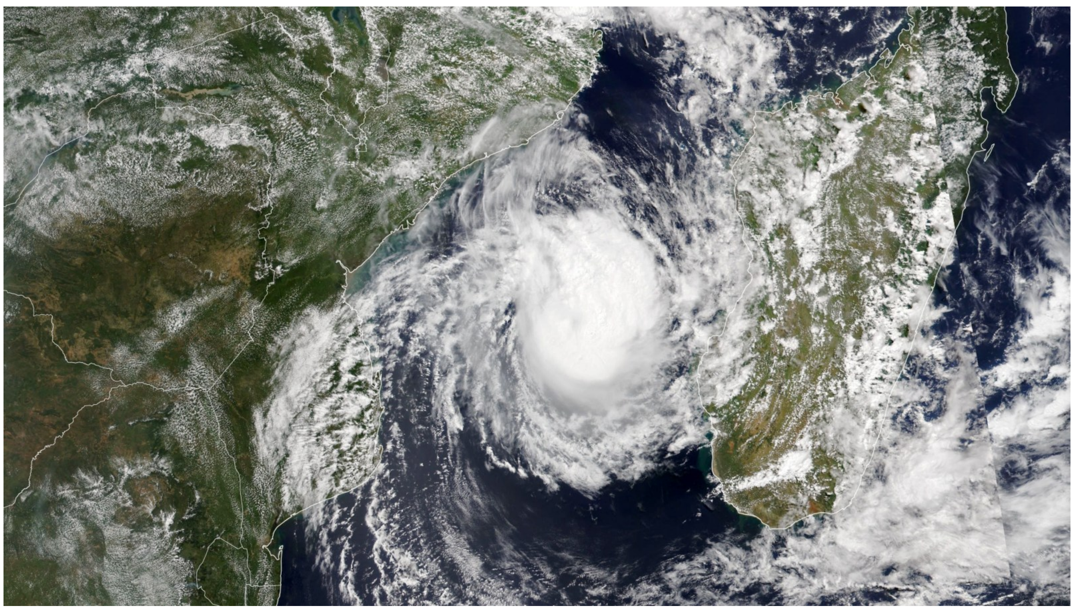
Tropical Cyclone Freddy: a Performance Assessment of AI Pangu-Weather Forecasts on ERA5-Data

Seminar in Climatology and Climate Risks Report



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Contents

1 Introduction

1.1 Tropical Cyclone Freddy

Tropical Cyclone (TC) Freddy broke many records. With a lifetime of 34 days, it was the longest tropical storm ever recorded, and had the highest accumulated cyclone energy (ACE), with 87 ACE units [5]. TC Freddy also travelled the second-longest distance, and went through record-breaking 7 rapid intensifications (wind speeds intensify by more than 56 kph in 24 h) [11]. These intensifications happened during TC Freddy's unique track over the Indian Ocean and Madagascar, after which it made landfall in Mozambique. Afterward, TC Freddy turned back to the ocean, intensified again and made landfall in Mozambique for a second time before finally decaying over land (see Figure 1 in Section 4.2).

1.2 Weather Forecasting

Weather forecasting is used in agriculture, energy management and to protect society from atmospheric hazards, like tropical Cyclones. The predictive accuracy of forecasting determines the preparedness of society for these extreme events. Traditionally, weather forecasting is done using numerical weather models (NWM) that are based on physical formulas and are initialized with current data from weather stations and other observations. However, from 2022 onwards, machine-learning techniques (or artificial intelligence (AI) models) have slowly established themselves in weather forecasting [4]. These models use deep neural networks to seize relationships inside historical observational data and use it to predict future weather based on current observational data [7]. The computational cost of these AI-model predictions is much lower than of conventional numerical models and consequently have a higher reach and availability across stakeholders [6, 7]. On the forefront of this change and one of the most prominent and powerful AI-models is Pangu-Weather (Pangu) [3].

1.3 Objectives

The objective of this report is to assess the performance of AI Pangu generated forecasts on an extreme event, the tropical cyclone Freddy. The performance will be investigated using different lead times prior to the chosen event: landfall in Madagascar on the 21.02.23. This event in the lifetime of Freddy was chosen, because precise forecasting of extreme events is most crucial in the moment of the highest possible damages and casualties, which is landfall.

Freddy will be researched in terms of its character using wind speed at 500 hPa and mean sea level pressure, representing the strength of the tropical Cyclone. Also, Freddy's potential for damages will be investigated using specific humidity as an indicator for potential rain and floods, and surface wind speed as an indicator for storm surges and wind damages. In addition, the track of Freddy will be studied, as not only the severity of a storm influences the potential damages, but also the proximity to urban areas and infrastructure.

2 Data

2.1 ERA5

In this report, the dataset provided by the European Centre for Medium-Range Weather Forecast (ECMWF), ECMWF Reanalysis v5 (ERA5), was used to assess the AI-Weather-Model Pangu. ERA5 is a global atmospheric reanalysis dataset, spanning from 1940 to present [8]. Reanalyses provide a numerical description of the recent climate by combining weather- and climate-models with atmospheric observations all over the globe. Observations include in-situ weather-stations, buoy-measurements in the oceans, satellite data, balloon soundings, airplane data, ship measurements, radar data and others. These observations are collected and used as input values for a numerical weather model, which then interpolates atmospheric variables numerically for each grid-cell [9]. ERA5 data has an hourly horizontal resolution of 31 km and a vertical resolution of 139 levels, from the surface up to 0.01 hPa (around 80 km) [8].

For this analysis, a dataset cropped to appropriate time and space resolutions was used. Spacially, the dataset consisted of 0.25° x 0.25° grid cells from 10°S to 30°S latitude and 25°E to 65°E longitude. The dataset contained observations of meteorological variables (Table 1) from 05.02.23 00:00 UTC to 15.03.23 18:00 UTC in 6 hourly time steps.

Table 1: Variables

Abbreviation	Variable	Unit
u10	10m u wind	m/s
v10	10m v wind	m/s
msl	mean sea level pressure	hPa
u	u wind at 850 and 500 hPa	m/s
v	v wind at 850 and 500 hPa	m/s
q	specific humidity	kg/kg

2.2 Pangu-Weather

Pangu-Weather is an AI model that has been trained on 39 years of ERA5 data from 1979-2017. It was tested using ERA5 data from 2018 and 2020 and validated with ERA5 data from 2019. Pangu-Weather kept the spatial and time dimensions of ERA5 [2, 1]. It has similar or superior performance compared to NWM with lower forecast variability on smaller time scales [4].

The dataset generated by Pangu for our case had the same spatial extent as the ERA5 dataset and the same variables (Table 1). However, the data consisted of three initializations of Pangu, leading to 3 datasets with different time scales of 6 hourly observations:

- 14.02.23 18:00 UTC - 27.02.23 12:00 UTC
- 19.02.23 18:00 UTC - 27.02.23 12:00 UTC
- 23.02.23 18:00 UTC - 27.02.23 00:00 UTC

3 Methods

3.1 Storm Tracks

Storm tracks were calculated in order to evaluate the spatial accuracy of predicting the location of TC Freddy of Pangu. The grid cell with the lowest mean sea level pressure was used in ERA5 and Pangu datasets as the reference for the location. The spatial accuracy was determined by the distance d between the two low pressure grid cells. This distance was calculated using the Haversine formula (Equation (1)) using latitude ϕ and longitude λ the Earths' radius r.

$$d = 2rsin^{-1}\left(\sqrt{sin^2(\frac{\phi_2 - \phi_1}{2}) + \cos\phi_1 * \cos\phi_2 * sin^2(\frac{\lambda_2 - \lambda_1}{2})}\right) \tag{1}$$

3.2 Wind Speed

Wind speed was observed in its magnitude in x-direction u (East-West) and y-direction v (South-North) with both directions being orthogonal to each other. The combined wind speed parallel to the Earths surface s was calculated using the Pythagorean theorem (Equation (2)).

$$s = \sqrt{u^2 + v^2} \tag{2}$$

3.3 ERA5-Pangu Differences

To gain insight in to the discrepancies between ERA5 and Pangu, Pangu data was subtracted from ERA5 data. The subtraction was done grid cell wise. Differences were only calculated from datasets that had the same observation time.

4 Results

4.1 Track of the Storm

Figure 1 shows the track of TC Freddy in the ERA5 dataset, which will be used as a reference for the track in Pangu. In ERA5, TC Freddy had quite a linear path until Madagascar, which was consistent in speed as indicated by the distances between the single points. In Pangu, TC Freddy's track deviated towards the north on its way to Madagascar, with greater variance in speeds and more slight changes in directions, but ultimately made landfall 1.5° further south in Madagascar (figure 2 left). It took TC Freddy 18h to pass Madagascar in both tracks. While this part of the propagation was steady in ERA5, TC Freddy covered more than half of this distance in the first 6h in Pangu. At the change of initializations (color change red to black), TC Freddy propagated the largest distance in 6h. Visually, TC Freddy's track in Pangu and ERA5 were quite similar from the second initialization onwards.

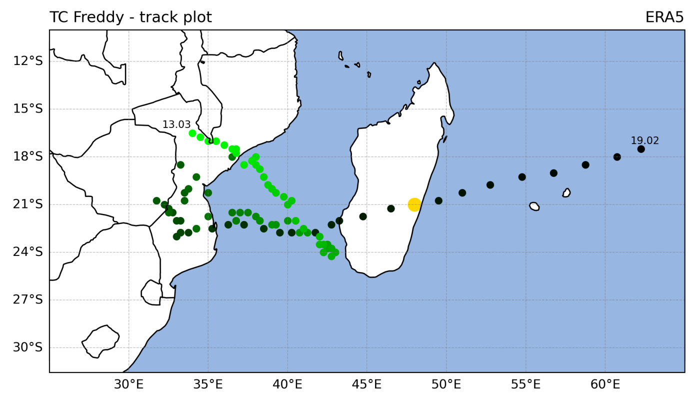

Figure 1: Storm track of TC Freddy in ERA5, with every 6 hours one point from 19.02 18:00 UTC (black) to 13.03 18:00 UTC (green). The yellow point indicates the location of TC Freddy in chapter 4.2.

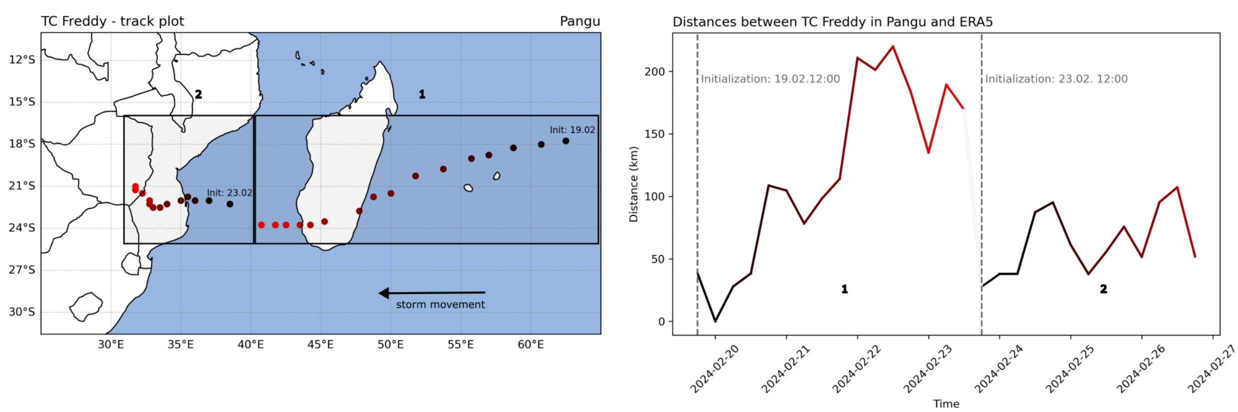

Figure 2: Left: Storm track of TC Freddy in Pangu , with every 6 hours one point. Pangu-data with two initializations: (1) from 19.02 18:00 UTC (black) to 23.02 12:00 UTC (red) and (2) 23.02 18:00 UTC (black) to 27.02 00:00 UTC (red). Right: Distance between the low pressure center of TC Freddy in ERA5 and Pangu in km.

These visual characteristics of northerly deviation, speed up over Madagascar, large jump between initializations and a similar track afterwards are detectable when investigating the distance between the center of TC Freddy in ERA5 and Pangu (figure 2 right). From both initializations onwards, the distance increased linearly with time, with 2.1 km/h for the first initialization ($R^2 = 0.72$) and 0.52 km/h for the second initialization ($R^2 = 0.21$). The speed-up over Madagaskar corresponded to the second-largest distance of 210 km and the largest jump in distance was observed with a decrease of 142 km between both initializations. The observation of a more similar path from the second initialization onwards is consistent with the slower increase in distance and lower maximum distances of 107 km, compared to 220 km for the first initialization. Although it has to be recognized, that the second initialization dataset is 1 day shorter than the first initialization dataset and the storm movement speed was lower.

4.2 Landfall Madagascar: 21.02

4.2.1 Storm Characteristics

The accuracy of Pangu in forecasting wind speeds at 500 hPa and mean sea level pressure varied between the two initializations from the 14.02.23 12:00 UTC (figure 3 bottom left) and from the 19.02.23 12:00 UTC (figure 3 top right) when comparing them with ERA5 data (figure 3 top left) for the landfall in Madagascar on the 21.02.23 at 18:00 UTC.

Compared to ERA5, the forecast from 14.02.23 12:00 UTC, initialized 7 days before landfall, predicted the landfall to be several hundred kilometers further north. The area with maximum wind speeds of 21-24 m/s had a larger spatial extent, covering almost half of Madagascar. The predicted minimum sea level pressure of 993 hPa was close to the 988 hPa in ERA5. The spatial prediction of the wind field and its intensity was forecasted more accurately in the Pangu dataset initialized at 19.02.23 12:00 UTC, 2 days prior, with a more accurate geographical location of the landfall. However, the minimum sea level pressure increased to 1000 hPa from the previous forecast, which is a decrease in accuracy in this variable.

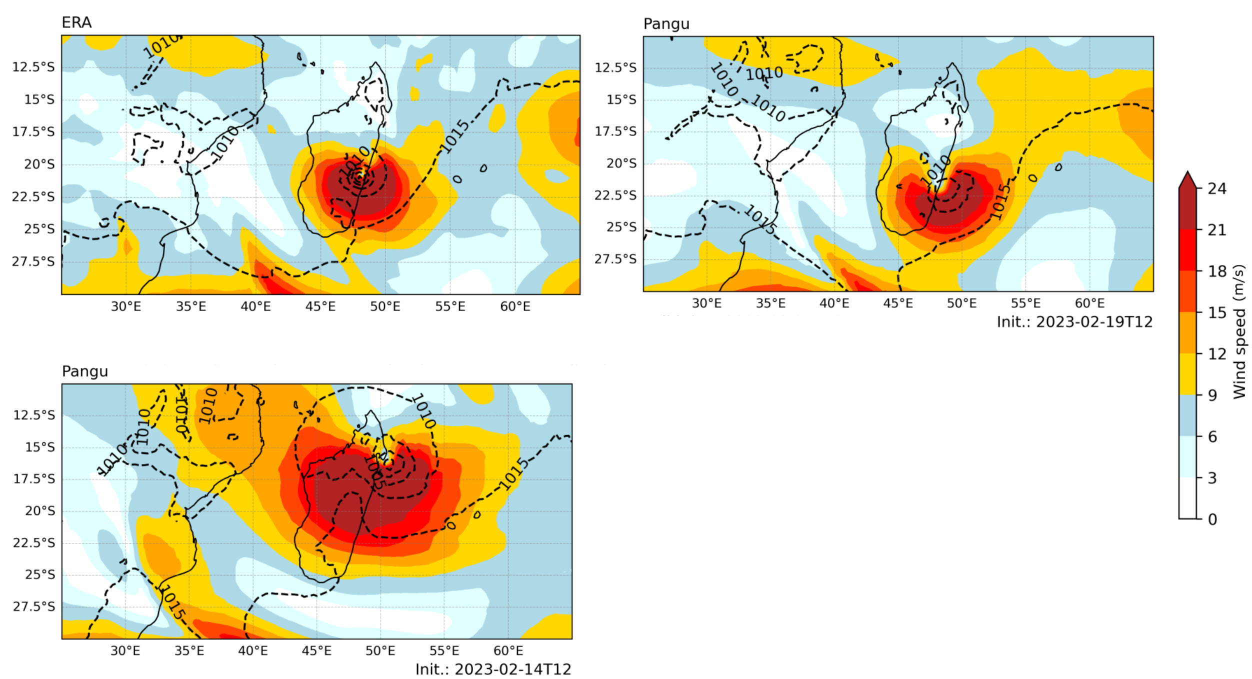

Figure 3: 21.02.23 18:00 UTC: Wind speed at 500 hPa niveau (m/s) and mean sea level pressure (hPa). top left: ERA5, top right: Pangu initialized 19.02.23 12:00 UTC, bottom left: Pangu initialized 14.02.23 12:00 UTC.

4.2.2 Storm Danger

In ERA5, TC Freddy had the highest specific humidity at its center with 0.016 kg/kg and surface wind speeds up to 26 m/s with a strong gradient around the Cyclone's eye (figure 4 top left). Both variables showed a circular gradient in ERA5.

The area of high humidity was predicted to be much larger in both initializations with a weaker gradient. Pangu initialized on the 19.02.23 12:00 UTC represented the spatial distribution and maximum humidity with 0.016 kg/kg better than the previous initialization. In the dataset initialized on 14.02.23 12:00 UTC, surface wind speeds were underestimated, with a maximum of 21 m/s instead of 26 m/s. Furthermore, they showed a less circular pattern than the ERA5 data which was skewed to the south-east of the Cyclone. The same also appeared in the 19.02.23 12:00 UTC dataset with even lower maximum wind speeds of 19 m/s.

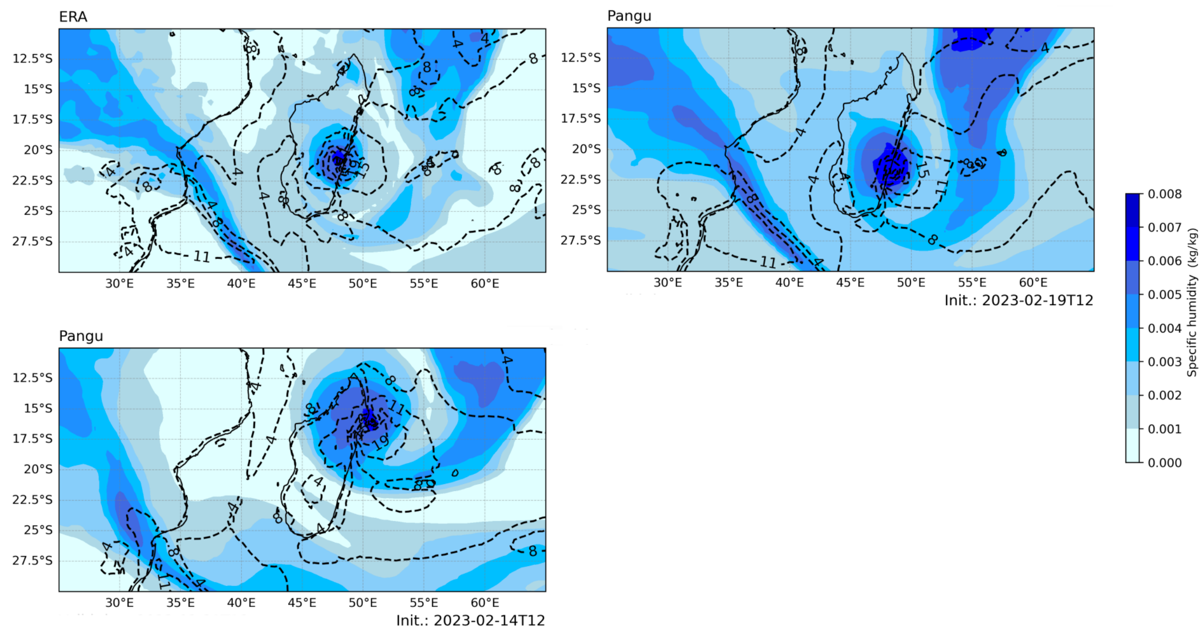

Figure 4: 21.02.23 18:00 UTC: Specific humidity at 500 hPa niveau (kg/kg) and surface wind speed (m/s). top left: ERA5, top right: Pangu initialized 19.02.23 12:00 UTC, bottom left: Pangu initialized 14.02.23 12:00 UTC.

4.2.3 Differences between ERA5 and Pangu

As observed in figure 2, TC Freddy was forecasted too far north in the forecast initialized on the 14.02.23 12:00 UTC (figure 5 right), leading to an overestimation of wind speeds at 500 hPa in the north of Madagascar (blue) and an underestimation in the south of Madagascar (red). The misrepresented spatial extend of TC Freddy is clearly visible there.

The dataset initialized at 19.02.23 12:00 UTC showed differences not based on geographical misrepresentation, but Pangu underestimated wind speeds at 500 hPa in the center of the TC with differences up to 28 m/s, and overestimated them with differences up to -7 m/s in the peripheral area of the Cyclone. In a grid box around the Cyclone (17.5°S - 25°S, 45°E - 50°E), Pangu on average underestimated wind speeds at 500 hPa with a difference of 3.3 m/s with an interquartile range between -1.4 and 5.6 m/s.

The mean sea level pressure difference over the above defined grid box was on average close to 0 between Pangu 19.02.23 12:00 UTC and ERA5, with a maximum of the difference of 8 hPa in the southeast of the TC and a minimum of the difference of -20 hPa in the center of the TC. This bipolar pattern corresponds to the skewed mean sea level pressure pattern observed in figure 3 (top right).

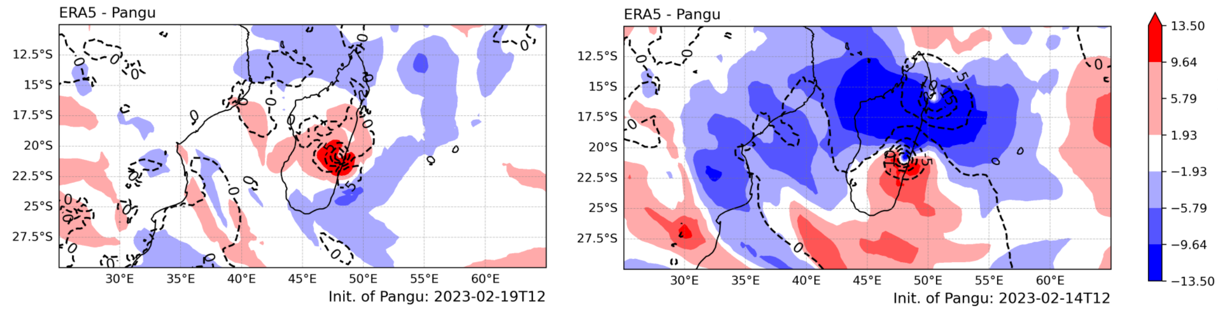

Figure 5: 21.02.23 18:00 UTC: Differences of ERA5 minus Pangu of wind speed at 500 hPa niveau (m/s) and mean sea level pressure (hPa). two initializations for pangu, left: 19.02.23 12:00 UTC, right: 14.02.23 12:00 UTC.

Analogously to figure 5 (right), the differences in ERA5 and Pangu 14.02.23 12:00 UTC in figure 6 (right) were mainly driven by the spatial displacement of TC Freddy.

Comparing Pangu 19.02.23 12:00 UTC with ERA5 (Figure 6 left), specific humidity differences in the grid box were between -0.0024 and 0.0012 kg/kg, and on average -0.0004 kg/kg. Specific humidity was overestimated on the southern flank of the TC. Surface wind speeds in the grid box were underestimated on average by Pangu (figure 6, left) with differences between -6 and 16 m/s. Here, 90% of all differences inside the grid box were between -5 and 8 m/s.

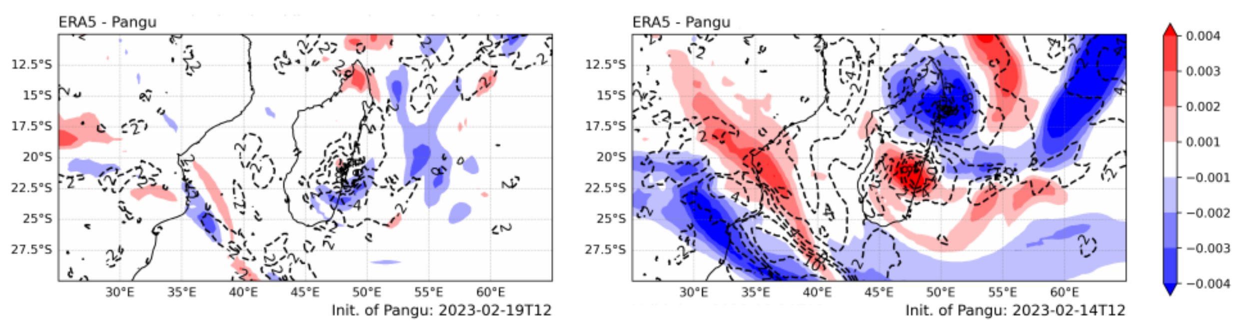

Figure 6: 21.02.23 18:00 UTC: Differences of ERA5 minus Pangu of specific humidity at 500 hPa niveau (kg/kg) and surface wind speed (m/s). two initializations for pangu, left: 19.02.23 12:00 UTC, right: 14.02.23 12:00 UTC.

5 Summary and Discussion

5.1 Performance Assessment

The primary objective of this report was to assess the accuracy of Pangu-Weather forecasts of the tropical Cyclone Freddy.

Pangu was able to predict the location of the pressure minimum realtively well, which is consistent with Bi et al. (2022), but underestimated its magnitude. The spatial accuracy decreased from the initialization onwards. Interestingly, mean sea level pressure showed a less radial pattern in Pangu than ERA5. The wind field at 500 hPA was forecasted relatively accurately, whilst surface wind speeds were severely underestimated and the spatial distribution of specific humidity slightly misrepresented. The performance of the forecast of all these variables decreased with increasing lead times to the investigated event. All these observations were validated by a secondary investigation of the landfall in Mozambique (see Figure 7 to 10 in the Appendix). Consistent with our findings, Bi et al. (2022) reported that Pangu underestimates the intensity, especially surface winds, of intense meteorological phenomena like a TC.

The underestimation of the TC intensity could be the result of an inadequate spatial resolution of the forecast. This could be considerably dangerous for coastal communities that have to be evacuated depending on the storm intensity. Also, the absence of a precipitation forecast, for which we used specific humidity, hinders the prediction of potential flooding. Pangu also struggles with the dynamic balance relationships and convection [3], which could explain the relatively poor representation of the pattern of humidity.

Nevertheless, Pangu has many advantages that offer great potential for the future. A higher spatial resolution [2] and an improvement of the initial conditions could enhance the forecast of Pangu of extreme events like a TC [4]. The significantly lower computing power needed compared to conventional numerical weather models is undisputed [7]. Forecast can be provided in a much shorter time, more frequently with very low costs. This is particularly important for extreme events on a local scale that change significantly in a short period of time [3]. Because of this, AI models like Pangu-Weather will play an increasingly important role in weather forecasting in the future [10]. In summary, our results indicate that Pangu is able to forecast extreme events like a TC relatively precisely, while underestimating the intensity slightly, compared with ERA5.

5.2 ERA5 as a Baseline

We compared Pangu-Weather forecasts to reanalysis data from ERA5. When determining the forecast performance, it would be more sensible to compare Pangu forecasts to numerical weather model forecasts, as Pangu is in the process of substituting for them. The comparison of Pangu in this report does not indicate, if Pangu would have outperformed conventional weather forecasts. Therefore, we cannot conclude whether AI models should and could fully replace numerical weather forecasts.

Also, Pangu-Weather has been trained on ERA5 data, and consequently inherits characteristics like the coarse resolution and subsequent inability to properly forecast small scale processes [2]. Additionally, ERA5 data does not even span a century and, as a result, is not likely to include extreme events which occur once a hundred or more years. This limitation in historical training data hinders the precise forecast of rare events through AI models [2]. In the age of climate change, a gradual shift towards different environmental conditions could decrease the performance of Pangu, due to its reliance on historical data.

In conclusion, Pangu-Weathers performance in the future should be assessed by comparing it with state of the art numerical weather model forecasts. In this comparison, only very recent AI forecasts should be considered, as the integral characteristic of low cost and computational needs allows forecasting in small intervals. Additionally, the training data should be expanded to ensure proper representation of rare extreme events which have particularly high impacts on humanity.

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Appendix

Landfall Mozambique: 24.02

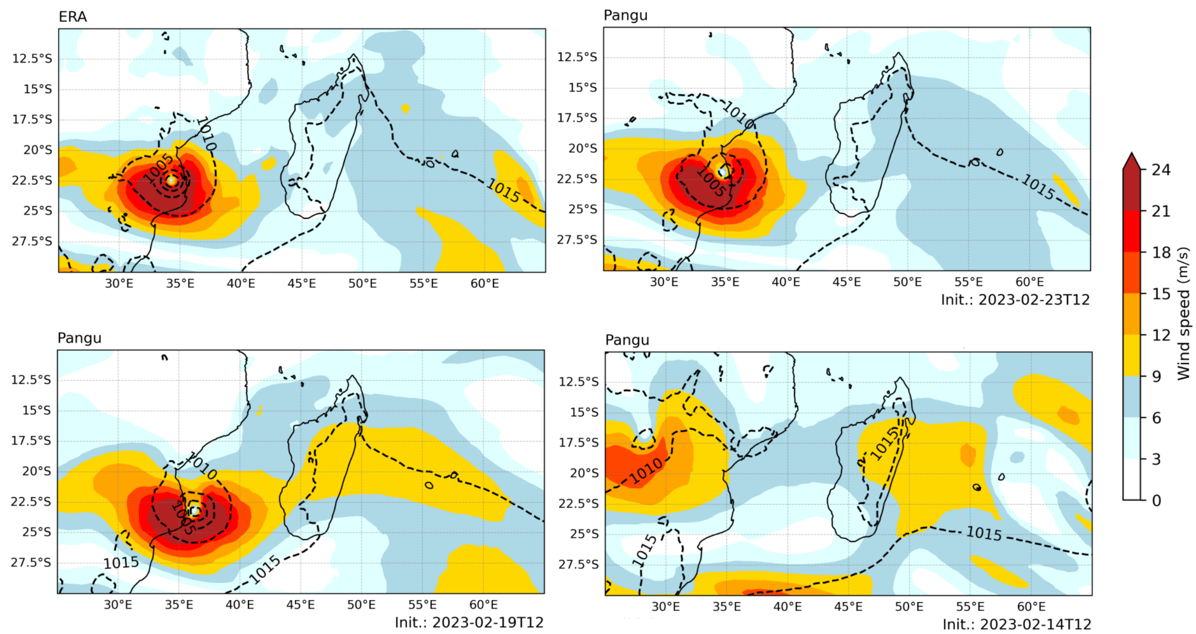

Figure 7: 24.02.23 18:00 UTC: Wind speed at 500 hPa niveau (m/s) and mean sea level pressure (hPa). top left: ERA5, top right: Pangu initialized 23.02.23 12:00 UTC, bottom left: Pangu initialized 19.02.23 12:00 UTC, bottom right: Pangu initialized 14.02.23 12:00 UTC.

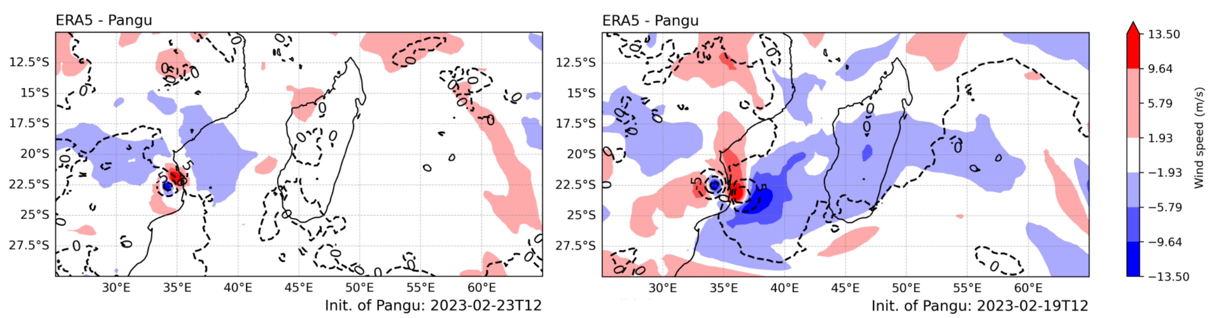

Figure 8: 21.02.23 18:00 UTC: Differences of ERA5 minus Pangu of wind speed at 500 hPa niveau (m/s) and mean sea level pressure (hPa). two initializations for pangu, left: 23.02.23 12:00 UTC, right: 19.02.23 12:00 UTC.

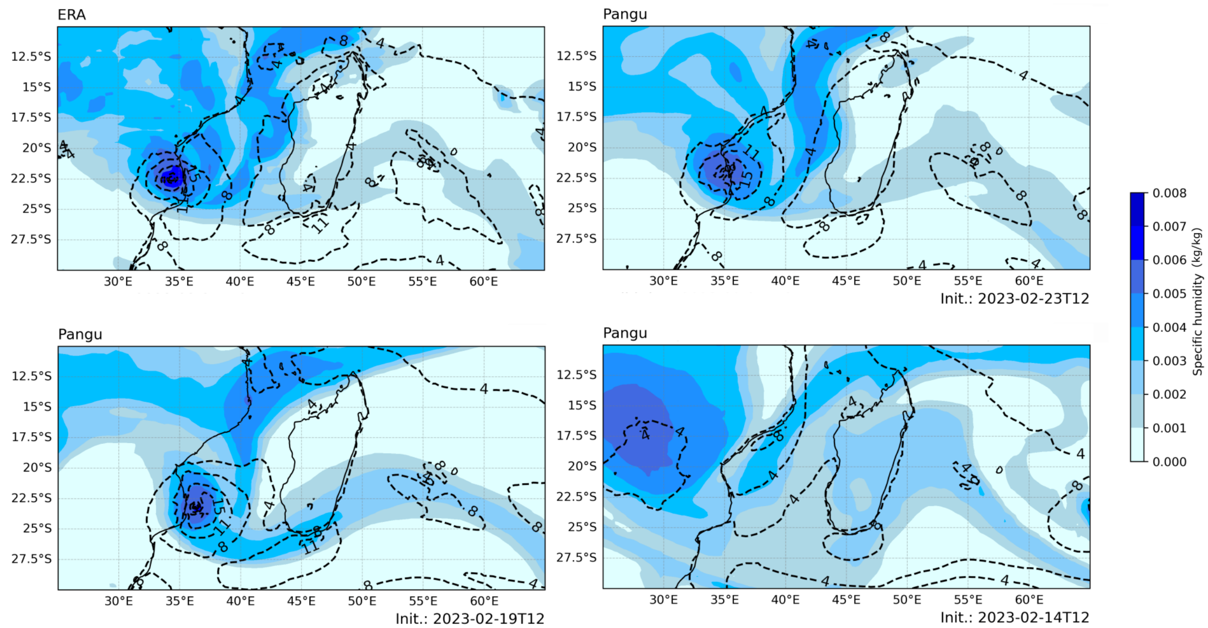

Figure 9: 24.02.23 18:00 UTC: Specific humidity at 500 hPa niveau (kg/kg) and surface wind speed (m/s). top left: ERA5, top right: Pangu initialized 23.02.23 12:00 UTC, bottom left: Pangu initialized 19.02.23 12:00 UTC, bottom right: Pangu initialized 14.02.23 12:00 UTC.

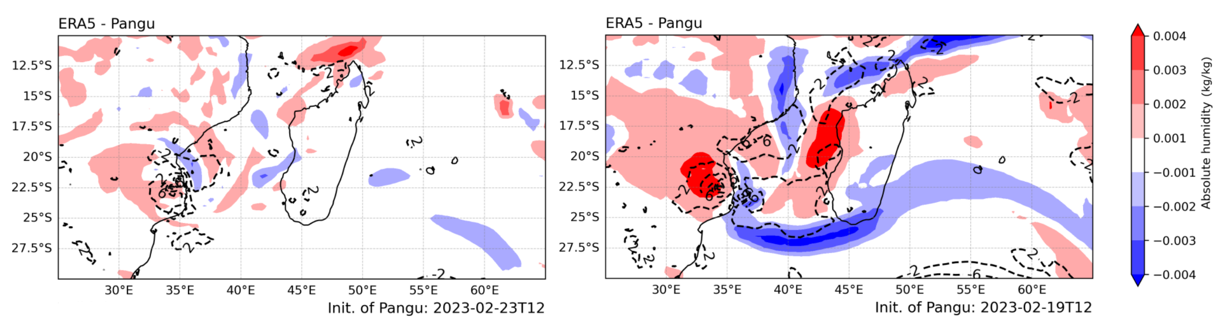

Figure 10: 21.02.23 18:00 UTC: Differences of ERA5 minus Pangu of specific humidity at 500 hPa niveau (kg/kg) and surface wind speed (m/s). two initializations for pangu, left: 23.02.23 12:00 UTC, right: 19.02.23 12:00 UTC.