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Research Article

Air Pollution Estimation and Trends in Mainz (2017–2022): A Case Study

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Abstract: Air pollution is a pressing global environmental challenge, with PM2.5 (particulate matter with a diameter of less than 2.5 micrometers) being recognized as one of the most hazardous pollutants to human health. Prolonged exposure to PM2.5 has been linked to respiratory diseases, cardiovascular conditions, and premature mortality. It has been shown that 99% of the world population is exposed daily to pollutant concentrations exceeding the World Health Organization's recommended safe levels. This study compares PM2.5 levels measured by satellite data from the Atmospheric Composition Analysis Group at Washington University in St. Louis with ground-based measurements from the Sensor Community initiative using SDS011 sensors deployed in Mainz, Germany. In addition, we investigated whether Mainz has achieved a positive trend in reducing PM2.5 concentrations and assessed how well the city complies with WHO standards. Our results indicate that: (a) satellite measurements consistently record higher PM2.5 values than ground-based sensors, (b) Mainz has experienced a decreasing trend in PM2.5 levels in recent years, although some of this reduction may be attributed to pandemic-related lockdowns, and (c) pollution levels in Mainz remain significantly above WHO guideline limits.

Keywords: PM2.5; air pollution; satellite data; ground sensors; Mainz

Mainz Şehrinde Hava Kirliliği Tahmini ve Eğilimleri (2017–2022): Bir Vaka Çalışması

Öz: Hava kirliliği, PM2.5'in (çapı 2,5 mikrometreden küçük partikül madde) insan sağlığı için en tehlikeli kirleticilerden biri olarak kabul edilmesiyle acil bir küresel çevre sorunudur. PM2.5'e uzun süre maruz kalmanın solunum yolu hastalıkları, kardiyovasküler rahatsızlıklar ve erken ölümle bağlantılı olduğu gösterilmiştir. Dünya nüfusunun %99'unun her gün Dünya Sağlık Örgütü'nün önerdiği güvenli seviyeleri aşan kirletici konsantrasyonlarına maruz kaldığı gösterilmiştir. Bu çalışma, St. Louis'deki Washington Üniversitesi'ndeki Atmosferik Kompozisyon Analiz Grubu'ndan alınan uydu verileriyle ölçülen PM2.5 seviyelerini, Almanya, Mainz'de konuşlandırılan SDS011 sensörlerini kullanan Sensör Topluluğu girişiminin yer tabanlı ölçümleriyle karşılaştırır. Ayrıca, Mainz'in PM2.5 konsantrasyonlarını azaltmada olumlu bir eğilim elde edip etmediğini araştırdık ve şehrin DSÖ standartlarına ne kadar uyduğunu değerlendirdik. Sonuçlarımız şunları göstermektedir: (a) uydu ölçümleri sürekli olarak yer tabanlı sensörlerden daha yüksek PM2.5 değerleri kaydetmektedir, (b) Mainz'da son yıllarda PM2.5 seviyelerinde bir düşüş eğilimi görülmüştür, ancak bu düşüşün bir kısmı pandemiyle ilgili karantinalara bağlanabilir ve (c) Mainz'daki kirlilik seviyeleri DSÖ kılavuz limitlerinin önemli ölçüde üzerinde kalmaya devam etmektedir.

Anahtar Kelimeler: PM2.5; hava kirliliği; uydu verileri; yer sensörleri; Mainz

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1. Introduction

Air pollution comprises a complex mixture of airborne substances that pose risks to environmental quality and human health. Among these, fine particulate matter ($PM_{2.5}$) has gained special attention due to its capacity to penetrate deep into the respiratory tract, potentially causing a variety of adverse health outcomes including cardiovascular disease, respiratory disorders, and premature death. The World Health Organization (WHO) revised its air quality guidelines in 2021, setting the annual $PM_{2.5}$ exposure limit at 5 μg/m³ due to growing evidence of its health impacts (WHO, 2021).

While global efforts to monitor and mitigate $PM_{2.5}$ levels have increased, localized assessments remain essential for designing effective policy interventions. The city of Mainz, situated in the federal state of Rheinland-Pfalz in Germany, presents a unique case due to its urban-industrial environment, its proximity to high-traffic areas, and the availability of both official and citizen-led monitoring networks. This study capitalizes on these resources to assess local pollution dynamics through the comparison of satellite- and ground-based $PM_{2.5}$ data sources.

Previous research has highlighted the benefits and drawbacks of both ground-based and satellite-based air quality monitoring. Ground sensors offer real-time, high-resolution data at specific locations but often suffer from limited spatial coverage and variability due to maintenance or calibration issues (Microcontrollers Lab, 2024). In contrast, satellite-based monitoring provides broader spatial information, yet struggles to capture localized pollution fluctuations due to lower spatial resolution and atmospheric interference (Hsu et al., 2019; Wang et al., 2020).

The central objectives of this study are to investigate the differences between these data sources in measuring $PM_{2.5}$ levels in Mainz and to examine whether a significant trend in air quality improvement is evident over the observed time period. By applying robust statistical methods and spatial matching techniques, the study contributes to a more nuanced understanding of air quality monitoring and offers valuable insights for future environmental policy design.

2. Theory

2.1. Particulate Matter and Health

Particulate matter, particularly $PM_{2.5}$, refers to fine particles that are less than 2.5 micrometers in diameter. These particles are significant due to their small size, which allows them to penetrate deep into the respiratory system and enter the bloodstream, causing severe health effects such as respiratory diseases, heart conditions, and even premature death (Mushtaq et al., 2019). $PM_{2.5}$ originates primarily from combustion processes, including emissions from vehicles, industrial facilities, power plants, and natural sources like wildfires and dust storms (Xue et al., 2019). Due to their health implications, $PM_{2.5}$ levels are closely monitored globally (Brook et al, 2010; Mushtaq et al, 2024). The WHO (2021) sharpened their guidelines considerably in 2021 and has now established a maximum of 5 μg/m³ as the threshold for damage to human health, based on widespread evidence of the link between exposure and adverse health outcomes.

2.2. PM2.5 Sensing

2.2.1. Ground-based sensors

Ground-based sensors offer real-time measurements of air quality at localized points, providing detailed data on specific areas. Their reliance on fixed locations and potential calibration issues may introduce challenges in data accuracy. Despite these limitations, ground sensors contribute valuable information for urban air quality monitoring. Mushtaq (Mushtaq et al, 2024) discussed the comparison between satellite and ground-based measurements for $PM_{2.5}$ and other pollutants, emphasizing the importance of evaluating the accuracy of each method in the context of their health implications, arguing that sensors could have a value for detecting local hotspots (Wang et al., 2020). An example of the lower grade SDS011 sensor is shown in Figure 1.

Figure 1. SDS011 $PM_{2.5}$ Sensor. Source: Microcontrollers Lab (2024).

2.2.2. Satellite observations

Satellite-based measurements, like those provided by the Atmospheric Composition Analysis Group at Washington University in St. Louis (Shen et al., 2024), offer a broader, regional perspective on $PM_{2.5}$ pollution levels. Satellites capture a vast array of data, providing a global overview of air quality trends and regional pollution patterns. The measurement method is based on air dispersion, and remote and displayed in (Figure 2).

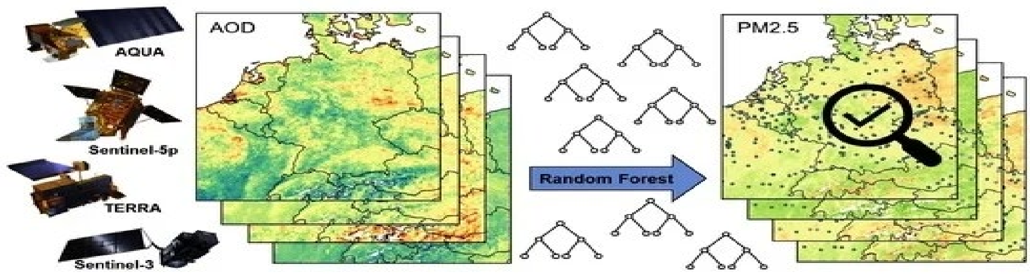


Figure 2. Remote Sensing. Copied with a CC-BY license from (Handschuh et al., 2023).

However, the spatial resolution of satellite measurements is typically lower compared to higher grade ground sensors, which can result in less precise data when assessing small-scale local pollution (Hsu et al, 2019). Additionally, satellite data may not capture transient pollution events or localized emissions (Wang et al, 2020).

2.3. Geospatial Alignment

To compare the effectiveness of satellite and sensor data, it is crucial to align both data sources spatially. Geospatial alignment ensures that satellite data points are compared to the nearest sensor locations, enabling meaningful comparisons. Additionally, temporal alignment is necessary, as satellite data may be available on a monthly or annual basis, while sensor data can provide more frequent, real-time readings. In this study, the KDTree method was employed to achieve precise spatial alignment between satellite and ground-based measurements (Xue et al, 2019).

KDTree is a spatial data structure used for organizing points in a k-dimensional space, allowing for fast nearest-neighbor searches (Bentley, 1975). This method is particularly useful when handling large geospatial datasets, such as air pollution measurements, where precise location matching is required. The KDTree (K-dimensional tree) is a space-partitioning data structure that is widely utilized in various contexts, including nearest neighbor searches, range searches, and multi-dimensional data indexing. It organizes points in a k-dimensional space efficiently by recursively dividing the space into two half-spaces, allowing for faster queries than a naive linear search.

A KDTree is constructed by recursively dividing the data points along one of the k dimensions. The basic algorithm for building a KDTree involves selecting a dimension (often cyclically) and a pivot point (typically the median of the chosen dimension). This pivot acts as the boundary between points that will reside in the left subtree and those that will go into the right subtree The construction process can be summarized in the following steps:

- Choose the dimension to split by, based on the depth of the node in the tree;
- Sort the points based on the selected dimension;
- Select the median point from the sorted list to minimize the number of comparisons in future searches.
- Recursively apply the same process to the left and right subsets of points

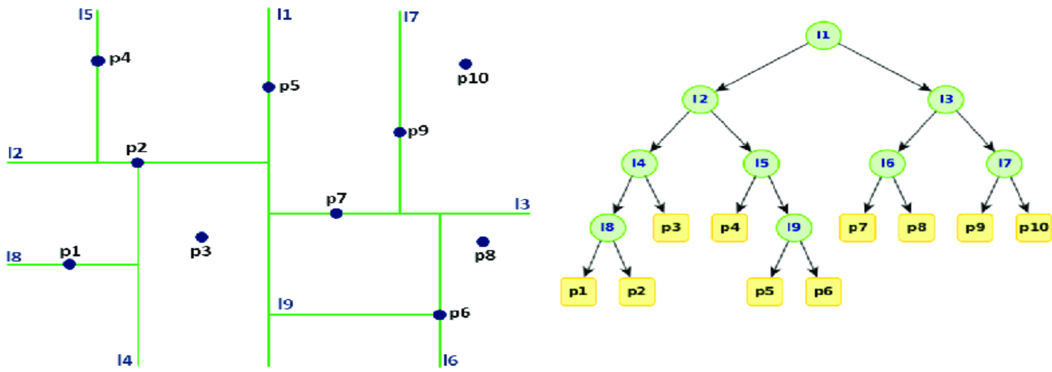


Figure 3. KDTree Algorithm Procedures. Copied with a CC-BY 4.0 License from (Anzola et al., 2018).

This recursive approach results in a binary tree structure where each node represents a point in k-dimensional space, with the left child containing points less than the parent node in the selected dimension and the right child containing points greater than or equal to the parent (Bentley, 1975). Searching in a KDTree can be performed efficiently for nearest neighbors and range queries. For nearest neighbor searches, the algorithm starts at the root of the tree and traverses down to the leaves while maintaining a list of potential nearest neighbors. Upon reaching a leaf node, the distance to the point is calculated. The algorithm then backtracks and checks the other branches of the tree, utilizing a bounding box defined by the current nearest neighbor distance to prune unnecessary searches (Baspinar, 2020).

The main advantage of using KDTree is its speed in performing multidimensional searches, commonly achieving average-case complexities of O(log n) for both nearest neighbor queries and range queries. This efficiency makes it particularly well-suited for applications such as computer graphics, machine learning, and spatial databases (Shapiro, 2018). However, KDTree has several limitations. Its performance can degrade in high-dimensional spaces — commonly referred to as the "curse of dimensionality" — where the tree becomes less efficient, leading to average-case complexities approaching O(n) (Liu, 2018). In addition, the construction of the KDTree itself can be time-consuming for very large datasets due to the need to sort points at each split.

KDTree finds extensive application in various domains, including computer vision, robotics, and geographic information systems. In computer vision, KDTree is often employed to accelerate image retrieval processes through efficient image feature indexing (Szeliski, 2010). In robotics, it aids in motion planning and obstacle avoidance by enabling fast spatial queries in dynamic environments (Kuffner & LaValle, 2000).

3. Methods

3.1. Data Sources

Satellite observations provide estimates of the PM2.5 distribution across large geographical regions. The “Atmospheric Composition Analysis Group at Washington University in St. Louis (WUSTL, 2025)” generates high-resolution data (x 0.0 from a combination of satellites, ground-based monitors and deep learning appraches as shown in Figure 4.

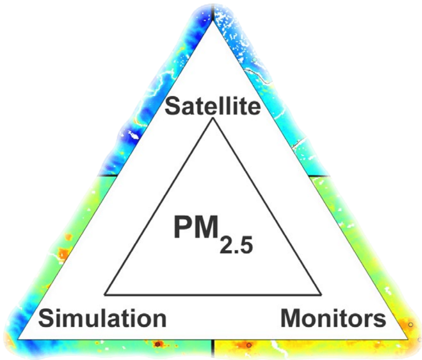


Figure 4. Washington University St. Louis ACAG System (WUSTL, 2025).

3.1.1. Sensor community

Ground-based PM2.5 measurements were obtained using SDS011 sensors deployed by volunteers in Mainz, Germany, as part of the citizen science initiative sensor.community (sensor.community, 2025). These sensors provide real-time measurements of PM2.5 and PM10 concentrations, uploaded to the public web site daily.

3.1.2. Official city data

The state (bundesland) Rheinland-Pfalz provides public access to particulate matter via their central emission net infrastructure. Rheinland-Pfalz State Environmental Agency's PM2.5 data (ZIMEN; 2023). The city uses sensors of the type shown in Figure 8.

4. Results

4.1. Geographical Alignment

The proximities of studied sensor and satellite points are seen in Figure 5 and Table 1.

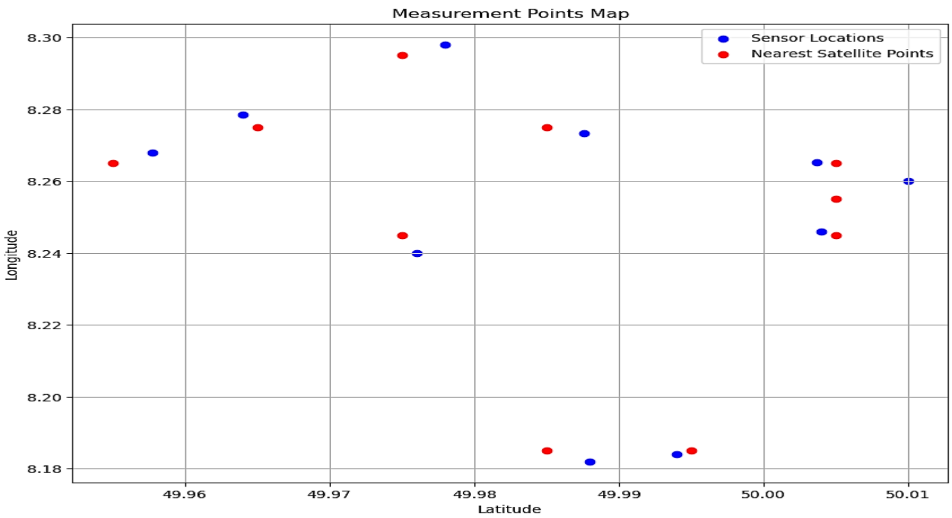


Figure 5. Locations of satellite and sensor points by the KDTree algorithm

Table 1. This is a table. Tables should be placed in the main text near to the first time they are cited.

Longitude	Nearest Satellite Point (lat, lon)	Distance (km)
8.240	(49.975, 8.245)	0.38
8.246	(50.005, 8.245)	0.13
8.182	(49.985, 8.185)	0.40
8.298	(49.975, 8.295)	0.40
8.260	(50.005, 8.255)	0.66
8.268	(49.955, 8.265)	0.37
8.279	(49.965, 8.275)	0.27
8.273	(49.985, 8.275)	0.31
8.265	(50.005, 8.265)	0.15
8.184	(49.995, 8.185)	0.13

The observed distances had a mean of 0,32 km (standard deviation 0.2 km). All points are depicted on the overview map of Mainz in Figure 6.

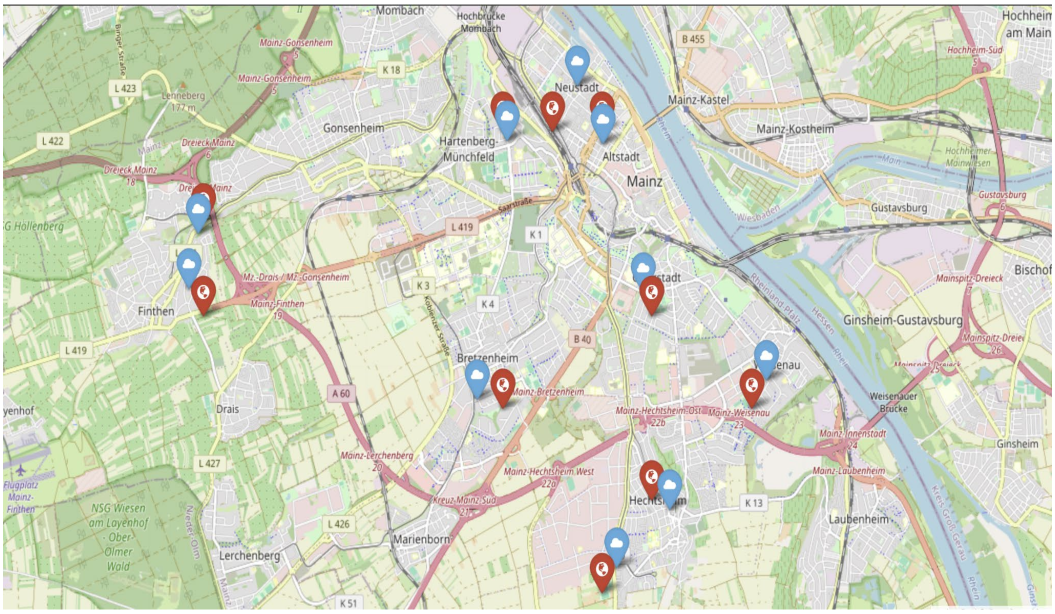


Figure 6. Locations of satellite and sensor points by the KDTree algorithm

4.2. PM2.5 Results by Measurement Source

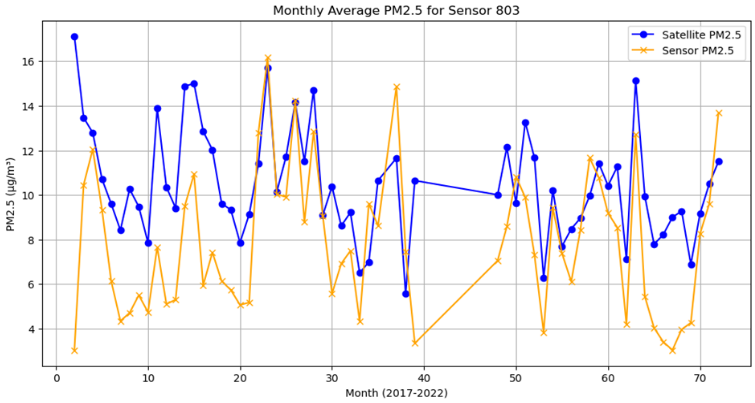
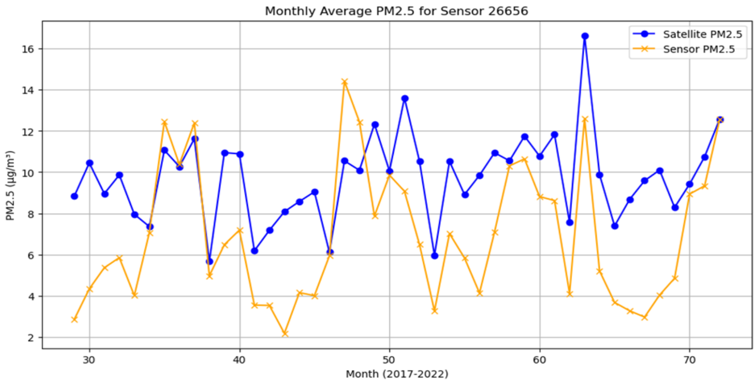
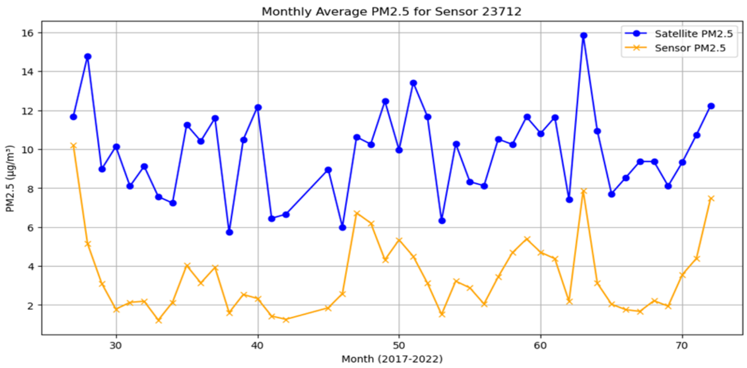
Two of the sensors were discarded due to unreliable results, and (Table 2) presents the recorded total average of all monthly measurements at the corresponding locations.

Table 2. Total average of monthly measurements.

Sensor ID	Satellite	Sensor	Difference
803	10.3	8.3	2.0
10701	10.4	4.6	5.8
21886	9.1	3.7	5.5
23712	9.9	3.3	6.6
26656	10.0	7.1	3.0
47739	10.0	3.7	6.3
48807	9.6	7.3	2.2
772200	10.6	8.0	2.0

The applied two sample Mann Whitney test revealed a mean difference of 4.16 micrograms per cubic meter (Satellite: 9.91, Sensor 5.75) and a p value < 0.001. The discrepancies between the satellite and sensor are further illustrated by the line graphs of the monthly averages of three randomly chosen points out of the eight locations in Table 3.

Table 3. Graphical comparison of satellite vs. sensor measurements.

Sensor	Graph
803 (Mainz-Kostheim,Wiesbaden)	
26656 (Mainz-Kastel,Wiesbaden)	
23712 (Mainz-Weisenau)	

4.3. Comparison to City Official Sources

The state (bundesland) Rheinland-Pfalz, where Mainz is located, provides public access to pollution data measured at a number of points as shown in Figure 7.However, only two of these stations ("Mainz Zitadelle" and "Mainz Parcusstraße") specifically measure $PM_{2.5}$ concentrations. These stations are highlighted in red on the map (Figure 7).

Figure 7. A map of the city sensor stations.

At the two locations where PM2.5 is measured, the city has utilized a sensor of the type shown in Figure 8.

Figure 8. Particulate monitor model SHARP5030 (Thermo Fisher Scientific Inc., 2018).

We show the yearly average from all three measurement sources in (Table 4).

Table 4. Yearly average PM2.5 (μg/m³).

Year	Satellite	City	Sensor
2017	9.6	12.9	9.0
2018	10.0	12.7	9.0
2019	8.4	11.2	9.9
2020	10.1	10.0	10.5
2021	11.5	10.7	9.9
2022	12.2	10.5	8.0

4.4. Pollution Trends

A regression model was fitted for the yearly means of each of the satellite locations. This table shows the coefficients of the sensors in Mainz. The data used is the air pollution PM2.5 from the period 2017 to 2022 as measured by the satellite system.

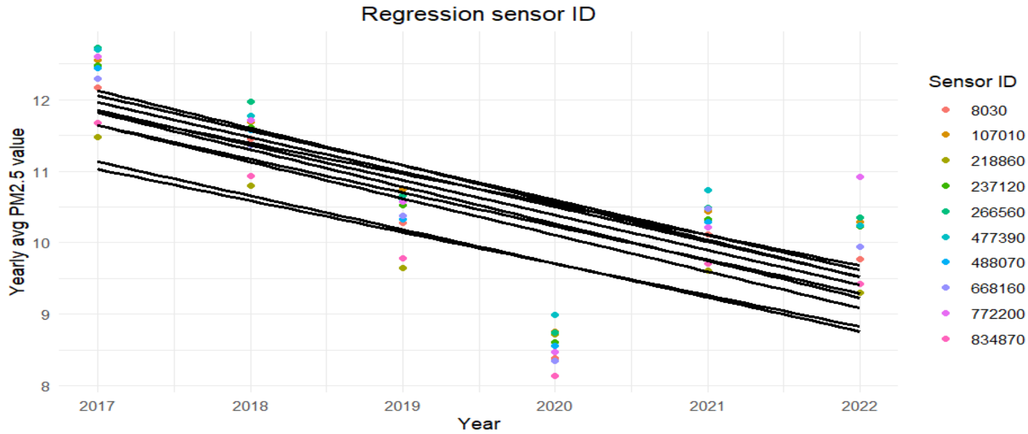


Figure 9. A regression analysis on air pollution PM2.5 between the period of 2017 and 2022.

This figure illustrates the decline in $PM_{2.5}$ air pollution in Mainz, based on the statistical analysis presented in Table 5. The trend exhibits an almost linear decrease in air pollution levels, with the exception of 2020. The significant drop in 2020 can likely be attributed to the impact of the COVID-19 pandemic.

Table 5. Reducing air pollution PM2.5 between 2017 to 2022.

Data Point (sensor.community ID)	Slope / (microg/m^3/year)	P Value
803	−0.511	0.107
10701	−0.488	0.119
21886	−0.440	0.0527
23712	−0.489	0.130
26656	−0.521	0.119
47739	−0.487	0.113
48807	−0.518	0.108
66816	−0.470	0.155
772200	−0.428	0.238
834870	−0.474	0.107

4.5. Levels Compared to WHO Safe Thresholds

The histogram of the recorded yearly mean values from every satellite station (10 points over six years) is shown in Figure 10.

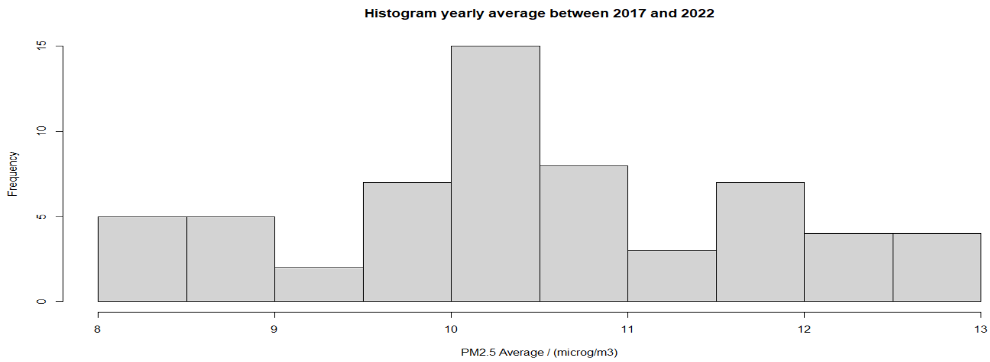


Figure 10. Histogram of recorded PM2.5 measurements all satellite points.

It was noted that the range of the yearly average concentration was 8.1 - 12.7 g/m³ or that in other words all points had levels at least 60 % above what the WHO deems as safe. In the final year, only three out of ten stations even had a level below twice the WHO guidelines.

5. Discussion

The comparison between satellite-derived and ground-based $PM_{2.5}$ measurements demonstrates a consistent pattern: satellite data typically reports higher concentrations than those recorded by ground-level sensors. This discrepancy, while statistically significant according to the Mann-Whitney U test, is not uniform across all time periods or measurement locations. Such variation implies that localized environmental conditions—including microclimatic effects, traffic density, and land use—play an important role in modulating air quality and can affect the performance and readings of different measurement systems. One primary source of variation arises from methodological differences in data collection. Ground-based sensors, such as those used in the Sensor Community initiative, provide high-frequency, localized measurements. These sensors are highly sensitive to immediate pollution sources such as road traffic, construction sites, or nearby industrial activity. However, their readings can be affected by environmental variables like temperature and humidity, as well as inconsistencies in device calibration and maintenance. The relatively low cost and simplicity of these sensors—while valuable for citizen science—also limit their technical precision.

In contrast, satellite-based measurements, such as those from the Atmospheric Composition Analysis Group, offer consistent regional coverage and incorporate sophisticated algorithms to estimate surface-level $PM_{2.5}$ from aerosol optical depth. These measurements inherently smooth out short-term or hyper-local pollution events due to their larger spatial footprint. Consequently, while satellites may more accurately reflect regional air quality trends, they are less responsive to acute local variations. This fundamental difference in resolution and methodology is likely a major contributor to the observed disparities between the datasets. Interestingly, comparisons with official data from the Rheinland-Pfalz State Environmental Agency revealed stronger alignment with satellite-derived values than with data from individual ground sensors. This may reflect the standardized maintenance and calibration of official stations, making them more compatible with the generalized estimates provided by satellite platforms. Some sensor locations exhibited strong correlation with satellite values, while others displayed weak or inconsistent relationships. These differences further support the hypothesis that environmental context, sensor placement, and maintenance quality significantly influence measurement agreement.

The linear regression analysis conducted on annual $PM_{2.5}$ averages across all measurement systems indicated a modest but clear downward trend in pollution levels, with an average annual reduction of approximately 0.5 μg/m³. These findings align with regional reports and suggest that local air quality has improved, potentially due to enhanced environmental regulations and the temporary decline in emissions during COVID-19 lockdowns. It matches similar findings where a falling trend has been observed in Europe (Aas et al., 2024).

Despite some positive trends, the persistent exceedance of WHO's recommended $PM_{2.5}$ limits across all data sources underscores a critical public health concern. The results suggest that current mitigation efforts are insufficient to achieve safe air quality levels in Mainz. In light of this, the implementation of stronger regulatory frameworks and long-term urban planning strategies is imperative. It should have a very high sense of urgency given that exposure to PM2.5 has been estimated to cause as much as 3 % of all deaths in Germany (Hahad et al., 2024) Finally, the study emphasizes the value of hybrid monitoring approaches that integrate satellite data with ground-level sensor observations and meteorological inputs. Such models, as demonstrated in previous studies (Wang et al., 2020), can substantially improve the spatial and temporal resolution of air quality estimates and provide a more accurate foundation for public health decision-making and environmental policy design.

6. Conclusions

This study provides a comprehensive assessment of $PM_{2.5}$ concentrations in Mainz from 2017 to 2022 by comparing satellite, citizen sensor, and official measurement systems. The findings show a general decline in $PM_{2.5}$ levels over time, but all measurements continue to exceed WHO guidelines. Discrepancies between data sources highlight the strengths and limitations of each method and emphasize the need for hybrid approaches that integrate multiple data streams. Future research should focus on enhancing data harmonization and improving the resolution of both satellite and ground-based monitoring to better capture the complex spatial and temporal dynamics of urban air pollution.

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