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ARTICLE

Meteorological Determinants of $PM_{2.5}$ and PM_{10} Concentrations During the Transition Season in Campo Grande, Central Brazil

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ABSTRACT

Air pollution remains a pressing environmental issue in Brazilian cities, particularly during the dry season when meteorological conditions favor pollutant accumulation. This study investigates the influence of meteorological variables on $PM_{2.5}$ and PM_{10} concentrations in the urban atmosphere of Campo Grande, Mato Grosso do Sul, Brazil, during the transition period between the wet and dry seasons (March to June 2021). Data were obtained from the air quality monitoring station at the Federal University of Mato Grosso do Sul (UFMS), including daily measurements of particulate matter and meteorological parameters such as temperature, humidity, precipitation, atmospheric pressure, wind speed, and wind direction. Descriptive statistics, Pearson's correlation, multiple linear regression, and Principal Component Analysis (PCA) were employed to explore the relationships between meteorological drivers and particulate matter. Results revealed that relative humidity and precipitation are negatively correlated with PM concentrations, indicating their role in atmospheric cleansing through wet deposition. Conversely, wind speed and atmospheric pressure were positively associated with PM levels, suggesting pollutant transport or accumulation under stable atmospheric conditions. The $PM_{2.5}/PM_{10}$ ratios of 0.55 (1-hour) and 0.44 (24-hour) point to a predominance of fine particles from anthropogenic sources. The findings highlight the complexity of pollutant-meteorology interactions and underscore the need to incorporate meteorological data into air

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quality forecasting and management strategies. This approach is especially critical for medium-sized tropical cities that experience seasonal climate extremes and are subject to both urban and biomass-burning emissions.
Keywords: Air Pollution; Particulate Matter; Meteorological Variables; Statistical Analysis; Campo Grande; Particulate Matter ($PM_{2.5}$, PM_{10}); Tropical Urban Climate

1. Introduction

Particulate matter (PM), particularly $PM_{2.5}$ and PM_{10}, poses significant environmental and public health challenges worldwide. These pollutants are associated with respiratory and cardiovascular diseases and are influenced by both anthropogenic sources and meteorological conditions [1–4]. Understanding the interactions between atmospheric variables and PM concentrations is essential for improving air quality management, especially in tropical urban environments that experience pronounced seasonal variability.

Meteorological factors—including temperature, relative humidity, wind speed, atmospheric pressure, and precipitation—play crucial roles in the dispersion, transformation, and removal of airborne particles [5,6]. Several studies in Brazilian metropolitan areas such as São Paulo, Rio de Janeiro, Porto Alegre, and Rondonópolis have demonstrated significant relationships between weather conditions and PM dynamics [7–11]. However, most of these investigations have been limited to large cities with dense monitoring networks, leaving medium-sized cities underrepresented despite their growing environmental and health challenges.

Moreover, methodological limitations remain. Many studies rely on descriptive statistics or simple correlations, with limited application of multivariate techniques that capture the complexity of pollutant-meteorology interactions. Principal Component Analysis (PCA), for example, has rarely been applied in Brazilian cities to simultaneously analyze $PM_{2.5}$, PM_{10}, and meteorological drivers. This gap is particularly relevant in the Cerrado biome, where seasonal droughts, biomass burning, and strong climatic variability play decisive roles in air quality [12–14].

Given these gaps, this study evaluates the temporal variability of $PM_{2.5}$ and PM_{10} concentrations and their relationship with meteorological variables during the transition season (March to June 2021) in Campo Grande, a mid-sized city in Central Brazil. By integrating descriptive statistics, regression models, and PCA, we provide one of the first assessments of how meteorological drivers influence particulate matter in this tropical environment. The results contribute to advancing methodological approaches and offer evidence to guide regional air quality management and public health strategies.

2. Materials and Methods

2.1. Study Area

Campo Grande (20°27′ S, 54°36′ W, 530 m altitude) has a humid tropical climate with distinct rainy (summer) and dry (winter) seasons. Summers are hot and humid (average > 25 °C), while winters are dry (15–20 °C). With a population density of ~95 inhabitants/km^2 and a high urban Human Development Index, the city's economy relies on agriculture and services, contributing to PM emissions via vehicular traffic and biomass burning [14].

2.2. Experimental Part: Location and Sampling Period

The Air Quality Monitoring Station of the Federal University of Mato Grosso do Sul (EMQAr) is located on the UFMS main campus in Campo Grande, State of Mato Grosso do Sul (MS), Brazil (20°27′ S, 54°36′ W; 530 m above sea level). The surroundings combine vegetated areas with nearby roads, parking lots, and campus activities, providing a representative environment influenced by both natural and anthropogenic emission sources.

The sampling campaign was carried out from May to December 2021, covering the transition from the dry season to the onset of the wet season. This period allowed the assessment of seasonal variability in particulate matter and meteorological conditions. Continuous 24 h measurements were classified into **daytime (06:00–18:00)** and nighttime (18:00–06:00) periods, enabling comparative analysis of diurnal and nocturnal atmospheric processes (**Figure 1**).

Figure 1. Photo by EMQAr of the UFMS campus, Campo Grande, MS, Brazil.

Source: UFMS Institute of Physics. https://lca-infi.ufms.br/qualiar/ (accessed on 26 June 2025).

(The photograph is at a public place at the Federal University of Mato Grosso do Sul, Brazil. Thus, it is free to use at any time and requires no copyright)[15].

Meteorological and air quality data were continuously collected at the EMQAr station on the UFMS campus. The monitoring system comprised high-precision instruments designed for environmental studies. Wind speed and direction were measured using a Vaisala WXT520 weather transmitter (Vaisala Oyj, Vantaa, Finland; accuracy: ±3°, ±0.3 m/s). Precipitation was recorded with a Tipping Bucket Rain Gauge (Davis Instruments, Hayward, CA, USA; accuracy: ±2%). Relative humidity and air temperature were monitored with a Vaisala HMP155 probe (Vaisala Oyj, Vantaa, Finland; accuracy: ±1.5%, ±0.2 °C), while atmospheric pressure was measured using a Vaisala PTB110 sensor (Vaisala Oyj, Vantaa, Finland; accuracy: ±0.3 hPa). Solar radiation was obtained from a CMP3 Pyranometer (Kipp & Zonen, Delft, The Netherlands; accuracy: ±5%). Data from all meteorological sensors were logged at 1-minute intervals and aggregated into hourly averages for subsequent analysis.

Particulate matter concentrations ($PM_{2.5}$ and PM_{10}) were continuously monitored using an automatic optical aerosol monitor (Thermo Scientific pDR-1500, Thermo Fisher Scientific Inc., Waltham, MA, USA; detection limit: 1 μg/m³; accuracy: ±5%). Calibration procedures followed the manufacturer's recommendations, including weekly zero and span checks for particulate matter monitors and annual factory calibrations to ensure traceability to international standards. In addition, field inspections were conducted before and after the study period to verify instrument stability and measurement accuracy[15–21].

2.3. Meteorological and Air Quality Data

Meteorological data were obtained from the UFMS monitoring station and included the following parameters: wind speed and direction, precipitation, relative humidity, air temperature (maximum and minimum), and atmospheric pressure. Particulate matter concentrations ($PM_{2.5}$ and PM_{10}) were recorded continuously at hourly intervals using automatic equipment calibrated according to Brazilian environmental standards.

A total of 2,589 hourly observations were collected. Data quality control involved two steps: (i) verification of instrument calibration and (ii) identification of missing or anomalous values. Missing data accounted for less than 2% of the total observations, resulting from short sensor interruptions or communication errors. To ensure data reliability, we adopted a conservative approach: only days with complete hourly records for both $PM_{2.5}$ and PM_{10} were included in the analysis (listwise deletion). This choice avoided introducing biases associated with imputation methods.

2.4. Statistical Analysis

The following statistical methods were applied: Descriptive statistics: mean, standard deviation, variance, skewness, kurtosis, and extreme values. Pearson correlation coefficient (r): to identify linear relationships between meteorological variables and PM concentrations. Multiple linear regression: to model the dependence of PM concentrations on meteorological factors.Principal Component Analysis (PCA): to reduce data dimensionality and identify key meteorological drivers influencing PM levels, minimizing multicollinearity[22–24].

3. Results

3.1. Descriptive Statistics

Table 1 presents the descriptive statistics of the hourly means of $PM_{2.5}$, PM_{10}, and meteorological variables observed in Campo Grande, MS.

Table 1. Descriptive statistics of hourly mean concentrations of $PM_{2.5}$, PM_{10}, and meteorological variables in Campo Grande, MS.

Variable	Mean	Std. Dev.	Median	Q1 (25%)	Q3 (75%)	Minimum	Maximum	Skewness	Kurtosis
$PM_{2.5}$ 1 h (μg/m³)	9.29	10.91	5.85	3.50	10.50	0.40	94.10	4.08	25.64
PM_{10} 1 h (μg/m³)	16.20	19.25	12.05	7.80	19.30	0.10	141.50	4.07	20.22
$PM_{2.5}$ 24 h (μg/m³)	7.44	3.71	6.60	4.60	8.90	2.40	20.30	1.50	2.75
PM_{10} 24 h (μg/m³)	15.51	7.40	13.25	10.20	19.60	0.10	33.40	0.95	0.43
T (°C)	21.26	3.53	21.55	19.20	24.20	6.00	29.90	−1.20	3.95
RH (%)	89.15	5.78	91.50	85.00	93.50	64.00	95.00	−1.67	2.98
Rain (mm)	2.47	4.54	1.00	0.50	2.20	0.20	31.40	4.09	20.01
ws (m/s)	1.87	1.29	1.34	0.90	2.30	0.45	6.26	1.41	1.78
wd (°)	164.05	107.08	135.00	76.00	258.00	2.00	355.00	0.44	−1.09
Pressure (hPa)	1,013.48	4.93	1,012.47	1,009.80	1,017.20	1,005.36	1,028.22	0.50	−0.36

Note: ws—daily average wind speed, rain—1-h cumulative precipitation, AP—daily average atmospheric pressure, MaxT—daily maximum temperature, MinT—daily minimum temperature, RH—daily surface air relative humidity. Q1 and Q3 (first and third quartiles).

For air pollutants, the hourly means of $PM_{2.5}$ (9.29 μg/m³) and PM_{10} (16.20 μg/m³) remained below the WHO guideline values[1]. However, the maximum concentrations (94.1 μg/m³ for $PM_{2.5}$ and 141.5 μg/m³ for PM_{10}) reveal the occurrence of critical short-term pollution episodes, likely associated with intense local emissions or unfavorable meteorological conditions for dispersion. The highly skewed and leptokurtic distributions (Skewness > 4; Kurtosis > 20) confirm that most hours presented low pollutant levels interspersed with extreme hourly peaks, a typical feature of mid-sized cities exposed to point sources and strong regional climate variability.

With respect to the meteorological variables, the reported values correspond to hourly averages. For air temperature, the observed extremes were 29.9 °C (maximum) and 6.0 °C (minimum), with an overall hourly mean of 21.3 °C. The distribution exhibited a slightly negative skewness, reflecting cooler conditions during the night and early morning, particularly in the dry season. For relative humidity, values ranged from 95% (RHmax) to 64% (RHmin), resulting in an hourly mean of 89.2%. The negative skewness indicates the predominance of humid conditions interspersed with episodes of dry air, which favor the accumulation of particulate matter.

Rainfall showed a low mean (2.47 mm) but with very high skewness (4.09) and kurtosis (20.01), confirming the predominance of dry hours interspersed with intense and isolated precipitation events, typical of the tropical convective regime. The mean wind speed (ws) was low (1.87 m/s), with strong positive skewness, indicating the predominance of calm conditions interrupted by occasional gusts (maximum = 6.26 m/s). This pattern is consistent with reduced pollutant dispersion most of the time. The mean wind direction (wd = 164°) indicates a predominance of southeasterly flows, which may transport pollutants from rural areas and major roads. Finally, atmospheric pressure remained stable (mean = 1013 hPa), with low variability and nearly symmetric distribution, reflecting the influence of large-scale atmospheric systems typical of Central-West Brazil.

In summary, the analysis of hourly means indicates that although average levels of $PM_{2.5}$ and PM_{10} are moderate, the highly episodic character of hourly concentrations, combined with calm winds, low humidity, and absence of rainfall, represents the main risk factor for air quality in Campo Grande.

The boxplots (**Figure 2**) provide a visual summary of the variability and distribution of particulate matter and meteorological variables. Hourly concentrations of $PM_{2.5}$ and PM_{10} (**Figure 2a**) exhibited wider interquartile ranges and extreme values compared with the 24-hour averages (**Figure 2b**), reinforcing that short-term peaks drive the skewness and heavy-tailed distributions observed in the descriptive statistics. The daily averages presented narrower ranges and fewer outliers, reflecting the smoothing effect of temporal aggregation.

Temperature distributions (**Figure 2c**) were relatively symmetrical, with small interquartile ranges and moderate variability between minimum and maximum values. This indicates stable thermal conditions during the study period, with no extreme events. Relative humidity (**Figure 2d**) showed broader dispersion, particularly for RHmin, confirming that dry episodes were frequent and likely played a critical role in modulating PM levels.

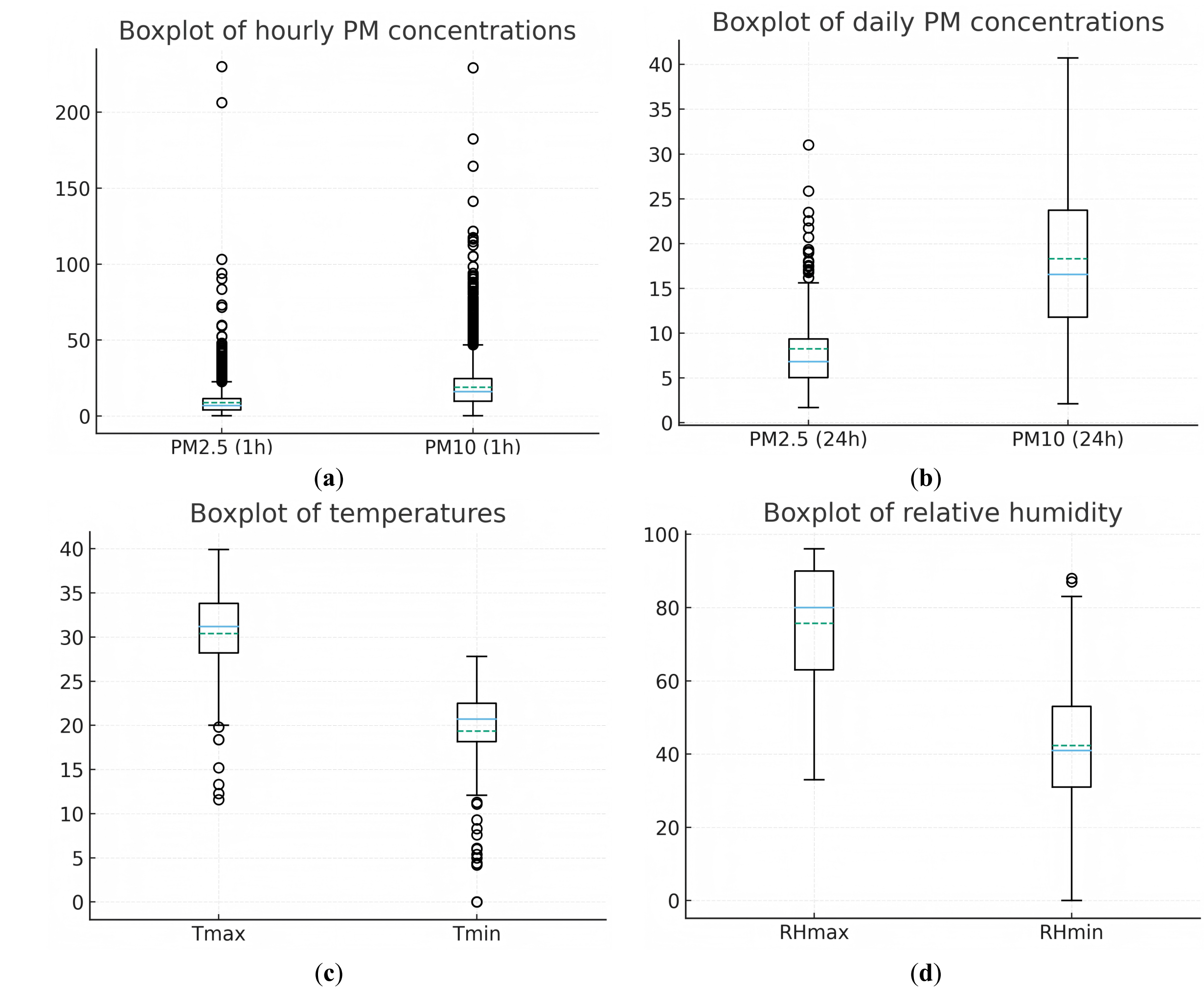


Figure 2. Boxplots of particulate matter concentrations and meteorological variables in Campo Grande, MS, during March–June 2021. (**a**) Hourly $PM_{2.5}$ and PM_{10}; (**b**) Daily $PM_{2.5}$ and PM_{10} (24 h averages); (**c**) Maximum and minimum air temperature; (**d**) Maximum and minimum relative humidity.

Note: Boxes represent interquartile ranges (Q1–Q3), horizontal lines indicate medians, and whiskers denote minimum and maximum values.

The histograms (**Figure 3**) further highlight the statistical properties of the dataset. $PM_{2.5}$ and PM_{10} hourly concentrations (**Figure 3a,b**) exhibited positively skewed distributions, dominated by low-to-moderate values with occasional high peaks. Wind speed (**Figure 3c**) displayed a leptokurtic distribution, with most observations clustered around calm conditions (near zero), interspersed with sporadic gusts. Rainfall (**Figure 3d**) was characterized by an extremely skewed distribution, with the vast majority of values concentrated near zero and rare but intense precipitation events, consistent with the high skewness and kurtosis reported in **Table 1**.

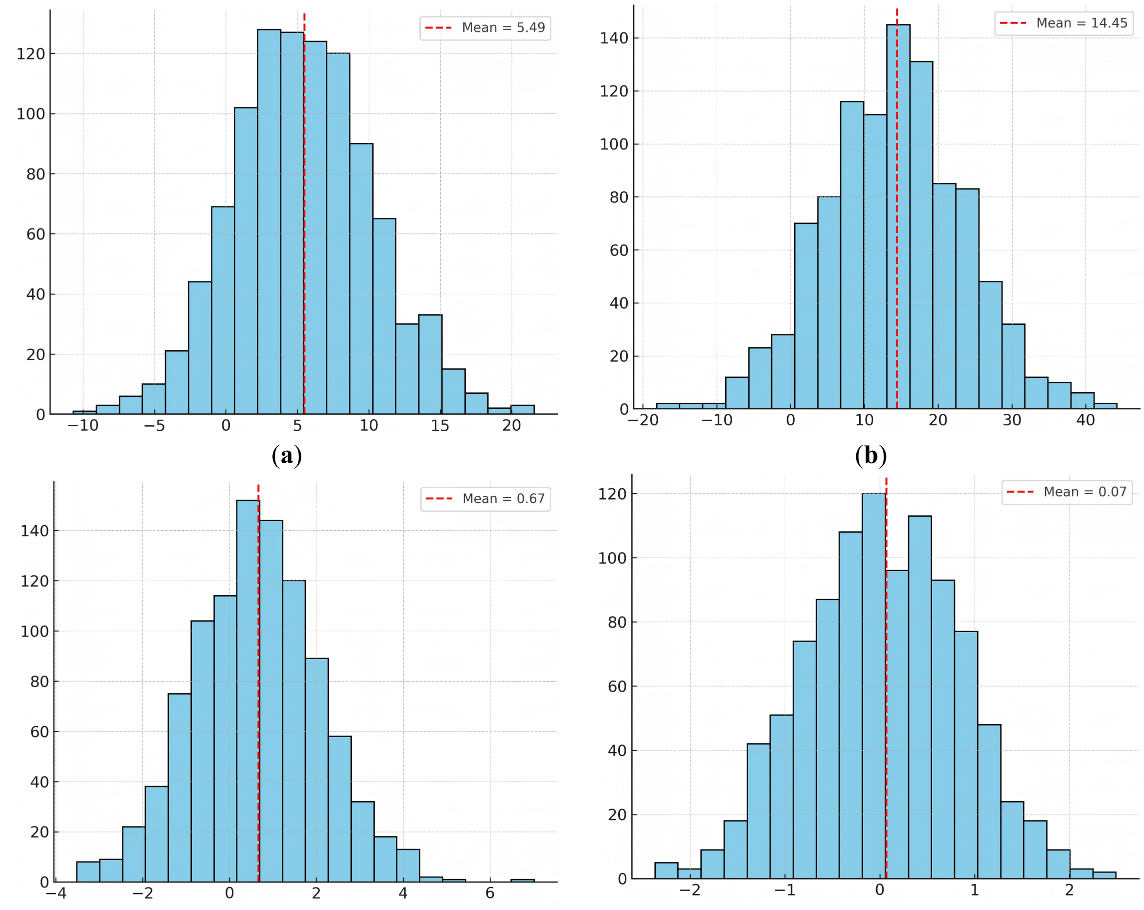


Figure 3. Histograms of selected variables in Campo Grande, MS, during March–June 2021. (**a**) Hourly $PM_{2.5}$ concentrations; (**b**) Hourly PM_{10} concentrations; (**c**) Wind speed; (**d**) Rainfall.

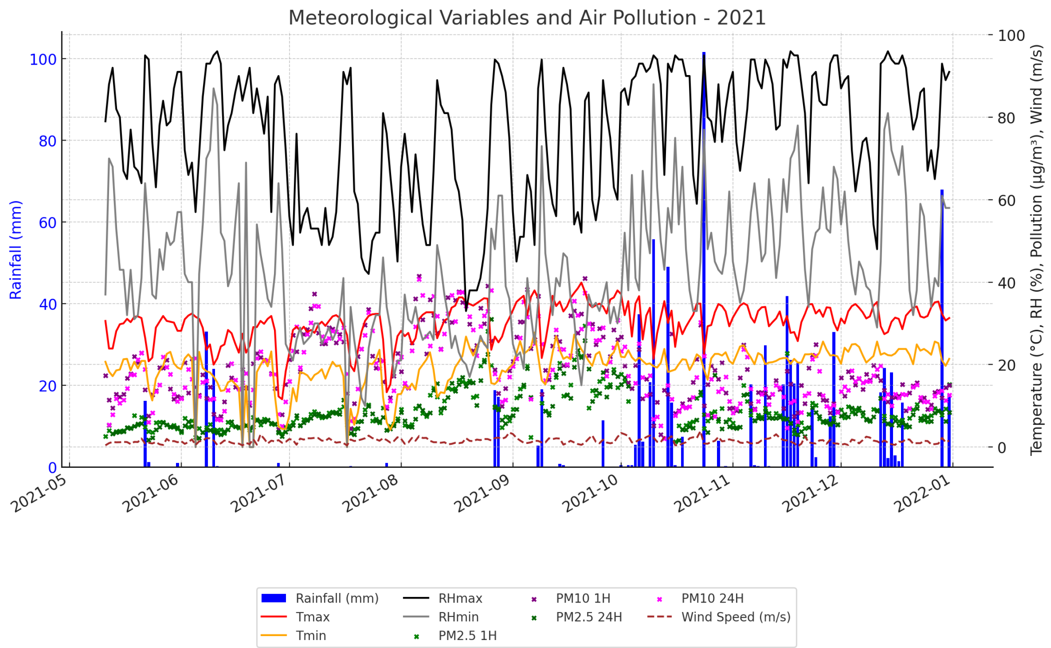
Note: Dashed vertical lines represent mean values, and the distributions highlight the positively skewed nature of particulate matter and rainfall, as well as the predominance of calm wind conditions.

Overall, these graphical representations confirm that particulate matter concentrations in Campo Grande are typically low but highly sensitive to meteorological variability. Episodes of dry air, stagnant winds, and the absence of precipitation create favorable conditions for pollutant accumulation, whereas rainfall and higher humidity act as effective removal mechanisms.

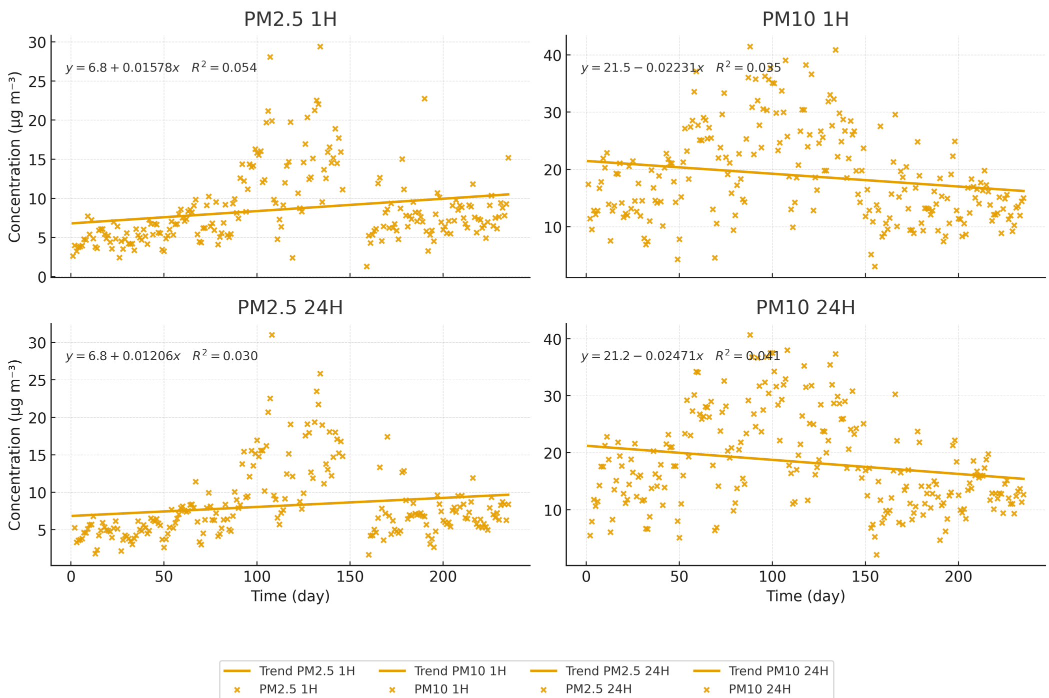
The results obtained for the accumulated meteorological variables can be observed in **Table 1** and **Figure 4** (Original figure—Rainfall, RH, Tmax, Tmin, PM and wind). Among the parameters analyzed, wind speed stands out as a determining factor for the dispersion of atmospheric pollutants. During the evaluated period (March to June 2021), the average wind speed was 0.64 m/s, with values varying between 0 and 7.6 m/s.

3.2. Correlations and Regression Analysis

Pearson correlation analysis revealed significant associations between particulate matter concentrations and meteorological drivers. $PM_{2.5}$ and PM_{10} showed positive correlations with air temperature and negative correlations with relative humidity and precipitation. Multiple regression confirmed that wind speed and relative humidity were the strongest predictors of reduced PM levels, whereas stagnant conditions favored pollutant accumulation.

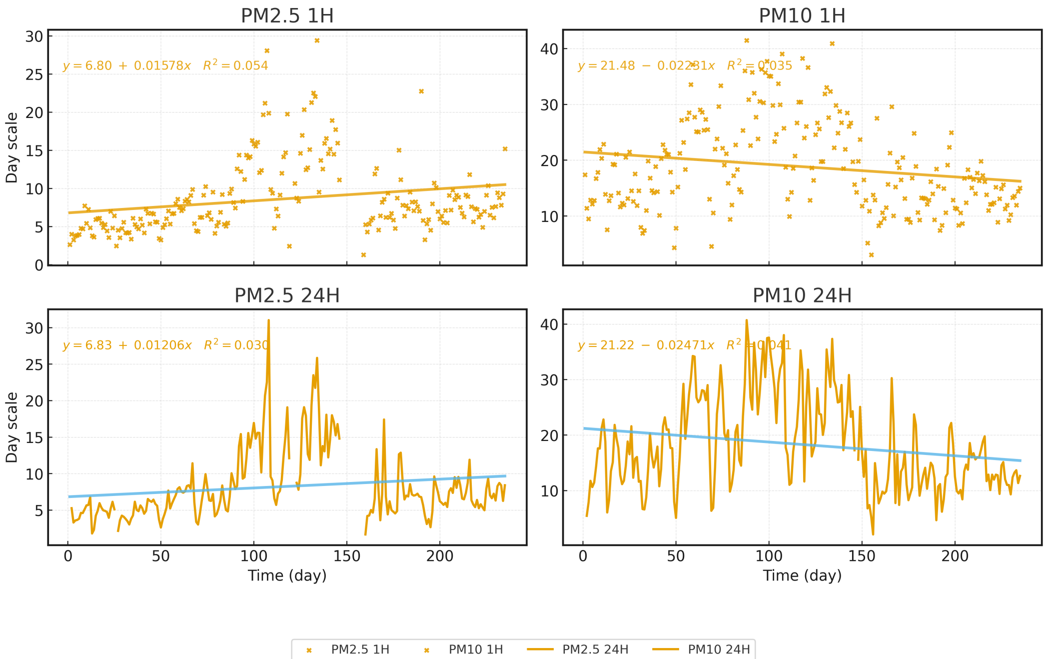


(**a**) $PM_{2.5}$ at hourly scale.

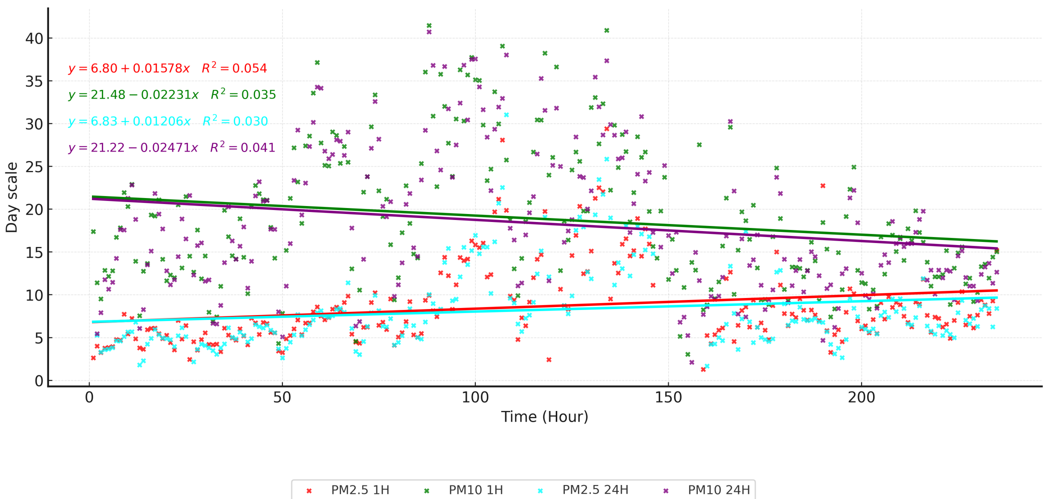


(**b**) PM_{10} at hourly scale.

Figure 4. *Cont.*



(**c**) $PM_{2.5}$ at daily scale (24 h).



(**d**) PM_{10} at daily scale (24 h).

Figure 4. Temporal distribution of particulate matter concentrations in Campo Grande, MS, from March to June 2021. (**a**) $PM_{2.5}$ at hourly scale; (**b**) PM_{10} at hourly scale; (**c**) $PM_{2.5}$ at daily scale (24 h); (**d**) PM_{10} at daily scale (24 h).

Note: The lines represent the fitted linear regressions with their respective coefficients of determination (R^2).

The correlogram (**Figure 5a**) shows that $PM_{2.5}$ and PM_{10} concentrations were negatively correlated with relative humidity and precipitation, confirming the role of moisture and rainfall in reducing particle accumulation. Conversely, positive correlations with temperature indicate that warmer and drier conditions favor higher PM levels.

Wind speed (ws) exhibited a weak negative correlation with both PM fractions, suggesting limited but consistent dispersion effects under stronger winds. Atmospheric pressure (APmax and APmin) showed only minor associations with pollutant levels.

Figure 5b highlights the statistical significance of these relationships. Stronger correlations, such as between relative humidity and $PM_{2.5}$/PM_{10}, remained significant ($p < 0.05$), whereas weaker associations (e.g., with pressure variables) were not statistically robust. These results confirm that humidity, rainfall, and temperature are the primary meteorological determinants of particulate matter dynamics in the study area.

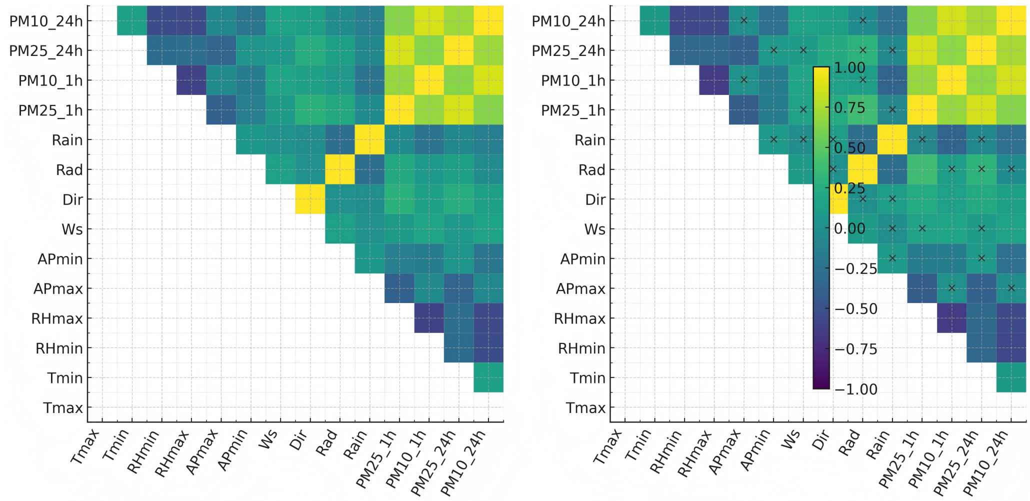


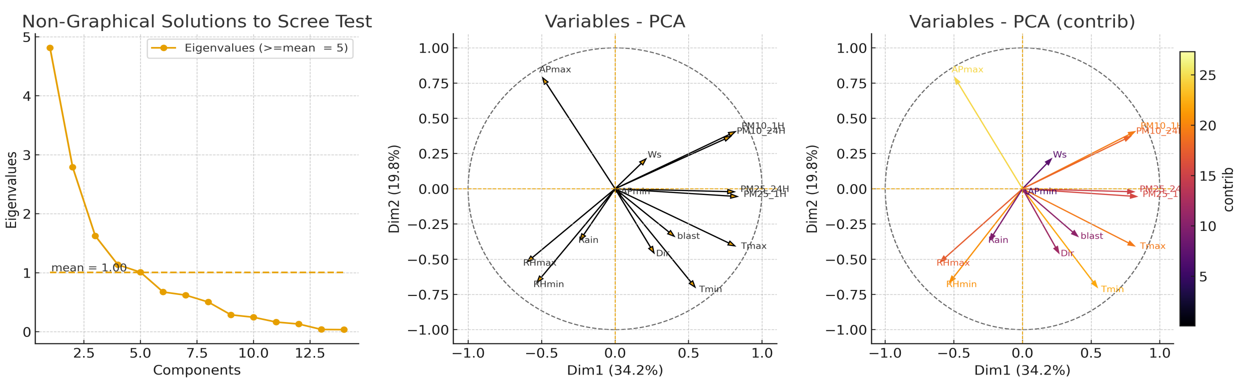
Figure 5. Correlation matrix between meteorological variables and particulate matter concentrations in Campo Grande, MS, during March–June 2021. (**a**) Pearson correlation coefficients (color scale: blue = positive, red = negative); (**b**) Same as (**a**), with statistically non-significant correlations ($p > 0.05$) marked with.

3.3. Principal Component Analysis (PCA)

The scree plot (**Figure 6a**) indicates that four components should be retained according to the parallel analysis and optimal coordinate methods, although the first two already explain 42% of the total variance.

The correlation circle (**Figure 6b**) shows that relative humidity (RHmin, RHmax) and precipitation (Rain) are strongly associated with Dim1, representing moisture-driven processes that reduce particulate matter concentrations. In contrast, temperature (Tmax, Tmin) and atmospheric pressure (APmax, APmin) align with Dim2, reflecting thermal and circulation influences.

The contribution plot (**Figure 6c**) highlights that humidity and temperature variables were the main contributors to the first two principal components. This result reinforces that moisture availability and thermal conditions are the dominant meteorological drivers of $PM_{2.5}$ and PM_{10} variability in the study area.



(**a**) (**b**) (**c**)

Figure 6. Principal Component Analysis (PCA) of meteorological variables and particulate matter concentrations in Campo Grande, MS, during March–June 2021. (**a**) Scree plot of eigenvalues with parallel analysis, optimal coordinates, and acceleration factor criteria; (**b**) Correlation circle of variables on the first two principal components (Dim1 = 26.8%, Dim2 = 15.2%); (**c**) Contribution of each variable to Dim1 and Dim2, with higher contributions indicated in red.

Dim1 is mainly associated with moisture-related processes, as it groups relative humidity (RHmax, RHmin) and precipitation, reflecting the influence of atmospheric water availability on particulate matter removal. Dim2 is dominated by temperature (Tmax, Tmin) and atmospheric pressure (APmax, APmin), representing thermal and circulation effects that modulate pollutant accumulation and dispersion.

3.4. Wind Rose Analysis

Figure 7 presents the pollution roses for $PM_{2.5}$ and PM_{10} at hourly and daily scales. A clear predominance of concentrations associated with winds from the eastern sector is observed in all panels, while the other directions show reduced contributions. This pattern suggests the presence of relevant emission sources located east of the monitoring station, possibly related to urban traffic, anthropogenic activities, or biomass burning in the region. The most frequent concentration classes are between 0–5 µg m^{-3} and 5–10 µg m^{-3}, indicating that most records correspond to low to moderate levels, although higher concentrations (>20 µg m^{-3}) are observed, especially for PM_{10}. The comparison between temporal scales shows that hourly means present greater variability and the occurrence of peaks, whereas 24-hour means smooth these extremes, as expected from a statistical perspective. The percentage of calm atmospheric conditions (<0.5 m s^{-1}) was low, indicating relatively favorable dispersion conditions during the analyzed period. These results reinforce the importance of directional analyses for understanding the spatial distribution of emission sources and for supporting air quality management strategies, considering that $PM_{2.5}$ is more strongly associated with combustion processes, whereas PM_{10} is also influenced by dust resuspension and soil particles.

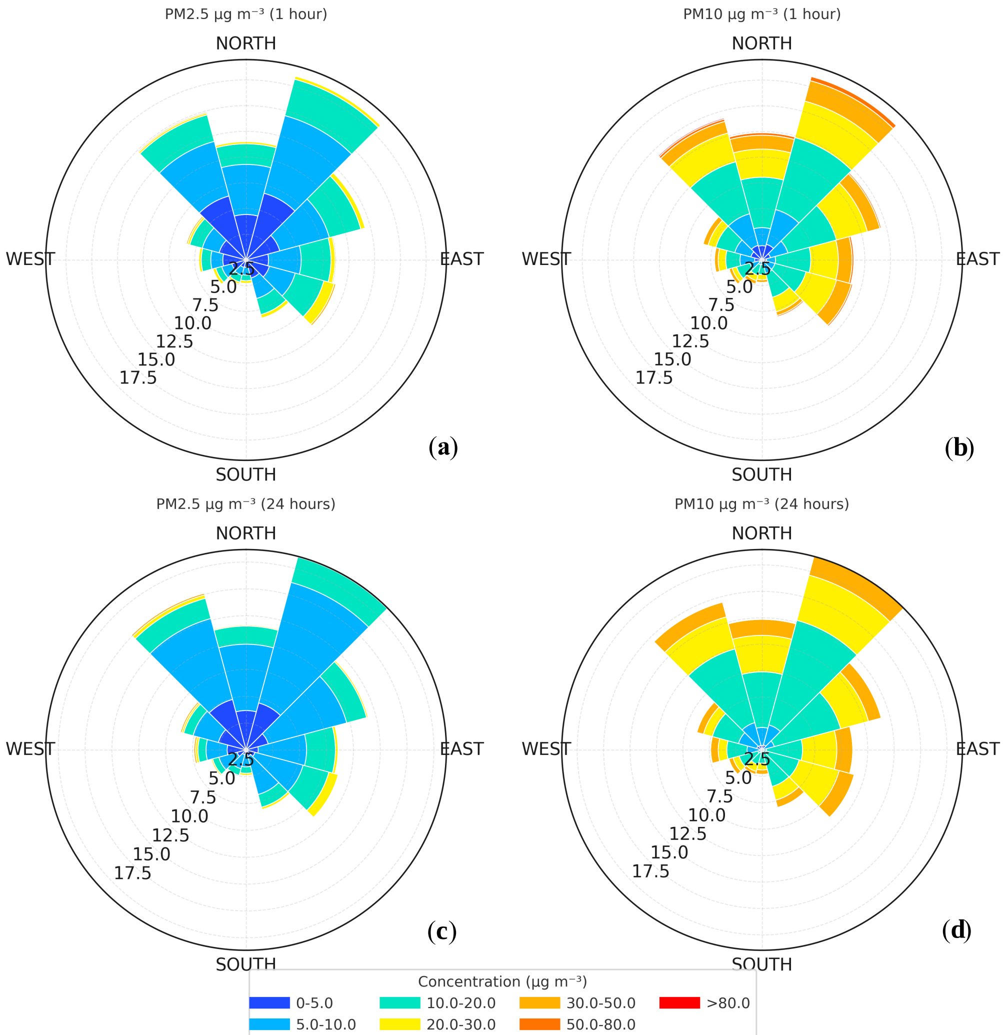


Figure 7. Wind rose diagrams showing the distribution of $PM_{2.5}$ and PM_{10} concentrations in Campo Grande, MS, during March–June 2021. (**a**) $PM_{2.5}$ at hourly scale; (**b**) PM_{10} at hourly scale; (**c**) $PM_{2.5}$ at daily scale (24 h); (**d**) PM_{10} at daily scale (24 h). Colors indicate concentration classes (µg/m³), while percentages represent the frequency of wind directions.

4. Discussion

This study provides new insights into the role of meteorology in shaping $PM_{2.5}$ and PM_{10} concentrations in a mid-sized tropical city. The results revealed that relative humidity and precipitation were strongly and negatively correlated with particulate matter, while temperature was positively associated with higher concentrations. These findings are consistent with studies conducted in Brazilian metropolitan areas such as São Paulo and Rio de Janeiro, where drier and hotter conditions have also been linked to pollutant accumulation [7,8]. Similar patterns have been reported internationally, including in China and India, where seasonal droughts and high temperatures contribute to critical PM episodes [4,6].

The patterns identified in this study are in agreement with recent investigations in other urban contexts. For example, Parra et al. [12], analyzing the Aburrá Valley (Colombia), demonstrated that $PM_{2.5}$ responds strongly to meteorological variations, a result similar to that observed in Campo Grande. Likewise, Zhang et al. [3] showed that in Kraków (Poland), low temperatures combined with thermal inversions intensify air pollution episodes during the winter months.

The importance of spatio-temporal analyses was highlighted by Rautela & Goyal [13], who demonstrated that the interaction between meteorological variables and pollutants can be better understood through approaches that integrate multiple temporal scales. This perspective broadens the interpretation of the results obtained in this study, suggesting that the variability observed in Campo Grande is not only local but also follows patterns recognized in different regions.

In addition, the effects of extreme events on air pollution deserve attention. Sun et al. [4] showed that heatwaves and intense rainfall can abruptly modify pollutant concentrations, creating new challenges for forecasting and monitoring. In this context, the findings of this study reinforce the need for environmental management strategies that take into account not only average conditions but also the increasing frequency of climatic extremes associated with global change.

The corrected PCA results indicated that the first two components explained 42% of the total variance. Dim1 was dominated by moisture-related variables (precipitation and relative humidity), while Dim2 reflected thermal and circulation effects (temperature, atmospheric pressure, and wind). Although the scree test suggested retaining four components, the first two were prioritized in the interpretation due to their stronger physical meaning, while the additional results are presented in the supplementary material. This clarification avoids misleading interpretations and strengthens the robustness of the multivariate analysis [25–28].

Wind rose diagrams confirmed the predominance of eastern winds, with higher $PM_{2.5}$ and PM_{10} levels occurring under easterly flows. This highlights potential sources located east of the monitoring station, such as biomass burning in rural areas and vehicular traffic along major regional highways. Similar associations between wind direction and pollutant transport have been documented in other regions of Brazil [10,25] and in Southeast Asia, where biomass burning during the dry season is strongly influenced by easterly winds and low humidity [26].

It is also important to note that solar radiation, although not directly analyzed in this study, plays a critical role in atmospheric processes related to particulate matter. High solar radiation enhances photochemical reactions, leading to the formation of secondary aerosols, and influences boundary layer dynamics, thereby affecting pollutant dispersion. Future studies in Campo Grande and similar tropical cities should incorporate solar radiation more explicitly to strengthen the interpretation of pollutant-meteorology interactions.

Overall, the discussion reinforces that meteorological variables, particularly humidity, precipitation, temperature, and wind patterns, are central drivers of $PM_{2.5}$ and PM_{10} variability in Campo Grande. These results underscore the importance of integrating meteorological data into air quality assessments, not only for large metropolitan areas but also for mid-sized tropical cities.

5. Conclusions

This study investigated the influence of meteorological variables on $PM_{2.5}$ and PM_{10} concentrations in Campo Grande, MS, during the seasonal transition from May to December 2021. The analysis confirmed that relative humidity and precipitation are key factors reducing particulate matter levels, while higher temperatures and stagnant wind conditions favor pollutant accumulation. PCA results demonstrated that moisture- and temperature-related processes are the main meteorological drivers of air quality variability in this tropical mid-sized city.

Wind rose analysis indicated the predominance of easterly winds, suggesting the presence of emission sources in that sector, likely related to biomass burning and vehicular traffic. These findings highlight the importance of considering regional transport processes in air quality management.

Based on the results, the following recommendations are proposed: (i) implementation of early-warning systems during periods of low relative humidity (<30%), enabling public health alerts and preventive measures; (ii) integration of meteorological forecasts into air quality monitoring to anticipate unfavorable conditions; (iii) stricter emission control policies, especially regarding biomass burning and vehicular emissions; and (iv) expansion of monitoring networks in mid-sized Brazilian cities to strengthen long-term pollutant forecasting and regional planning.

Authors Contributions

Conceptualization: A.S., W.A.F., H.G.P., J.F.O.-J, I.P., K.R.A.C.; Methodology: A.S., W.A.F., H.G.P., J.F.O.-J, I.P., K.R.A.C.; Validation A.S., W.A.F., H.G.P., J.F.O.-J, I.P., K.R.A.C.; Formal analysis writing: A.S., W.A.F., H.G.P., J.F.O.-J, I.P., K.R.A.C.; Preparation of original draft: A.S., W.A.F., H.G.P., J.F.O.-J, I.P., K.R.A.C.; Writing—proofreading and editing: A.S., W.A.F., H.G.P., J.F.O.-J, I.P., K.R.A.C.; Visualization: A.S., W.A.F., H.G.P., J.F.O.-J, I.P., K.R.A.C.; Supervision: A.S., W.A.F., H.G.P., J.F.O.-J, I.P., K.R.A.C. All authors read and agreed with the published version of the manuscript.

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Informed Consent Statement

Not applicable.

Data Availability Statement

Not applicable.

Conflicts of Interest

The authors declare no conflicts of Interest.

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