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RESEARCH

Detecting cyclones with seasonal forecasts? Development of a novel standardised Windstorm Index for the forecasting and impact-oriented analysis of extreme wind events

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Abstract

This preliminary study introduces the Standardised Windstorm Index (SWI), a novel tool designed to quantify the impact of extreme wind events in different geographical regions. The SWI is developed by first fitting the Weibull distribution to daily maximum wind speed data, followed by an inverse normal transformation to obtain a standardised index. This method enhances the accuracy of extreme wind event detection compared to conventional standardisation techniques. Using seasonal forecasts from the SEAS5 system, the SWI demonstrates its ability to effectively detect tropical cyclones and windstorms in the Southern African Development Community (SADC) region, showing an improvement of more than 20% in the accuracy metric compared to raw standardised SEAS5 data. However, it is important to note that this improvement is primarily driven by better identification of non-events rather than an increase in cyclone detection sensitivity, as discussed in the main text. This study also acknowledges some limitations, including assumptions in the extreme event detection procedure, which may not fully capture the variability and uncertainty within seasonal forecasts.Moreover, the use of ERA5 for the bias correction of SEAS5 wind speed data may introduce inaccuracies in the input data used for calculating the SWI, due to the scarcity of observations assimilated in ERA5 within the SADC area. Future work will focus on refining these methods, extending the geographical and temporal scope to improve its robustness and applicability. Although preliminary, our results emphasise the potential of the SWI as a valuable tool for improving the predictive skills of seasonal forecasts and supporting proactive efforts for climate risk management and adaptation strategies.

Keywords Windstorms · Extreme Events · Seasonal Forecasts · Cyclones · Climate Indexes

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1 Introduction

The development and application of indices for extreme winds is crucial for monitoring and forecasting purposes. These indices, which aim to quantify both the severity and potential impacts of windstorms, offer the possibility to improve regional climate forecasts and climate risk assessments. The integration of such indices into seasonal forecasting models enables the prediction of extreme events and facilitates timely preparation and response, which are essential for minimising the negative impacts on agriculture, energy supply, infrastructure and the overall resilience of communities (An-Vo et al. 2021; Arnone et al. 2020a, b; Eccel et al. 2016; Goodess et al. 2022; Lledó et al. 2019; Marcos et al. 2017; Vajda and Hyvärinen 2020).

Here we introduce a novel index, the Standardised Windstorm Index (SWI), and describe its application using seasonal forecasts. The SWI provides a robust approach to quantitatively assess the likelihood and impact of extreme wind events. This innovative index is characterised by its ability to standardise the assessment of wind events across the different climate zones, providing a consistent and interpretable benchmark for assessing the risk of windstorms and tropical cyclones. The SWI can be easily integrated into seasonal forecasting models to improve the accuracy of extreme event predictions. It can also be seamlessly aligned with extreme climate indices like the Extreme Climate Index (Helmschrot et al. 2017; Petitta et al. 2016) for an improved understanding of different climate hazards and their interconnections.

There are various methods and indices in the literature for analysing and detecting extreme wind events. Mayne (1979) reviewed extreme value analysis methods, emphasising the need for utilising tailored distributions for specific weather systems and regions. (Leckebusch et al. 2008) introduced a Storm Severity Index (SSI) based on the exceedance of site-specific thresholds in gridded data, proposing two levels of aggregation—an Area-aggregated SSI (ASSI) and an Event-aggregated SSI (ESSI)—and tested its capability of describing storms in reanalysis data. Dotzek et al. (2009) in their review of research on severe convective storms in Europe with a focus on the European Severe Weather Database (ESWD), stress the need for standardising storm severity assessments. Trenberth and Owen (1999) analysed storm trends using wind indices based on surface pressure measurements and highlighted the need for homogeneous data. Hofherr and Kunz (2010) presented a methodological innovation for extreme winter storm climatology in Germany using spatially detailed wind field modelling and defining hazard curves based on the extreme value theory. Nixon and Qiu (2005) developed a storm severity index for infrastructure management, acknowledging its relatively narrow area of application and potential subjectivity issues. For what concerns the forecasting of extreme wind events, Petroliagis and Pinson (2014) defined the Extreme Forecast Index (EFI) for forecasting extreme winds, with a specific focus on northern Germany. They illustrated the challenges associated with setting thresholds that effectively strike a balance between the need for accuracy and the prevention of false alarms. Walz et al. (2017) introduced the Distributional Index-Storm Severity Index (DI-SSI) for effective storm severity estimates in regions where this phenomenon is infrequent.

Compared to previous works in this field, the SWI provides a comprehensive framework that not only quantifies but also standardises the impact of extreme wind events consistently, even across different geographic areas. A distinctive feature of the SWI is its methodology, which is designed based on the widely accepted Standardised Precipitation Index (SPI, Mckee et al. (1993) used for drought monitoring. The use of the SPI as a framework aims to improve the integration of the novel SWI into multi-hazard indices and also leverages the characteristics of easy interpretability and scalability of the SPI. By directly linking to the probability of occurrence and impact of extreme wind events, the SWI addresses many limitations of other existing indices, such as the intensive data processing of the DI-SSI and the forecasting challenges associated with the EFI. In addition, the application of the SWI to the SADC region using seasonal forecasts aims to assess its value as a scalable tool for climate risk management and adaptation strategies.

This paper is structured as follows. First, the methodology used to build the SWI is presented and described, along with the dataset used. Section 3 deals with the detection of windstorms and tropical cyclones. The last part of the paper discusses the results and conclusions and gives an outlook for further improvements and future studies.

2 Methods

2.1 The standardised Windstorm Index (SWI)

The formal definition of SWI resembles that of the Standardised Precipitation Index (SPI, Mckee et al. (1993), applied to the maximum daily wind speed instead of precipitation. Importantly, SWI is calculated using the cube of the maximum daily wind speed. This approach is common in studies focusing on damages caused by severe windstorms, as the cube of wind speed is proportional to the work done by the wind in terms of the dynamic pressure exerted on surfaces (Leckebusch et al. 2008).

As known, a sample of data from a given variable can be standardised by computing the z-score, which involves subtracting the mean of the sample from each data point and dividing the result by the standard deviation of the sample. However, wind speed typically does not follow a Gaussian distribution, but it is instead skewed with a long tail towards higher wind speeds. The distribution of wind speed is usually described using a Weibull distribution (Stevens et al. 1979), with parameters depending on the location. Therefore, before computing standardised deviations for wind speed, a transformation needs to be applied to the data to convert the original distribution to a standard normal distribution with a mean of zero and a variance of one. The calculation of the SWI can be summarised as follows:

1. Fitting the data from each location and each month within a reference period (e.g., all the data from January), to the Weibull distribution, resulting in a set of month- and site-specific parameters;
2. We use the specific parameters to fit the Weibull distribution to the data of the resulting month- and site-specific, establishing a relationship between each value of wind speed and its probability;
3. Computing SWI by using the inverse normal distribution technique to map the probability values associated with each wind speed value on a standard normal distribution.

The resulting index is distributed as a standard normal distribution, which inherently has two tails, with negative and positive values. Since the left tail corresponds to low wind speed events, it is excluded from this analysis, as our focus is on identifying extreme windstorm events, associated with very high wind speeds.

2.2 Study area

We focus on the Mozambique area (from −25°S to -11°S, 31°E to 40°E, an area encompassing both land and ocean), selected here as a case study of relevance for the FOCUS-Africa Horizon2020 project (https://focus-africaproject.eu/, GA 869575).

Located along the southeastern coast of Africa and member of SADC states, Mozambique experiences a predominantly tropical to subtropical climate, with distinct wet and dry seasons influenced by the Indian Ocean (Mawren et al. 2023). This region is frequently affected by tropical cyclones, especially from November to April, with an average of 1–2 major cyclones making landfall annually (Mavume et al. 2009). Cyclones pose disruptive socio-economic risks, including casualties, and damage to infrastructure, to agriculture and fisheries, which are vital to Mozambique's economy. Cyclone forecasting is thus crucial here to enhance disaster preparedness (Nhundu Kenneth et al. 2021).

2.3 Input data and preprocessing

In this study, the Standardised Windstorm Index (SWI) is calculated using seasonal forecasts of daily maximum wind speed data from the SEAS5 forecasting system, developed by the ECMWF (Johnson et al. 2019). SEAS5 includes 25 hindcast ensemble members covering the period from 1981 to 2016, and 51 members starting from 2017 onward, with global coverage and a spatial resolution of 1° × 1°. These forecasts are initialised every month on the first day of the month and span over the upcoming 7 months. Data is accessed through the Copernicus Climate Data Store (CDS, https://cds.climate.copernicus.eu/*)*.

Before computing SWI, wind speed data is bias-corrected using a methodology specifically designed to correct the bias of extreme events in seasonal forecasts (Trentini et al. 2022). For this study, we used data from ECMWF's ERA5 reanalysis (Hersbach et al. 2020) as a reference dataset, which has a horizontal resolution of 0.25° over both land and ocean. The choice of the ERA5 system was driven specifically by the need to include the ocean in our analysis, given its significance in the formation and behaviour of windstorms and cyclones. Importantly, incorporated within this methodology is a downscaling component, which brings the resolution of seasonal forecasts to the finer spatial scale of the reference dataset: as a result of the bias correction procedure (Crespi et al. 2021), SEAS5 data is downscaled to a 0.25° horizontal resolution.

A preliminary validation of the capability of the SWI indicator to detect windstorms is performed using records of extreme wind events from EM-DAT, The International Disaster Database (https://www.emdat.be/, Delforge et al. (2023), a global up-to-date inventory of major disasters.

2.4 Detecting extreme windstorms with SWI

The procedure for detecting windstorms from the SWI data has to account for the probabilistic nature of seasonal forecasts. Seasonal forecasts, albeit often provided with a daily temporal resolution, as in the case of SEAS5, shall not be interpreted on a day-by-day basis.

Instead, the primary utility of these forecasts lies in their ability to discern trends over longer timescales, taking into account their inherent variability and uncertainty. In the case of the SEAS5 product, the uncertainty of the forecast is described by the differences (the “spread”) of its ensemble members.

For these reasons, we define the following procedure for detecting extreme windstorm events:

1. Selection of the top-10 members that display the highest SWI values; the remaining ensemble members are discarded.
2. Identification, within each of the top-10 ensemble members, of areas where the SWI exceeds 2 (i.e. the cube of wind speed exceeds the 97.7th percentile compared to the reference period) for at least three consecutive days during a specific month; regions extending for less than 5% of the geographic domain under consideration are discarded.
3. Detection of an extreme windstorm event if the identified regions overlap for at least 3 of the 10 members.

It is important to note that the selection of the top-10 members with the highest SWI values is a deliberate methodological choice designed to prioritize the detection of rare, severe events. While this approach may introduce a slight bias towards overestimation, it serves a crucial purpose in potential applications of SWI for forecasting and decision support systems. Specifically, this method plays a key role in reducing false negatives—situations where an extreme windstorm event occurs but is not detected by the ensembles. In the context of severe weather events, the consequences of false negatives can be particularly dire, potentially leading to significant risks and losses.

This selection strategy, combined with the subsequent steps that require persistence both in time (at least three consecutive days) and space (at least 5% of the domain), as well as agreement among multiple ensemble members (at least 3 out of 10), provides a balanced approach. It aims to maximize the detection of extreme events while still maintaining a reasonable threshold to filter out potential false positives. In particular, the selection of the top members by their SWI values is aimed at focusing on ensemble members that may represent the most extreme atmospheric conditions in a given seasonal forecast. Importantly, the occurrence of a few days with high values of SWI is not sufficient to detect an extreme windstorm, given the uncertainty of the forecast: for this reason, we impose that at least 30% of the most extreme ensemble members agree on the area impacted by the extreme wind event. Furthermore, this event must show persistence in the forecast, both in terms of duration and in the geographic extent affected. This procedure yields a binary result, indicating whether an extreme event has been detected or not.

2.5 Testing the SWI for tropical cyclone detection

In this study, we have chosen to focus on tropical cyclone events in Mozambique, taking advantage of the seasonal forecast’s ability to capture seasonal phenomena as tropical cyclones are. In particular, we focus on the Mozambique area (from −25°S to -11°S, 31°E to 40°E, encompassing both land and ocean), selected here as a case study of relevance for the FOCUS-Africa Horizon2020 project (https://focus-africaproject.eu/, GA 869575).

The SWI index is calculated following the steps detailed in Sect. 2.1: the month parameters of the underlying Weibull distribution of SWI (Step 1 in Sect. 2.1) are calibrated on the hindcast period of SEAS5 seasonal forecasts, i.e. 1992–2016, corresponding to a 25-year reference period. Considering that SEAS5 forecasts cover a 7-month period starting from the day of the initialisation of the forecast (refer to Sect. 2.3), each month is forecasted multiple times at different lead times in subsequent forecasts. Therefore, a set of parameters is fit for each lead time, resulting in 7 distinct sets of parameters for each month of the year. Then, Steps 2 and 3 of the SWI methodology (Sect. 2.1) are applied to bias-corrected SEAS5 data (see Sect. 2.3) from January 1993 to December 2022 using the appropriate set of Weibull parameters depending on location, month, and lead time. This procedure produces a SWI dataset that spans across both the SEAS5 hindcast and forecast period. Furthermore, SWI is also calculated using ERA5 data from the same period for comparison.

Historical records of tropical cyclones impacting Mozambique are extracted from EM-DAT, by filtering for events labelled as "TROPICAL CYCLONE" within the region in the period 1993–2022. A total of 24 events matches the selection criteria. Then, we test the effectiveness of our SWI and of the methodology for extreme windstorm detection in SEAS5 seasonal forecasts as detailed in Sect. 2.4 on a list of 50 dates, comprising 24 actual EM-DAT events and 26 dates without events, randomly selected. Importantly, the dates that do not feature cyclone events include periods both outside of and during the peak cyclone season in the southwest Indian Ocean, which typically span from mid-January to early March (Holton and Hakim 2012). The procedure detailed in Sect. 2.4 is applied to different runs of SEAS5 seasonal forecasts in order to include the date to be analysed at different lead times, yielding a binary outcome (event detected/no event detected).

The procedure for detecting tropical cyclones is replicated on standardised, raw SEAS5 wind speed data, i.e. data that has not been bias-corrected with ERA5 data, without calculating SWI. In this case, standardisation is applied to daily maximum wind speed data by using the average and standard deviation related to the specific month and lead time of relevance. This approach is designed to differentiate the impact of SWI on tropical cyclone detection from that of the testing procedure used.

Finally, the effectiveness of the methodology is measured by calculating the sensitivity, specificity, and accuracy metrics. In detail, sensitivity refers to the ability of a test to correctly identify true positives (actual events that are detected), specificity measures the test's ability to correctly identify true negatives (non-cyclones that are correctly identified as such), and accuracy represents the overall proportion of correct classifications, i.e. true positive and true negative results, among all evaluated cases (Wilks 2011).

It is important to note that, in meteorology and climate science, these metrics are often referred to using different terminology: sensitivity is commonly termed the hit rate, 1 minus specificity corresponds to the false alarm rate, and accuracy is often described as the proportion correct.

3 Results

Figure 1 provides a visualisation of a SWI storm footprint calculated on ERA5 data. It depicts the maximum SWI values recorded during the period from March 8, 2022 to March 11, 2022, corresponding to the occurrence of tropical cyclone Gombe (see e.g. Reliefweb,

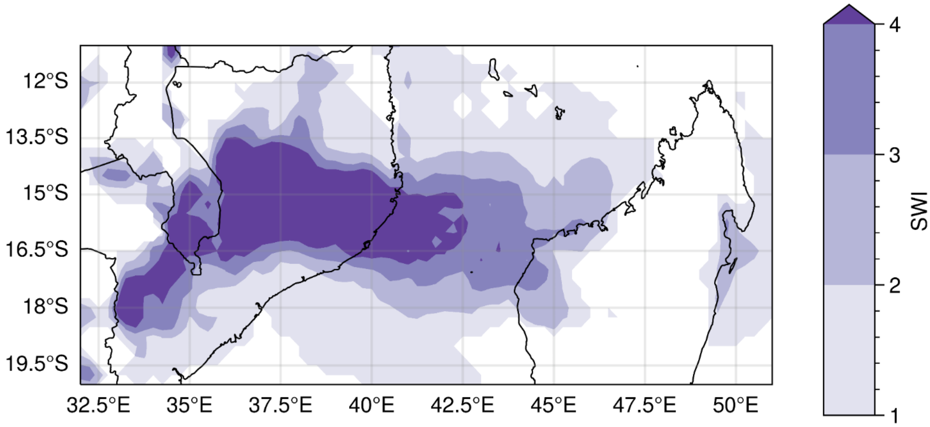

Fig. 1 Footprint of Tropical Cyclone Gombe (March 8, 2022 to March 11, 2022) as maximum SWI values during the period calculated using ERA5; only SWI values > 1 (i.e. cube of wind speed exceeding one standard deviation compared to historical data) are depicted

Table 1 Sensitivity, specificity, and accuracy metrics for the tropical cyclone detection procedure applied on SWI computed on bias-corrected SEAS5 data, as detailed in 2.4

Lead time	Sensitivity	Specificity	Accuracy
0	37.5%	88.5%	64.0%
1	37.5%	100.0%	70.0%
2	29.2%	96.2%	64.0%
3	30.4%	92.3%	62.0%
4	30.4%	84.6%	58.0%
5	43.5%	88.5%	66.0%
6	30.4%	88.5%	60.0%
Average	34.1%	91.2%	63.4%

2022, and the Tropical Cyclone Gombe map from the European Commission's Emergency Response Coordination Centre (ERCC) issued on 14/03/2022). The SWI correctly describes the dynamics of this severe weather event, including the landfall on the eastern coast of Madagascar, its subsequent transformation into a lower-intensity tropical depression (SWI values lower than 1), and passage over Madagascar with this intensity. After crossing Madagascar, it intensified again into a severe tropical cyclone off the coasts of Mozambique. After landfall, Gombe penetrated inland reaching Malawi, turned southward, and re-entered the ocean, once again downgraded to a tropical depression.

Table 1 presents the results of the tropical cyclone detection test in Mozambique on bias-corrected SEAS5 seasonal forecasts for the 50 mixed dates in the period 1993–2022, which includes both cyclone events and non-event days. No clear pattern emerges by examining the sensitivity, specificity, and accuracy metrics across different lead times: slightly higher values of these metrics are found at lead times 0 and 1 (i.e. when the event occurs in the same month as the forecast's initialisation). The values of the metrics tend to decrease at lead times 2 to 4, and increase again at lead time 5. However, this apparently parabolic behaviour entails rather small variations: therefore, only lead time-averaged sensitivity, specificity, and accuracy values will be discussed further.

Table 2 Sensitivity, specificity, and accuracy metrics for the tropical cyclone detection procedure applied on raw, standardised wind speed data from SEAS5 data, as detailed in 2.4. The values shown are averaged on lead time

	Sensitivity	Specificity	Accuracy
Average	100%	0.5%	42.8%

The lead time-averaged sensitivity score is 34.1%, indicating that, out of the 24 tropical cyclone events from the EM-DAT records, only about 8 are correctly classified as such. The specificity score averaged across lead times is 91.2%, meaning that about 24 out of 26 cases are recognised as true negatives. The overall accuracy, i.e. correct cyclone-no cyclone classifications, is 63.4%.

The performance metrics reveal a significant trade-off in the detection capabilities of the SWI-based methodology. While the SWI-based detection method demonstrates a marked improvement in reducing false alarms (as evidenced by the high average specificity of 91.2%), this comes at a significant cost: approximately two-thirds of actual tropical cyclone events are missed (sensitivity of only 34.1%). This trade-off between false alarm reduction and event detection represents a crucial limitation of the current methodology. From an operational forecasting perspective, missing two-thirds of tropical cyclone events could have serious implications for disaster preparedness and risk management. This highlights the need for further refinement of the detection methodology to achieve a better balance between false alarm reduction and event detection capability.

Table 2 shows the outcomes of the application of the tropical cyclone detection methodology on standardised raw wind speed data from SEAS5 in terms of sensitivity, specificity, and accuracy. The sensitivity metric, which measures the proportion of actual positive cases correctly identified, shows a lead time-averaged value of 100%, indicating that each tropical cyclone event considered is correctly identified by the methodology. However, the specificity—the ability of correctly rejecting non-events—is nearly zero, meaning that almost all dates are systematically classified as cyclone events, regardless of ground truth. The overall rate of correct classifications, represented by the accuracy metric, is about 43%.

When comparing the averaged values in Table 2 with those in Table 1, focusing on the accuracy metric, it is evident that the cyclone detection procedure applied to raw standardised SEAS5 result in accuracy lower than a random guess (42.8%). However, the application of said procedure to SWI data significantly improves the accuracy (63.4%), representing a consistent improvement in overall correct classifications compared to raw SEAS5 data.While accuracy is a commonly used metric that accounts for both true positives and true negatives, we recognise its limitations, particularly for rare events such as tropical cyclones. The improvement observed is largely due to enhanced performance in detecting true negatives, while the sensitivity remains consistently high. Although alternative skill scores could offer additional perspectives, we maintain that the accuracy metric, applied consistently across datasets, provides a valid basis for comparison in this preliminary study."

4 Conclusions and discussions

This preliminary study introduces the Standardised Windstorm Index (SWI), a novel approach to quantify the impact of extreme wind events in different geographical regions. Differently from similar indices, our SWI can be easily applied to gridded data such as climate model products, and yields results that enable comparisons between different extreme wind events as well as across geographic regions. In fact, our SWI accounts for the inherent variability and skewness of the wind speed distribution in different regions and seasons by fitting wind speed data with the Weibull distribution. This choice is aimed at improving the description of the typical distribution of wind speed, which is indeed often skewed with a long tail towards higher values. This characteristic is something that the standard normal distribution methods cannot describe correctly. This approach ensures that extreme wind events are effectively identified and quantified, making SWI a robust and reliable tool to assess the likelihood and impact of windstorms.

Our analysis on the Southern African Development Community (SADC) demonstrates the ability of the SWI to enhance the accuracy of seasonal forecasts in detecting tropical cyclones and other extreme wind events. Compared to standardised, non-bias-corrected seasonal forecasts, the application of SWI on bias-corrected SEAS5 improves the accuracy metric by more than 20%, reflecting its potential to increase correct classifications of cyclone/no-cyclone events. It is important to note, however, that this improvement stems primarily from better performance in rejecting non-events, while the detection of cyclones remains robust. Future work will explore additional skill scores, such as the equitable threat score (ETS) or critical success index (CSI), to provide a stronger evaluation of SWI's performance for rare event detection.Despite these promising results, it is important to recognise that this study is preliminary. Further analyses and refinements are needed to improve the robustness and applicability of the SWI. First, a criticality could be represented by the reference dataset used for the bias correction of SEAS5 seasonal forecasts. Here we use ERA5, yet we acknowledge that it incorporates relatively few observations from the SADC area (Roffe and van der Walt 2023), which may lead to inaccuracies in the bias-corrected, downscaled wind speed data used to compute SWI. This emphasises the need for more comprehensive observational data from the region to improve the quality of the bias correction and subsequent SWI calculations.

Furthermore, the extreme storm detection method described in Sect. 2.4 might have some limitations. One of the most important assumptions is the selection of the top-10 ensemble members based on SWI values: while this method extracts the members that are most likely to forecast extreme wind events, it may not fully capture the variability and uncertainty within seasonal forecasts.

The results obtained with bias-corrected SEAS5 suggest that the sensitivity, specificity and accuracy of tropical cyclone detection are relatively independent of the lead time. This could be due to the inherent uncertainties in seasonal forecasts and the complex nature of tropical cyclone formation and development. Further research is needed to understand these dynamics and improve the lead-time-specific performance of the SWI. The use of EM-DAT datasets as a validation tool is also subject to limitations. Indeed, EM-DAT only records events with a significant impact, e.g. events that cause at least 10 fatalities, affect at least 100 people, require a country to declare a state of emergency or to request international assistance. This threshold can exclude less severe but still impactful wind events, potentially limiting the completeness of our validation.

The SWI developed in this preliminary work shows great potential for improving the detection and analysis of extreme wind events. However, some methodological and data-related limitations need to be addressed. Future work should aim to refine the cyclone detection procedure and incorporate more extensive observational data, to enable full exploitation of the SWI, both as a standalone index and in multi-hazard frameworks, for climate risk management and adaptation.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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