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Seasonal Characteristics of Particulate Matter by Pollution Source Type and Urban Forest Type

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Abstract: To provide consistent air purification benefits from urban forests, it is crucial to identify common characteristics that allow for similar experimental setups. This study aimed to analyze PM_{10} concentrations in urban forests near pollution sources and understand their mitigation effects. Data from the Asian Initiative for Clean Air Networks, Korea, were used, focusing on three urban forests adjacent to road and industrial pollution sources in Korea, with PM_{10} concentrations collected during 2021. Considering high PM_{10} concentrations during winter and spring, these seasons were divided into two sub-periods, resulting in six seasonal periods for analysis. To address the right-skewed PM_{10} distribution and reduce outlier influence, the Kruskal–Wallis test was used. The results showed that "good" PM_{10} levels were lowest in early spring, increasing to a peak in summer before declining. High PM_{10} events were concentrated in spring, early spring, and early winter. The Kruskal–Wallis test indicated lower median PM_{10} concentrations in urban forests compared to pollution sources in the latter half of the year, while no significant median differences were found in the first half. Distribution visualizations further confirmed that even during high PM_{10} periods, all urban forests showed lower PM_{10} values compared to pollution sources. In conclusion, PM_{10} concentrations in urban forests were consistently lower than in pollution sources across all seasons, demonstrating their effectiveness in air purification at both road and industrial pollution sources. Future research should consider additional variables, such as $PM_{2.5}$, to further explore differences between pollution sources.

Keywords: particulate matter; particulate matter concentration reduction; urban forest; nature-based solutions

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1. Introduction

Fossil fuels and various industrial processes release pollutants into the atmosphere, contributing significantly to air pollution. Air pollutants, especially particulate matter (PM), affect diverse regions and generations without distinction. PM exposure is ubiquitous, affecting the health of humans, animals, and plants, thereby posing a significant threat to public health and air quality. Given these challenges, PM has garnered attention as a crucial environmental issue that requires immediate action for reduction.

Accordingly, both public and private institutions are actively developing strategies to manage and mitigate PM, with South Korea adopting similar approaches [1,2]. Effective strategies, such as reducing vehicle exhaust emissions, have led to decreased pollutant concentrations in South Korea over time (National Academy of Environmental Sciences, 2022). However, challenges persist, especially in regions with low wind speeds or stagnant air, where PM concentrations tend to rise [3]. Additionally, rising temperatures in high-latitude regions and a decline in the northwest monsoon could foster conditions favorable for atmospheric stagnation, potentially reversing the trends in reducing PM concentrations, even with ongoing reduction policies [4,5]. As urbanization progresses globally over the next three decades, all regions are expected to experience heightened urban growth (UN-Habitat Core Team, 2022). Urban residential areas tend to exhibit higher PM levels than rural areas, with urban roadsides experiencing elevated PM exposure from non-exhaust vehicular sources, such as tire and road abrasion, as well as vehicular emissions [6]. Furthermore, industrial emissions from oil combustion, coal burning, and metal processing in urban settings result in higher oxidative output than that in rural areas, exacerbating adverse effects on human health [7,8].

This confluence of climate change, urbanization, and persistent pollution has resulted in an increasing number of factors contributing to higher particulate matter (PM) concentrations, with their relationships becoming more complex. As such, research into complementary measures to mitigate these trends is essential. The limitations of traditional approaches necessitate complementary strategies, thereby driving the demand for innovative solutions to promote sustainability (National Institute of Forest Science, 2021). Nature-based solutions (NbSs) involve leveraging natural processes to tackle socio-environmental challenges, enhancing sustainability and providing diverse benefits to both society and the environment (National Institute of Forest Science, 2021). NbSs offer adaptive management approaches for complex socio-ecological challenges and may be an effective solution for PM reduction [9].

Particulate matter (PM) can be divided into two types depending on how it is formed: primary PM, which is emitted directly from the source in solid form, and secondary PM, which is formed when gaseous substances from the source undergo chemical reactions with other substances in the air (Ministry of the Environment, Understanding Particulate Matter, 2017). PM refers to particles smaller than 10 μm, most of which are produced by primary emissions. In 2021, the primary sources of PM emissions in South Korea include manufacturing combustion and production processes (8.22%), road traffic-related pollution (2.39%), and fugitive dust (65.86%) (Korean Statistical Information Service, 2024).

In general, the formation of PM varies depending on the source. On roads, PM is released by processes such as fuel combustion in internal combustion engines (exhaust emissions), tire wear, and road surface abrasion (non-exhaust vehicle emissions) [10]. In industrial complexes, PM is generated by the combustion of fossil fuels such as petroleum and coal, metal processing, handling of powdered raw and auxiliary materials in factories, and emissions from incinerators (Ministry of the Environment, Understanding Particulate Matter, 2017).

Meanwhile, the reduction in PM by plants can be classified into two processes: external (adsorption and accumulation on leaves) and internal (absorption and storage in plant tissues). The external process is influenced by various factors, including leaf microstructure (trichomes, leaf structure, stomatal density, etc.), macrostructure (total leaf area, leaf arrangement, leaf shape, etc.), canopy size, tree age, and physiological factors (such as transpiration and boundary layer conductance). In addition, physicochemical properties (such as wax layer composition) and interactions between leaves and the surrounding environment play a critical role in PM reduction. PM accumulated on leaf surfaces can be washed off by rain or resuspended by wind. It can also settle and disperse under the influence of environmental factors, such as humidity and temperature. These processes are further categorized into dry deposition, which includes the settling, diffusion, and resuspension of PM on leaves, trees, and forest surfaces, and wet deposition, where PM accumulated on leaves is washed off by precipitation [11–19]. The internal process refers to the uptake of PM through stomata or cuticles. PM can be absorbed through stomatal openings, cell membranes, and roots, where it accumulates on the surface or inside the roots [20,21].

Researchers are actively developing methods to utilize forests in reducing PM concentrations. These studies can be categorized into micro-, mezzo-, and macro-research approaches based on the scope, duration, and complexity of this study. Micro-research focuses on the mechanisms of PM absorption and removal through the biological properties of trees [22–24], such as the differences in accumulation among various vegetative organs and identifying species that efficiently absorb PM. Mezzo-research expands the focus to include the trees, their surrounding environments, and human interactions [25–30], examining the interplay of ecological factors such as forest structure, meteorological and spatial factors, and anthropogenic activities. Macro-research takes a broader perspective, encompassing longer study periods and wider areas, including the previously mentioned subjects [31–34]. These studies explore PM concentration differences among observation stations, estimating PM removal and accumulation by urban forests and converting these estimates into annual values. Furthermore, they analyze the positive impacts of these forests on air quality.

This study analyzed the concentration of particulate matter in urban forests where both non-point source pollution (e.g., roads) and point source pollution (e.g., industrial complexes) are present using long-term monitoring data from the AICAN (Asian Initiative for Clean Air Networks, Korea) system operated by the National Institute of Forest Science in Korea. This research aims to identify the common characteristics of particulate matter (PM) concentrations in urban forests located near different pollution sources, examine the differences in PM concentrations between pollution sources and forest plots, and explore the significance of these differences to better understand the role of urban forests in reducing PM.

2. Materials and Methods

2.1. Study Sites

The National Institute of Forest Science strategically established from 2019 to 2023 a total of 132 plots across 44 sites for AICAN in the Korean peninsula to investigate the role of forests in mitigating or obstructing PM pollution. To identify suitable sites, urban forests were categorized into four main construction backgrounds. The selection process also involved analyzing three years of meteorological data, conducting atmospheric modeling, and performing on-site surveys and evaluations.

To address pollutant reduction at the source, this study is on urban forests and proximal pollution sources. The pollution sources were divided into industrial complexes (point-source pollutants) and road areas (non-point-source pollutants). Several AICAN plots were installed near these pollution sources. When selecting the research sites, two primary criteria were considered. First, the installation timeline of each region, and the time to finalize confirmation of the collected data, had to be accounted for based on site selection. Second, each site needed to provide a full year of data for seasonal comparisons, with missing values comprising no more than 5% of the total data. Within the AICAN pollutant groups, the road areas included Gomae, Yangjae, and Gwanak, while the industrial complexes covered Goyang, Sihwa, and Gijang (Table 1). Data were collected throughout 2021.

At the Gomae site, plots were installed 50 m and 150 m away from the highway (source), with broadleaved forests occupying the area. The Yangjae site, located along the same highway, included plots at distances of 200 m and 300 m and featured mixed forests. Both sites are situated near the Gyeongbu Expressway, which had an average traffic volume of 192,000 vehicles per day in 2021 (Seoul Metropolitan Facilities Management Corporation, 2022). At the Gwanak site, measurement points were installed on the rooftop of the Seoul National University Graduate School of Public Health, SNUGPI observation station, with the traffic island near the university's main gate serving as the pollution source. This site features both coniferous and mixed forests and is located near the Gangnam Circle City Expressway, which had a daily traffic volume of 90,451 vehicles in 2021 (Seoul Metropolitan Government and Seoul Metropolitan Facilities Management Corporation, 2022). The Gijang site is situated near the Jeonggwan General Industrial Complex (source), with measurement plots in both forested and residential areas. The forest plots contain mixed forests, while the residential area plot consists of broadleaved forests. The Goyang site, located near the Ilsan Urban High-Tech Industrial Complex, includes source plots near LNG facilities. Forest plots in this area feature mixed forests, while the residential area contains broadleaved forests. Lastly, the Sihwa site, positioned near the Sihwa Industrial Complex, has plots in barrier forests and residential areas. The forest plot contains a mixed forest, while both the forest and residential plots include coniferous forests.

Table 1. Characteristics of study sites.

Pollution Division	Site	Plot		Plot Type	Forest Type
		Original	Latest		
Road (non-point source pollution)	Gomae	Road 50 m from road 150 m from road AirKorea	Road Forest interior 1 Forest interior 2 AirKorea	Road Forest Forest School	Deciduous -
	Yangjae	Road 200 m from road 300 m from road AirKorea	Road Forest interior 1 Forest interior 2 AirKorea	Road Park Park Road	Mixed Mixed Mixed -
	Gwanak	Road Univ. campus Forest AirKorea	Road Forest interior 1 Forest interior 2 AirKorea	Road Etc. Forest Office	Coniferous - Mixed -
Industrial area (point-source pollution)	Gijang	Industrial area Forest Residential area AirKorea	Industrial area Forest Residential area AirKorea	Industrial area Park Park Office	Mixed Mixed Deciduous -
	Goyang	Industrial area Forest Residential area AirKorea	Industrial area Forest Residential area AirKorea	Industrial area Forest Downtown Park	- Mixed Coniferous -
	Sihwa	Industrial area Forest Residential area AirKorea	Industrial area Forest Residential area AirKorea	Industrial area Park Park Office	Mixed Coniferous Coniferous -

This table was created by referencing the Forest PM AICAN Utilization I and the Forest PM AICAN Green Infrastructure Research Report, both published by the National Institute of Forest Science in 2021).

2.2. PM Concentration Measurements

Three plots were established at each site of AICAN to represent varying environmental contexts. Here, we studied urban forests by source. In this case, plots near a road source encompassed a source area, an interior forest site, and a location at another interior part of the forest. Plots near an industrial complex encompassed a source area, a forest, and a residential area (Figures 1 and S1).

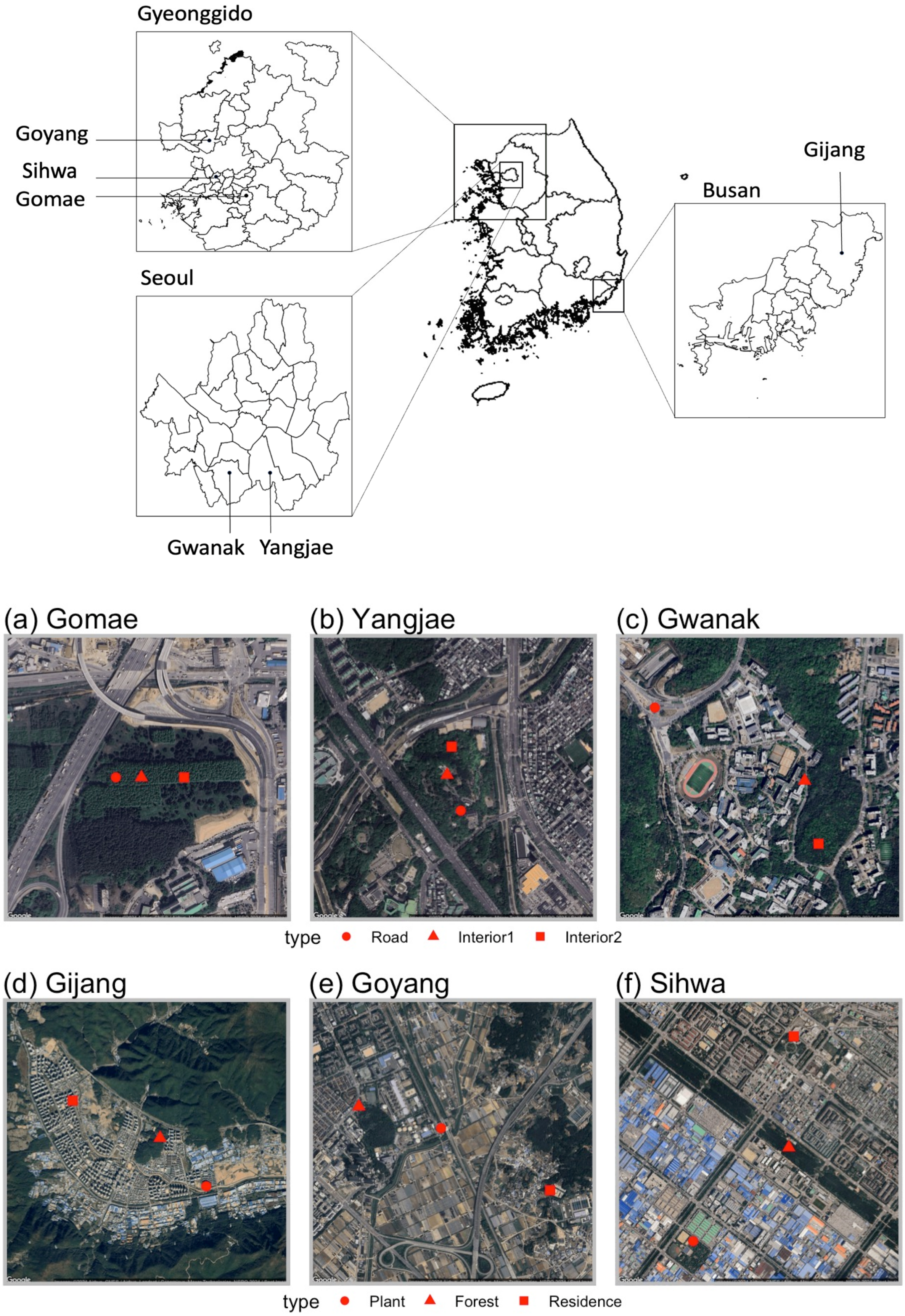

Figure 1. Locations of study sites and AICAN plots for each site, labeled (**a**–**f**).

For the measuring instrument, the EDM-365 SVC (Grimm Aerosol Technik GmbH & Co. KG, Ainring, Germany; Figure 2) was employed. It utilizes light-scattering measurements to continuously monitor PM concentrations (PM_{10}, $PM_{2.5}$, and $PM_{1.0}$; PM in the atmosphere in and out through a sampling head), wind direction, wind speed, temperature, humidity (these are observed by a weather senor), and both anthropogenic and biogenic volatile organic compounds, among other parameters (National Institute of Forest Science, 2020). Raw data were observed every 10 min continuously.

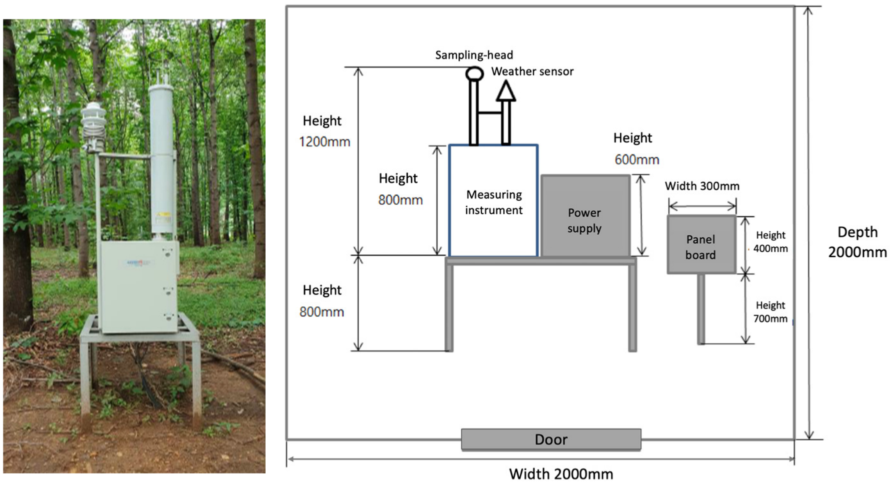

Figure 2. Measuring instrument at each plot.

Further, PM data from AirKorea, a city center observation station near AICAN, were utilized to facilitate a comparative assessment. This study specifically drew on data from a roadside atmospheric network to evaluate air quality in areas with significant automobile and pedestrian traffic (Ministry of Environment and National Academy of Environmental Sciences, 2023).

2.3. Monitored Data

To investigate the PM reduction effects of urban forests, AICAN data were obtained from the Korea Public Data Portal (Korea Public Data Portal, 2023), while downtown plot data were obtained from AirKorea [35]. Because AICAN data were observed every 10 min and AirKorea data were observed hourly, the AICAN data were averaged hourly to synchronize the data timelines for AICAN and AirKorea. Then, the location data for road areas and industrial complexes were merged by PM_{10} concentration (source, forest, residential area (AICAN) and downtown area (AirKorea)) together with the corresponding city data from AirKorea by date and were ordered in the format of year/month/day/hour. In this study, the Kruskal–Wallis test (KW test; it is a non-parametric counterpart to the parametric one-way analysis of variance (ANOVA)) was used to compare medians by ordering the data for each group. Because this method is rank based, it is less affected by outliers, and given the multiple causes of high PM concentrations at pollution sources, outlier removal was not performed. Due to the varying distances of measurements from the road source, the plots were categorized as road, forest interior 1, forest interior 2, and downtown areas (Table 1). In addition, since PM concentrations are high in spring and winter in South Korea, these seasons were further divided in half, resulting in a total of six periods for comparing PM concentrations.

Seasonal criteria were established using the method provided by Choi, Kwon, and Robinson [36], defined by Equation (1). This equation calculates the Summed Daily Temperature (SDT_i) as the seven-day moving average of the daily maximum $(MaxT_i)$, minimum

$(Min\mathrm{T}_{\mathrm{i}})$, and mean $(MeanT_i)$ temperatures, where i refers to the number of days, and i = 1, . . ., 365.

$$SDT_i = \frac{\sum_{n=i-3}^{i+3}(MinT_n + MeanT_n + MaxT_n)}{7}. \tag{1}$$

The seasonal transitions were identified as follows. Winter ends and spring begins on the last day when the SDT falls below 15 °C, calculated as 24 February 2021. Spring ends and summer begins on the first day when the SDT reaches or exceeds 60 °C, noted as 6 June. Summer ends and autumn begins on the last day with the SDT is at or above 60 °C, calculated as 11 October. Autumn transitions to winter on the first day when the SDT drops below 15 °C, which was November 28. Given the typically high PM concentrations during winter and spring in Korea, the analysis was segmented into six periods: early winter (1 January 2021–23 February 2021), early spring (24 February 2021–16 April 2021), late spring (17 April 2021–5 June 2021), and late winter (28 November 2021–31 December 2021). PM concentration levels were categorized according to environmental ministry standards as good (0–30 μg/m^3), not bad (31–80 μg/m^3), bad (81–150 μg/m^3), and very bad (above 150 μg/m^3).

2.4. Statistical Analysis

When testing for differences in the means of three or more independent groups, an F-test is typically used to compare between-group variance and within-group variance to determine whether the differences in means are statistically significant. However, to use well-known parametric statistical methods based on a normal distribution, certain assumptions must be satisfied, such as normality, homogeneity of variances ($F = \frac{s_1^2}{s_2^2}$, here, s_1^2, s_2^2 are the variances of each group), and independence of observations. However, PM data often exhibit a right-skewed distribution, with many low values and fewer high values. The pronounced skewness in the observation values violated the assumption of a normal distribution, which undermined the F-test's effectiveness in controlling Type I errors (rejecting a true null hypothesis) [37]. In such situations, non-parametric statistical methods, which do not assume a specific parametric model for the population and can analyze data based solely on signs or ranks, are more appropriate. The Kruskal–Wallis test, which uses permutation combination-based ranks, serves as a suitable alternative. This method is advantageous for analyzing data that do not satisfy the normality assumption, as it employs rankings based on the entire data set rather than raw data from each group. After conducting a one-way analysis of variance (ANOVA), the Bonferroni post hoc test is used to effectively control Type I errors when making multiple comparisons. It also works relatively well when the distribution does not follow normality or when variances are unequal.

The KW statistics are calculated by dividing the variance (V) derived from the ranked data by the sample variance of the rankings (S_R^2). The total number of observations is $n = \sum_{i=1}^{k} n_i$, where i = factors that are categorical variables. X_{ij} = the jth observation from the ith population, where $i = 1, \ldots, k$, $j = 1, \ldots,\ n_i$. R_{ij} = ranking transformation of X_{ij}. The mean of all rankings {1, . . ., n} $\overline{R} = \frac{1}{n}\sum_{i=1}^{n} i = \frac{n+1}{2}$, $\overline{R}_i$ = the mean of rankings according to process i, $V = \sum_{i=1}^{k} n_i\left(\overline{R}_i - \frac{n+2}{2}\right)^2$, $S_R^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(i - \overline{R}\right)^2 = \frac{n(n+1)}{12}$. The KW statistics, when considering ties, are calculated as follows:

$$KW = \frac{\sum_{i=1}^{k} n_i\left(\overline{R}_i - \frac{n+2}{2}\right)^2}{S_R^2} \tag{2}$$

When R_{ij} is the X_{ij}'s ranking, consider $R_{11}, \ldots, R_{kn_k}$ as observed values. The calculated formula is as follows:

$$F_R = \frac{\frac{\sum_{i=1}^{k} n_i\left(\overline{R}_i - \overline{R}\right)^2}{k-1}}{\sum_{i=1}^{k}\frac{\sum_{i=1}^{n_i}\left(R_{ij} - \overline{R}_i\right)^2}{n-k}} \tag{3}$$

When the observed KW statistics from the data are KW_{obs}, their *p*-value is $p = P\ (k \geq KW_{obs})$ [37]. To identify groups with significant differences, a post hoc test (Bonferroni adjustment for multiple comparisons) was conducted. The analysis was performed using R version 4.3.1.

3. Results

3.1. Analyzing Wind Direction and PM Concentrations

Due to the characteristics of South Korea's climate, the prevailing wind direction is northwest in winter and southwest in summer. For road pollution sources, Gomae and Yangjae were mostly affected by northerly winds, while Gwanak showed northwesterly winds in early winter and early spring, gradually shifting to northwesterly and southeasterly winds in fall. For industrial pollution sources, northwesterly winds were the most common overall, although there were seasonal variations (Figure 3). Notably, PM concentrations significantly increased during the spring months. The concentrations were the lowest in summer and then increased in autumn. Within the industrial complexes, PM_{10} concentration trends were similar to those of road pollution sources, though the frequency and levels of high PM_{10} events were greater (Figure 4). The boxplot analysis of the maximum values (defined as 1.5 times the interquartile range, which is the midpoint of the upper half minus the midpoint of the lower half of the data) shows that high PM_{10} concentrations predominantly occurred from early in the year through spring. Figure 4 also highlights that the median PM_{10} concentrations did not align with the frequency and levels of high PM_{10} events. When cross-referenced with the wind rose data, it is evident that high PM_{10} concentrations, classified as "high" or "bad" (Figure 3, red and orange), primarily occurred from early in the year to early spring. Conversely, "good" PM_{10} concentrations were more frequent during spring. In summary, PM_{10} concentrations were relatively high from early in the year through spring, but the frequency of high PM_{10} events peaked in spring, suggesting that PM_{10} occurrence characteristics vary across seasons.

The relationship between wind direction and PM concentrations at each measurement point was examined for each site by analyzing the most frequently observed wind direction and the distribution of PM concentrations by season (Figure 3). Although there were seasonal differences in Table S1, generally, Gomae's forest interior 1, Yangjae's forest interior 2, and Gwanak's forest interior 1 showed the highest wind speeds among the road pollution sources. For industrial pollution sources, wind speeds were higher in the industrial and residential areas compared to the forest. The average wind speed of the most frequent wind direction was higher in winter and lower in summer. However, when broken down by season and plot, the wind speed in forests or forest interiors was lower than in other plots. Due to the variation in wind speeds across different regions and plots, it was challenging to identify a consistent pattern.

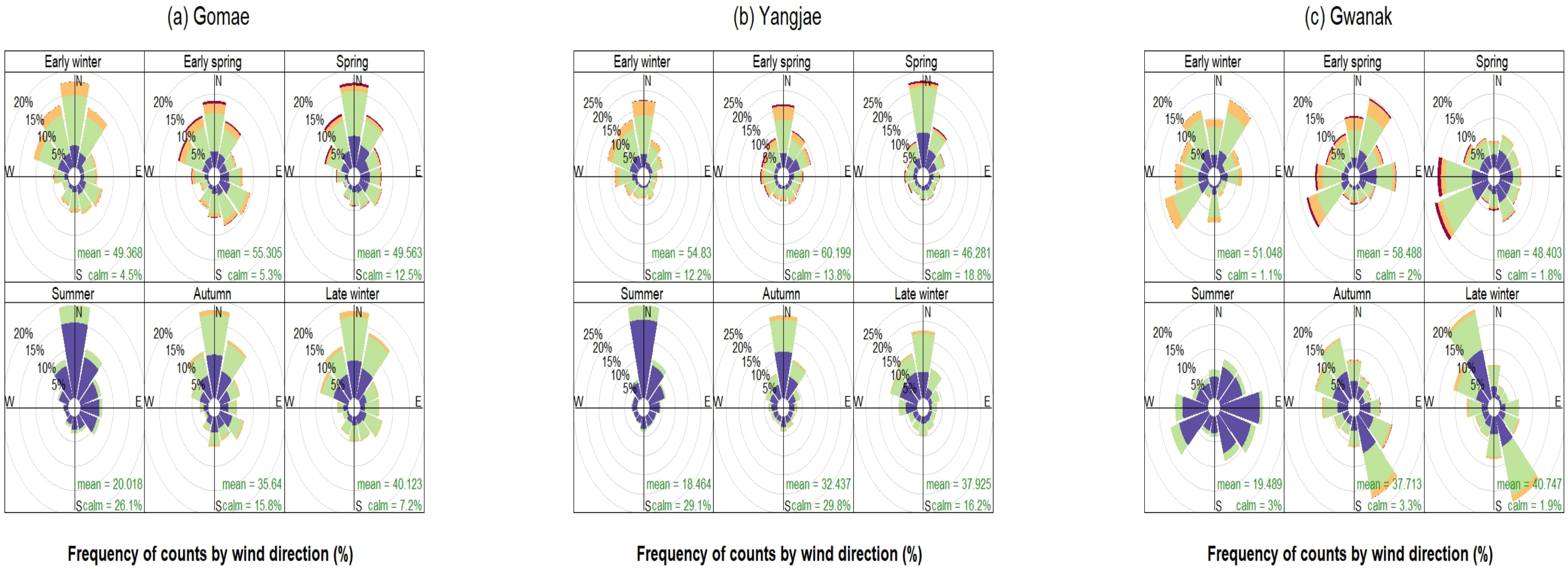

Figure 3. *Cont.*

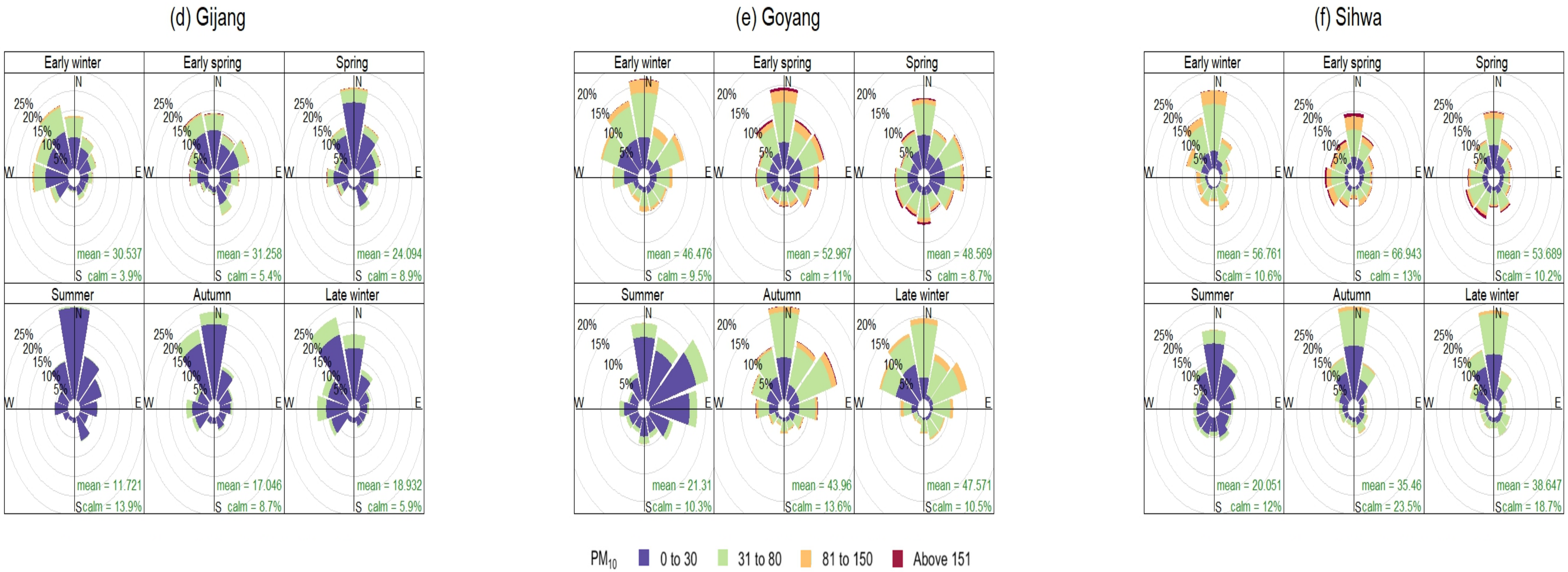

Figure 3. Pollution rose for PM_{10} during the study period. It emphasizes the wind directions that significantly influence overall pollutant concentrations. The percentage within the circle indicates the frequency of each wind direction. The pie chart is segmented to show the frequency of PM_{10} levels for each direction. At the right bottom, "mean" is the mean PM_{10} concentration in each season, and "calm" means the ratio of wind speed (0–0.2 m/s). The legend shows that the PM_{10} levels are "good", "not bad", "bad", and "very bad", respectively.

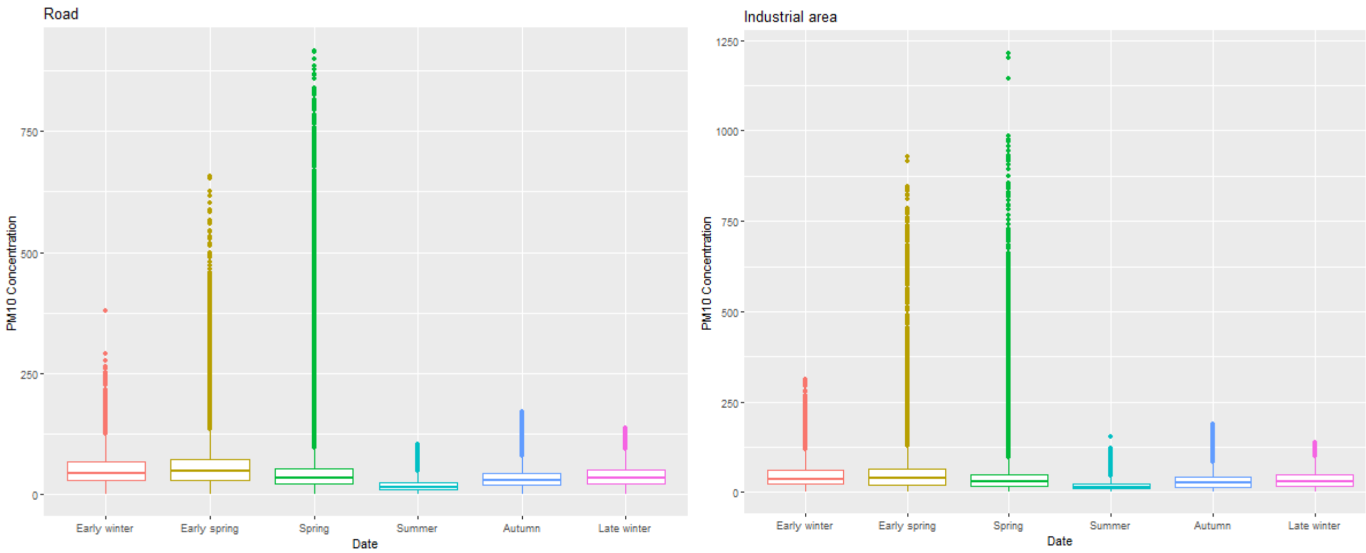

Figure 4. Seasonal boxplot of PM_{10} concentrations by pollution source.

3.2. Analysis of PM_{10} Concentrations in Each Plot

3.2.1. ANOVA of the Plot PM Concentration Results

The Kruskal–Wallis test was employed to assess the difference in the median PM concentrations among groups. In the last row in Table 2, the chi-square value, which serves as the test statistic following a chi-square distribution, indicates whether the null hypothesis can be rejected. The results of the KW test in this study reveal significant differences in median PM concentrations among the four plots across all seasons (Table 2). The post hoc test was conducted to identify which groups exhibited significant differences in their median values. The results revealed distinct patterns: from the beginning of the year to early spring, no median difference was observed in forest areas. However, during spring, the median concentrations in both the road and downtown plots were higher than those in forest plots. In summer, significant differences were noted among the downtown, road, forest interior 1, and forest interior 2 plots, with downtown plots exhibiting the highest median concentration, followed by road, forest interior 1, and forest interior 2 plots in decreasing order. Similarly, at the end of the year, while there were no significant differences in median concentrations between the road, forest interior 1, and downtown areas, the results were significant, with each plot recording higher medians than those of forest interior 2. From the beginning of the year to early spring, there were no noticeable differences in the median PM concentrations between the plots. However, from spring to the end of the year, the PM concentrations in interior forest plot 1 remained consistently lower than those in urban and pollution source areas. Table 2 revealed the results in the industry complexes, and the post hoc test results highlighted distinct patterns. At the beginning of the year, industrial complexes and forests exhibited higher concentrations, with subsequent decreases in downtown and residential areas. In early spring, downtown areas displayed the highest concentrations, followed by industrial complexes, and residential areas had the lowest. PM concentration changes decreased in the order of industrial areas, forests, and residential areas throughout spring. Industrial complexes and downtown areas maintained higher PM concentrations than forests and residential areas. During summer, concentrations decreased in the order of downtown areas, industrial complexes, forests, and residential areas. In autumn, both industrial complexes and downtown areas showed higher concentrations than those of forests and residential areas. At year end, industrial complexes recorded higher concentrations than residential areas. Except for the winter season (the beginning of the year and at year end), the PM concentration of the forest was lower than the industrial area.

Table 2. The Kruskal–Wallis test results of road site PM_{10} concentrations (μg/m^3) in each season.

		Early Winter (M ± SD)	Early Spring (M ± SD)	Spring (M ± SD)	Summer (M ± SD)	Autumn (M ± SD)	Late Winter (M ± SD)
Non-point pollution	Forest interior1	51.27 ± 26.69	54.62 ± 37.98	40.76 ± 36.23	18.70 ± 12.15	37.43 ± 22.52	40.30 ± 20.87
	Forest interior2	51.43 ± 27.67	56.64 ± 40.45	39.50 ± 31.66	17.77 ± 11.74	33.48 ± 20.23	35.80 ± 19.09
	Road	51.07 ± 26.90	54.96 ± 38.28	42.71 ± 39.93	20.13 ± 12.36	37.61 ± 21.99	40.54 ± 20.37
	Downtown	43.47 ± 26.32	56.37 ± 57.44	57.09 ± 93.66	23.67 ± 14.92	37.97 ± 28.85	41.07 ± 24.01
	χ^2	316.37 *	27.59 *	50.76 *	998.79 *	105.33 *	62.18 *
Point pollution	Forest	46.17 ± 29.16	49.90 ± 39.33	39.68 ± 43.25	17.51 ± 11.68	31.36 ± 24.05	34.04 ± 22.50
	Residency	37.68 ± 25.84	38.76 ± 34.28	33.55 ± 34.37	16.12 ± 11.92	31.11 ± 26.24	34.21 ± 23.84
	Industrial area	48.25 ± 30.07	52.38 ± 39.88	39.90 ± 34.98	18.46 ± 12.26	33.07 ± 24.32	35.26 ± 22.34
	Downtown	41.07 ± 26.98	55.47 ± 70.68	50.60 ± 78.88	24.00 ± 14.09	34.39 ± 26.49	34.27 ± 22.41
	χ^2	356.15 *	399.62 *	270.79 *	2378.16 *	70.46 *	8.83 *

Early winter (beginning of the year): 1.1–2.23; early spring: 2.24–4.15; spring: 4.16–6.5; summer: 6.6–10.10; autumn: 10.11–11.27; late winter (end of the year): 11.28–12.31. * $p < 0.05$.

3.2.2. Comparison of PM Concentration Distribution

Table 3 presents the probability of PM_{10} concentrations reaching levels classified as "bad" or above (above 81 μg/m^3). For Gomae, the lowest probability of "bad" PM_{10} levels were found at forest interior 1, while Yangjae and Gwanak exhibited the lowest probabilities at forest interior 2. Among these sites, the forest interior at Gomae, which is composed solely of trees, showed the most significant difference in the likelihood of "bad" PM_{10} concentrations compared to surrounding areas. Similarly, the forest interiors in Yangjae, which is a park, and in Gwanak, located within a university campus, also demonstrated lower probabilities of high PM_{10} levels than the pollution sources. For the industrial complexes, excluding Gijang, which had generally low PM_{10} concentrations, Goyang and Sihwa industrial areas showed a higher probability of PM_{10} levels exceeding the "bad" threshold compared to the road areas. However, urban forests and residential areas showed a gradual decrease in PM_{10} concentrations compared to the pollution sources.

Table 3. Probability of PM_{10} concentrations reaching levels classified as "Bad" or above (above 81 μg/m^3).

	Non-Point Pollution				Point Pollution		
	Road	Interior1	Interior2		Industrial Area	Forest	Residential Area
GM	0.0686	0.0544	0.0830	GJ	0.0159	0.0154	0.0083
YJ	0.0822	0.0821	0.0784	GY	0.1050	0.0918	0.0399
GW	0.0894	0.0845	0.0790	SH	0.1056	0.0969	0.0932

In addition, Figure 5 illustrates the overall distribution of PM_{10} concentrations throughout the year (0–200 μg/m^3) as well as the distribution of concentrations in the 0–80 μg/m^3 range, which represents typical conditions and constitutes a substantial portion of the data set. The overall distribution of data across the entire study period (Figure 5) indicates a right-skewed pattern, with many values clustering within the 0–100 μg/m^3 range, with no significant differences observed across regions or plots. However, when examining the data by subdivided periods, distinct differences between plots emerged.

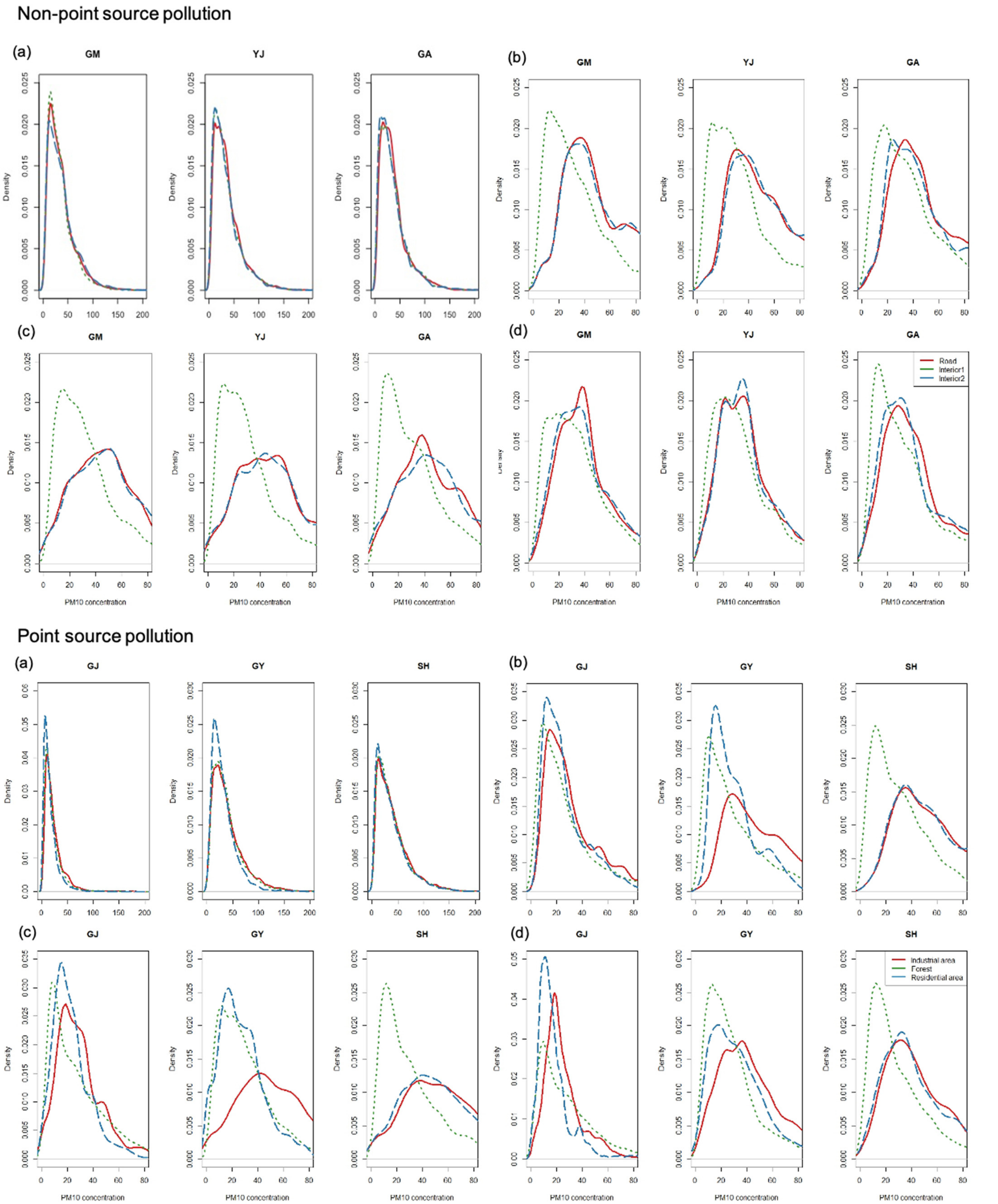

Figure 5. Distribution of PM_{10} concentration in each pollution source and season. Non-point pollution source: (**a**) All study periods (the year 2021), (**b**) the beginning of the year, (**c**) early spring, (**d**) spring. Point pollution source: (**a**) All study periods (the year 2021), (**b**) the beginning of the year, (**c**) early spring, (**d**) spring.

For the road pollution source, the probability density distribution for concentrations below 80 μg/m^3 showed that forest interior 1 had a higher clustering of lower PM_{10} concentrations compared to surrounding areas. This trend was most prominent in early spring, with similar patterns observed in early year and spring data. All three regions exhibited a distinct pattern where forest interior 1 and surrounding areas were clearly differentiated, showing similar distribution shapes across different time periods. During early winter, the distribution of measurement points was similar, and the distances between them remained relatively consistent. In early spring, forest interior 1 maintained its previous distribution shape, while data from surrounding areas spread more widely, increasing the distance between measurement points. By spring, PM_{10} concentrations in all measurement points had clustered at lower values, causing significant overlap between the distributions at the three locations, resulting in minimal differences between them.

For the industrial complex pollution sources, the overall annual PM_{10} concentration distribution (0–200 μg/m^3) showed that the likelihood of low concentrations in residential areas (represented by the y-value corresponding to the *x*-axis values) was significantly higher compared to other plots, differing from road pollution sources. When examining the seasonal distribution patterns for Gijang, no notable changes were observed in the forest over the three seasons. However, in early year and early spring, the differences between the three plots were minimal, while during spring, PM_{10} concentrations were predominantly clustered in the lower range for both residential and industrial areas, increasing the likelihood of lower concentrations. In Gijang, low concentrations were prevalent in the pollution sources and surrounding areas across all three seasons, resulting in minimal differences between measurement points. For Goyang, in early year and early spring, PM_{10} concentrations were mostly concentrated in the lower range for both forest and residential areas, while the pollution source exhibited a broader distribution extending to higher concentrations. However, during the spring season, when high PM_{10} events were frequent, the concentrations in the forest remained stable, while data density in residential areas around the mode decreased, leading to a wider distribution. The pollution source also saw an increase in observations in the lower concentration range, reducing the differences between the three measurement points. In Sihwa, the differences between the forest and other plots remained consistent throughout all three seasons, with the forest consistently showing lower concentrations. Overall, in the case of road pollution sources, even though surrounding areas were affected by the pollution source, the interior of the forest appeared to be less impacted. This trend was particularly evident during periods with higher median PM_{10} concentrations. For industrial pollution sources, the higher median concentrations observed in early year and early spring seemed to influence PM_{10} concentration changes at Gijang and Goyang. During spring, the increase in high PM_{10} events led to an increase in extreme values, while low-concentration observations also increased, resulting in a lower median concentration compared to previous periods. Ultimately, even during periods of high PM_{10} concentrations, the forest consistently showed a lower concentration distribution compared to other monitoring sites.

4. Discussion

Urban forests have been studied and evaluated for their effectiveness in mitigating or purifying pollutants and reducing their negative impacts from increasingly diverse pollution sources. Although it is challenging to quantify the various forms and structures of urban forests using a consistent standard, efforts to identify common characteristics of urban forests to consistently reproduce the benefits of green spaces are essential.

When examining the characteristics of PM_{10} concentrations at the study sites, the concentration-based proportions of each wind direction varied by period. The proportion of "good" air quality was relatively lower in the first half of the year, with early spring showing the lowest proportion of "good" levels and the highest proportion of "bad" levels. Seasonal differences in PM_{10} concentrations (Figure 4) indicated that the median concentrations were the highest at the beginning of the year and early spring, whereas short-term, extreme events, such as high PM_{10} occurrences, were more frequent in the spring.

When comparing the average wind speeds of the most frequently observed wind directions by season and region with the Beaufort wind scale, summer wind speeds generally fell into category 1 (0.3–1.5 m/s, "light air"), whereas winter wind speeds were classified as category 2 (1.6–3.3 m/s, "light breeze"), indicating relatively higher wind speeds during winter compared to summer. However, calm wind speeds were more prominent in summer and autumn, yet PM_{10} concentrations were higher in winter (Figure 3, Table S1). These results contrast with previous studies, which suggest that low wind or calm wind conditions promote the accumulation of particulate matter [35,36]. Further detailed studies incorporating various forest environments, wind directions, and speed conditions are needed to better understand the impact of wind conditions on PM_{10} concentrations.

To investigate the median differences between plots to understand the PM_{10} reduction effect of urban forests, the Kruskal–Wallis (KW) test was performed. For road pollution sources, during the early year to early spring period and for industrial pollution sources during all periods except early year, the median PM_{10} concentration was lowest in forest interior 1 plots (road source) and forest plots (industrial source). However, when examining the differences in the probability of PM_{10} values exceeding "bad" levels (Table 3) and the distribution at lower levels (Figure 5), it was found that, even during periods of high PM_{10} levels in the first half of the year, the PM_{10} concentrations observed in urban forests were predominantly clustered in the lower range. Additionally, even during seasons with high PM_{10} concentrations, the characteristics of PM_{10} occurrences varied by period.

For road pollution sources, unlike early year winter and early spring, during spring, there were frequent high PM_{10} events, yet PM_{10} concentrations were relatively low during normal conditions, even at the pollution sources, resulting in smaller differences between plots. In contrast, for industrial pollution sources, no significant differences in trends were found between plots within the area across all three seasons in the first half of the year. The differences in the interaction between surrounding environments and forests could be attributed to the differing PM emission sources, compositions, and particle sizes for road and industrial pollution sources [37,38]. Moura BB et al. (2024) analyzed seasonal and regional PM concentration differences across urban traffic, urban background, industrial, and rural areas, classifying particulate matter as fine (0.2–2.5 µg), coarse (2.5–10 µg), and large (>10 µg). The study found that during winter, coarse and large particle concentrations were higher for urban traffic than in industrial areas, with lower potassium (K) and higher calcium (Ca) levels for roads compared to industrial sources. Popek R et al. (2022) [39] reported that the presence of inorganic PM on plant leaves within forest interiors suggests that non-exhaust road emissions can penetrate deep into forest areas. Although this study identified seasonal and plot-specific differences in PM_{10} concentrations, further research is necessary to understand the PM_{10} reduction effects of urban forests near pollution sources. Such research should involve more detailed classifications of PM concentration levels or methods for distinguishing the PM composition between pollution sources.

In summary, during the first half of the year, when PM_{10} concentrations were high, it was confirmed through the distribution of data that PM_{10} levels in forest interiors and forests were clustered in the lower concentration range. In the second half of the year, lower concentrations in forest interiors and forests were confirmed through median differences. Notably, during early year and early spring—periods when PM_{10} median concentrations remained high—the distributions of PM_{10} concentrations in pollution sources and forests were distinctly separated. Given the lack of consistent, prominent patterns in meteorological conditions, such as wind speed, wind direction, temperature, and humidity, it is likely that both road and industrial areas are more influenced by physical and environmental factors, such as the distance from pollution sources and the barrier effect of forests. Previous studies conducted at specific sites suggest that the amount of PM accumulated on trees increases as the distance from the pollution source to the forest increases [40,41]. Vegetative barriers act as physical barriers that spatially separate pollution sources, thereby reducing exposure to air pollutants [12,39]. The lower PM_{10} concentrations in forests, in particular, can be attributed to the physical structure of the vegetation, which restricts airflow through the forest and causes particle deposition on plant surfaces [42]. Additionally, the more extensive the vegetative barrier, the greater the amount of PM removal [43–46].

In the non-parametric analysis of variance (ANOVA) used to analyze PM_{10} concentrations—characterized by a skewed distribution—no significant median differences were observed between groups, whereas differences were evident in the overall distribution. This suggests that it is challenging to identify group differences using means or medians due to the highly asymmetric nature of PM_{10} data. In such cases, applying logarithmic or square root transformations can narrow the range between variables, making the distribution more similar to a normal distribution. Alternatively, utilizing homoscedasticity tests rather than relying solely on summary statistics, such as means or medians, could better explain the difference between groups through variance comparison.

In this study, we aimed to identify the consistent characteristics of PM_{10} concentrations in urban forests near similar pollution sources by focusing on regions with common environmental conditions rather than limiting the analysis to individual locations or specific environmental conditions. However, there are limitations, such as not fully accounting for geographic and environmental differences, including coastal versus inland areas and latitudinal variations. Additionally, PM_{10} data are not simple continuous numerical data but are categorized into distinct levels, such as "good", "not bad", and "bad". Moreover, since the distribution is not normally distributed around the mean but instead is right skewed with data clustering in lower value ranges, relying solely on summary statistics, such as means and medians, it was insufficient to fully capture PM characteristics. There is a need to consider statistical methods that can adequately account for the complex distributional characteristics of the data and incorporate various visualization methods to better address these limitations. Future studies should fully consider factors such as geographical and environmental differences, as well as the nature of the data, to provide more comprehensive insights.

Given the significant health impacts of PM, it is crucial to minimize seasonal variability in abatement effects. The results of this study will inform policies for the establishment and management of urban forests to reduce PM concentrations effectively.

5. Conclusions

This study aimed to identify consistent patterns in PM_{10} concentrations near pollution sources and interpret the PM_{10} reduction effects of urban forests. Seasonal, regional, and pollution source-specific data were analyzed using wind speed, wind direction, and PM_{10} distribution characteristics to understand these patterns. Our findings showed that the proportion of "good" PM_{10} levels was lowest in early spring and highest in summer, with frequent high PM_{10} events occurring in spring, early spring, and early year winter. Most wind speeds were below 3.3 m/s, and while winter generally had higher wind speeds, PM_{10} concentrations were also highest in winter.

To assess differences in PM_{10} concentrations between urban forests and pollution sources, we compared the median PM_{10} values of plots using the Kruskal–Wallis test. Given the right skewness of the PM_{10} data, non-parametric methods were employed; yet, the complex nature of PM_{10} data as both numeric and categorical, along with the presence of extreme events, presented challenges in fully assessing PM_{10} reduction by urban forests. To address these challenges, we analyzed the distribution of PM_{10} data during the first half of the year, when median differences were minimal, and confirmed that PM_{10} concentrations were clustered at lower levels within forest interiors. During early year and early spring—when median PM_{10} levels were highest—the distributions for pollution sources and forests were distinctly different, while spring saw lower PM_{10} concentrations across all plots, reducing the differences. In the second half of the year, median PM_{10} concentrations were consistently lower in forest interiors and forests, as confirmed by the Kruskal–Wallis test.

Overall, across all seasons, urban forests exhibited lower PM_{10} concentrations compared to pollution sources, reaffirming their role as an effective nature-based solution for air purification. These findings highlight the importance of urban forests in mitigating air pollution, and their potential as a strategy for enhancing urban air quality should be further explored in urban planning initiatives.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/app14219988/s1, Figure S1: The location of study and AICAN and AirKorea plots; Table S1: The most frequent wind direction and average wind speed for each plot by season.

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