

Subseasonal Prediction of Idai and Other Tropical Cyclones and Storms in the Mozambique Channel

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Abstract

On average, two tropical storms or cyclones enter the Mozambique Channel between the African mainland and Madagascar each year. Their impact can be devastating. The tropical cyclone Idai, which hit land in Mozambique in 2019, was one of the deadliest storms on record in the Southern Hemisphere. Previous studies have found that the tracks and strengths of tropical storms and cyclones are difficult to predict more than a few days ahead. An extension of this forecast horizon would be crucial for enabling authorities to take precautionary actions. Here, the ability of a state-of-the-art ensemble prediction model to predict Idai and 38 other tropical systems is assessed. It is found that the minimum sea level pressure (SLP) associated with Idai was only skilfully predicted at lead times up to three days. When considering all the systems, less than a quarter of the ensemble members predicted lower minimum SLP than the MERRA-2 reanalysis at lead times of five days and longer. However, several variables are found to be useful precursors of tropical storms and cyclones, and some of these are skilfully predicted at long lead times. In particular, area-averaged anomalies of geopotential height and specific humidity at 500 hPa and SLP one week before the passage of storms are significantly correlated with minimum SLP anomalies during the storms. As these precursor variables are skilfully predicted by the model at lead times of 10–12 days, it should be possible to include their forecasted values in hybrid statistical–dynamical prediction systems at lead times beyond a few days. An additional interesting finding is that warm sea surface temperature anomalies and weak vertical wind shear, which are generally considered to be favourable for tropical storms and cyclones, do not qualify as precursors of the systems investigated here.

Prediction of Idai and 38 Other Tropical Cyclones and Storms in the Mozambique Channel

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Abstract

On average, two tropical storms or cyclones enter the Mozambique Channel between the African mainland and Madagascar each year. Their impact can be devastating. The tropical cyclone Idai, which hit land in Mozambique in 2019, was one of the deadliest storms on record in the Southern Hemisphere. Previous studies have found that the tracks and strengths of tropical storms and cyclones are difficult to predict more than a few days ahead. An extension of this forecast horizon would be crucial for enabling authorities to take precautionary actions. Here, the ability of a state-of-the-art ensemble prediction model to predict Idai and 38 other tropical systems is assessed. It is found that the minimum sea level pressure (SLP) associated with Idai was only skilfully predicted at lead times up to three days. When considering all the systems, less than a quarter of the ensemble members predicted lower minimum SLP than the MERRA-2 reanalysis at lead times of five days and longer. However, several variables are found to be useful precursors of tropical storms and cyclones, and some of these are skilfully predicted at long lead times. In particular, area-averaged anomalies of geopotential height and specific humidity at 500 hPa and SLP one week before the passage of storms are significantly correlated with minimum SLP anomalies during the storms. As these precursor variables are skilfully predicted by the model at lead times of 10–12 days, it should be possible to include their forecasted values in hybrid statistical–dynamical prediction systems at lead times beyond a few days. An additional interesting finding is that warm sea surface temperature anomalies and weak vertical wind shear, which are generally considered to be favourable for tropical storms and cyclones, do not qualify as precursors of the systems investigated here.

1. Introduction

Tropical cyclones in the Mozambique channel can have disastrous impacts (e.g., Mong *et al.*, 2001; Reason and Keibel, 2004; Brouwer and Nhassengo, 2006; Reason, 2007; Matyas and Silva, 2013; Fitchett and Grab, 2014). In March 2019, one of the deadliest storms on record in the Southern Hemisphere, the cyclone named Idai caused widespread damage and the loss of hundreds of lives in Mozambique, Zimbabwe, and Malawi (Warren, 2019). It is shown here that the location and strength of Idai were only skilfully predicted three days ahead. The focus in the article is on the prospect of prediction beyond a few days, which if skilful could provide a valuable time window needed for evacuation and other preparedness measures (Huang *et al.*, 2015; White *et al.*, 2017; Das, 2019).

A crucial part of forecasting tropical storms and cyclones is knowing the environment in which they form (e.g., McBride and Zehr, 1981; Kaplan and DeMaria, 2003). On the local scale, precursors include low vertical wind shear, high sea surface temperature (SST), and vertical profiles of humidity and temperature (Gray, 1998). Matyas (2015), in her study of 94 TCs in the Mozambique channel between 1948 and 2010, found that the clearest local features associated with tropical cyclogenesis in the Mozambique channel were high SSTs (29.6° C on average) a (southerly) wind shear with height and below-normal geopotential height anomalies at 500 hPa (her Figure 3). Weak vertical shear and low-level convergence are factors that have been pointed to in numerous case studies (Reason and Keibel, 2004; Reason, 2007; Chikoo *et al.*, 2015; Rapolaki and Reason, 2018) and climatological studies (Mavume *et al.*, 2009; Rosa *et al.*, 2019) of tropical cyclones in the region studied here.

On larger spatial scales, the El Niño–Southern Oscillation (ENSO) is an important modulator of tropical systems (Ho *et al.*, 2006; Mavume *et al.*, 2009; Ash and Matyas, 2012; Fitchett and Grab, 2014). The Madden–Julian Oscillation (MJO; Madden and Julian, 1971; Zhang, 2013) has also been shown to influence the formation of tropical systems in general (Camargo *et al.*, 2009) and specifically in the southern part of the Indian Ocean (Bessafi and Wheeler, 2006; Duvel, 2015; Matyas, 2015; Finney *et al.*, 2019). In recent years, dynamical models have exhibited increasing subseasonal skill in predicting the MJO (Vitart, 2017; Lim *et al.*, 2018). Lee *et al.* (2018) studied how well the models in the Subseasonal to Seasonal (S2S) Prediction Project database (Vitart *et al.*, 2016) could predict tropical cyclones and found a “relationship between the models’ skill scores and their ability to accurately represent the MJO and the MJO–tropical cyclone relation”. This relationship is one of the reasons for a hope that the forecast horizon of tropical cyclones can be extended beyond a few days (e.g., Camp *et al.*, 2018).

An early study by Vitart *et al.* (2003), in which the active 2000 tropical cyclone season in the Mozambique channel was to some extent reproduced by a dynamical model, suggested that subseasonal prediction of tropical systems in the region might be possible. Yet, although Yamaguchi *et al.* (2015) concluded that the operational ensemble forecast system of the European Centre for Medium-Range Weather Forecasts (ECMWF) performed quite well in predicting tropical cyclones in the South Indian Ocean region, which included the Mozambique channel, the skill even of that system was negligible more than ten days into the future. This result was corroborated by Lee *et al.* (2018). Unfortunately, successful forecasts of tropical storm tracks beyond two weeks ahead remain rare (Vitart and Robertson, 2018). However, important precursors such as the vertical wind shear have been shown to be predictable beyond one week (Komaromi and Majumdar, 2014). Well-predicted precursor anomalies can potentially be used to raise awareness about upcoming dangerous developments. In addition, probabilistic predictions on subseasonal time scales are based on ensemble systems (Buizza, 2008). As these systems generate a large number of possible outcomes, they can potentially be useful for detecting likelihoods of extremes that are not revealed by the ensemble mean (Hudson *et al.*, 2011; White *et al.*, 2017; Vitart and Robertson, 2018).

The two main questions motivating this study are:

1. How many days in advance can the ensemble-based ECMWF subseasonal forecasting model system predict tropical storms and cyclones in the Mozambique Channel with higher skill than a climatological forecast?
2. Which variables exhibit clear anomalies prior to and during tropical storms and cyclones in the Mozambique Channel, and how long in advance can the model skilfully predict these precursors?

A total of 39 systems from 1999 to 2019 are studied in an attempt to answer these questions, with a special emphasis on Idai.

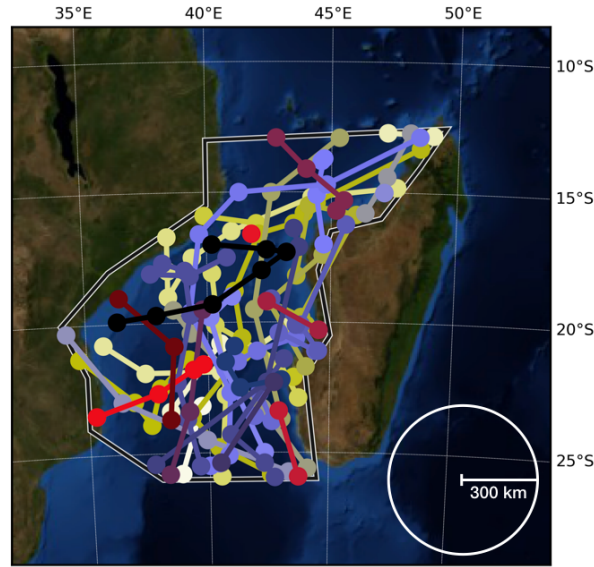


Figure 1. The tracks of the 39 storms, with Idai in black and each storm shown with unique colours. The outline of the study region is indicated with line segments, and the size of the storm-following circular region is shown in white.

2. Data and Methods

2.1. Data sources

The dynamical model system used here is the ECMWF’s monthly forecasting system, which has two components: a real-time forecasting system with 51 ensemble members, and hindcasts with 11 members. Each member is a 46-day coupled ocean-atmosphere integration. The hindcast runs start on the same day and month as each real-time forecast, going back 20 years. The model version used here is CY45R1, which became operational on 6 June 2018. The horizontal resolution of the model is about 16 km at lead times of up to 15 days and 32 km thereafter. The data were downloaded from the S2S database (Vitart *et al.*, 2016), where instantaneous data for 00:00 UTC on each day are available at a resolution of 1.5 degrees. The following variables were downloaded: SLP, SST, zonal and meridional wind components at 10 metres, 200 hPa and 850 hPa, and geopotential height, temperature and specific humidity at 500 hPa.

Reanalysis data from MERRA-2 (Gelaro *et al.*, 2017) was used as the reference dataset. The data are provided on different forms depending on the variable. Some fields are given as instantaneous values, while others are calculated as mean values over 3-hour periods. In the latter case, values averaged from 00:00 to 03:00 UTC were used. The variables mentioned above were downloaded, using the variable named TSKINWTR, which corresponds to open water skin temperature, as SST. The downloaded data had been regridded (using bilinear interpolation) to match the 1.5-degree grid used for the S2S data.

The times and locations of the tropical storms and cyclones were extracted from version 4 of the IBTrACS (International Best Track Archive for Climate Stewardship) database (Knapp *et al.*, 2010; Knapp *et al.*, 2018),

which contains longitude and latitude pairs on a 3-hourly resolution. All times for which an entry had at least tropical storm strength and its centre was located inside the region outlined in Figure 1 were selected. The search was performed for dates between 1 December and 30 April, from 1998/99 to 2018/19. When there was more than one entry for a given date, the time closest to 00:00 UTC was used. All storms and cyclones were recorded, with no regard to category. This yielded 39 storms, each with a set of unique dates and locations. Each date that a storm or cyclone was recorded (referred to as a “storm date” henceforth) is shown in Figure 2.

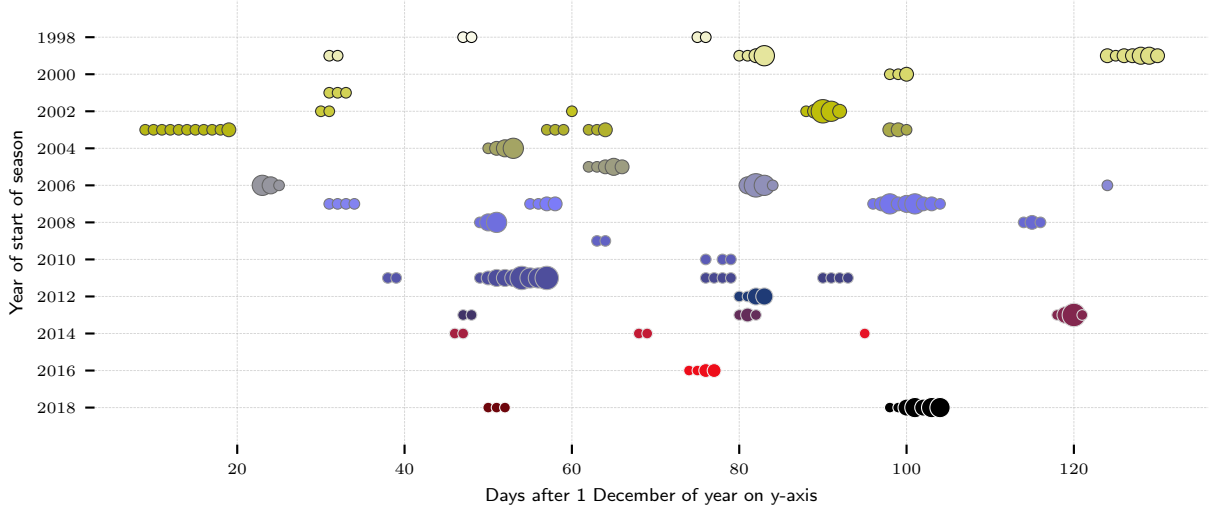


Figure 2. The timing of each storm is indicated by its position in the graph, using the same colours as in Figure 1. The size of each circle corresponds to the intensity, ranging from tropical storms (smallest circles) to category 5 cyclones (largest circles). The last seven circles on the last line represent the storm dates of Idai.

2.2. Methods

For each storm date and location, a number of variables x were calculated inside a circular area with a radius of 300 km from the storm centre. The following quantities were calculated inside the storm-following region: area-averaged and minimum SLP (denoted p_S and $p_{\min}$, respectively); area-averaged temperature, specific humidity and geopotential height at 500 hPa (T_{500} , q_{500} and H_{500} , respectively); area-averaged SST (T_S); vertical wind shear between 200 and 850 hPa ($|\Delta \mathbf{v}|$), divergence at 200 hPa ($\nabla \cdot \mathbf{v}_{200}$); and convergence at 850 hPa ($-\nabla \cdot \mathbf{v}_{850}$). The wind shear was calculated as follows. First, the area-averaged zonal and meridional wind components at 200 and 850 hPa were computed. Second, the vertical wind shear of the wind components were calculated separately. Third, the wind shear was computed as the absolute value of the vector consisting of the two wind shear components. As the source data sometimes had invalid values over land (probably due to vertical interpolation issues over topography), the wind shear was only calculated for oceanic grid points, even if the circular region extended over land.

For all the storm dates of Idai and the variables mentioned above except $p_{\min}$, area-averages were calculated inside the circular region following the storms. In addition, the area-averages of the same variables were computed for the same circular region that surrounded the system on the storm date for a time window from three days before to the storm dates themselves. It is evident from the storm track of Idai (shown in black in Figure 1) and the size of the circular region shown in the same figure that its centre was sometimes located inside the search area for a specific storm date several days before and after that date. This is unfortunate when

the evolution of precursors from day to day is investigated, as it leads to a “smoothing” from one day to the next. On the one hand, the use of a smaller region would have mitigated this problem, but on the other hand this would have penalised the model for misplacing the storm centre when forecast errors are studied. The choice of a 300 km radius was made subjectively after testing several smaller and larger radii and did not have a strong influence on the results.

To facilitate comparisons, all the area-averaged variables were standardised by subtracting the localised climatological average for each date and dividing by the climatological standard deviation (referred to as σ henceforth). The same calculations were also performed for all the 39 storms and aggregated.

As part of the analysis of the precursors, relationships between forecast errors and the variables’ anomalies with respect to climatology are assessed. For each storm date, the area-average of a variable x was calculated inside the region surrounding the storm, based on the reanalysis. The same region was then used to calculate the area-averaged variable for all the other 20 years in the study period, yielding 21 values x_i , where the subscript denotes that there is one value per year. Using the 21-year mean value $\bar{x}$ as a reference, the anomaly $x'_i = x_i - \bar{x}$ was then calculated for all the years. For each year, the forecast error $e_i = f_i - x_i$ was also calculated, where f_i is the ensemble mean forecasted value, area-averaged inside the reference region. The correlation coefficient R between the time series of x'_i and e_i is the key variable of interest. When R is strongly negative, it means that negative anomalies x'_i are accompanied by positive values of e_i (and vice versa). This corresponds to a poor forecast performance. In the analysis of R , it is contrasted with the correlation between e_i and synthetic time series of forecasted values that were drawn randomly from a normal distribution with the same mean and standard deviation as x'_i .

When the word “significant” is used below, it means “statistically significant at the 5% level”. Significance is only calculated for Pearson’s correlation coefficients, using the SciPy (Virtanen *et al.*, 2020) function `scipy.stats.pearsonr`. In cases where the question of whether or not a correlation coefficient is significant is important, the p -values were also calculated using the SciPy function `scipy.stats.spearmanr`, which computes the Spearman rank correlation.

3. Results

3.1. Cyclone Idai

Idai had severe consequences in Mozambique and several neighbouring countries. Figure 3a shows a satellite image of the cyclone just before it hit land near Beira in Mozambique on 14 March 2019. An estimate of the total rainfall during Idai based on remote sensing is shown in Figure 3b.

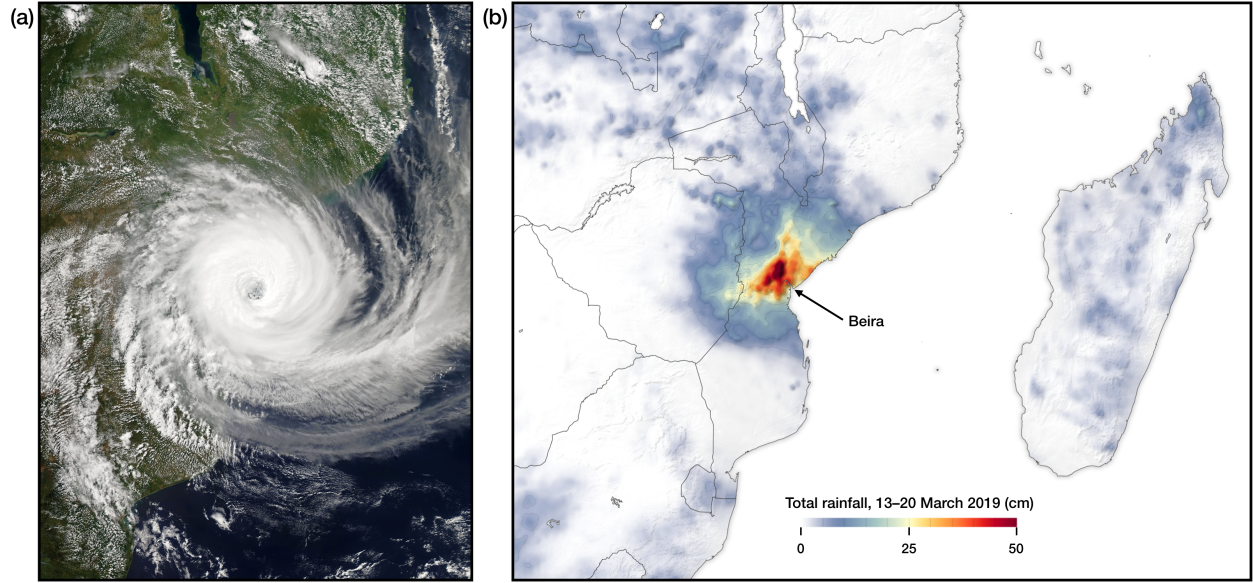


Figure 3. (a) Satellite image of Idai at 11:35 UTC on 14 March 2019. The picture is a MODIS image captured by NASA’s Aqua satellite (Wikimedia Commons, 2019). (b) Total rainfall estimates between 13 and 20 March 2019, based on an image from NASA’s Earth Observatory (NASA, 2019). According to NASA, the “data are remotely-sensed estimates that come from the Integrated Multi-Satellite Retrievals (IMERG), a product of the Global Precipitation Measurement (GPM) mission. Local rainfall amounts can be significantly higher when measured from the ground.”

3.1.1. Wind speed forecasts

To illustrate how the ensemble forecast reproduced the wind speeds during Idai relative to MERRA-2, a threshold u_0 was defined as the maximum MERRA-2 wind speed within 300 km from Idai’s center minus 10 ms^{-1} . The results were not sensitive to the choice of threshold. Figure 4 shows the fraction of ensemble members with wind speeds higher than u_0 on 13 and 15 March 2019, at different lead times. The dark red circles near the centre of Idai in Figure 4a indicate that most of the ensemble members placed the cyclone correctly at two days’ lead time on 13 March. At a lead time of six days (Figure 4b), few ensemble members had strong winds, and the high wind speeds occurred too close to the coast. The forecasts at 9 and 13 days’ lead times gave no indication of a cyclone (Figures 4c–d). Figure 4e shows that the forecast with one day of lead time correctly predicted strong winds along the coast south of the cyclone centre just before landfall, but the forecast also yielded too strong winds in the southern part of the Channel. The forecast with four days of lead time (Figure 4f) was also good near the centre of the cyclone, but an increasing number of coloured squares reveals a scattering in the positioning of the system. At lead times of 8 and 11 days (Figures 4g and 4h, respectively), the ensemble erroneously predicted strong winds near the southern tip of Madagascar, probably unrelated to Idai.

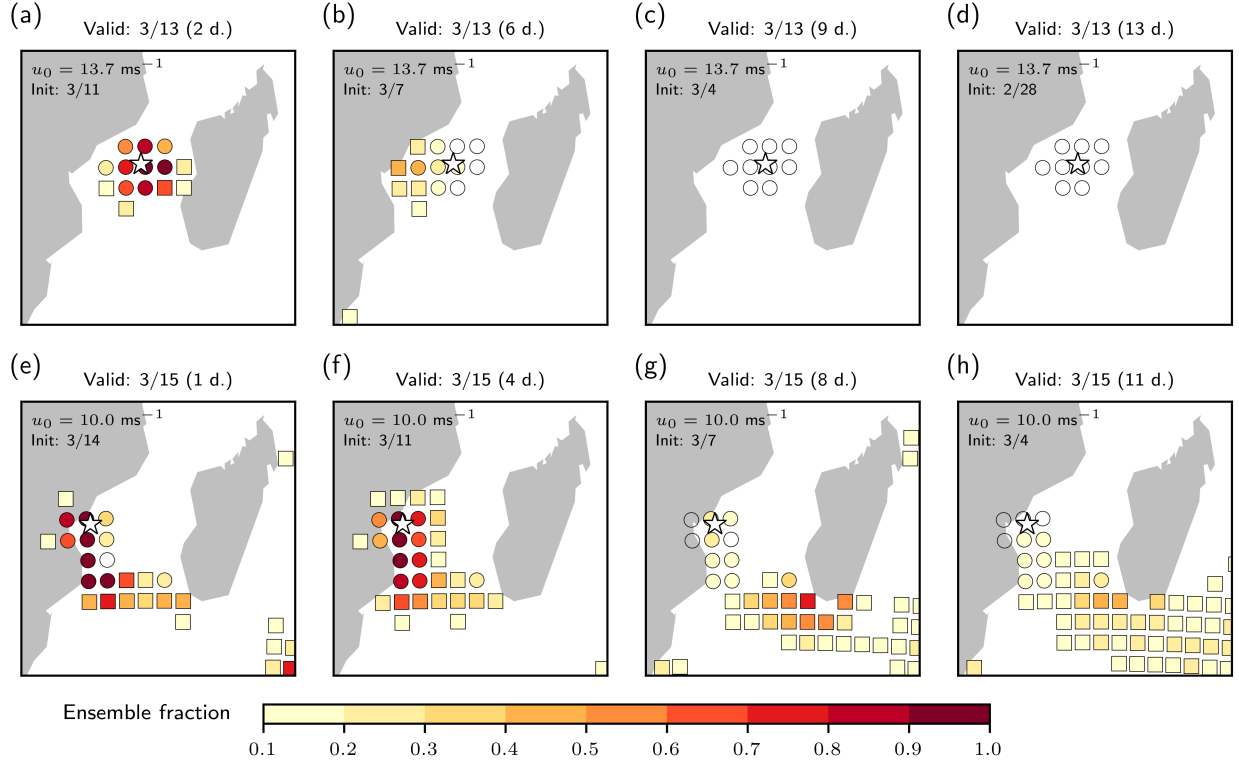


Figure 4. The circles denote grid points where the MERRA-2 wind speed exceeds the threshold u_0 (indicated in the left corner of each panel) during two of Idai’s storm dates. The colours illustrate the fraction of the 51 ensemble members with wind speeds larger than u_0 . Fractions below 0.1 are not shown. The squares indicate grid points for which more than 10% of the ensemble members’ wind speed exceeded u_0 but the MERRA-2 wind speed did not. The following dates are shown: 13 March 2019 in (a)–(d), and 15 March 2019 in (e)–(h). The forecast lead time in days is indicated in parentheses. The centre of Idai is shown with a star symbol for each date.

3.1.2. Minimum SLP forecasts

The box plot in Figure 5 depicts the $p_{\min}$ (minimum SLP) forecast errors of the ensemble at different lead times. Errors with a positive sign are primarily due to two factors: 1) A missing or underdeveloped system, which does not produce low enough $p_{\min}$; or 2) A misplaced system, for which the lowest SLP values occur outside the search area. Errors with a negative sign indicate that the forecast produces a cyclone that is too strong. At a lead time of one day, the median of the $p_{\min}$ forecasts is lower than $p_{\min}$ in MERRA-2. A few ensemble members had $p_{\min}$ values of about 20 hPa lower than the reanalysis, predicting a stronger cyclone than Idai. The tendency to forecast a too-deep cyclone is also clear at lead times of two and three days, when the 5th percentile of the forecasts is more negative in magnitude than the 95th percentile is positive. At lead times of five days and above, the 5th percentile is positive, which means that at least 95% of the ensemble members had higher $p_{\min}$ than the reanalysis.

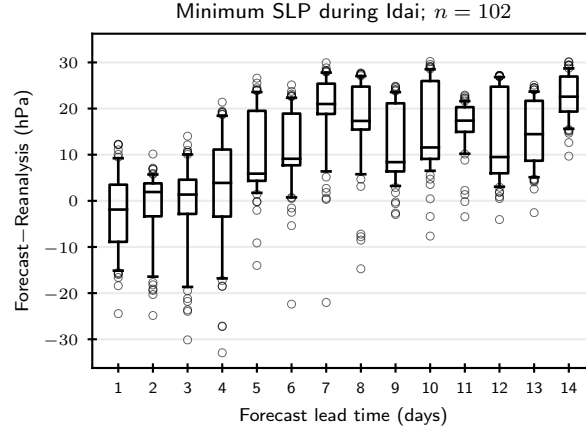


Figure 5. This box plot (Wilks, 2011) shows the minimum SLP forecast error inside a circular region following Idai’s centre, aggregated for all its seven storm dates and lead times of 1–14 days. The error is defined as the difference between each forecast ensemble member and MERRA-2. For each lead time, two forecasts were available, yielding a total of 102 ensemble members. Each box extends from the 25th to the 75th percentile, and the horizontal line inside each box shows the median. The lower and upper “whiskers” extend to the 5th and 95th percentile, respectively. Outlier values are indicated with circles.

3.1.3. Precursors

Standardised anomalies of nine variables before and during the passage of Idai are shown in Figure 6. The first panel (Figure 6a) shows that the minimum SLP anomalies inside the storm-following regions were only consistently negative one day before and on the storm dates, but the anomalies during the last two days before the last three storm dates (red circles) were all lower than -2σ and about -4σ on the storm dates themselves. The area-averaged SLP anomalies appear to be a more robust metric, exhibiting a gradual decline during the days before the storm dates (Figure 6b). The local SST anomalies were negative for all the storm dates and lead times shown in Figure 6c. Although not shown here, this was also the case for lead times of up to seven days, demonstrating that Idai developed over an ocean surface that was unusually cold for the season. The vertical wind shear (Figure 6d) was low on and one day before each of the storm dates on which Idai was a tropical cyclone, but three days before the storm dates the wind shear was not consistently below-normal regardless of the storm category. The following variables were consistently positive on the storm dates and one day before: specific humidity at 500 hPa (Figure 6e); temperature at 500 hPa (Figure 6f); divergence at 200 hPa, which was also consistently positive two days before the storm dates (Figure 6h); and convergence at 850 hPa (Figure 6i). The geopotential height at 500 hPa was negative during the storm dates and one day before (Figure 6g).

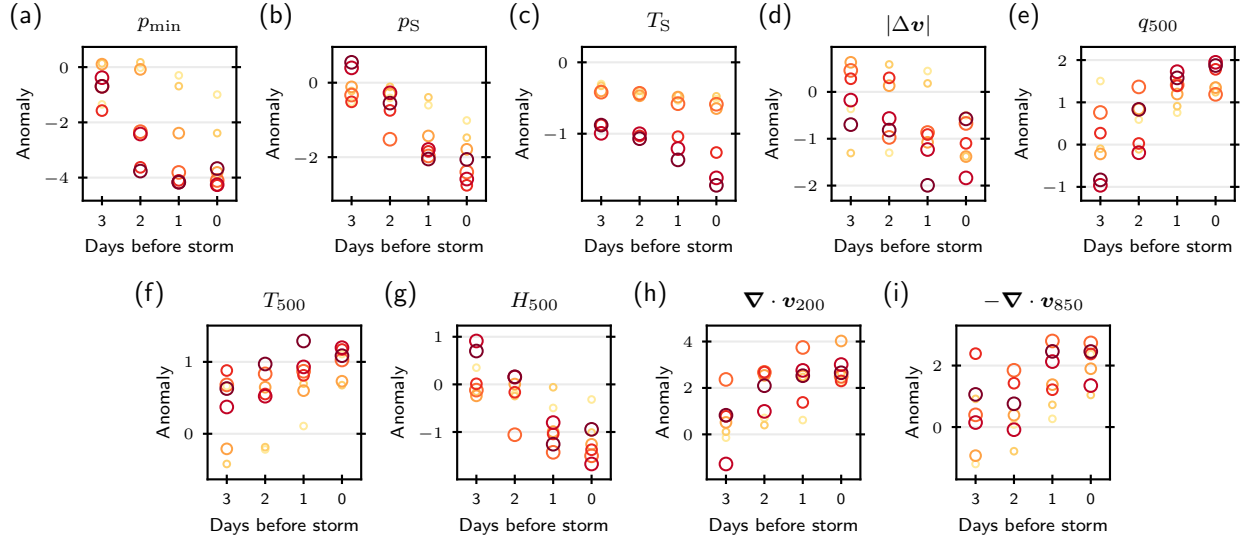


Figure 6. Standardised anomalies during Idai, from three days before up to the seven storm dates (see Data and Methods for details). The colours of the circles reflect the chronology of the seven storm dates, from 9 March 2019 (light yellow) to 15 March 2019 (dark red), and their sizes denote the storm category, from tropical storm (smallest) to category three (largest). The variables shown are indicated above each panel.

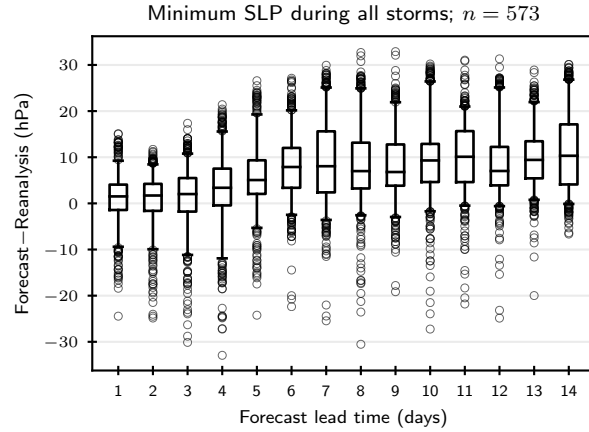


Figure 7. This box plot (Wilks, 2011) shows the minimum SLP forecast error inside a circular region following each storm or cyclone centre, aggregated for all the storm dates and lead times of 1–14 days. The error is defined as the difference between each forecast ensemble member and MERRA-2. For each lead time, two forecasts were available, yielding a total of 573 ensemble members. Each box extends from the 25th to the 75th percentile, and the horizontal line inside each box shows the median. The lower and upper “whiskers” extend to the 5th and 95th percentile, respectively. Outlier values are indicated with circles.

3.2. All 38 storms and cyclones

3.2.1. Minimum SLP forecasts

Figure 7 gives the same kind of information as Figure 5 but aggregated for all the 39 storms and cyclones instead of just for Idai. Overall, the aggregated forecasts performed better than the Idai forecast. The 5th percentile of the forecast errors is negative up to a lead time of 13 days, meaning that at least 5% of the ensemble members had a lower minimum SLP than the reanalysis for lead times of 1–12 days. Although this means that a considerable amount of ensemble members predicted low minimum SLP values at long lead times, it must be pointed out that an even higher number of ensemble members predicted high minimum SLP values. At five days of lead time, for instance, the 5th percentile of the forecast errors is about -5 hPa, while the 95th percentile is nearly $+20$ hPa. Moreover, the 25th percentile of the forecast errors is positive for all lead times of five days and more. This means that less than a quarter of the ensemble members had lower minimum SLP than the reanalysis inside the storm-following regions at those lead times.

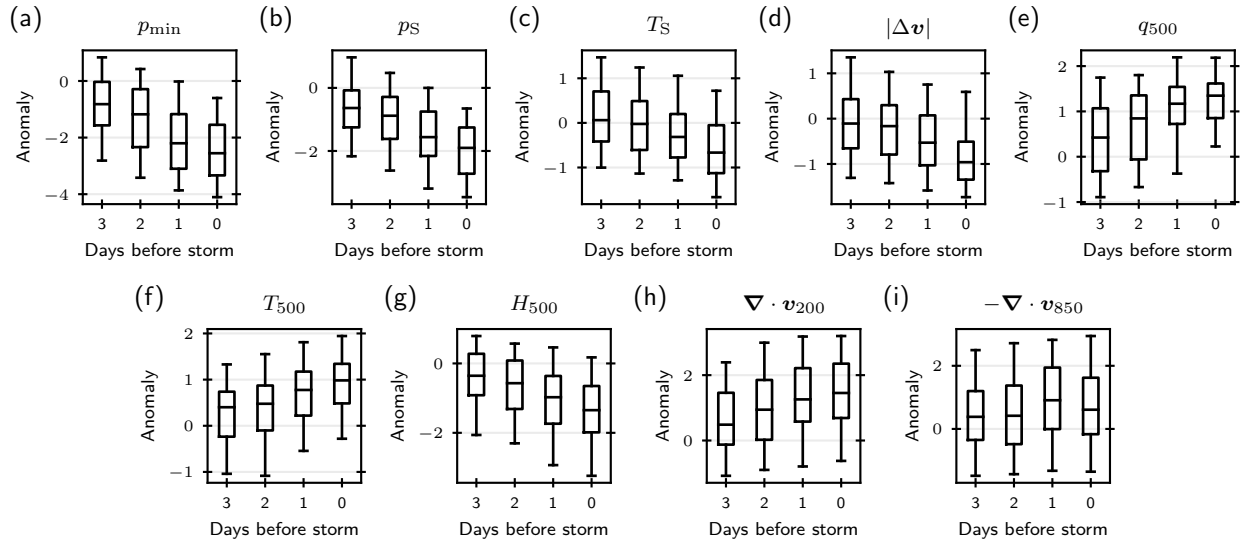


Figure 8. Standardised anomalies during all the 39 storms and cyclones, shown as box plots (Wilks, 2011) from three days before up to the storm dates (see Data and Methods for details). Each box extends from the 25th to the 75th percentile, and the horizontal line inside each box shows the median. The lower and upper “whiskers” extend to the 5th and 95th percentile, respectively. The variables for which the anomalies were calculated are indicated above each panel.

3.2.2. Precursors

Figure 8 sums up the distributions of the anomalies of the precursor variables, aggregated for all 39 storms and cyclones. Rather than showing each anomaly as was done for Idai in Figure 6, box plots are used. Special emphasis is given to anomalies two days prior to storm dates. This was argued by Foltz *et al.* (2018) to be a reasonable lead time “because it represents a balance between avoiding possible contamination from the storm and limiting the spatial and temporal offsets enough so that the values are representative of the conditions felt by the storm”.

Starting with minimum SLP in Figure 8a, the imprint of the systems at their peaks is manifested through a strong negative median anomaly on the storm dates of about -2.6σ . Already three days before the storm dates, the median anomaly is about $-\sigma$. There are probably two main reasons for this early negative anomaly. First, there is likely a degree of “contamination” because some systems are located inside the reference region too early, which again could be because the systems move slowly from one day to the next, or because the size of the circular region inside which the anomalies are calculated is too large. The second likely reason is that many of the systems develop gradually over several days, so that low SLP values are a precursor in their own right. Figure 8b shows that the evolution of area-averaged SLP, which is a more robust variable than minimum SLP because it is not based on single grid point values, is qualitatively similar to the evolution of minimum SLP in Figure 8a, although the median anomaly on the storm dates is slightly smaller in magnitude at about -1.9σ instead of -2.6σ .

Three days before the storm dates, the median local SST anomalies are marginally positive (Figure 8c). A gradual decrease in the SSTs takes place leading up to the storm dates, on which the median SST anomaly is about -0.7σ .

Figure 8d shows that the median vertical wind shear on the storm dates is about $-\sigma$. On day before the median is -0.5σ , but two and three days before the median is only -0.2σ and -0.1σ , respectively. This suggests that wind shear is not a reliable precursor of tropical storms and cyclones in this region several days in advance. The remaining variables have more consistently large median anomalies two days before the storm dates: specific humidity at 500 hPa (0.9σ ; Figure 8e); temperature at 500 hPa (0.5σ ; Figure 8f); geopotential height at 500 hPa (-0.6σ ; Figure 8g); divergence at 200 hPa (0.9σ ; Figure 8h); and convergence at 850 hPa (0.4σ ; Figure 8i).

An alternative way to assess the usefulness of each variable as a precursor of storms and cyclones is to calculate the lag correlation between the minimum SLP of a system on its storm date and the anomalies of the variable two days before the storm dates. Figure 9 shows the results of this analysis for all the area-averaged variables. Mean SLP (Figure 9a) and geopotential height at 500 hPa (Figure 9f) both have statistically significant lag correlation coefficients above 0.5 for two days’ lead time. The positive correlations for these variables are also significant for lead times of up to seven days (the longest lead time that was checked). Only one other variable investigated here has a significant lag correlation at seven days’ lead time: specific humidity at 500 hPa, for which the correlation coefficient is -0.17 at that lead time (not shown) and -0.30 at two days’ lead time (Figure 9d).

Figure 9b shows that area-averaged SST anomalies are significantly correlated with minimum SLP for lead times up to five days, and the sign of the correlation is positive. Wind shear is considered to be an important variable for tropical systems, but the lag correlation with minimum SLP is only significant at one day’s lead time, when the correlation coefficient is 0.18 (not shown). For longer lead times, including two days (Figure 9c), the correlation is not significant. Temperature at 500 hPa is negatively and significantly correlated with minimum SLP at two days’ lead time (Figure 9e), but not at longer lead times (not shown). The same is the case for divergence at 200 hPa (Figure 9g). The lag correlation between SLP minima and convergence at 850 hPa is negative and significant for lead times of up to four days (not shown), including two days’ lead time (Figure 9h).

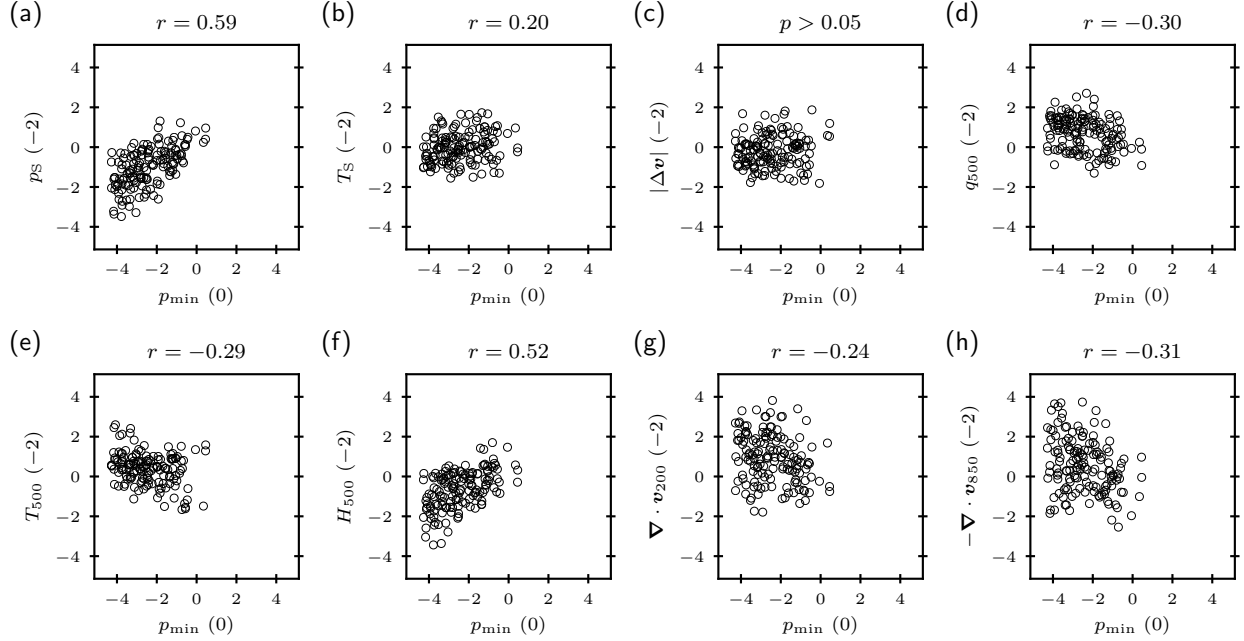


Figure 9. Scatter plots of standardised minimum SLP anomalies during the storm dates on the x-axes, and standardised anomalies of the indicated variables two days before the storm dates (calculated inside the same region that surrounded the system on the storm dates) on the y-axes. When statistically significant at the 5% level, the correlation coefficients are indicated above the panels.

3.3. Forecasting of the precursor variables

In the previous section, it was shown that anomalies of several variables are significantly correlated with minimum SLP at different lead times. Here, the skill of the model ensemble in predicting these variables is quantified. The method was described in Section 2. The first variable to be assessed is area-averaged SLP. Figure 10a shows that the forecast error (i.e., the forecasted value minus the reanalysis value) is uncorrelated with the reanalysis anomaly with respect to climatology when the model’s lead time is one day. This means that the strength of the SLP anomaly is independent of the forecast error. As the lead time increases, the correlation becomes more and more negative. This is because the correlation between a random forecast (drawn from the normal distribution with the same mean and standard deviation as the forecast) and the same reanalysis anomaly is strongly negative (shown with a dashed line). Using the said correlation as a metric, the SLP forecast performs better than a random forecast for lead times up to and including 11 days. The SST forecast outperforms a random forecast for all the lead times shown in Figure 10b, in other words at least 21 days. The corresponding lead times for the remaining variables are as follows. Wind shear: 12 days (Figure 10c); specific humidity at 500 hPa: 10 days (Figure 10d); temperature at 500 hPa: 11 days (Figure 10e); geopotential height at 500 hPa: 12 days (Figure 10f); divergence at 200 hPa: 8 days (Figure 10g); and convergence at 850 hPa: 9 days (Figure 10h).

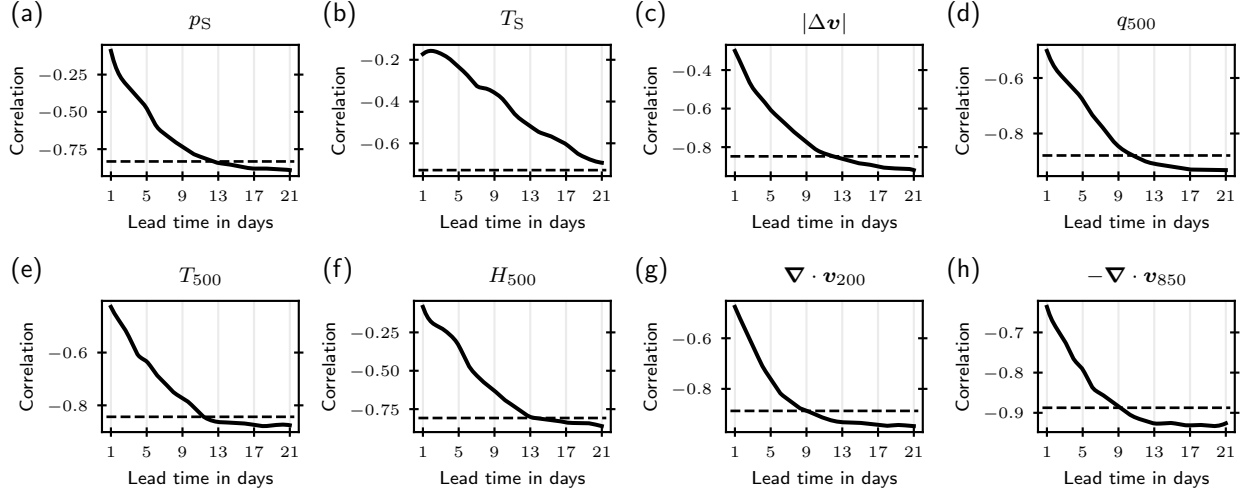


Figure 10. Correlation between the forecast error (forecast minus reanalysis) and the reanalysis anomaly, calculated for all years on the same dates as the storm dates and inside the same circular regions as the ones surrounding the storms on the storm dates, organized by lead time, for the variables indicated above each panel. Between 2 and 20 days of lead time, a three-day running mean filter was applied. The dashed lines show correlations between randomized forecast errors and reanalysis anomalies (see Data and Methods).

4. Discussion

The analysis above has revealed that local SLP minima associated with tropical storms and cyclones in the Mozambique Channel are not skilfully predicted more than a few days ahead using a state-of-the-art ensemble-based forecasting model. In the case of Idai, only a few ensemble members predicted lower minimum SLP than the value from the reanalysis MERRA-2 at lead times of four days and longer (Figure 5). As pointed out above, the storm might still have been forecasted but misplaced and located outside the 300 km radius surrounding the observed centre of Idai, but the results did not improve when a larger search radius of 500 km was used (not shown). This suggests that the poor results are not due to the choice of method; the storm simply was not forecasted at lead times of more than three days. The corresponding analysis of all the 39 storms showed that at lead times of four days and more, less than a quarter of the ensemble members produced lower minimum SLP than the reanalysis (Figure 7). This result was identical when a search radius of 500 km was used (not shown). A more promising result was that at lead times of up to 12 days, at least 5% of the ensemble members produced lower minimum SLP than the reanalysis during storms and cyclones (Figure 7). This raises the prospect that an early indication of an impending storm could potentially have been spotted by an experienced forecaster before several of the cases.

When tropical storms and cyclones are not predicted directly, an alternative approach could be to predict favourable conditions for such systems. Here, eight potential precursor variables have been investigated. The only variables that are significantly lag correlated with minimum SLP at a lead time of one week are (area-averaged) SLP, geopotential height at 500 hPa, and specific humidity at 500 hPa. The latter variable is negatively correlated with minimum SLP, meaning that high humidity precedes low SLP.

High SSTs and weak vertical wind shear are often considered to be among the key precursors of tropical storms and cyclones. Yet, the present analysis revealed that SST is only significantly correlated with minimum SLP at

lead times of up to five days, and the sign of the lag correlation is positive. In other words, negative SLP anomalies on storm dates are associated with negative SST anomalies during the preceding days. It is conceivable that above-normal SSTs were important in earlier phases of the life cycles of the systems and consequently not captured by the method used here, for instance if the warm anomalies occurred when the systems were located outside the search area. It is also possible that the correlation between SST anomalies and minimum SLP is weak because the SSTs during the storms were so high that small variations did not matter for the development. The influence of SSTs on the maximum potential intensity of tropical cyclones has been shown to decrease for SSTs greater than about 28°C (Emanuel, 1986; Holland, 1997; Tonkin *et al.*, 2000). The median of the area-averaged SST during all the storm dates was 28.6°C, and the climatological value for the same circular regions was 28.9°C. In summary, it is not unlikely that the positive correlation between SST anomalies and minimum SLP is simply due to the cooling effect of storms and cyclones on the sea surface (Schade and Emanuel, 1999; Dare and McBride, 2011).

Still, the possibility that lower-than-normal SSTs are a precursor of tropical storms and cyclones in the Mozambique Channel cannot be dismissed. Another result that might be surprising to some readers (it was to the author) is that vertical wind shear is not a particularly useful precursor variable for tropical storms and cyclones in the region, at least not according to the criteria used in this study.

Having identified a set of useful precursors, the skill of the model in forecasting them was assessed. It was found that all of them are skilfully predicted at lead times of 8 days and upwards. Some variables are skilfully forecasted at very long lead times, including SST (at least three weeks) and geopotential height at 500 hPa (12 days). This result supports the argument for using hybrid statistical–dynamical prediction systems to enhance the forecast skill (e.g., Wang *et al.*, 2009; Kim and Webster, 2010; Vecchi *et al.*, 2010; Vitart *et al.*, 2010; Murakami *et al.*, 2016). An emerging strategy that has already shown potential is to use artificial intelligence (AI) to combine dynamical model predictions with empirical data such as observations, satellite imagery and reanalysis data to forecast high-impact weather (McGovern *et al.*, 2017; Reichstein *et al.*, 2019). Several promising studies using AI for tropical cyclone detection and prediction have already been published (e.g., Jin *et al.*, 2008; Loridan *et al.*, 2017; Mercer and Grimes, 2017; Matsuoka *et al.*, 2018; Wimmers *et al.*, 2019). It is to be hoped that a continuing increase in computing power and the development of AI technology can be used to enhance high-impact weather forecasting in regions with a vulnerable population, such as south-eastern Africa.

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References

- Ash, K.D. and Matyas, C.J. (2012) The influences of ENSO and the subtropical Indian Ocean Dipole on tropical cyclone trajectories in the southwestern Indian Ocean. *International Journal of Climatology*, 32(1), 41-56.

- Bessafi, M. and Wheeler, M.C. (2006) Modulation of South Indian Ocean Tropical Cyclones by the Madden–Julian Oscillation and Convectively Coupled Equatorial Waves. *Monthly Weather Review*, 134(2), 638–656.
- Brouwer, R. and Nhassengo, J. (2006) About Bridges and Bonds: Community Responses to The 2000 Floods in Mabalane District, Mozambique. *Disasters*, 30(2), 234–255.
- Buizza, R. (2008) The value of probabilistic prediction. *Atmospheric Science Letters*, 9(2), 36–42.
- Camargo, S.J., Wheeler, M.C. and Sobel, A.H. (2009) Diagnosis of the MJO Modulation of Tropical Cyclogenesis Using an Empirical Index. 66(10), 3061–3074.
- Camp, J., Wheeler, M.C., Hendon, H.H., Gregory, P.A., Marshall, A.G., Tory, K.J., Watkins, A.B., MacLachlan, C. and Kuleshov, Y. (2018) Skilful multiweek tropical cyclone prediction in ACCESS-S1 and the role of the MJO. *Quarterly Journal of the Royal Meteorological Society*, 144(714), 1337–1351.
- Chikoore, H., Vermeulen, J.H. and Jury, M.R. (2015) Tropical cyclones in the Mozambique Channel: January–March 2012. *Natural Hazards*, 77(3), 2081–2095.
- Dare, R.A. and McBride, J.L. (2011) Sea Surface Temperature Response to Tropical Cyclones. *Monthly Weather Review*, 139(12), 3798–3808.
- Das, S. (2019) Evaluating climate change adaptation through evacuation decisions: a case study of cyclone management in India. *Climatic Change*, 152(2), 291–305.
- Duvel, J.-P. (2015) Initiation and Intensification of Tropical Depressions over the Southern Indian Ocean: Influence of the MJO. *Monthly Weather Review*, 143(6), 2170–2191.
- Emanuel, K.A. (1986) An air-sea interaction theory for tropical cyclones. Part I: Steady-state maintenance. *Journal of the Atmospheric Sciences*, 43(6), 585–605.
- Finney, D.L., Marsham, J.H., Walker, D.P., Birch, C.E., Woodhams, B.J., Jackson, L.S. and Hardy, S. (2019) The effect of westerlies on East African rainfall and the associated role of tropical cyclones and the Madden-Julian Oscillation. *Quarterly Journal of the Royal Meteorological Society*.
- Fitchett, J.M. and Grab, S.W. (2014) A 66-year tropical cyclone record for south-east Africa: temporal trends in a global context. *International Journal of Climatology*, 34(13), 3604–3615.
- Foltz, G.R., Balaguru, K. and Hagos, S. (2018) Interbasin Differences in the Relationship between SST and Tropical Cyclone Intensification. *Monthly Weather Review*, 146(3), 853–870.
- Gelaro, R., McCarty, W., Suárez, M.J., Todling, R., Molod, A., Takacs, L., Randles, C.A., Darmenov, A., Bosilovich, M.G., Reichle, R., Wargan, K., Coy, L., Cullather, R., Draper, C., Akella, S., Buchard, V., Conaty, A., da Silva, A.M., Gu, W., Kim, G.-K., Koster, R., Lucchesi, R., Merkova, D., Nielsen, J.E., Partyka, G., Pawson, S., Putman, W., Rienecker, M., Schubert, S.D., Sienkiewicz, M. and Zhao, B. (2017) The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). *Journal of Climate*, 30(14), 5419–5454.
- Gray, W.M. (1998) The formation of tropical cyclones. *Meteorology and Atmospheric Physics*, 67(1), 37–69.
- Ho, C.-H., Kim, J.-H., Jeong, J.-H., Kim, H.-S. and Chen, D. (2006) Variation of tropical cyclone activity in the South Indian Ocean: El Niño–Southern Oscillation and Madden-Julian Oscillation effects. *Journal of Geophysical Research: Atmospheres*, 111(D22).
- Holland, G.J. (1997) The Maximum Potential Intensity of Tropical Cyclones. *Journal of the Atmospheric Sciences*, 54(21), 2519–2541.
- Huang, S.-K., Lindell, M.K. and Prater, C.S. (2015) Who Leaves and Who Stays? A Review and Statistical Meta-Analysis of Hurricane Evacuation Studies. *Environment and Behavior*, 48(8), 991–1029.
- Hudson, D., Alves, O., Hendon, H.H. and Marshall, A.G. (2011) Bridging the gap between weather and seasonal forecasting: intraseasonal forecasting for Australia. *Quarterly Journal of the Royal Meteorological Society*, 137(656), 673–689.
- Jin, L., Yao, C. and Huang, X.-Y. (2008) A Nonlinear Artificial Intelligence Ensemble Prediction Model for Typhoon Intensity. *Monthly Weather Review*, 136(12), 4541–4554.
- Kaplan, J. and DeMaria, M. (2003) Large-Scale Characteristics of Rapidly Intensifying Tropical Cyclones in the North Atlantic Basin. *Weather and Forecasting*, 18(6), 1093–1108.
- Kim, H.-M. and Webster, P.J. (2010) Extended-range seasonal hurricane forecasts for the North Atlantic with a hybrid dynamical-statistical model. *Geophysical Research Letters*, 37(21), L21705.
- Knapp, K.R., Diamond, H.J., Kossin, J.P., Kruk, M.C. and Schreck, C.J. (2018). *International Best Track Archive for Climate Stewardship (IBTrACS) Project, Version 4*. <https://doi.org/10.25921/82ty-9e16>
- Knapp, K.R., Kruk, M.C., Levinson, D.H., Diamond, H.J. and Neumann, C.J. (2010) The International Best Track Archive for Climate Stewardship (IBTrACS). *Bulletin of the American Meteorological Society*, 91(3), 363–376.

- Komaromi, W.A. and Majumdar, S.J. (2014) Ensemble-Based Error and Predictability Metrics Associated with Tropical Cyclogenesis. Part I: Basinwide Perspective. *Monthly Weather Review*, 142(8), 2879-2898.
- Lee, C.-Y., Camargo, S.J., Vitart, F., Sobel, A.H. and Tippett, M.K. (2018) Subseasonal Tropical Cyclone Genesis Prediction and MJO in the S2S Dataset. *Weather and Forecasting*, 33(4), 967-988.
- Lim, Y., Son, S.-W. and Kim, D. (2018) MJO Prediction Skill of the Subseasonal-to-Seasonal Prediction Models. *Journal of Climate*, 31(10), 4075-4094.
- Loridan, T., Crompton, R.P. and Dubossarsky, E. (2017) A Machine Learning Approach to Modeling Tropical Cyclone Wind Field Uncertainty. *Monthly Weather Review*, 145(8), 3203-3221.
- Madden, R.A. and Julian, P.R. (1971) Detection of a 40–50 Day Oscillation in the Zonal Wind in the Tropical Pacific. 28(5), 702-708.
- Matsuoka, D., Nakano, M., Sugiyama, D. and Uchida, S. (2018) Deep learning approach for detecting tropical cyclones and their precursors in the simulation by a cloud-resolving global nonhydrostatic atmospheric model. *Progress in Earth and Planetary Science*, 5(1), 80.
- Matyas, C.J. (2015) Tropical cyclone formation and motion in the Mozambique Channel. *International Journal of Climatology*, 35(3), 375-390.
- Matyas, C.J. and Silva, J.A. (2013) Extreme weather and economic well-being in rural Mozambique. *Natural Hazards*, 66(1), 31-49.
- Mavume, A.F., Rydberg, L., Rouault, M. and Lutjeharms, J.R. (2009) Climatology and landfall of tropical cyclones in the south-west Indian Ocean. *Western Indian Ocean Journal of Marine Science*, 8(1), 15-36.
- McBride, J.L. and Zehr, R. (1981) Observational Analysis of Tropical Cyclone Formation. Part II: Comparison of Non-Developing versus Developing Systems. *Journal of the Atmospheric Sciences*, 38(6), 1132-1151.
- McGovern, A., Elmore, K.L., Gagne, D.J., Haupt, S.E., Karstens, C.D., Lagerquist, R., Smith, T. and Williams, J.K. (2017) Using Artificial Intelligence to Improve Real-Time Decision-Making for High-Impact Weather. *Bulletin of the American Meteorological Society*, 98(10), 2073-2090.
- Mercer, A. and Grimes, A. (2017) Atlantic Tropical Cyclone Rapid Intensification Probabilistic Forecasts from an Ensemble of Machine Learning Methods. *Procedia Computer Science*, 114, 333-340.
- Mong, Y., Kaiser, R., Ibrahim, D., Rasoatiana, Razafimbololona, L. and Quick, R.E. (2001) Impact of the Safe Water System on Water Quality in Cyclone-Affected Communities in Madagascar. *American Journal of Public Health*, 91(10), 1577-1579.
- Murakami, H., Villarini, G., Vecchi, G.A., Zhang, W. and Gudgel, R. (2016) Statistical–Dynamical Seasonal Forecast of North Atlantic and U.S. Landfalling Tropical Cyclones Using the High-Resolution GFDL FLOR Coupled Model. *Monthly Weather Review*, 144(6), 2101-2123.
- NASA (2019) Devastation in Mozambique. Retrieved from <https://earthobservatory.nasa.gov/images/144712/devastation-in-mozambique> on 2 March 2019.
- Rapolaki, R.S. and Reason, C.J.C. (2018) Tropical storm Chedza and associated floods over south-eastern Africa. *Natural Hazards*, 93(1), 189-217.
- Reason, C.J.C. (2007) Tropical cyclone Dera, the unusual 2000/01 tropical cyclone season in the South West Indian Ocean and associated rainfall anomalies over Southern Africa. *Meteorology and Atmospheric Physics*, 97(1), 181-188.
- Reason, C.J.C. and Keibel, A. (2004) Tropical Cyclone Eline and Its Unusual Penetration and Impacts over the Southern African Mainland. *Weather and Forecasting*, 19(5), 789-805.
- Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N. and Prabhat (2019) Deep learning and process understanding for data-driven Earth system science. *Nature*, 566(7743), 195-204.
- Rosa, M.B., Satyamurty, P., Ferreira, N.J. and Silva, L.T. (2019) A comparative study of intense surface cyclones off the coasts of southeastern Brazil and Mozambique. 39(8), 3523-3542.
- Schade, L.R. and Emanuel, K.A. (1999) The Ocean’s Effect on the Intensity of Tropical Cyclones: Results from a Simple Coupled Atmosphere–Ocean Model. *Journal of the Atmospheric Sciences*, 56(4), 642-651.
- Tonkin, H., Holland, G.J., Holbrook, N. and Henderson-Sellers, A. (2000) An Evaluation of Thermodynamic Estimates of Climatological Maximum Potential Tropical Cyclone Intensity. *Monthly Weather Review*, 128(3), 746-762.
- Vecchi, G.A., Zhao, M., Wang, H., Villarini, G., Rosati, A., Kumar, A., Held, I.M. and Gudgel, R. (2010) Statistical–Dynamical Predictions of Seasonal North Atlantic Hurricane Activity. *Monthly Weather Review*, 139(4), 1070-1082.
- Virtanen, P., Gommers, R., Oliphant, T.E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S.J., Brett, M., Wilson, J., Millman, K.J., Mayorov, N., Nelson, A.R.J., Jones, E., Kern, R., Larson, E., Carey, C.J., Polat, İ., Feng, Y., Moore, E.W., VanderPlas, J.,

- Laxalde, D., Perktold, J., Cimrman, R., Henriksen, I., Quintero, E.A., Harris, C.R., Archibald, A.M., Ribeiro, A.H., Pedregosa, F., van Mulbregt, P., Vijaykumar, A., Bardelli, A.P., Rothberg, A., Hilboll, A., Kloeckner, A., Scopatz, A., Lee, A., Rokem, A., Woods, C.N., Fulton, C., Masson, C., Häggström, C., Fitzgerald, C., Nicholson, D.A., Hagen, D.R., Pasechnik, D.V., Olivetti, E., Martin, E., Wieser, E., Silva, F., Lenders, F., Wilhelm, F., Young, G., Price, G.A., Ingold, G.-L., Allen, G.E., Lee, G.R., Audren, H., Probst, I., Dietrich, J.P., Silterra, J., Webber, J.T., Slavič, J., Nothman, J., Buchner, J., Kulick, J., Schönberger, J.L., de Miranda Cardoso, J.V., Reimer, J., Harrington, J., Rodríguez, J.L.C., Nunez-Iglesias, J., Kuczynski, J., Tritz, K., Thoma, M., Newville, M., Kümmerer, M., Bolingbroke, M., Tartre, M., Pak, M., Smith, N.J., Nowaczyk, N., Shebanov, N., Pavlyk, O., Brodtkorb, P.A., Lee, P., McGibbon, R.T., Feldbauer, R., Lewis, S., Tygier, S., Sievert, S., Vigna, S., Peterson, S., More, S., Pudlik, T., Oshima, T., Pingel, T.J., Robitaille, T.P., Spura, T., Jones, T.R., Cera, T., Leslie, T., Zito, T., Krauss, T., Upadhyay, U., Halchenko, Y.O., Vázquez-Baeza, Y. and SciPy, C. (2020) SciPy 1.0: fundamental algorithms for scientific computing in Python. *Nature Methods*, 17(3), 261-272.
- Vitart, F. (2017) Madden–Julian Oscillation prediction and teleconnections in the S2S database. *Quarterly Journal of the Royal Meteorological Society*, 143(706), 2210-2220.
- Vitart, F., Anderson, D. and Stockdale, T. (2003) Seasonal Forecasting of Tropical Cyclone Landfall over Mozambique. *Journal of Climate*, 16(23), 3932-3945.
- Vitart, F., Ardilouze, C., Bonet, A., Brookshaw, A., Chen, M., Codorean, C., Déqué, M., Ferranti, L., Fucile, E., Fuentes, M., Hendon, H., Hodgson, J., Kang, H.S., Kumar, A., Lin, H., Liu, G., Liu, X., Malguzzi, P., Mallas, I., Manoussakis, M., Mastrangelo, D., MacLachlan, C., McLean, P., Minami, A., Mladek, R., Nakazawa, T., Najm, S., Nie, Y., Rixen, M., Robertson, A.W., Ruti, P., Sun, C., Takaya, Y., Tolstykh, M., Venuti, F., Waliser, D., Woolnough, S., Wu, T., Won, D.J., Xiao, H., Zaripov, R. and Zhang, L. (2016) The Subseasonal to Seasonal (S2S) Prediction Project Database. *Bulletin of the American Meteorological Society*, 98(1), 163-173.
- Vitart, F., Leroy, A. and Wheeler, M.C. (2010) A Comparison of Dynamical and Statistical Predictions of Weekly Tropical Cyclone Activity in the Southern Hemisphere. *Monthly Weather Review*, 138(9), 3671-3682.
- Vitart, F. and Robertson, A.W. (2018) The sub-seasonal to seasonal prediction project (S2S) and the prediction of extreme events. *npj Climate and Atmospheric Science*, 1(1), 3.
- Wang, H., Schemm, J.-K.E., Kumar, A., Wang, W., Long, L., Chelliah, M., Bell, G.D. and Peng, P. (2009) A Statistical Forecast Model for Atlantic Seasonal Hurricane Activity Based on the NCEP Dynamical Seasonal Forecast. *Journal of Climate*, 22(17), 4481-4500.
- Warren, M. (2019). Why Cyclone Idai is one of the Southern Hemisphere's most devastating storms. *Nature*.
- White, C.J., Carlsen, H., Robertson, A.W., Klein, R.J.T., Lazo, J.K., Kumar, A., Vitart, F., Coughlan de Perez, E., Ray, A.J., Murray, V., Bharwani, S., MacLeod, D., James, R., Fleming, L., Morse, A.P., Eggen, B., Graham, R., Kjellström, E., Becker, E., Pegion, K.V., Holbrook, N.J., McEvoy, D., Depledge, M., Perkins-Kirkpatrick, S., Brown, T.J., Street, R., Jones, L., Remenyi, T.A., Hodgson-Johnston, I., Buontempo, C., Lamb, R., Meinke, H., Arheimer, B. and Zebiak, S.E. (2017) Potential applications of subseasonal-to-seasonal (S2S) predictions. *Meteorological Applications*, 24(3), 315-325.
- Wikimedia Commons (2019) File:Idai 2019-03-14 1135Z.jpg. Retrieved from https://commons.wikimedia.org/wiki/File:Idai_2019-03-14_1135Z.jpg on 16 March 2020
- Wilks, D.S. (2011). *Statistical Methods in the Atmospheric Sciences* (Third ed.): Academic Press.
- Wimmers, A., Velden, C. and Cossuth, J.H. (2019) Using Deep Learning to Estimate Tropical Cyclone Intensity from Satellite Passive Microwave Imagery. *Monthly Weather Review*, 147(6), 2261-2282.
- Yamaguchi, M., Vitart, F., Lang, S.T.K., Magnusson, L., Elsberry, R.L., Elliott, G., Kyouda, M. and Nakazawa, T. (2015) Global Distribution of the Skill of Tropical Cyclone Activity Forecasts on Short- to Medium-Range Time Scales. *Weather and Forecasting*, 30(6), 1695-1709.
- Zhang, C. (2013) Madden–Julian Oscillation: Bridging Weather and Climate. 94(12), 1849-1870.