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Use of Kolmogorov-Zurbenko Filter Technique to Evaluate $PM_{2.5}$ Air Quality Trends in New Jersey

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ABSTRACT

This study aimed to investigate long-term trends of PM2.5 in New Jersey by comparing two different methods the 3-year average of highest annual average and KZ filter technique. The 3-year average of the highest annual average method provides a simple way to track air quality trends over time. This method is commonly used by regulatory agencies to assess compliance with air quality standards and to identify areas that require additional controls to meet those standards. However, this method can be affected by short-term variations and may not capture longer-term trends in air quality. The KZ filter-based method is a statistical technique that can be used to identify and remove short-term fluctuations in the data to reveal underlying long-term trends. This method is particularly useful for analyzing air quality trends over a long period of time, such as decades, and can help to distinguish between natural variability and changes caused by human activities. However, the KZ filter-based method can be sensitive to outliers and may not capture sudden changes or short-term events that may have an impact on air quality. In this study the PM2.5 air quality trends in New Jersey were examined to highlight the importance of understanding long-term air quality trends from a regulatory perspective and the use of a rigorous statistical rolling average technique such as the KZ filter in trend analysis.

Introduction

The study of long-term trends in air quality is essential for regulatory agencies to evaluate the effectiveness of their efforts to improve air quality. It is crucial to determine whether air quality standards are being met or not, and if not, to identify the areas where further regulatory action is needed. Long-term air quality trends can also inform resource allocation decisions, such as where to focus monitoring efforts and what types of pollution control measures are most effective. However, it is important to consider that long-term air quality trends can be influenced by various factors, such as meteorology, missing data, and seasonal or annual averaging processes, which may intervene better understanding of the true trends. Therefore, it is necessary to carefully consider these factors when interpreting long-term air quality trends and use additional information, such as statistical analysis, modeling, and meteorological data, to better understand the trends.

This study aimed to investigate long-term trends of PM2.5 in New Jersey by comparing two different methods the 3-year average of highest annual average and KZ filter technique. The 3-year average of the highest annual average method provides a simple way to track air quality trends over time. This method is commonly used by regulatory agencies to assess compliance with air quality standards and to identify areas that require additional controls to meet those standards. However, this method can be affected by short-term variations and may not capture longer-term trends in air quality. The KZ filter-based method is a statistical technique that can be used to identify and remove short-term fluctuations in the data to reveal underlying long-term trends. This method is particularly useful for analyzing air quality trends over a long period of time, such as decades, and can help to distinguish between natural variability and changes caused by human activities. However, the KZ filter-based method can be sensitive to outliers and may not capture sudden changes or short-term events that may have an impact on air quality. In this study the PM2.5 air quality trends in New Jersey were examined to highlight the importance of understanding long-term air quality trends from a regulatory perspective and the use of a rigorous statistical rolling average technique such as the KZ filter in trend analysis.

Background

The Current Status of Complying with National Ambient Air Quality Standard of PM2.5 in the United States and New Jersey

PM2.5 refers to fine particulate matter with a diameter of less than 2.5 micrometers, which can be inhaled deep into the lungs and cause adverse health effects. These health effects include respiratory and cardiovascular diseases, reduced lung function, and premature death. PM2.5 is a serious public health concern and efforts are needed to reduce its emissions and exposure. The current status of complying with the National Ambient Air Quality Standards (NAAQS) for PM2.5 in the United States and New Jersey is a mixed picture. According to the US Environmental Protection Agency (EPA), the levels of PM2.5 have decreased significantly in the United States over the past 20 years. In 2000, the national annual PM2.5 concentration was 12.9 micrograms per cubic meter ($\mu g/m^3$), and in 2020, it was 7.4 µg/m3, a decrease of 43 percent. This significant improvement is due to the implementation of the Clean Air Act and the EPA's efforts to reduce emissions from transportation, industry, and power plants. However, despite the progress made nationally, there are still areas in the United States that do not meet the NAAQS for PM2.5. In 2020, 17 counties in California, 5 counties in Utah, and 1 county in Idaho were designated as nonattainment areas for the annual PM2.5 standard. Nonattainment means that the air quality in these areas is not meeting the NAAQS and action must be taken to reduce emissions. In New Jersey, the current status of complying with the NAAQS for PM2.5 is mixed as well. According to the New Jersey Department of Environmental Protection (NJDEP), the state has made significant progress in reducing PM2.5 levels since the 1990s. However, there are still areas in the state, mainly in urban centers and near major highways, where the PM2.5 levels exceed the NAAQS. In 2020, six counties in New Jersey were designated as nonattainment areas for the annual PM2.5 standard. The NJDEP is taking measures to reduce emissions from transportation, industry, and power plants to improve air quality in these areas and meet the NAAQS for PM2.5.

Historical Reduction of PM2.5 in the United States and New Jersey

The United States Environmental Protection Agency (EPA) has reported on the trends in air quality for both ozone and PM2.5 over the past several decades. According to their data, ozone levels have decreased by about 21% since 2000, while PM2.5 levels have only decreased by about 6% over the same time period (U.S. EPA, 2021a). A study published in the journal Atmospheric Chemistry and Physics in 2019 analyzed trends in ozone and PM2.5 concentrations across the U.S. between 2000 and 2015 (Huang, 2019). The authors found that while ozone concentrations had decreased in most regions, PM2.5 concentrations had not decreased significantly over the same time period. Another study published in the journal Environmental Science & Technology in 2018 analyzed trends in air quality across the U.S. between 1980 and 2014 (Silva, 2018). The authors found that while there had been significant improvements in air quality overall, ozone had decreased more rapidly than PM2.5.

There are several reasons why there are many scientific references that discuss the trend of decreasing ozone and relatively stagnant levels of PM2.5 in the U.S. over the past several decades. Firstly, ozone and PM2.5 are both air pollutants that come from different emissions sources. Ozone is formed when nitrogen oxides (NOx) and volatile organic compounds (VOCs) react in the presence of sunlight, while PM2.5 comes from a variety of sources including vehicle exhaust, power plants, and wildfires (U.S. EPA, 2021b). It is possible that the sources of PM2.5 emissions have been more difficult to control than the sources of ozone-forming pollutants, leading to a slower decrease in PM2.5 levels over time (U.S. EPA 2021c). Secondly, the U.S. government has implemented a number of regulations and policies aimed at reducing air pollution over the past several decades, including the establishment of the PM2.5 rule in 1997 (U.S. EPA 2021b). However, some researchers including U.S. EPA and the institutions have suggested that these control measures may not have been as effective at reducing PM2.5 levels as they have been at reducing ozone levels (Liu, 2016; Bell, 2014; Kelly, 2017; Zhang, 2017; Franklin, 2015). Lastly, the monitoring methods used to measure ozone and PM2.5 levels have changed over time, which could potentially affect the trends observed in the data. For example, some studies have suggested that changes in the monitoring methods used to measure PM2.5 levels may have led to an underestimation of the true levels of this pollutant (Bell, 2005; Hopke, 2016; Jerrett, 2009; Kim, 2015; Lippmann, 2014; National Research Council, 2004).

According to the New Jersey Department of Environmental Protection (NJDEP), there have been significant improvements in air quality in New Jersey over the past several decades, with reductions in both ozone and PM2.5 levels. The NJDEP reports that between 2000 and 2020, the annual average concentration of ozone in New Jersey decreased by 19%, from 94 parts per billion (ppb) to 76 ppb. Similarly, the annual average concentration of PM2.5 in New Jersey decreased by 33% during the same time period, from 13.1 micrograms per cubic meter ($\mu g/m^3$) to 8.8 $\mu g/m^3$. However, despite these improvements, the NJDEP notes that New Jersey still experiences poor air quality on certain days, particularly during the summer months when ozone concentrations can be elevated. The agency continues to implement air quality improvement initiatives and regulations to further reduce ozone and PM2.5 levels in the state. (New Jersey DEP, 2020)

Importance of Evaluating Long-term Trends of Air Quality

From a regulatory perspective, it is of critical importance to understand long-term air quality trends (U.S. EPA, 2021a; Bloomer, 2009; Cooper, 2014; Huang, 2015; Levy, 2019; Parrish, 2014). Long-term trends in air quality can be used to evaluate whether regulatory efforts to improve air quality are effective. This information is critical for assessing whether air quality standards set by regulatory agencies are being met. If long-term trends indicate that air quality is not improving or is getting worse, regulatory agencies can use this information to identify areas where further regulatory action may be needed (U.S. EPA, 2021a). This could involve tightening emissions standards, expanding monitoring programs, or implementing other measures to reduce air pollution. Long-term air quality trends can also inform resource allocation decisions, such as where to focus monitoring efforts and what types of pollution control measures are most effective (Huang, 2015; Hopke, 2016). However, it is important to note that long-term air quality trends can be affected by various factors, such as meteorology, missing data, and seasonal or annual averaging processes (Parrish, 2014; Levy, 2019). These factors can distort the trends, making it difficult to accurately assess the true state of air quality. Therefore, it is important to carefully consider these factors when interpreting long-term air quality trends and to use additional information, such as statistical analysis, modeling and meteorological data, to better understand the trends.

Impact of Different Statistical Approaches on Evaluation of Long-Term Trends

Statistical rolling averages are important in air quality trend analysis because they help to smooth out short-term fluctuations in the data, which can be caused by factors such as weather and seasonal variations (Dominici, 2013). A simple average of the data, which is calculated by adding up all the values and dividing by the total number of values, does not account for these fluctuations and can result in misleading trends. In contrast, a statistical rolling average calculates the average of a specified number of data points over a specific time period, which is then moved forward one time period at a time until the entire dataset is covered (Koutrakis, 2005). This process helps to smooth out the data by reducing the influence of short-term fluctuations while preserving the overall trend. Statistical rolling averages are particularly important in air quality trend analysis because the concentration of pollutants can vary greatly over short periods of time due to weather patterns, such as wind and temperature changes, and seasonal variations (Bell, 2014). By using a statistical rolling average, the long-term trend in the data can be more accurately assessed, which is important for understanding the effectiveness of pollution control measures and developing future air quality policies.

Three-Year Average of the Highest Annual Average Method

The 3-year average of the highest annual average method is a popular tool for assessing air quality trends due to its simplicity, transparency, and consistency. This method uses the highest annual average value over a three-year period to capture the most severe air quality events that may have a significant impact on human health and is commonly used by regulatory agencies to assess compliance with air quality standards. However, this method may not be sensitive enough to detect long-term trends in air quality, and it may not capture short-term variability or spatial variations in air quality. Additionally, this method is generally used for assessing trends in criteria air pollutants, which are regulated by national air quality standards, and may not be appropriate for assessing trends in other air pollutants that are not regulated in the same way. Therefore, it is important to consider the limitations of this method and to use it in combination with other methods to gain a more comprehensive understanding of air quality trends over time.

Kolmogorov-Zurbenko Filter in Air Quality

The KZ filter is a statistical method used to smooth time series data, which is commonly used in air quality trend analysis. The KZ filter is a modified form of the Hodrick-Prescott filter, which is used to separate a time series into a trend component and a cyclical component. Compared to simple averaging, the KZ filter is considered to be a more robust method for trend analysis because it is less sensitive to short-term fluctuations in the data. Simple averaging can be influenced by short-term variations, which can make it difficult to detect long-term trends. The KZ filter, on the other hand, is able to smooth out short-term fluctuations, allowing for a clearer picture of the long-term trend.

The KZ filter has been widely used to evaluate long-term trends in air quality, as demonstrated in several studies. Zhang and Yang (2004) and Cheng et al. (2006) both used the KZ filter to analyze PM2.5 data in Beijing, allowing for the identification of long-term trends and seasonal variations in particle concentrations and chemical composition. Li and Chen (2009) used the KZ filter to examine long-term trends and seasonal variations in visibility, influenced by PM2.5 concentrations, in Hong Kong. Additionally, Zhang et al. (2015) used the KZ filter to analyze the long-term trends of PM2.5 concentrations in China, finding that it improved the accuracy of trend analysis by reducing the impact of short-term fluctuations. Li et al. (2019) used the KZ filter to detect statistically significant declines in PM2.5 levels in the United States, even in regions where simple averaging did not show significant trends. Thus, the KZ filter is a valuable tool in analyzing air quality trends and can improve the accuracy of trend analysis over traditional methods.

Methods

Data

In 2023, NJDEP operates 30 air monitoring stations across New Jersey, as shown in Figure 1. The study utilizes data compiled by the NJDEP Air Quality Monitoring Network database and downloaded from the USEPA website (U.S. EPA, 2023). Nine active PM2.5 monitoring stations in New Jersey were selected for this study, as indicated in Figure 1. Table 1 shows that the study focuses on three counties for long-term trend analysis: Camden County, characterized as an urban site, Bergen County, an intensive residential area with predominant transportation sources, and Middlesex County, a suburban area. The study examines a 22-year period (2000-2022) for long-term trend analysis in Camden and Bergen counties, while the Middlesex County site has an eight-year period since the New Brunswick site started in 2016. Descriptive statistical analysis and KZ filter-based long-term trend analysis were performed using these collected data in this study. According to NJDEP, PM2.5 concentrations have decreased from 16.4 ug/m3 in 2001 to 9.6 ug/m3 in 2021, a 41% reduction in PM2.5 between 2001 and 2021, as displayed in Figure 2 retrieved from NJDEP's 2021 Air Quality Report (NJDEP, 2021). NJDEP's long-term trend calculation follows EPA's NAAQS method (USEPA, 2021a) which is 3-year average of the highest annual average concentration.

Figure 1. New Jersey Air Monitoring Site Network as of 2021 (Courtesy from NJDEP, 2021)

Table 1. PM2.5 Monitoring Sites and Data Collection Used for This Study

County	Years	Site Characteristic	No. of Available Monitoring Sites Used for This Study
Camden	2000-2022	Urban	4 (340070002 340070003, 340070010, 340071007)
Bergen	2000-2022	Residential	2 (340030003, 340030010)
Middle-sex	2016-2022	Suburban	1 (340230011)

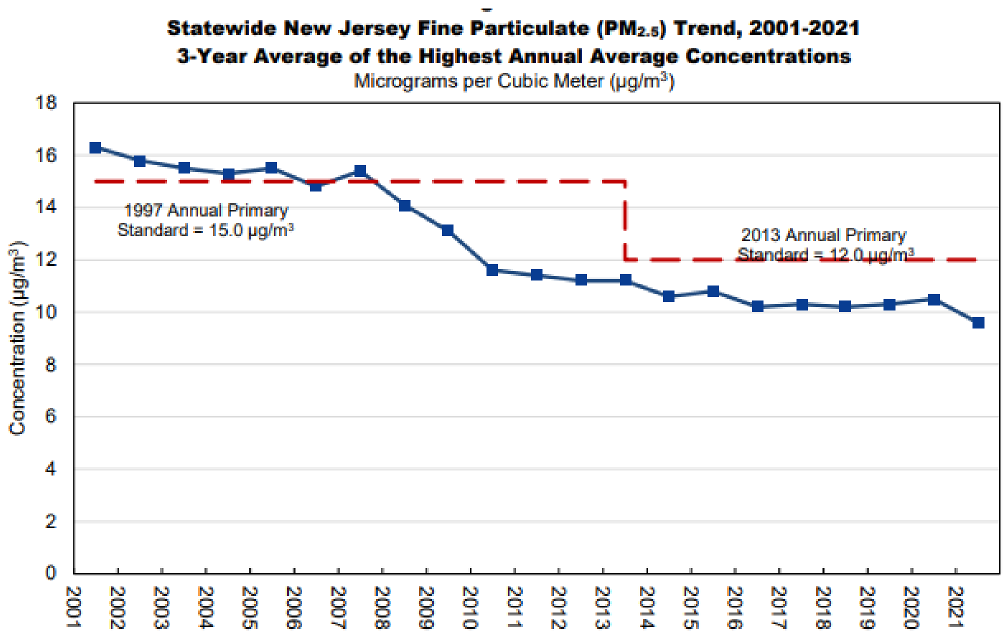

Figure 2. PM2.5 Trend (3-Year Average of the Highest Annual Average Concentration), 2001-2021 in New Jersey Air Monitoring Site Network (Courtesy from NJDEP, 2021)

Descriptive Statistics

Prior to KZ filter-based long-term evaluation, descriptive statistics were tested as below using the box plot in R® statistical package that typically includes the following descriptive statistics. A box plot in R provides a comprehensive visualization of the distribution of a data set, and is a useful tool for identifying outliers, skewness, and other features of the data:

Median: The median is the value that divides the data set into two equal parts. It is represented by a horizontal line inside the box.

Mean: The mean is the value that divides the sum of individual points by the total number of samples, representing arithmetic average of the data distribution.

Quartiles: The quartiles divide the data set into four equal parts. The lower quartile (Q1) represents the 25th percentile of the data set, and the upper quartile (Q3) represents the 75th percentile of the data set. They are represented by the bottom and top of the box, respectively.

Interquartile range (IQR): The IQR is the range between the first and third quartiles and represents the middle 50% of the data set. It is represented by the height of the box.

Minimum and Maximum values: The minimum and maximum values of the data set are represented by the end points of the whiskers.

Outliers: Outliers are data points that fall outside the whiskers and are represented by individual points on the plot.

In this study, the mean values were compared among annual means, the NJDEP-estimated trends and KZ filter-based trends.

KZ Filter Procedure

The Kolmogorov-Zurbenko (KZ) filter is a digital filter used for smoothing and reducing noise in time series data. It involves performing multiple moving average operations on the data to improve its signal-to-noise ratio. The KZ filter is defined by the following equation:

Equation 1:

$$y[n] = \left(\frac{1}{M}\right) * sum(x[n-i+1] + x[x-i+\ 2] + \cdots + x[n-i+M], where\ i = 0, 1, 2, \ldots, (N-M)$$

In this equation, x[n] is the input time series data, y[n] is the output smoothed data, M is the order of the filter (i.e., the number of data points in each moving average window), and N is the length of the time series data. The value of M is typically chosen based on the characteristics of the data and the desired level of smoothing. The KZ filter involves performing multiple iterations of this equation on the input data, with the output from each iteration serving as the input to the next. This process effectively performs a smoothing operation on the data, while preserving its underlying trends and patterns. KZ(365, 3) indicates 365-days rolling average and 3rd iterations. In this study, KZ(30, 5), KZ(120, 3), and KZ(365, 3) were investigated to represent monthly rolling average, quarterly rolling average and yearly rolling average.

Results

Descriptive Statistics Using Box Plots

Descriptive statistics for overall long-term trends were tested as below using the box plot in R® statistical package that typically includes the following descriptive statistics. Figures 3 to 5 exhibit box-whiskers plots for PM2.5 air quality long-term trends for 2000 to 2022 in Camden, Bergen, and Middlesex counties, respectively. The mean values are represented by the thick lines in the gray box. The Camden, Bergen, and Middlesex (2016-2022) counties showed significant reductions between 2000 and 2022 for the PM2.5 annual average level by 26%, 25%, and 14%, respectively.

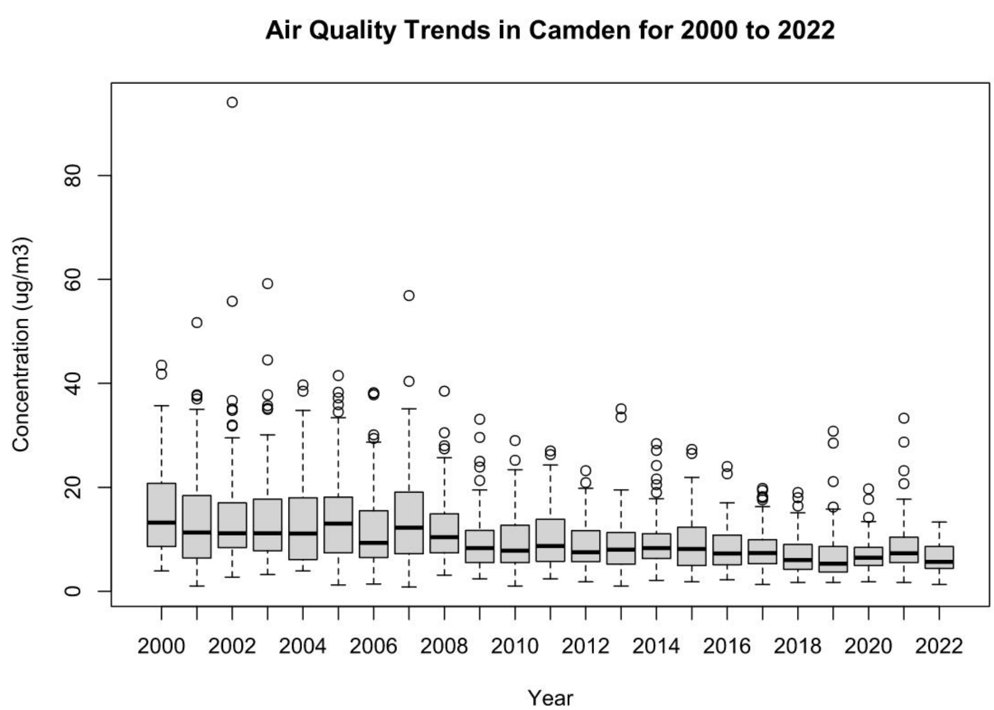

Figure 3. PM2.5 Long-Term Trend in Camden County for 2000-2022

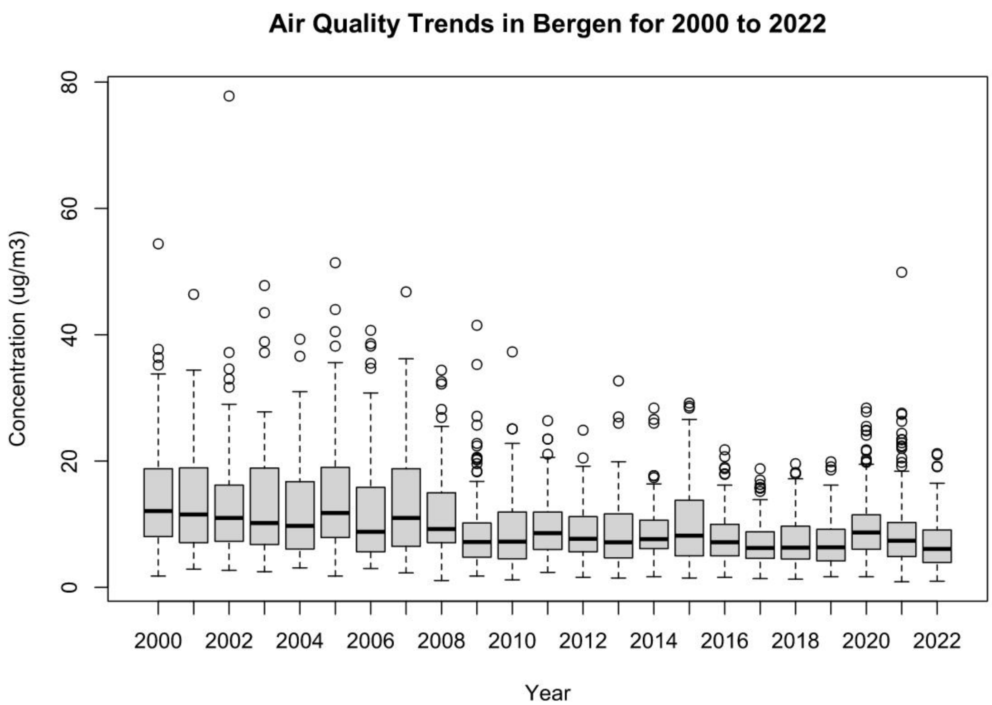

Figure 4. PM2.5 Long-Term Trend in Bergen County for 2000-2022

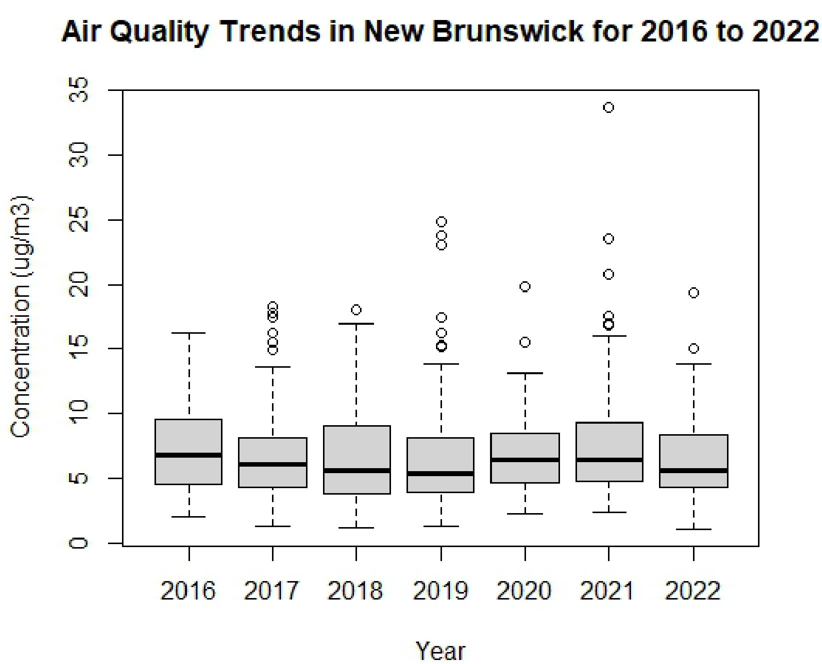

Figure 5. PM2.5 Mid-Term Trend in Middlesex County for 2016-2022

Descriptive statistics for monthly trends were examined as below using the box plot in R® statistical package to evaluate impact of seasonal meteorology and anthropogenic activities. Figures 6 to 8 display box-whiskers plots for PM2.5 air quality monthly trends for 2000 to 2022 in Camden, Bergen, and Middlesex (2016-2022) counties, respectively. The mean values are represented by the thick lines in the gray box. The monthly pattern analysis of PM2.5 concentrations in NJ suggested that PM2.5 levels were higher in winter and summer and were lower in spring and fall in all the Camden, Bergen, and Middlesex counties.

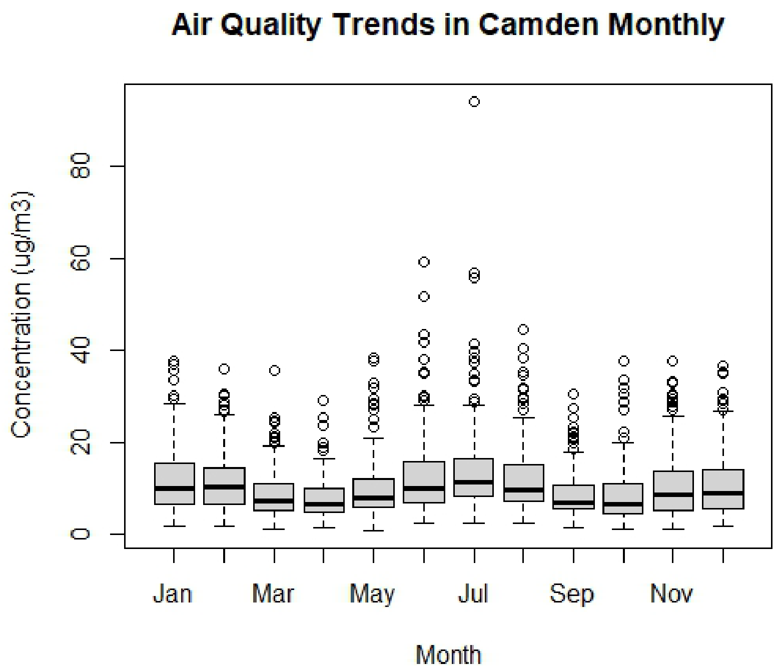

Figure 6. PM2.5 Monthly Trend in Middlesex County for 2000-2022

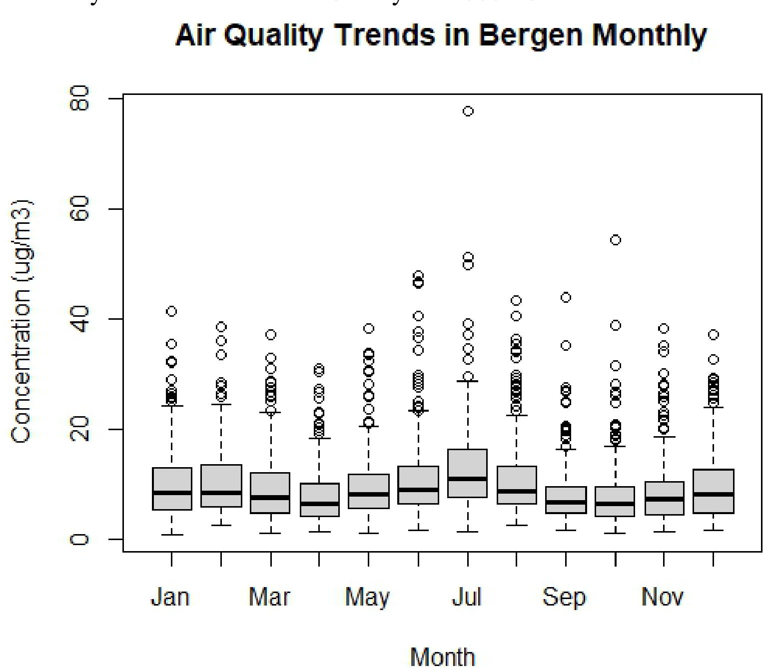

Figure 7. PM2.5 Monthly Trend in Bergen County for 2000-2022

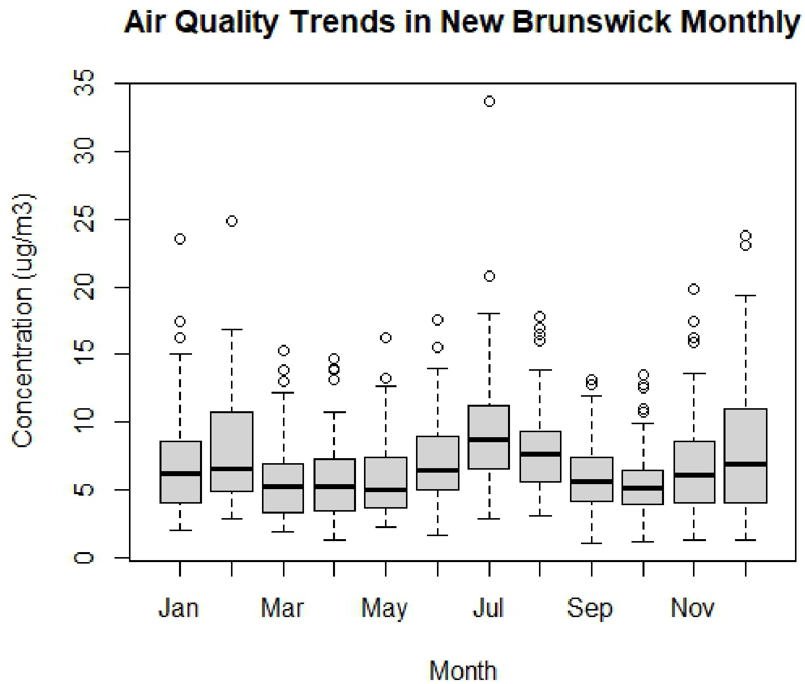

Figure 8. PM2.5 Monthly Trend in New Brunswick, Middlesex County for 2016-2022

KZ Filter-Calculated Long-Term Trends

Descriptive statistics for overall long-term trends were tested as below using the box plot in R® statistical package that typically includes the following descriptive statistics. Figures 9 to 11 display box-whiskers plots for PM2.5 air quality long-term trends for 2000 to 2022 in Camden, Bergen, and Middlesex counties, respectively. The gray lines indicate raw data, blue lines seasonal trends of KZ(365, 3)., yellow line denotes long-term of KZ(365, 3). KZ filter-based long term trend analysis showed that the Camden, Bergen, and Middlesex (2016-2022) counties showed significant reductions between 2000 and 2022 for the PM2.5 annual average level by 43%, 29%, and 14%, respectively.

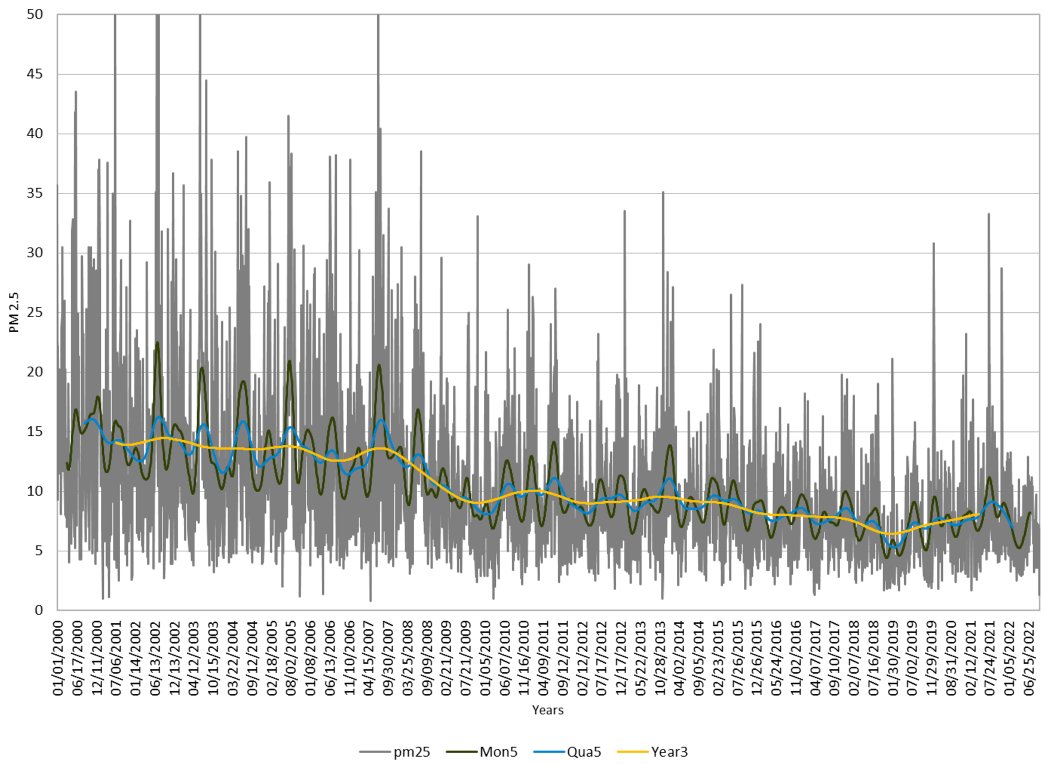

Figure 9. KZ-filter Long-term Trend in Camden County for 2000-2022

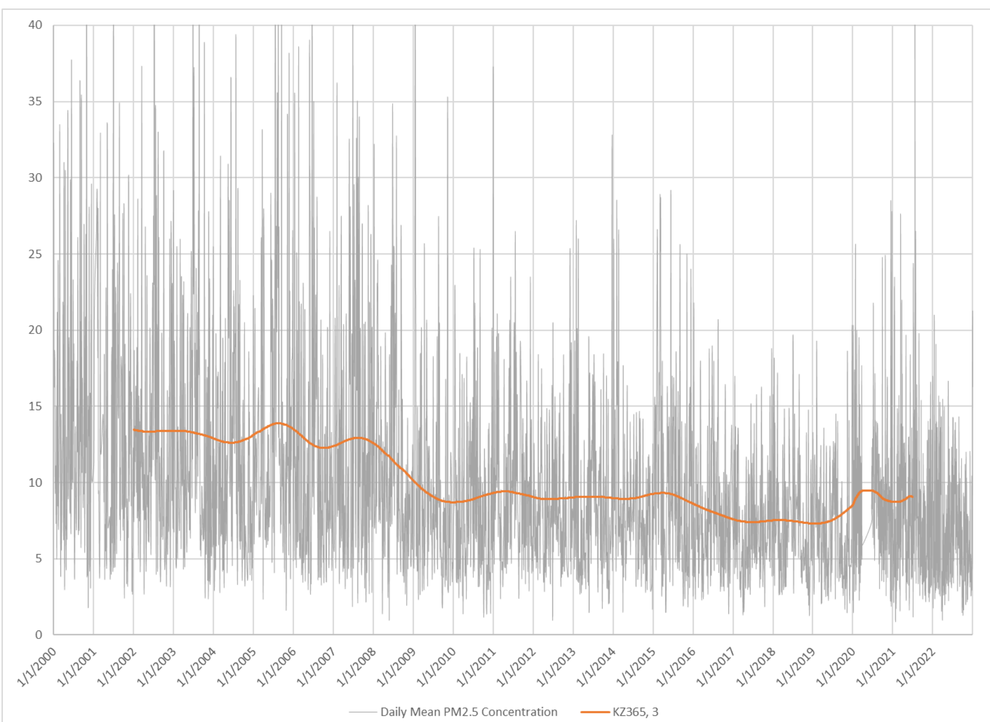

Figure 10. KZ-filter Long-term Trend in Bergen County for 2000-2022

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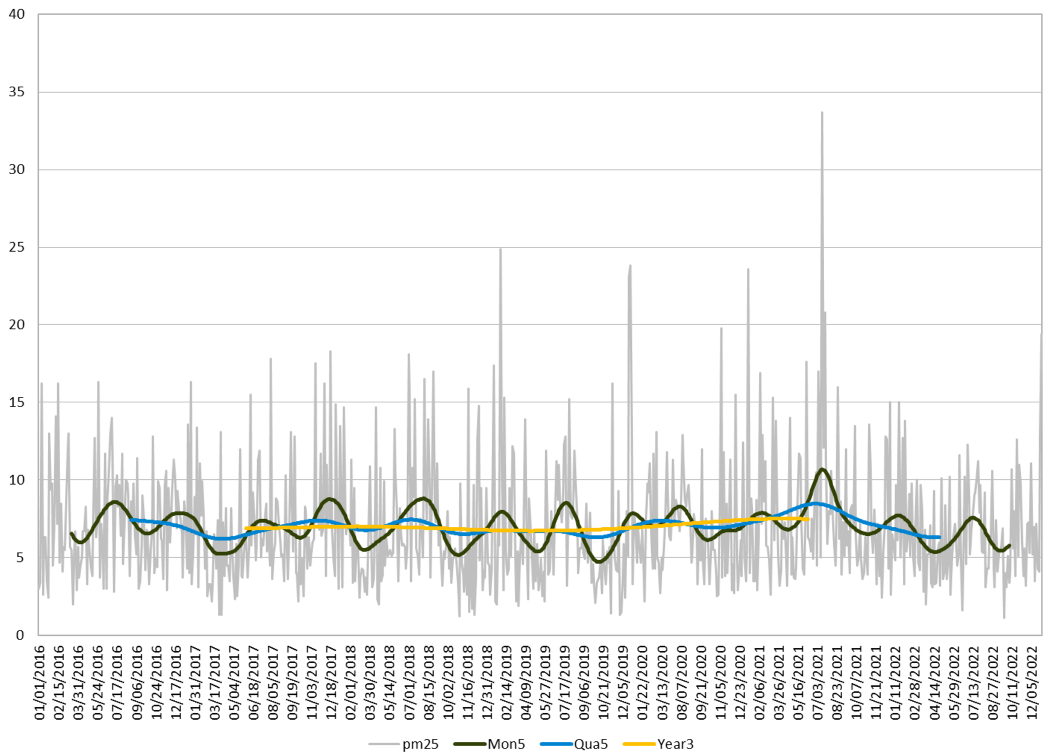

Figure 11. KZ-filter Long-term Trend in Middlesex County for 2016-2022

Discussion

Monthly Trends in PM2.5 for 20 Years

The monthly pattern analysis of PM2.5 concentrations in NJ suggested that PM2.5 levels were higher in winter and summer and were lower in spring and fall in all the Camden, Bergen, and Middlesex counties. This can be attributed to several factors. One major factor is the seasonal variation in weather patterns. In winter, the air temperature is colder and the air tends to be more stagnant, which can lead to the accumulation of pollutants such as PM2.5 (NASA, 2018). Additionally, in winter, many areas experience an increase in residential heating demand, which can result in increased emissions from sources such as wood-burning stoves and fireplaces. In summer, higher temperatures can increase the volatility of organic compounds, leading to the formation of secondary organic aerosols (SOAs), which contribute to PM2.5 levels. Additionally, increased sunlight and warmer temperatures can lead to increased photochemical reactions, resulting in the formation of other secondary pollutants such as ozone, which can contribute to overall PM2.5 concentrations (Chow, 2016). The low levels of PM2.5 in spring and fall can be attributed to a combination of factors, including increased precipitation and stronger winds that help to disperse pollutants, as well as the absence of temperature inversions, which can lead to the accumulation of pollutants at ground level (Lim, 2012). It is worth noting that the specific factors that contribute to the seasonal pattern of PM2.5 concentrations can vary depending on the location and local sources of pollution. However, in general, weather patterns and changes in emissions from various sources are key factors that contribute to the seasonal variation in PM2.5 concentrations.

Conclusion

The KZ filter-based method is a statistical technique that can be used to identify and remove short-term fluctuations in the data to reveal underlying long-term trends. This method is particularly useful for analyzing air quality trends over a long period of time, such as decades, and can help to distinguish between natural variability and changes caused by human activities. However, the KZ filter-based method can be sensitive to outliers and may not capture sudden changes or short-term events that may have an impact on air quality.

On the other hand, the 3-year average of the highest annual average method provides a simple way to track air quality trends over time. This method is commonly used by regulatory agencies to assess compliance with air quality standards and to identify areas that require additional controls to meet those standards. However, this method can be affected by short-term variations and may not capture longer-term trends in air quality.

In conclusion, the choice of method depends on the specific objectives of the study and the nature of the data being analyzed. In some cases, it may be appropriate to use both methods to provide a more comprehensive assessment of air quality trends.

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