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Proceeding Paper

Verification of the Short-Term Forecast of the Wind Speed for the Gibara II Wind Farm according to the Prevailing TSS †

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Abstract: In Cuba, short-term predictions have been developed for wind speed in the Gibara wind farms. These predictions present an absolute mean error (MAE) that sometimes exceeds 3 m/s. This study has the aim of verify the wind forecast generated by SisPI using the Synoptic Situation Types Catalog (TSS), a wind speed observation data provided by the anemometers installed in the wind turbine. The study period spanned from May 2020 to April 2021. For the evaluation were used the metrics: root mean square error (RMSE) and MAE, and the analysis was made in the rainy and dry seasons, through the methodology developed by Patiño, (2023). Results indicate that the subtype 3 (Extended undisturbed anticyclonic flow) was the one with the highest frequency of cases between very good and good in both seasonal periods. Subtype 19 (migratory anticyclone in an advanced state of transformation) was the system that produced the worst results in the dry season, with the largest number of cases of bad wind speed forecasts. The results of the statisticians: bias (BIAS) and Pearson's Correlation Coefficient (R), were very favorable.

Keywords: wind energy; short-term forecast; wind speed; types of synoptic situations

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1. Introduction

Wind energy is a renewable source that harnesses the power of the wind to generate electricity. However, from an energy perspective, wind exhibits significant variations in both time and space. These variations can be quite pronounced even over short periods, which means that wind energy generation can be intermittent and subject to large changes in short spans. This, in turn, suggests that accurately predicting the amount of energy that wind farms will generate can be a challenging task.

Unlike other power plants, which can adjust their production according to demand, wind farms are at a disadvantage due to their intermittent nature. This situation has led to the need for developing wind forecasting models that allow for more accurate prediction of the amount of energy that will be generated at any given time. In this way, the aim is to minimize the impact of wind variability on the operation of wind farms and ensure a constant supply of electricity.

According to the most recent report from the Global Wind Energy Council (GWEC, 2023), 77.6 GW of wind power capacity was added to electrical grids in 2022. This resulted in a 9% increase in the total installed wind power capacity, which now stands at 906 GW compared to the previous year, 2021.

Cuba, on its part, has 4 experimental wind farm installations with a total capacity of 11.8 MW. Out of these, the ones installed in northern Holguin, Gibara I and II (9.6 MW), have achieved an annual capacity factor exceeding 27% (Ministerio de Energía y Minas, 2021).

Having accurate wind speed forecasts is essential due to the significant economic investments made in the Gibara region. These forecasts play a crucial role in predicting the amount of energy generated by wind farms, which is vital for the daily planning of the National Load Dispatch (DNC).

Currently, short-term forecasts for wind energy production are widely used internationally. One of the most relevant projects in this field is ANEMOS (Giebel et al., 2011), whose main objective was to develop advanced prediction models that improve upon existing tools. Additionally, there are other important works in this area, such as those conducted by Senkal & Ozgonenel (2013), Xiaodan et al., (2013), Sapronova et al. (2015), Li et al., (2016), Xie et al., (2021), Li et al., (2022) Lv et al., (2023), Saini et al., (2023), and Wang et al., (2023).

In Cuba, studies have been conducted to predict short-term wind in wind farms, as in the case of Roque et al., (2015a, 2015b, 2016), Martínez & Roque, (2019), Fuentes et al., (2022), Sierra et al., (2023), and Roque et al., (2022), where it was found that improving the resolution of the SisPI model (WRF) to 1km yielded better results compared to previous studies. However, there were days when the forecast was not accurate, with errors exceeding 4 m/s at a resolution of 3km. In order to understand the causes of this behavior, a study was carried out by Patiño, (2023). In this work, wind speed forecasts based on MAE were analyzed in relation to TSS as the main wind generating factor in Cuba. The study was conducted in the Gibara I Wind Farm during the period from May 2020 to April 2021.

To expand on the previous research, it was decided to extend the study to the Gibara II Wind Farm, using additional metrics to gain a more comprehensive understanding of the forecasts, considering that one of the possible factors influencing accurate forecasts is the behavior of synoptic-scale winds, which may not be well represented by the forecast model, and therefore, the results may not be as expected.

2. Materials and Methods

The Gibara I and Gibara II wind farms are located in the province of Holguin, near the coastline, about 300 meters away, and have an elevation of 3 meters above sea level. The Gibara II Wind Farm (PEGII), manufactured by GOLDWIND, has a capacity of 4.5 MW and has six wind turbines.

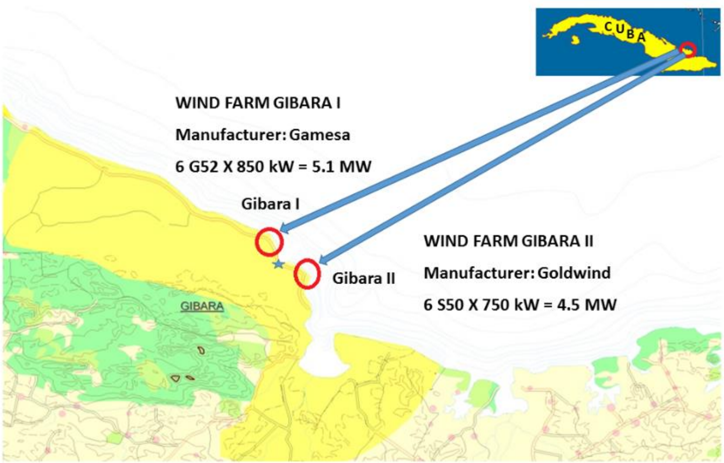


Figure 1. Location of the Gibara I and II wind parks in the Holguin province (Patiño, 2023).

2..1. Data Used

The research period spanned from May 1, 2020, to April 30, 2021. During this period, the Gibara II Wind Farm (PEGII) had its 6 wind turbines in operation.

Hourly wind speed values from anemometers located on the nacelles of the wind turbines, at a height of 55 meters, were used. Hourly wind speed forecast values were provided by the Immediate Forecast System (SisPI), which uses the Weather Research and Forecasting (WRF) atmospheric model.

The subTSS database was provided by Soler et al., (2020), as well as the Catalogue of Synoptic Situation Types, where they are characterized. However, in this study, we used the thirteen subTSS that were observed daily in Gibara during the 2020-2021 research period, which are included in Patiño, (2023) study, and are shown in Table 1 and Figure 2.

Table 1. Subtipos de Situaciones Sinópticas que se presentaron en Gibara (Patiño, 2023).

No	SubTSS
1	Subtropical anticyclone with first quadrant flow
2	Subtropical anticyclone with second quadrant flow
3	Extended undisturbed anticyclonic flow
4	Extended flow in the divergent sector of waves
5	Weak barometric gradient
6	Influence of a tropical cyclone
7	East waves and troughs
8	West convergence and troughs
13	Classic cold front
14	Reverse cold front
17	Migratory continental anticyclone
18	Migratory anticyclone in the process of transformation
19	Migratory anticyclone in an advanced stage of transformation

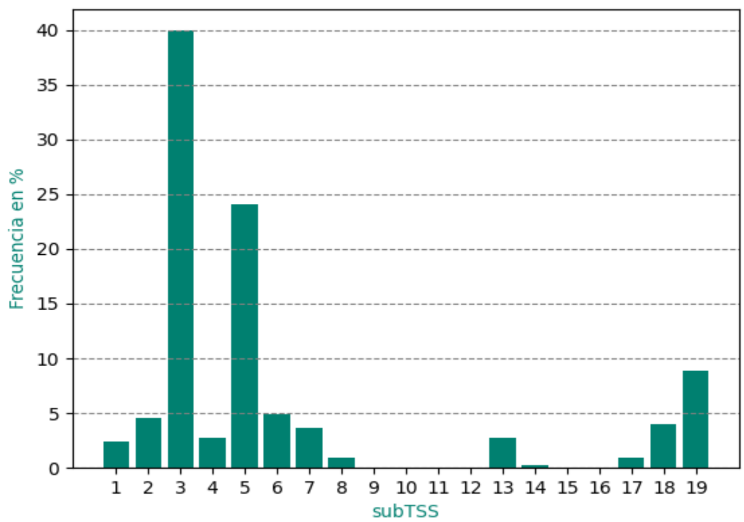


Figure 2. Annual behavior of the SubTSS in the study period (May 2020 to April 2021) (Patiño, 2023).

2.2. Immediate Forecast System (SisPI)

Wind speed forecast data were generated by SisPI, a system that predicts short-term weather phenomena. This system has a forecast range of 24 hours, with four daily updates every six hours (0000, 0600, 1200, and 1800 UTC) and three domains with resolutions of 27, 9, and 3 km. SisPI is initialized with data from the Global Forecast System (GFS) and uses the Weather Research and Forecasting (WRF) atmospheric model, widely used in wind resource research around the world Sierra *et al.*, (2017).

2.3. Used Metrics

The metrics used were: Mean Absolute Error (MAE) (1); Root Mean Square Error (RMSE) (2); Bias (BIAS) (3); Pearson correlation coefficient (R) (4).

$$EMA = \frac{1}{n}\sum_{i-1}^{n}|\hat{x}_i - x_i| \quad \textbf{(1)}$$

$$RMSE = \frac{1}{n}\sum_{i-1}^{n}(\hat{x}_i - x_i)^2 \quad \textbf{(2)}$$

$$BIAS = \frac{1}{n}\sum_{i-1}^{n}(\hat{x}_i - x_i) \quad \textbf{(3)}$$

$$R = \frac{\sum(x_i-\overline{x_i})(y_i-\overline{y_i})}{\sqrt{\sum(x_i-\overline{x_i})^2(y_i-\overline{y_i})^2}} \quad \textbf{(4)}$$

Where $\boldsymbol{x\hat{}i}$ is the observed value and $\boldsymbol{xi}$ is the forecast value at time $\boldsymbol{i}$.

2.4. Methodology

Based on the subTSS that occurred in Gibara during the research period conducted by Patiño, (2023), the same methodology used by the author was applied. Firstly, the daily variation of wind speed for the specific area was studied. Subsequently, the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) of the wind speed forecast in Gibara II were determined, and their behavior with respect to the subTSS was analyzed. In such a way that the MAE and RMSE could be classified as very good if the values were between 0 and 1 m/s; good between 1 and 2 m/s; fair between 2 and 3 m/s; and poor when the values were greater than 3 m/s. The values classified as fair and poor with respect to the subTSS were analyzed in the two seasonal periods (PLL) and (PPLL) to determine if there was any relationship between them. Finally, unlike Gibara I, the BIAS and R statisticians were analyzed in this research.

3. Discussion of Results

3.1. Analysis of Wind Speed Behavior in Gibara during the Period from May 2020 to April 2021

Figure 3 shows that wind speed in Gibara decreases during the early hours of the morning until 7:00 am local time, similar to Gibara I in the previous study conducted by Patiño, (2023). This behavior was pointed out by Carrasco et al., (2011); Roque et al., (2015); Martínez et al., (2015). These authors explain that this decrease is due to the interaction between the predominant synoptic flow and the local circulation of sea breezes on the north coast. Starting at 7:00 am local time, wind speed begins to increase and reaches its maximum value at 3:00 pm local time, but after 5:00 pm local time, it decreases again.

In addition, the figure also shows that the highest values of wind speed occur during the characteristic period of the passage of frontal systems and the presence of the Migratory Continental Anticyclones, which was reported by Rodríguez & Perdigón (2011). Despite these differences, the average maximum values occur at the same times in both analyzed periods.

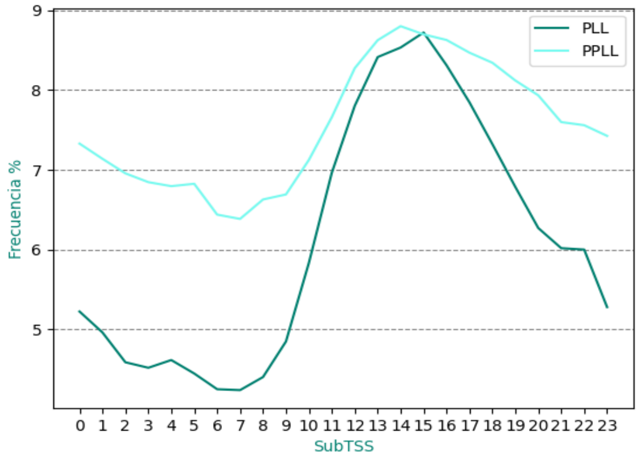


Figure 3. Daily wind speed behavior in PEGII during the period (May 2020 to April 2021).

3.2. Forecast Behavior of Wind Speed in the Period from May 2020 to April 2021 through MAE Analysis

Figure 4 shows that the forecasts of the studied cases were classified as very good in 10.4% of the cases; good in 53% of the cases; regular in 26.8% of the cases, and 9.8% of the cases were classified as bad.

In more detail, more than 60% of the forecasts resulted in very good and good classifications, a significant figure. However, around 37% of the remaining forecasts were classified as regular and bad, which represented a considerable percentage and focused the analysis on the relationship or link of each subTSS with the classified forecast (figure 5).

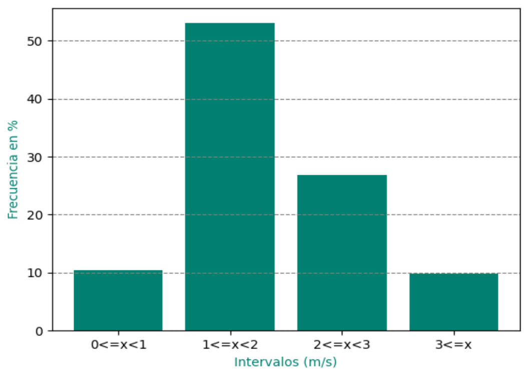


Figure 4. Frequency of the MAE statistic in 4 defined intervals for PEGII.

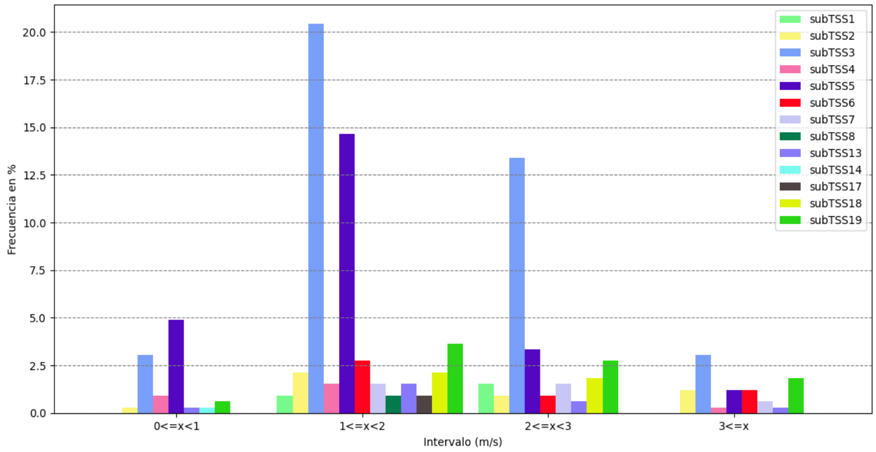


Figure 5. Frequency of the MAE statistic associated with the SubTSS.

In general, it was noted that subtypes 3 and 5 were the most predominant and were present in all analyzed intervals. Of all the subtypes presented during the period, 8 (Convergence and west troughs), 14 (Reversing cold front), and 17 (Migratory continental anticyclone) did not show MAE values in the range of regular and bad. It was also found that subtypes 1 (Subtropical anticyclone with first quadrant flow) and 18 (Migratory anticyclone in the process of transformation) were never classified as bad by the MAE. This indicates that the SisPI had a good performance in representing these subTSS, despite their low frequencies of occurrence.

3.3. Analysis of the Association between MAE and subTSS in the Rainy Period (RP) and Less Rainy Period (LRP)

3.3.1. Rainy Period (RP)

Figures 6 and 7 show the frequency distribution of MAE for the RP of May-October 2020. It presented a similar distribution to what was found for the annual case, with the good interval being the most frequent. 64.6% of the cases were classified as very good and good, while 35.4% were considered regular and bad.

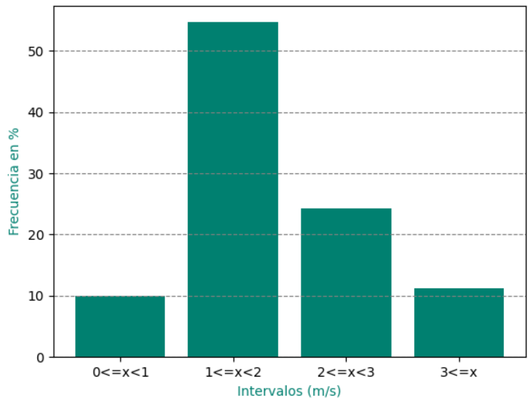


Figure 6. Frequency distribution of the MAE statistic for the Rainy period (May - October 2020).

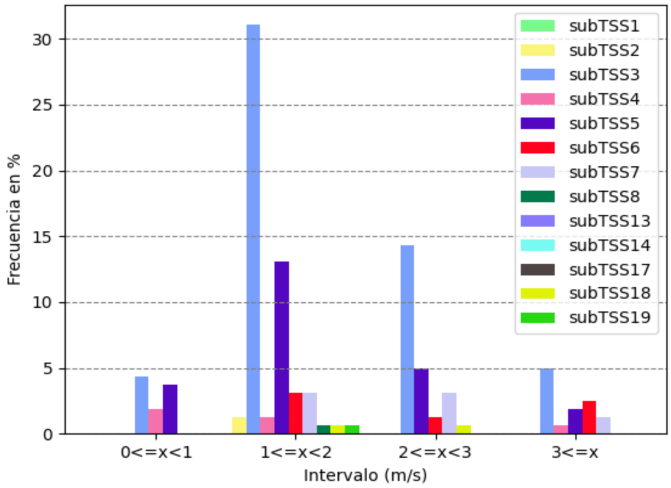


Figure 7. Behavior of the MAE statistic in the rainy period according to the SubTSS (May - October 2020).

3.3.2. Less Rainy Period (LRP)

Figures 8 and 9 show the association between MAE and subTSS for the LRP, displaying a similar behavior to what has been analyzed so far. Once again, the intervals of very good and good encompassed the majority of cases, with 62.3%, while 37.7% represented the cases of regular and bad.

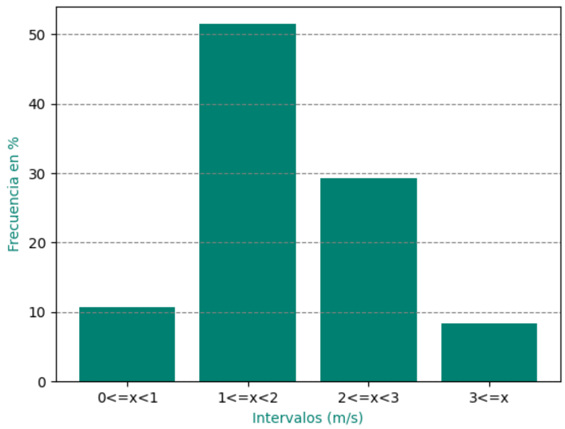


Figure 8. Frequency distribution of the MAE statistic for the Less Rainy period (November 2020 - April 2021).

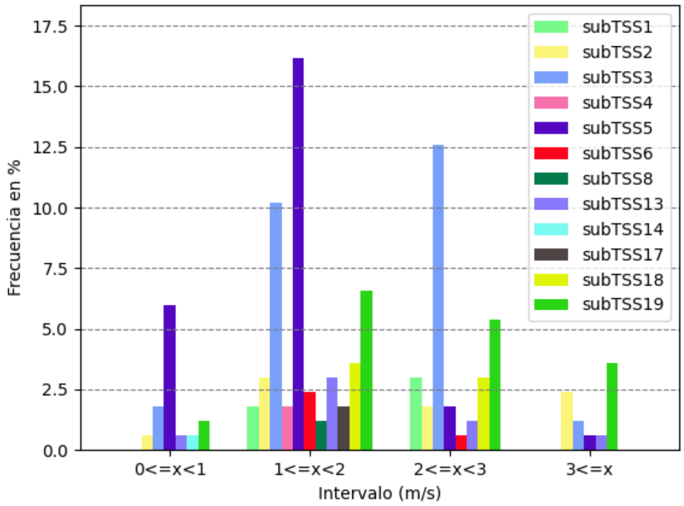
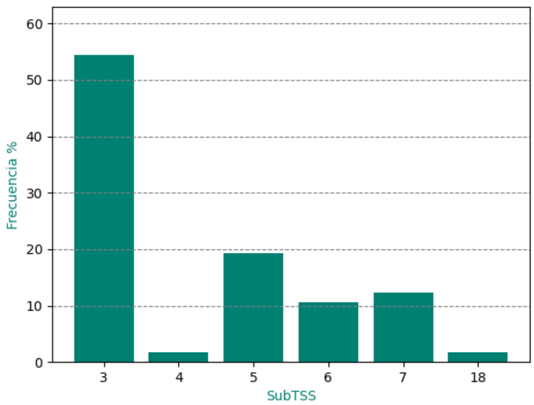


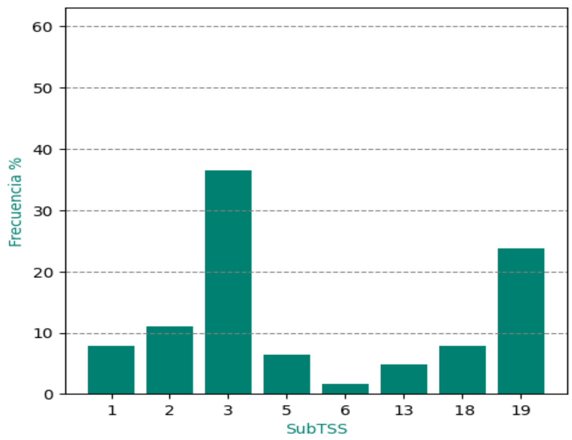
Figure 9. Behavior of the MAE in the Less Rainy period according to the SubTSS (November 2020 - April 2021).

3.3. Analysis of the Association between Regular and Bad MAE Values and subTSS in the Rainy Period (RP) and Less Rainy Period (LRP)

Considering that the cases classified as regular and bad represented around 37% of the entire sample studied, it was of interest to determine if there was any preferential relationship between the behavior of MAE and subTSS in either of the two seasonal periods for Cuba. The results for the RP and LRP are shown in figure 10.



(a)



(b)

Figure 10. Frequency distribution of regular and bad MAE cases by TSS subtypes for the rainy period (a) and the Less Rainy period (b).

3.3.1. RP Analysis

In figure 10a, it can be observed that over 50% of the cases with a MAE between regular and bad corresponded to subtype 3, around 20% to subtype 5, approximately 12% to subTSS 7, about 11% to subTSS 6, and the rest with less than 5%. It was noteworthy that subtype 3 continued to have a high incidence of cases with a MAE index classified as regular and bad. This trend could be related to the lack of precision of SisPI in correctly predicting the position of the subtropical ridge, as pointed out by Paula, (2021). However, it is important to note that this statement requires further experiments to confirm it in the context of this study.

3.3.2. LRP Analysis

Despite the low frequency of subTSS 19 in the study year, this subtype had a high percentage of cases where the wind speed forecast was classified as regular and bad according to the MAE, indicating that attention should be paid to this subtype by SisPI developers and weather forecasters in general.

3.4. Wind Speed Forecast Behavior during the Period May 2020–April 2021 through RMSE Analysis

Similar to the MAE analysis, it was decided to apply this classification of forecast error to analyze the root mean square error (RMSE).

Figure 11 illustrates the performance of the examined cases. A percentage greater than 42% of the forecasts were classified between very good and good, reflecting more favorable results. It is important to note, however, that 58% of the forecasts were classified as regular or bad, which motivated a more detailed analysis.

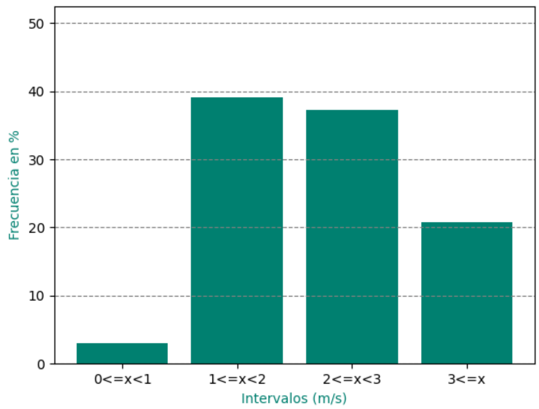


Figure 11. Frequency of the RMSE statistic.

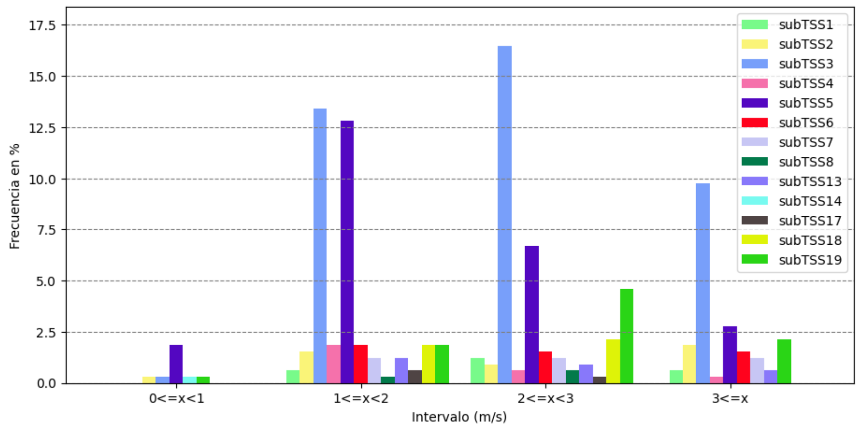


Figure 12. Frequency of the RMSE statistic associated with the SubTSS.

The dynamics of RMSE in relation to the TSS subtypes are shown explicitly in Figure 12. In general terms, subtypes 3 and 5 presented the highest prevalence.

3.5. Analysis of the Association between RMSE and subTSS in the Rainy Period (RP) and Dry Period (DP)

3.5.1. Rainy Period (RP)

Figures 13 and 14 show the frequency distribution of RMSE for the RP corresponding to the period May-October 2020. 40.4% of the cases were classified as very good and good, while 59.6% were considered as regular and bad.

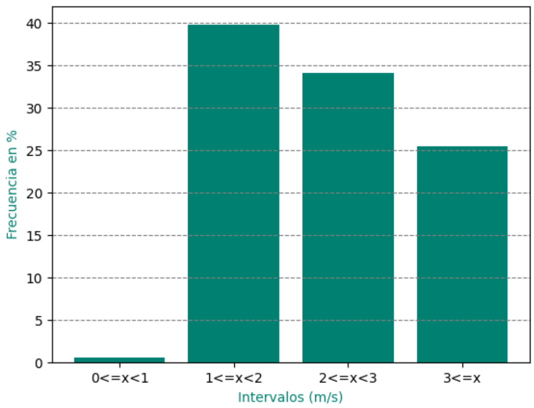


Figure 13. Frequency distribution of the RMSE statistic for the Rainy period (May - October 2020).

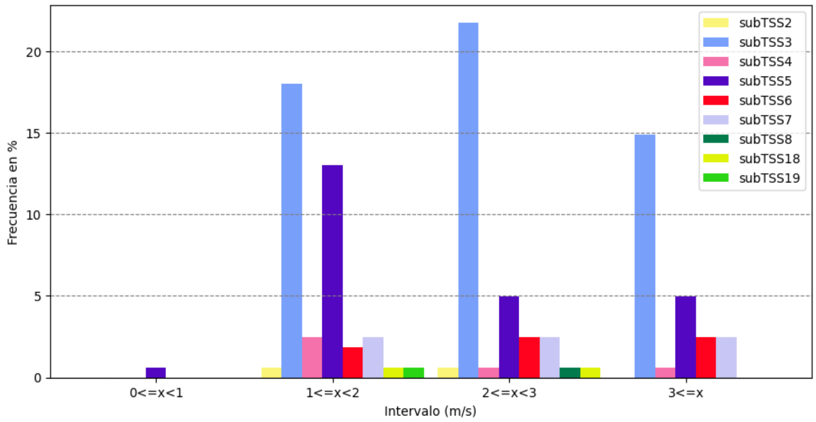


Figure 14. Frequency distribution of the RMSE statistic for the Rainy period (May - October 2020).

3.5.2. Dry Period (DP)

Figures 15 and 16 show the relationship between RMSE and subTSS in the DP. 43.7% were considered as very good and good, while 56.3% were categorized as regular and bad.

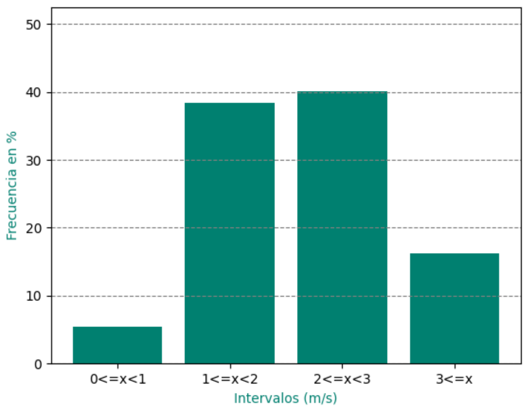


Figure 15. Frequency distribution of the RMSE statistic for the Less Rainy period.

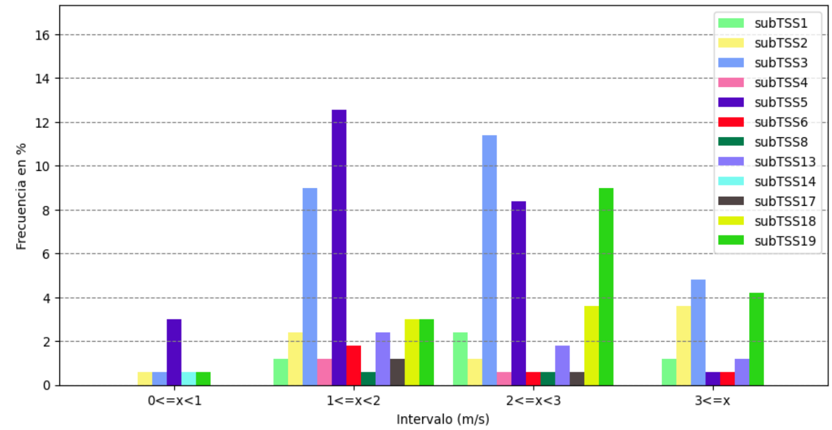
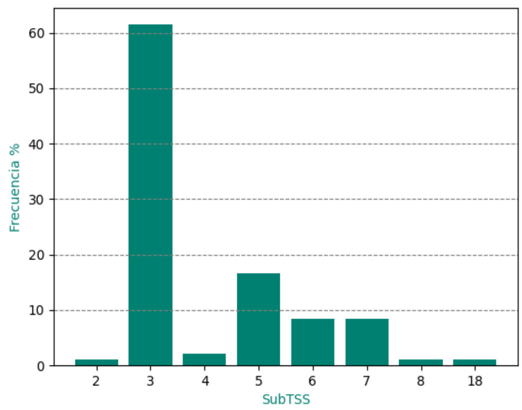


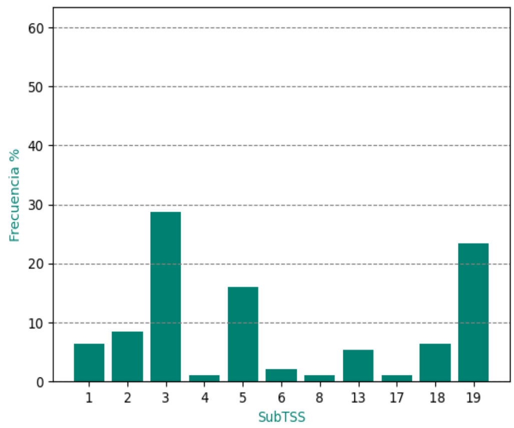
Figure 16. Behavior of the RMSE in the Less Rainy period according to the SubTSS (November 2020 - April 2021).

3.6. Analysis of the Association between Bad and Regular RMSE Values and subTSS in the Rainy Period (RP) and Dry Period (DP)

It is noteworthy that a high percentage of cases showed results between regular and bad, representing 58% of the analyzed sample. Therefore, it was considered necessary to further analyze these cases. Similar to the approach used in the MAE study, the analysis was carried out considering the two seasons of the year in Cuba, with the aim of evaluating if there was any correlation between the behavior of RMSE and subTSS during seasonal periods. The results during the Rainy Period (RP) and Dry Period (DP) are presented clearly in Figure 17.



(a)



(b)

Figure 17. Frequency distribution of regular and bad RMSE cases by TSS subtypes in the rainy period (a) and the Less Rainy period (b).

3.6.1. Analysis of RP

Figure 17(a) shows that subTSS 3 has a prevalence greater than 60%. While subTSS 5 is evident with more than 15%. The remaining subtypes had less than 10% of the instances. Subtype 3, similar to the MAE analysis, concentrates the majority of cases with regular or bad RMSE, indicating a possible relationship with the tendency of SisPI to not correctly predict the position of the subtropical high, as indicated in the MAE observation.

3.6.2. Analysis of DP

When examining the behavior of RMSE for the cases of regular and bad in the DP (Figure 17(b)), it can be observed that although subTSS 3 has decreased its frequency to less than 30%, demonstrating a lower presence compared to RP, it still prevails among the cases of regular and bad classification. This suggests that subTSS 3 is better represented by SisPI in this period of the year. However, the analysis highlights subTSS 5 with around 15%.

3.7. Behavior of Wind Speed Forecast in the Period from May 2020 to April 2021 through BIAS Analysis

The analysis of the BIAS statistic (Figure 18) allows us to see a general trend, where an overestimation is observed in all hours.

It was evident that subTSS 19, which represented more than 20% of the cases, had a significantly high frequency of wind speed forecasts classified as regular or bad, despite its low frequency in the year of study, indicating that this subtype is being poorly represented by SisPI and should receive more attention. The rest of the subTSS had frequencies below 10%.

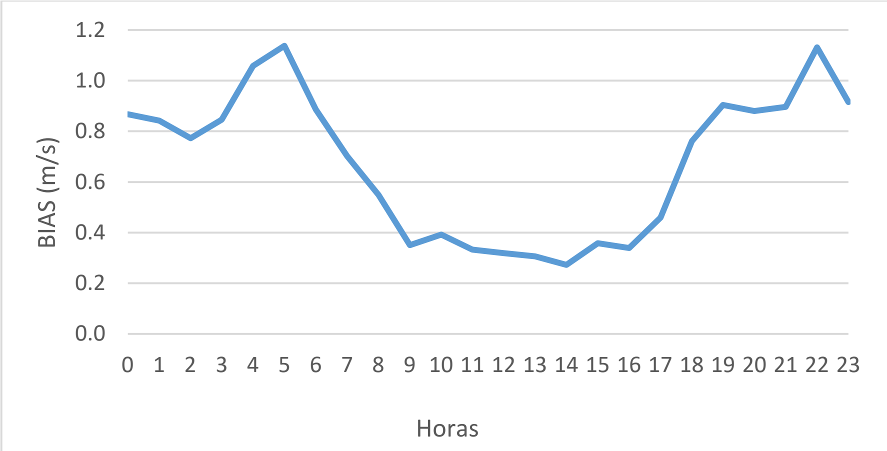


Figure 18. BIAS of wind spee.

The forecast overestimation was most noticeable during the early hours until 9 am, and then in the evening-night between 6 pm and 11 pm, with a behavior between 0.3 m/s and 1.2 m/s. In the timeframe from 9 am to 5 pm, the behavior was more favorable, as it was closer to zero. This behavior turned out to be better compared to what was found by (Roque et al., 2022), whose BIAS values for PEGI and PEGII were underestimated in all timeframes, with a behavior between 0m/s and -4m/s.

3.8. Behavior of Wind Speed Forecast in the Period from May 2020 to April 2021 through R Analysis

Figure 19 shows the Pearson correlation coefficient R, the other analyzed statistic. It is easy to appreciate that there is a positive correlation, with values greater than 0.7 in the early morning hours until 9 am, from which the values begin to decrease to approximately 0.5 m/s at 5 pm, after which they start to increase again up to 0.7m/s.

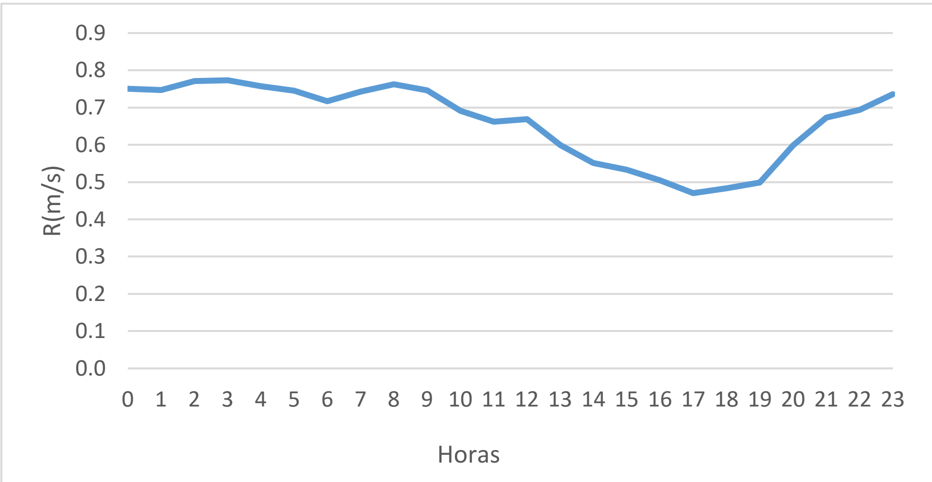


Figure 19. Pearson correlation coefficient between the values predicted by the model and the actual measurements.

4. Conclusions

The research conducted yielded the following conclusions:

- •It was obtained that, in the case of MAE, 63.4% of the wind speed forecasts were classified as very good or good, while 36.6% were classified as regular and bad, which reflects the good representation of most subTSS by SisPI. However, for RMSE, it was obtained that 42% of the values fell between very good and good, and 58% of the forecasts were classified as regular and bad, which was not as favorable.

- The MAE analysis of the cases classified as regular and bad for both seasonal periods yielded well-defined results, highlighting subtype 3 (Unperturbed Extended Anticyclonic Flow) which represented over 50% of the cases in PLL and just over 35% in PPLL, reflecting the improvement by SisPI in forecasting this subtype in the low rainfall period. In the case of RMSE analysis, it was obtained that this subtype had a prevalence of over 60% in PLL and less than 35% in PPLL, showing a lower presence compared to PLL.
- Subtype 19 was the system that achieved the worst results, as despite its low frequency in the study year, over 50% of the days it was present, the wind speed forecast was classified as regular and bad.
- In the case of BIAS analysis, both parks showed a favorable behavior, with overestimated values between 0 and 1.2 m/s. On the other hand, in the R analysis, it also showed good behavior, between 0.4 and 0.8 m/s.

5. Recommendations

- Share the results of this research with SisPI developers, as well as with weather forecasters in general.
- Further investigate the relationship between TSS and forecast errors through new experiments.
- Incorporate the underlying subTSS into wind speed forecas.

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