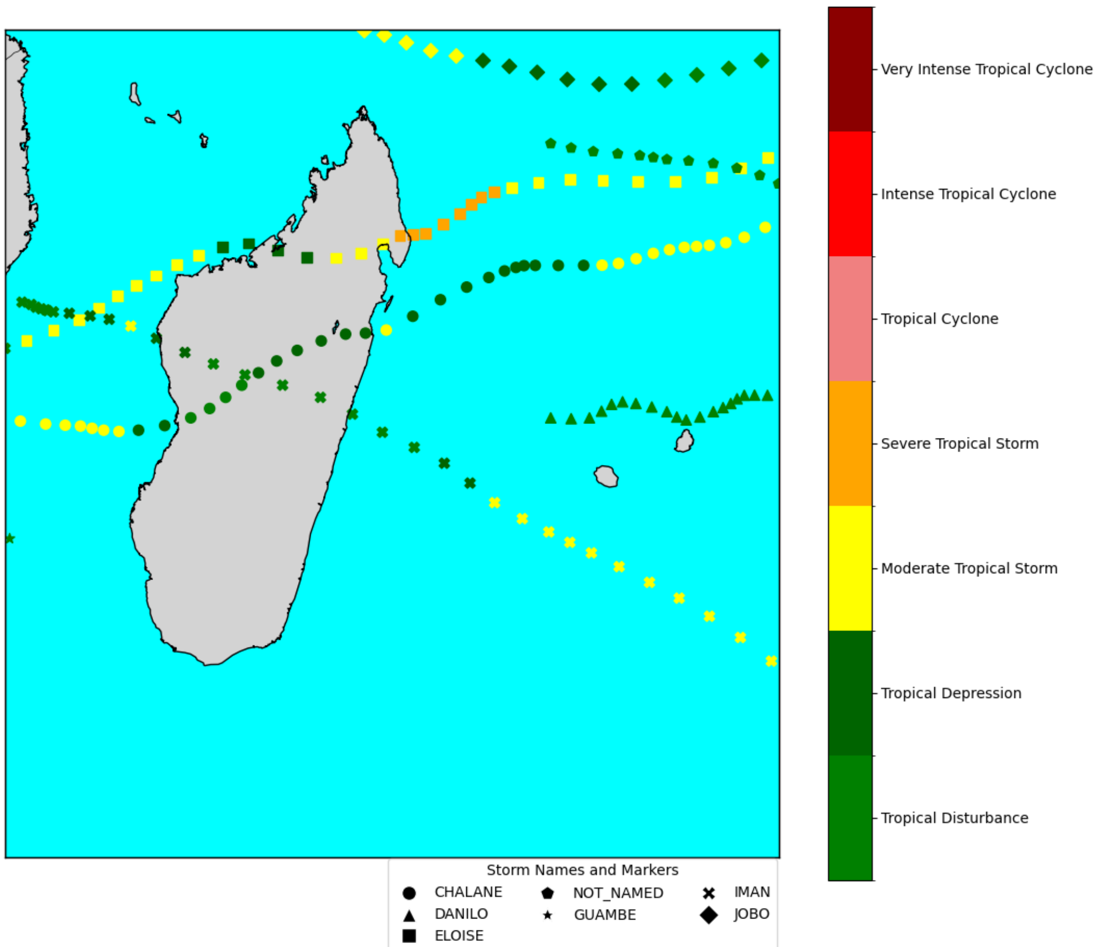
Storm Name	Start Date	End Date	Max Strength	Made Landfall?
NOT_NAMED	9/17/2018	9/18/2018	Tropical Disturbance	N
ALCIDE	11/7/2018	11/13/2018	Intense Tropical Cyclone	N
CILIDA	12/19/2018	12/23/2018	Intense Tropical Cyclone	N
EKETSANG	1/23/2019	1/26/2019	Moderate Tropical Storm	N
GELENA	2/4/2019	2/9/2019	Intense Tropical Cyclone	N
IDAI	3/9/2019	3/13/2019	Intense Tropical Cyclone	N
KENNETH	4/22/2019	4/25/2019	Intense Tropical Cyclone	N

Tracks of Storms in 2020 by Intensity (SWIO Scale)



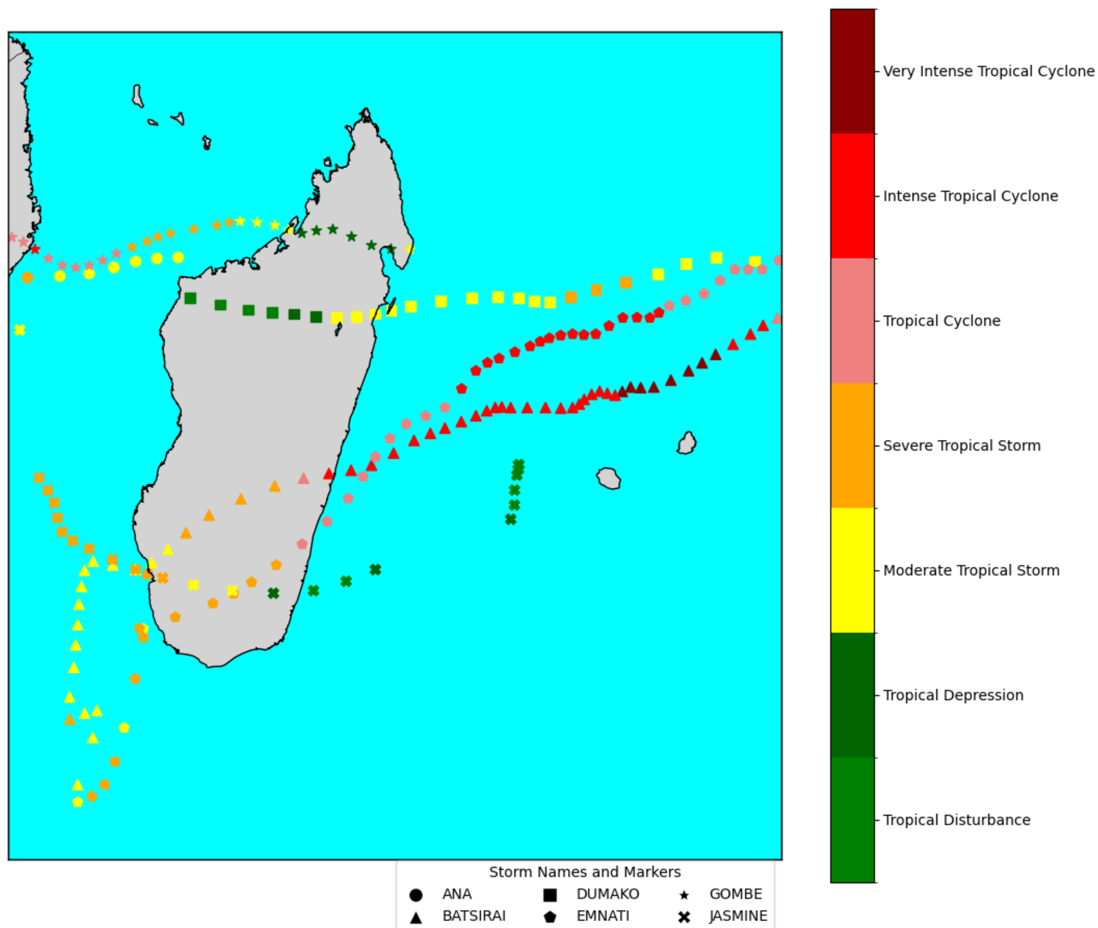
Storm Name	Start Date	End Date	Max Strength	Made Landfall?
BELNA	12/7/2019	12/11/2019	Tropical Cyclone	Y
AMBALI	12/9/2019	12/9/2019	Tropical Disturbance	N
CALVINIA	12/22/2019	1/1/2020	Tropical Cyclone	N
DIANE	1/22/2020	1/25/2020	Moderate Tropical Storm	Y
ESAMI	1/22/2020	1/23/2020	Tropical Disturbance	N
FRANCISCO	2/11/2020	2/15/2020	Moderate Tropical Storm	Y
HEROLD	3/12/2020	3/17/2020	Tropical Cyclone	N

Tracks of Storms in 2021 by Intensity (SWIO Scale)

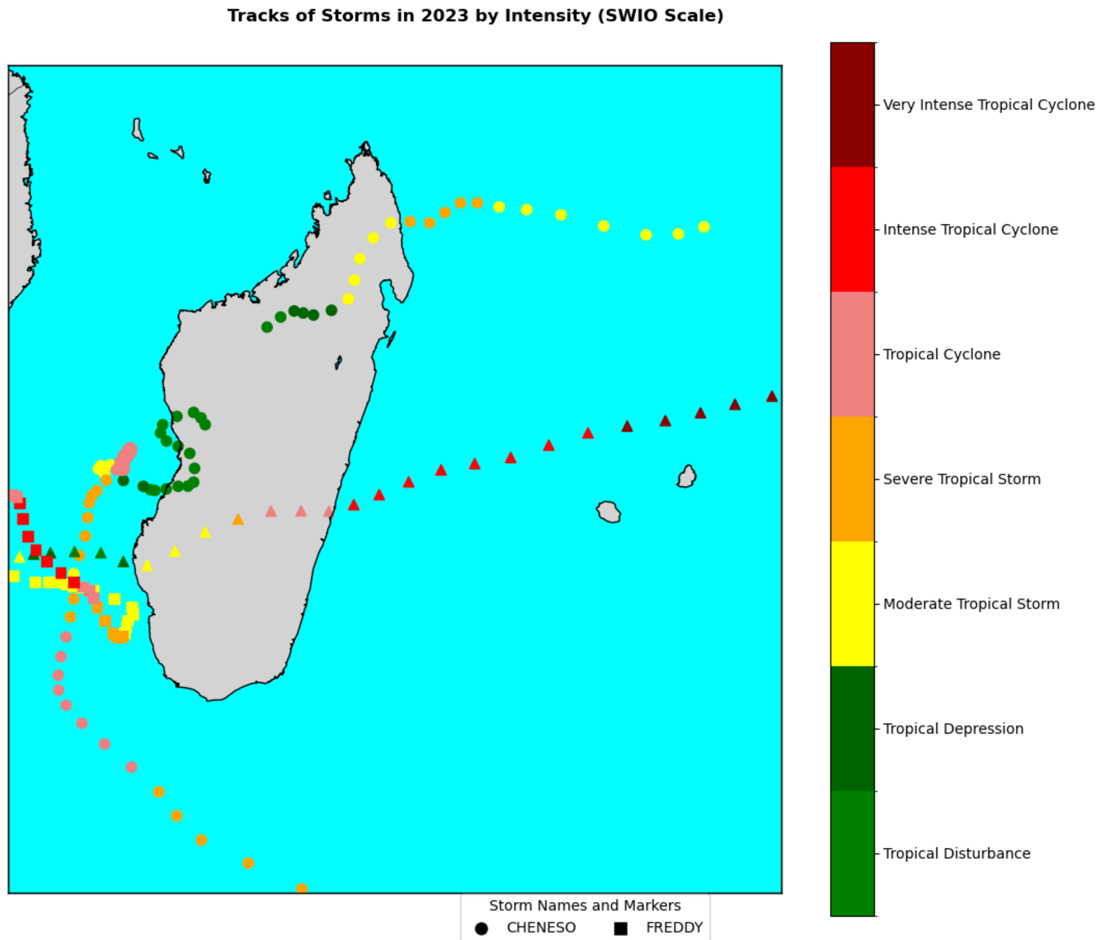


Storm Name	Start Date	End Date	Max Strength	Made Landfall?
CHALANE	12/24/2020	12/29/2020	Moderate Tropical Storm	Y
DANILO	1/10/2021	1/12/2021	Tropical Disturbance	N
ELOISE	1/17/2021	1/21/2021	Severe Tropical Storm	Y
NOT_NAMED	1/31/2021	2/2/2021	Tropical Disturbance	N
GUAMBE	2/11/2021	2/11/2021	Tropical Disturbance	N
IMAN	3/2/2021	3/8/2021	Moderate Tropical Storm	Y
JOBO	4/19/2021	4/20/2021	Moderate Tropical Storm	N

Tracks of Storms in 2022 by Intensity (SWIO Scale)

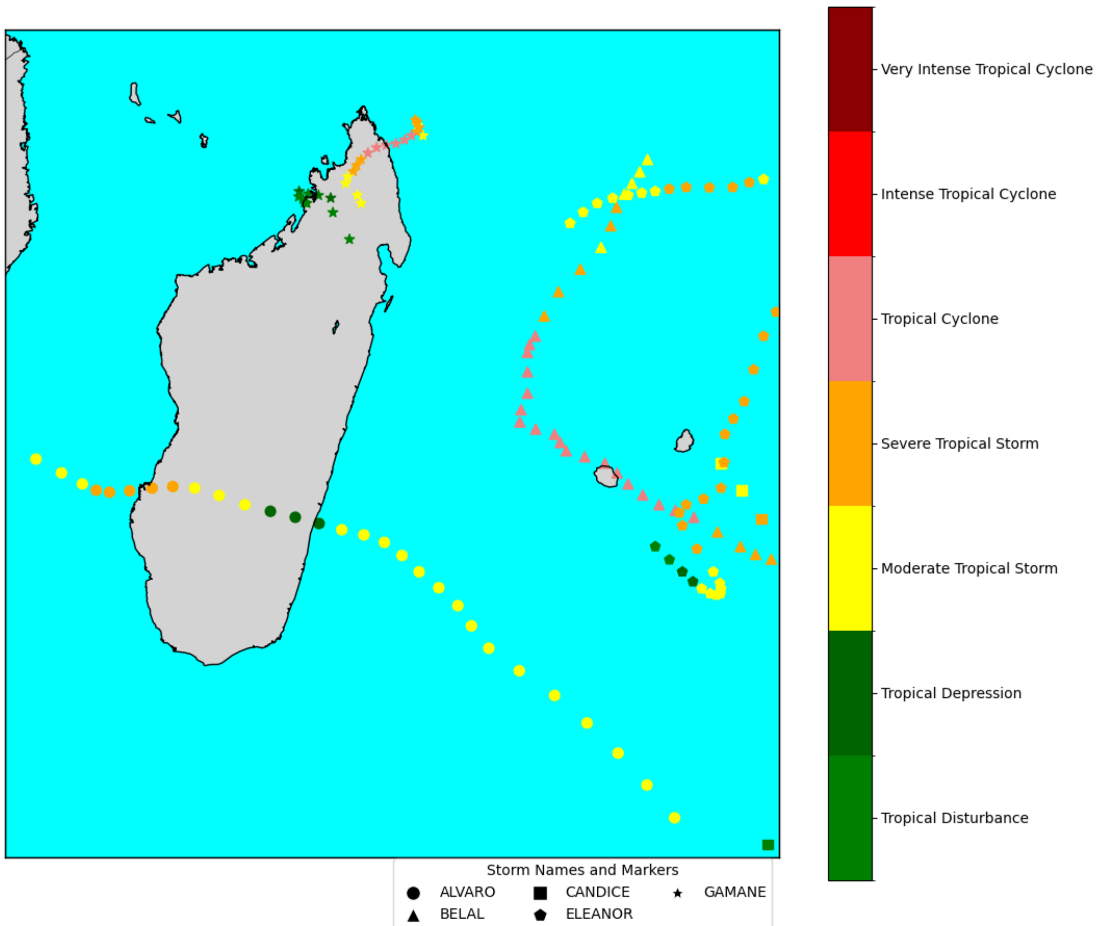


Storm Name	Start Date	End Date	Max Strength	Made Landfall?
ANA	1/23/2022	1/24/2022	Severe Tropical Storm	N
BATSIRAI	2/1/2022	2/8/2022	Very Intense Tropical Cyclone	Y
DUMAKO	2/13/2022	2/16/2022	Severe Tropical Storm	Y
EMNATI	2/18/2022	2/24/2022	Intense Tropical Cyclone	Y
GOMBE	3/8/2022	3/11/2022	Intense Tropical Cyclone	Y
JASMINE	4/24/2022	4/29/2022	Severe Tropical Storm	Y



Storm Name	Start Date	End Date	Max Strength	Made Landfall?
CHENESO	1/17/2023	1/29/2023	Tropical Cyclone	Y
FREDDY	2/20/2023	2/23/2023	Very Intense Tropical Cyclone	Y
FREDDY	3/4/2023	3/8/2023	Intense Tropical Cyclone	N

Tracks of Storms in 2024 by Intensity (SWIO Scale)



Storm Name	Start Date	End Date	Max Strength	Made Landfall?
ALVARO	1/1/2024	1/4/2024	Severe Tropical Storm	Y
BELAL	1/12/2024	1/16/2024	Tropical Cyclone	N
CANDICE	1/25/2024	1/27/2024	Severe Tropical Storm	N
ELEANOR	2/19/2024	2/24/2024	Severe Tropical Storm	N
GAMANE	3/26/2024	3/29/2024	Tropical Cyclone	Y