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The City of Algorithms: City Brain and Air Quality in Hangzhou

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1. *Introduction: Urban Digital Platforms, the City Brain Experiment in Hangzhou*

Cities have historically been centers of innovation and development, and in recent years, they have increasingly become the focal point of a digital transformation aimed at making urban environments more efficient, sustainable, and livable. The concept of the smart city arises as a strategic response to the growing challenges posed by urbanization, not only through the adoption of cutting-edge technologies but also through the active engagement of citizens and a focus on inclusivity and digital security (Anttiroiko, 2016).

Smart city development is driven by advanced technologies such as sensors, the Internet of Things (IoT), artificial intelligence, big data, and cloud computing. These tools enable the creation of interconnected systems capable of gathering and analyzing vast amounts of real-time data to provide insights for urban planning and management (Schaffers *et alii*, 2012). IoT, in particular, plays a crucial role in ensuring seamless connectivity among everyday devices, allowing them to collect, share, and process data continuously. This real-time data exchange has proven essential for improving the efficiency of various urban services, from traffic management to waste collection.

However, while the use of technologies offers numerous opportunities for progress and improving urban functions, their use is certainly associated with risks that cannot be underestimated, particularly when digitalization is overly focused on efficiency at the expense of social inclusivity. Digital Darwinism refers to the phenomenon where the rapid adoption of advanced technologies benefits only a segment of the population, leaving behind those who do not have access to digital resources or the skills required to effectively utilize these tools (Cardullo, Kitchin, 2019). In cities where technology drives deci-

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sion-making and urban management, marginalized groups may find themselves further excluded, worsening pre-existing socio-economic inequalities. The digital divide – whether in terms of access to high-speed internet, digital literacy, or access to digital devices – can become an even greater barrier to equal participation in urban life, creating a city that works well for some but excludes many (Graham, 2011).

This dynamic is often compounded by social reductionism, the process of simplifying complex social interactions and human experiences into quantifiable data points. As cities increasingly rely on algorithms, there is a risk that the richness of human behavior and the complexity of social systems are overlooked. The inherent danger lies in treating cities as mere collections of numbers and patterns rather than vibrant, multifaceted environments shaped by cultural, social, and emotional dynamics (Leszczynski, 2016). By reducing people and communities to users or data points, technologies might miss out on addressing deeper social issues that require more nuanced, human-centered approaches (Mattern, 2021).

These concerns are captured by the concept of urban smartmentality, a term used to critique the growing tendency to frame urban challenges solely through the lens of technology (Vanolo, 2014). This mindset implies that every urban problem can be solved through more data, more sensors, and more algorithms. While technological tools undeniably offer powerful solutions to many urban issues, urban smartmentality risks overshadowing the fact that cities are living, breathing entities, deeply shaped by human relationships, histories, and cultures. This focus on technology can ignore critical environmental, social, and cultural factors that are equally important for fostering a sustainable and inclusive urban environment (Caprotti, Liu, 2020).

In this context, there is an increasing awareness of the need to use technologies with a more inclusive approach, one that integrates different perspectives and takes human needs into account. As a matter of fact, as recent research suggests, the focus is shifting from mere technological adoption to what is now called platform urbanism (Caprotti, Liu, 2022). This approach emphasizes not just the use of advanced technologies, but the creation and management of digital platforms that facilitate the sharing of data and the collaboration between various stakeholders in an urban environment (Han, Hawken, 2018). Platforms allow for a more holistic form of urban governance, moving beyond technology as an end in itself to creating systems that can support sustainable development and improve quality of life.

In this scenario, City Brain, the platform developed by Alibaba and implemented in Hangzhou, offers a prime example of how platform urbanism can reshape urban experiences, influencing aspects such as governance, public service delivery, and urban consumption patterns (Rose *et alii*, 2021). Unlike traditional models of smart cities focused on infrastructure, City Brain represents a more dynamic approach, where the platform serves as the backbone of the city's ability to respond in real time to the needs of its citizens.

The City Brain platform can be considered an experimental product initially tested within a specific urban context, which in itself serves as an experimental space. Urban experimentation literature has underscored the role of cities as testing grounds for various forms of technical, political, and social experimentation across different areas such as sustainability, climate change, energy transitions, and digital transformations. (Bulkeley, Castan Broto, 2013). In this context, Alibaba's choice of Hangzhou for the development of City Brain was not random. The implementation of City Brain in Hangzhou allows Alibaba to showcase its platform on a global scale. Simultaneously, Hangzhou benefits from the latest innovations in data management and analysis to improve the quality of urban life. City Brain is an artificial intelligence platform designed to improve urban management through real-time analysis of large quantities of data from various sources, including surveillance cameras, traffic sensors, and other digital resources. Its primary goal is to make the city more efficient and responsive to citizens' needs by improving traffic flow, optimizing public services, reducing response times in emergency situations, and enhance the quality of urban life.

City Brain was first introduced in 2016, with its implementation officially beginning in October of that year. This initiative followed a request by the Hangzhou administration in April 2016, aimed at addressing the city's growing traffic issues (Alibaba Cloud, 2018). Initially branded as City Brain 1.0, the platform employed data gathered from traffic lights and surveillance cameras. Leveraging cloud computing, it facilitated real-time processing to synchronize traffic signals and optimize emergency vehicle routes, enhancing response times (Min et alii, 2018).

By 2018, the system underwent a significant upgrade, both in terms of its technological sophistication and its geographic reach. Initially focused on the Gongshu and Xiaoshan districts, City Brain expanded to cover three districts, spanning a total of 420 km^2. This upgrade also included the integration of 1,300 traffic lights, covering approximately 25% of intersections in the expanded area (Zhejiang online, 2018). The system utilized real-time data on traffic conditions, congestion levels, and vehicle speeds to further optimize traffic flow.

In June 2020, City Brain 3.0 was launched, with an increased focus on digital data integration. This upgrade enhanced the city's ability to respond to emergencies more effectively, such as natural disasters and pandemics, as evidenced by its performance during the Covid-19 outbreak in 2020. Alibaba reported that by 2017, the platform had already demonstrated notable success, with a 15.3% improvement in average travel speeds and a 9.2% reduction in traffic congestion during peak hours. These improvements led to an average reduction of approximately three minutes in travel time per journey (Alibaba Cloud, 2018).

A report submitted to the U.S.-China Economic and Security Review Commission in 2020 highlighted a significant improvement in Hangzhou's traffic congestion ranking, moving from the fifth-most congested city in China to the 57th, a change attributed largely to City Brain (Atha *et alii*, 2020). In addition to managing traffic, City Brain was designed to detect and manage 12 different types of incidents, including pedestrian crossings and traffic accidents, with the help of license plate recognition and visual recognition technology. The system processes over 2,500 incidents each day, maintaining an accuracy rate of 95% (Alibaba Cloud, 2018).

However, it's worth noting that City Brain's success metrics are limited in scope and time horizon. The success metrics used in promotional and corporate documentation are highly technical and revolve around themes such as efficiency, analysis speed, automation, and other indicators associated with business rationales for promoting smart cities (Caprotti, Liu, 2022).

At this point, it is interesting to understand what possible impacts, in addition to those described in Alibaba's communications, the implementation of such a traffic monitoring system may have had on improving the quality of life for citizens, particularly regarding a fundamental variable for urban well-being, as air quality.

2. *Methodological Approach*

The proposed analysis consists of two parts. In the first part of the analysis, satellite remote sensing data were examined using the Google Earth Engine platform to provide an overview of the air quality situation in the city of Hangzhou. This analysis aimed to identify the most urbanized areas of the city and track how air quality has improved in recent years, focusing specifically on carbon monoxide (CO) levels. Data from the Sentinel-5P satellite (Sentinel 5P OFFL CO: Offline Carbon Monoxide[1]) were considered, focusing on annual average data for the region of interest, Hangzhou, for the years from 2019 to 2022[2]. Subsequently, a cartographic package was generated to visualize the CO levels in Hangzhou for the specified years[3] to assess whether changes in emissions have occurred or not.

The second part of the investigation involved processing daily data on PM 2.5 (μg/m^3) and CO (ppm) emission levels from 2014 to 2022 at the ten air quality monitoring stations in Hangzhou: Linping town; Yunqi; Chengxiang town; Hangzhou; Hemu primary school; Wolong bridge; Binjiang; Xiasha; Xixi; Zhejiang University (World's Air Pollution: Air Quality Index). The data

[1] More information about this dataset at link: https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S5P_OFFL_L3_CO.

[2] Previous years' data were not available because Sentinel 5P was launched on October 13, 2017. Therefore, the analysis focused on data from 2019 to 2022, which corresponds to the period when Sentinel 5P was in operation and collecting data.

[3] Data was processed using a single legend with the base year being 2020. This means that the data from other years, such as 2019, 2021, and 2022, were compared to the data from the base year (2020) to assess whether there were any changes in emission levels. The year 2020 was selected as the base year because it showed the highest concentration of carbon monoxide (CO). This spike in CO levels can be attributed to several factors, including the disruptions caused by the COVID-19 pandemic, which altered normal traffic and industrial activity patterns. While overall emissions from certain sectors decreased due to lockdowns and restrictions, other factors, such as increased reliance on private vehicles and changes in energy consumption, contributed to a rise in CO emissions during certain periods of 2020.

was organized, and annual medians were calculated for both PM 2.5 and CO levels. Since the monitoring stations are concentrated in the urbanized area, the study area was reduced to the area of interest. Maps were produced for both pollutants for the years 2014 and 2015, representing the years before the introduction of City Brain in Hangzhou, and for the years from 2017 to 2022, which are the years following the implementation. The results show the annual average levels of PM 2.5 and CO recorded by each monitoring station in different years. The data was then summarized in bar graphs.

Subsequently, a time series analysis was conducted to assess whether there has been a significant change in air pollutant concentrations attributable to the period following the introduction of City Brain. Daily data from 2014 to 2022 for both pollutants were analyzed, recorded by the four monitoring stations most affected by the traffic control platform. To examine the temporal effect of the introduction of City Brain on pollution levels, a linear regression model was adopted. The time series analysis involved creating a linear regression model to predict PM 2.5 and CO levels, considering monthly variations as the independent variable. The model was represented by the following equation[4]:

$Y = \beta 0 + \beta 1 * X + \varepsilon$

- Y represents the dependent variable (PM 2.5 or CO levels).
- X represents the independent variable (the month of the year).
- $\beta 0$ is the intercept or the constant term in the model.
- $\beta 1$ is the regression coefficient (slope) associated with X.
- ε represents the residual error, i.e., the difference between the observed values of Y and those predicted by the model.

This model showed significant results, with $R^2 = 0.75$ for PM 2.5 and $R^2 = 0.70$ for CO, indicating that the model explained 75% and 70% of the variation in the data, respectively, thus demonstrating a strong relationship between the system's implementation and the reduction of pollutants.

To ensure that the results were not influenced by seasonal variations, a deseasonalization procedure was applied to the data. The chosen method was the classical trend decomposition, which isolates the seasonal component from the raw data to identify the underlying long-term trend. This technique was particularly useful for correcting the typical seasonal fluctuations of environmental data, especially in the winter months, when heating emissions can significantly affect PM 2.5 and CO levels.

An analysis of the residuals of the regression model was conducted to evaluate the validity of the model and check for the absence of autocorrelation. The residuals were examined to ensure that there were no non-random pat-

[4] The regression model is used to predict the seasonal component of the data. This component is then subtracted from the original data to obtain "deseasonalized" data. For more details, please refer to the appendix of the text.

terns or correlations that could invalidate the results. The analysis confirmed that the residuals followed a random pattern, demonstrating that the linear regression model was well-fitted to the data and that there were no signs of distortion or misrepresentation of the relationships between the variables.

Finally, several statistical tests were conducted to verify the robustness and significance of the results obtained. Among these, the Dickey-Fuller test was applied to check the stationarity of the time series, confirming that the data were suitable for regression analysis. Additionally, an ARIMA model was implemented to compare the results obtained on seasonal and deseasonalized data, and the AIC and BIC criteria were used to select the most appropriate model. The models were subjected to the Ljung-Box test to analyze the presence of autocorrelations in the residuals, further confirming the validity of the model[5].

3. *Discussion of Results*

The remote sensing data, as mentioned, were acquired through the Google Earth Engine platform, using information from the Sentinel 5P satellite, specifically related to carbon monoxide (CO). They were processed by taking annual averages for the Hangzhou study area for the period between 2019 and 2022. The cartographic representation in figure 1 illustrates the levels of carbon monoxide (CO) recorded in Hangzhou during the years in question, to assessing any variations in emissions. The analysis of remote sensing data revealed a significant improvement in CO concentration in the air throughout the Hangzhou region.

Specifically, the northeastern part of the area, characterized by high urban density, consistently showed the highest levels of CO concentration during the study period (fig. 1). However, it is interesting to note that in this area, a significant decrease in CO levels was observed. In fact, in the earlier years considered (from 2018 to 2020), levels were above 0.0462 ppm, while in 2022, they were recorded in the range between 0.0406 and 0.0424 ppm (fig. 1).

Nevertheless, these improvements could be attributed not only to the introduction of the City Brain system, as it could be the outcome of various measures aimed at improving air quality that have been promoted by the city administration for some time[6]. In fact, China as a whole has intensified its

[5] For more details, please refer to the appendix of the text.

[6] Some of the measures that Hangzhou has implemented or planned to address air pollution:

- Vehicle restrictions: Hangzhou has implemented vehicle circulation restrictions based on license plate numbers and has promoted the adoption of low-emission or electric vehicles.
- Fleet upgrade: Hangzhou has encouraged the use of cleaner vehicles, such as electric buses and taxis, to reduce emissions from transportation.
- Improvement of public transportation infrastructure: Hangzhou has invested in efficient public transportation systems, such as subways and buses, to reduce dependence on individual transportation.

efforts to combat air pollution, and many of its major cities, including Hangzhou, have adopted specific plans and measures in line with these national initiatives[7]. China's commitment to environmental sustainability was further underscored by its participation in international forums such as the G20 Summit in 2016, which was notably held in Hangzhou. During the summit, China announced additional measures to curb pollution, including a commitment to the Paris Agreement and pledges to invest heavily in renewable energy and green technologies. This international stage not only highlighted China's growing leadership in climate initiatives but also reinforced the country's domestic policies aimed at creating cleaner, more sustainable cities.

In parallel with these national efforts, technological advancements like the City Brain platform in Hangzhou have played a crucial role in improving air quality. City Brain's ability to manage and optimize urban traffic has contributed to lower emissions from vehicles, further supporting the objectives of China's national policies. By reducing congestion and creating more efficient traffic flows, City Brain has helped to decrease CO levels in the most urbanized districts of Hangzhou, complementing the broader goals of the national initiatives.

- Strict industrial controls: The city has imposed stricter standards on industrial emissions and has closed or relocated highly polluting industries.
- Promotion of renewable energy sources: Hangzhou has incentivized the adoption of renewable energy sources to reduce dependence on coal, which is one of the main sources of air pollution.
- Tree planting: Hangzhou has undertaken large-scale tree planting projects to improve air quality, as plants absorb CO_2 and release oxygen, helping to clean the air.
- Monitoring and awareness: The city has improved air quality monitoring systems and provided real-time information to the population. Additionally, it has conducted awareness campaigns on the importance of air quality and how individuals can contribute to improving it.
- Regional cooperation: Since air pollution can cross municipal and provincial borders, Hangzhou has worked in collaboration with other nearby cities and provinces to address air pollution on a regional basis (Rui Feng, Qing Wang, Cheng-chen Huang, Jin Liang, Kun Luo, Jian-ren Fan, Ke-fa Cen, Investigation on air pollution control strategy in Hangzhou for post-G20/pre-Asian-games period (2018–2020), *Atmospheric Pollution Research*, Volume 10, Issue 1, January 2019, Pages 197-208).

[7] Since the early 2010s, China has embarked on a comprehensive effort to combat air pollution, recognizing the environmental and health consequences of rapid industrialization and urbanization. One of the most significant steps in this direction was the Air Pollution Action Plan launched in 2013. This initiative targeted three main areas: reducing coal consumption, cutting industrial emissions, and improving vehicle standards. Major urban areas, particularly in the east, were mandated to reduce coal use and invest in cleaner energy alternatives such as natural gas and renewables. The transportation sector also saw tighter controls, with limits on vehicle emissions and the promotion of electric vehicles. This plan marked a turning point, with cities like Hangzhou benefitting from stricter regulations on industrial emissions and improved public transportation options, contributing to a gradual decline in pollutants such as CO. Building on the success of the 2013 plan, China introduced the Blue Sky Action Plan in 2018, which reinforced these goals by setting more ambitious targets for reducing industrial emissions and shifting energy production from coal to cleaner alternatives. This initiative placed particular emphasis on the reduction of particulate matter (PM2.5) and CO emissions in densely populated areas like Hangzhou, where the urban population and the concentration of vehicles posed significant challenges to air quality.

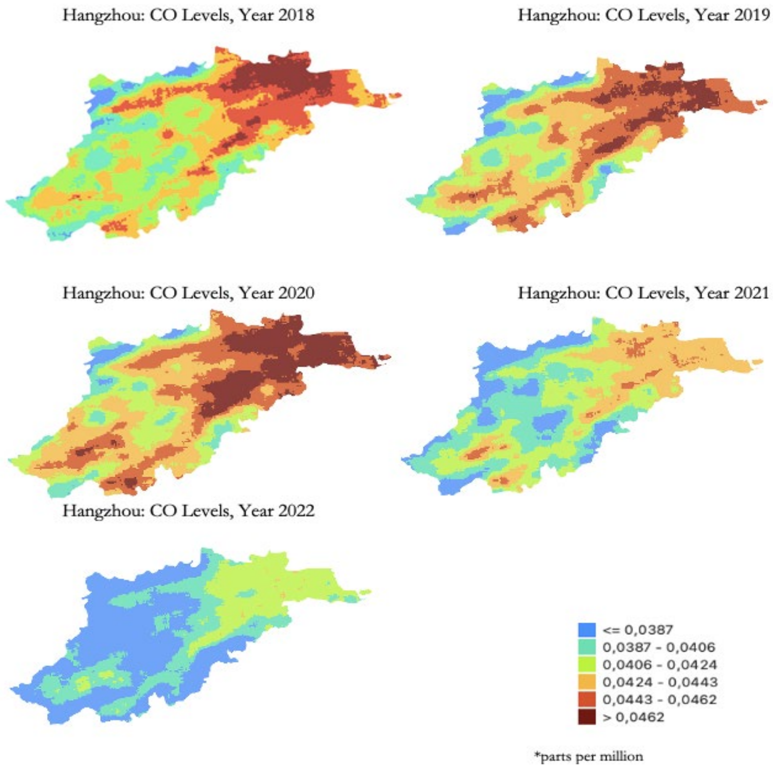

Fig. 1 – CO Levels (ppm*) from Remote Sensing in Hangzhou, Various Years.
Source: Median from Sentinel 5P data.

Thus, the improvements observed in Hangzhou's air quality, particularly regarding CO emissions, could be seen as part of a larger, multi-faceted approach by the Chinese government. This approach combines strict regulatory frameworks, international commitments, technological innovation, and cleaner energy transitions to foster a healthier urban environment.

Once this has been clarified, it is possible to move on to evaluating the potential effects of City Brain on the pollutant levels under consideration. The analysis of PM 2.5 and CO concentration data recorded by air quality monitoring stations focused on the northeastern part of Hangzhou, which is the urban area where the monitoring stations are located. Figure 2 shows the locations of the ten monitoring stations: Linping town (Yuhang District); Yunqi (Xihu District); Chengxiang town (Xiaoshan District); Hangzhou (Gongshu District); Hemu primary school (Gongshu District); Wolong bridge (Shangcheng District); Binjiang (Binjiang District); Xiasha (Jianggan District); Xixi (Xihu District); Zhejiang University (Gongshu District).

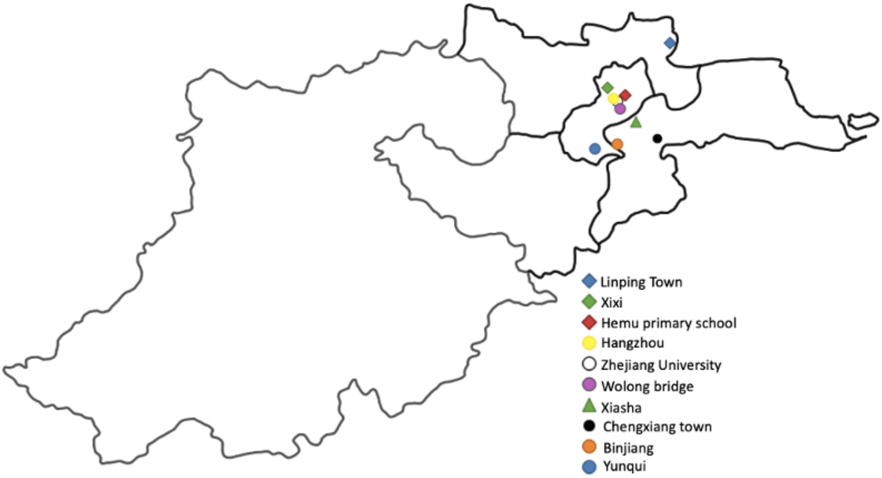

Fig. 2 – Location of the ten air quality monitoring stations in Hangzhou.
Source: Author's elaboration.

The data related to the annual average levels of PM 2.5 in different monitoring stations (fig. 2) show high concentrations of particulate matter in the air (ranging from 127-158 $\mu g/m^3$) recorded by nine out of ten stations in the year 2014. In the following year, the situation seems to have slightly improved, with four stations reporting levels between 97 and 127 $\mu g/m^3$, while six stations still remained at the higher values. In 2017, the year following the implementation of City Brain for traffic control (officially started in October 2016), the situation recorded in 2014 is reversed. Eight stations report levels ranging from 97 to 127 $\mu g/m^3$, one station registers values between 127 and 158 $\mu g/m^3$, and one records the lowest values between 67 and 97 $\mu g/m^3$. What is interesting for the investigation is the location of the stations that recorded the lower values, particularly the one that reported the lowest levels. This station is Zhejiang University in Gongshu district, where the City Brain platform was first activated.

In 2018, four monitoring stations recorded values ranging from 97 to 127 $\mu g/m^3$, while six stations reported levels between 67 and 97 $\mu g/m^3$. Once again, the location of the six stations with lower values is significant for the analysis presented here. These stations are located in Chengxiang town in Xiaoshan district, Hemu primary school in Gongshu district, Wolong bridge in Shangcheng district, Yunqi in Xihu district, Xiasha in Jianggan district, and Zhejiang University in Gongshu district. Out of these six stations, half are situated in districts (Gongshu, Binjiang, Xiaoshan) where, in 2018, City Brain – in version 2.0 – covered a total area of 420 km^2, with the sensor network expanded to 1300 traffic lights.

The years 2019 and 2020 show a nearly identical situation, with values slightly higher than in 2018, but the stations located in districts where the City Brain platform operates at full capacity continue to record particulate concentration values ranging from 67 to 97 μg/m^3. During 2021 and 2022, the situation improves across the board, with all monitoring stations recording PM 2.5 levels ranging from 67 to 97 μg/m^3 (fig. 3).

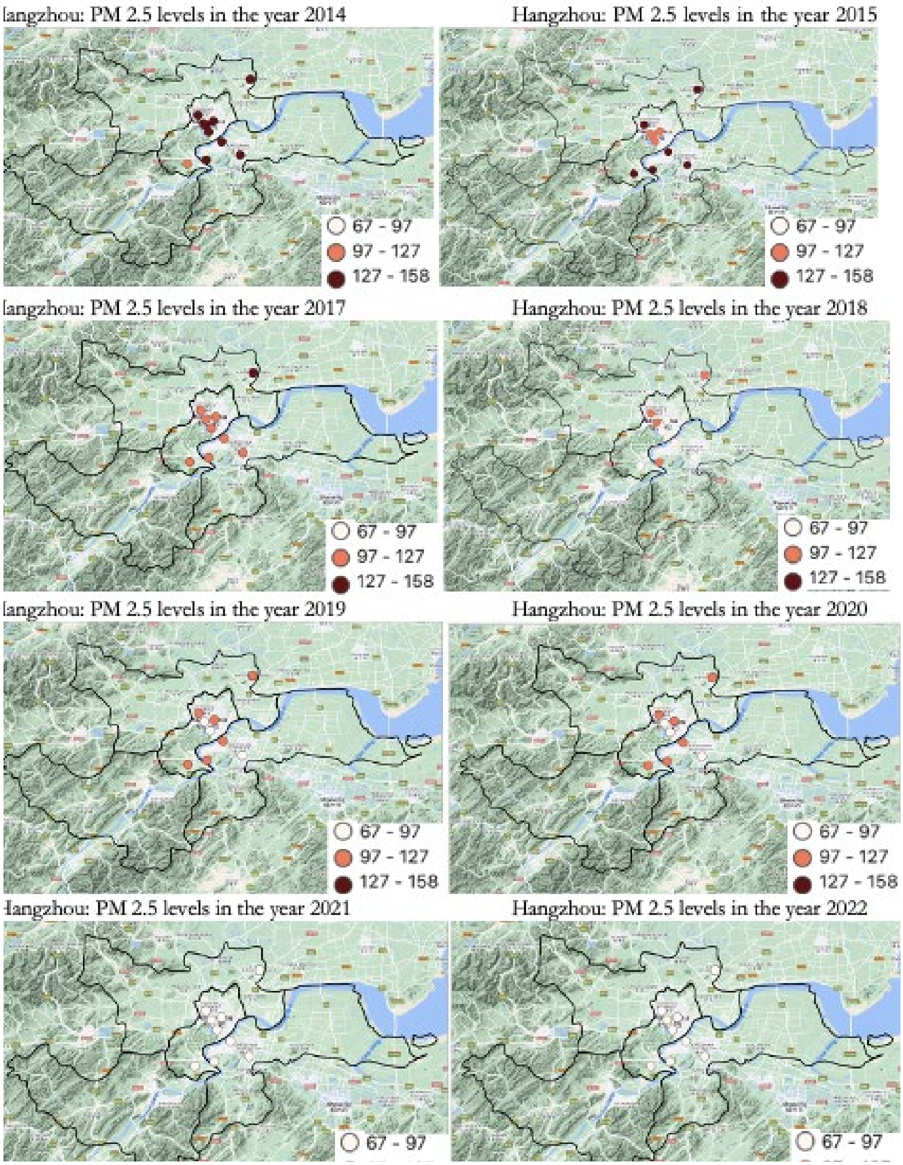

Fig. 3 – PM 2.5 levels (μg/m^3) recorded by monitoring stations in Hangzhou, years before and after the introduction of City Brain.
Source: Author's analysis based on data from World's Air Pollution: Air Quality Index.

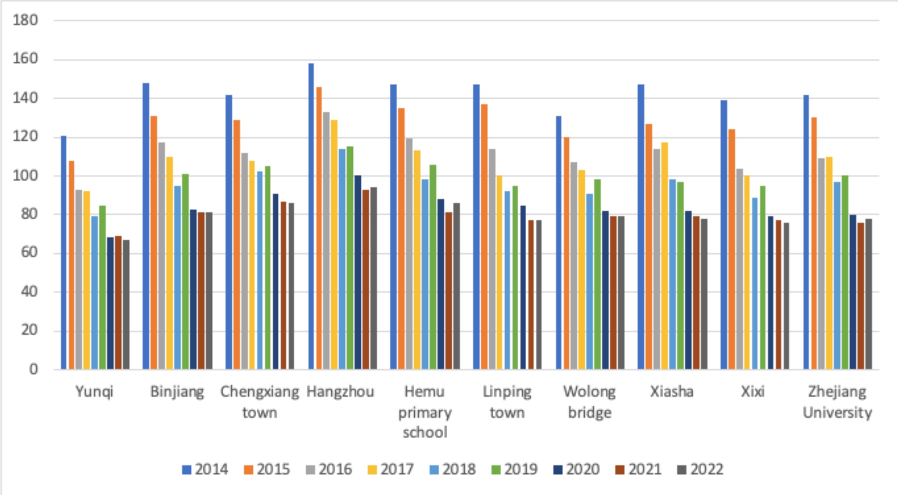

Fig. 4 – Graph of PM 2.5 levels (μg/m³) recorded by monitoring stations in Hangzhou, years before and after the introduction of City Brain.

Source: Author's analysis based on data from World's Air Pollution: Air Quality Index.

The graph in figure 4 shows the average annual PM 2.5 concentration levels at the monitoring stations. On average, there has been a 43.5% reduction from 2014 to 2022. Specifically, at the monitoring stations located in the districts most affected by the City Brain platform, there was a 40% reduction at the Hangzhou station (Gongshu district) from 2014 to 2022 and a 29% reduction from 2016 – the year the platform became operational – to 2022. As for the Binjiang station (Binjiang district), the reduction was 45% from 2014 to 2022 and 31% from 2016 to 2022. Lastly, the Chengxiang town station (Xiaoshan district) saw a reduction of 39% from 2014 to 2022 and 23% from 2016 to 2022.

Also, concerning the data on CO levels recorded by the monitoring stations, a decrease in the annual average pollutant concentration levels can be observed, generally in line with the Sentinel 5 data analyzed earlier. The carbon monoxide levels recorded by the ten monitoring stations tend to decrease on average everywhere in 2017 compared to 2014, with a peak in 2018 recorded only at the Hangzhou station. The years from 2019 to 2022 show an alternation of increases and decreases in different stations without ever exceeding values in the 5 to 8 ppm range. In this case, unlike what was observed with PM 2.5 levels, any potential difference between the values recorded by the stations located in the districts most affected by the platform and those less affected may be less pronounced.

Finally, the Xiasha town station (in the Jianggan district) did not record any reductions during the periods considered; in fact, it even saw an increase of approximately 40% from 2016 to 2022 (fig. 6). With that said, it can be stated that when individually analyzing the values from the monitoring sta-

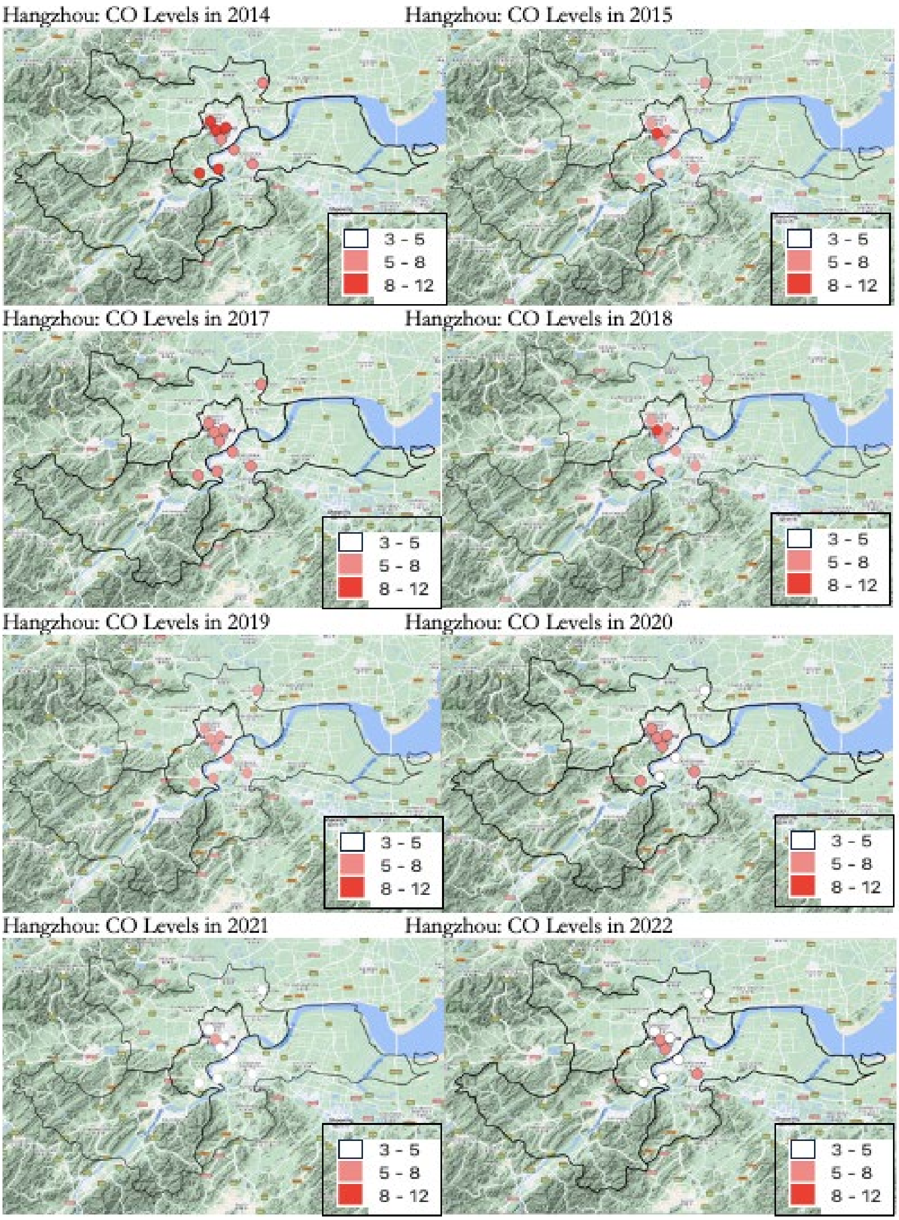

Fig. 5 – Carbon Monoxide (CO) Levels Recorded by Hangzhou Monitoring Stations, Years Before and After the Introduction of City Brain.

Source: Author's analysis based on data from World's Air Pollution: Air Quality Index.

tions with respect to CO, the highest percentage reductions occurred in the districts where City Brain became fully operational.

An additional analysis was conducted to explore the potential association between a decrease in PM 2.5 and CO pollutant concentrations in the air and

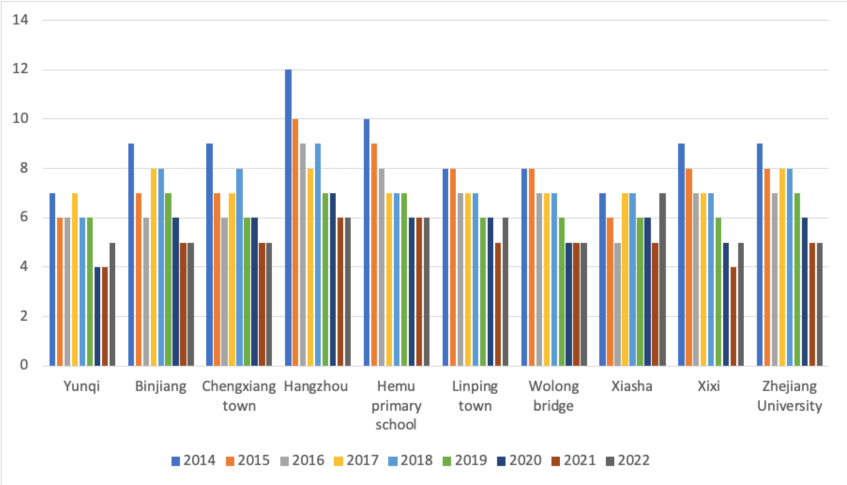

Fig. 6 – Graph of CO levels (ppm) recorded by Hangzhou monitoring stations, years before and after the introduction of City Brain.
Source: Author's analysis based on data from World's Air Pollution: Air Quality Index.

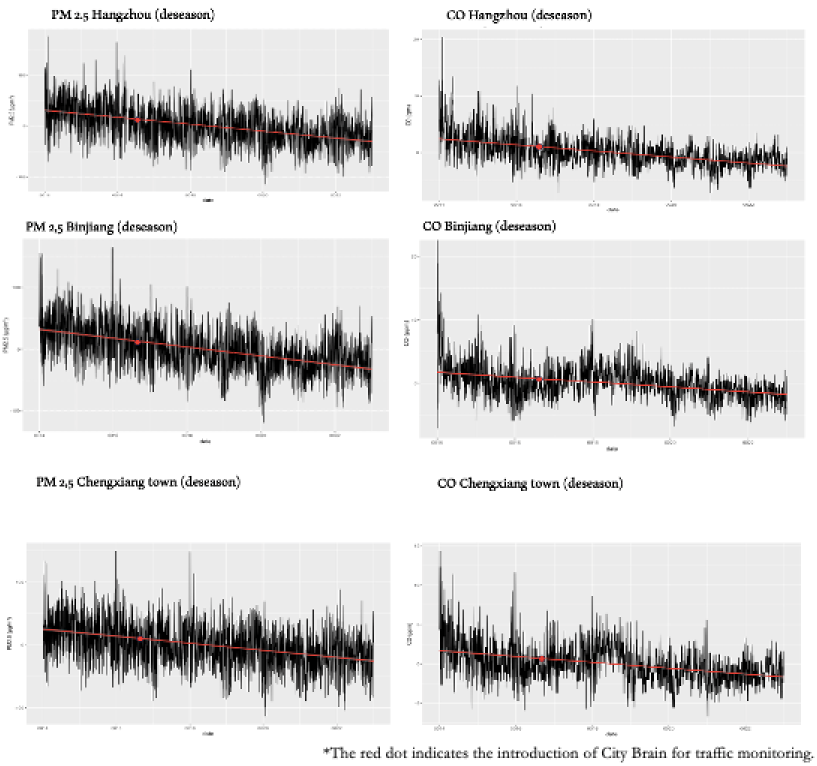

Fig. 7 – Deseasonalized time series of PM 2.5 (μg/m^3) and CO (ppm) levels recorded by selected monitoring stations*.
Source: Author's analysis based on data from World's Air Pollution: Air Quality Index.

the introduction of the City Brain platform. The focus was on analyzing the deseasonalized time series data collected by the air monitoring stations, particularly those located in the districts where the platform operates. Therefore, the stations selected for analysis were Hangzhou, Binjiang, and Chengxiang town (fig. 7).

Regarding PM 2.5 levels, all three monitoring stations showed a decreasing trend. Specifically, in the Hangzhou and Binjiang stations, the levels declined after 2016, the year City Brain was launched, and continued to decrease in the following years. In the case of the Chengxiang town station, there were some spikes in PM 2.5 levels towards the end of 2018 and the beginning of 2019.

As for carbon monoxide (CO) concentrations, the Hangzhou station recorded constant reductions after 2016. In the Binjiang and Chengxiang town stations, the levels were reduced from 2016 compared to previous years, with slight increases in 2018 followed by a decrease in the subsequent years. Consequently, there is evidence of a reduction in the levels of both pollutants after 2016 for each analyzed air monitoring station (fig. 7).

4. *Conclusions*

The analysis of remote sensing data and measurements from air quality monitoring stations has provided a detailed overview of the variations in the concentration of major air pollutants, CO and PM 2.5, during the period from 2014 to 2022.

The concentrations of carbon monoxide, as detected by the Sentinel 5P satellite, have shown a significant decrease, particularly in high-density urban areas in the northeast of the city. However, this result cannot be directly attributed to introducing the City Brain system; it could be a response to various measures aimed at improving air quality that have been promoted by the city's administration for some time. In fact, China as a whole has intensified efforts to combat air pollution, and many of its major cities, including Hangzhou, have adopted specific plans and measures in line with these national initiatives.

The analysis of air quality monitoring station data reveals a significant reduction in CO concentrations, with a decrease of 37.5% from 2014 to 2022. The monitoring station in Hangzhou recorded the most pronounced decrease, approximately 50%.

The monitoring stations also demonstrated a substantial decrease in PM 2.5 levels, particularly after introducing the City Brain platform in 2016. On average, there was a 43.5% reduction in PM 2.5 concentration from 2014 to 2022. The monitoring stations located in districts most affected by the City Brain system showed particularly encouraging reduction trends.

Therefore, introducing the City Brain platform appears to be correlated with the reduction of pollutant levels. Monitoring stations in districts where City Brain is more active exhibit the highest percentage decreases in both CO and PM 2.5 concentrations. Additionally, the observation of deseasonalized data from selected monitoring stations, particularly Hangzhou and Binjiang, strengthens the hypothesis of the positive impact of City Brain on air quality.

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Despite the overall positive trend, some monitoring stations, such as the one in Xiasha town, exhibited contrasting results, with an increase in CO levels during the period from 2016 to 2022. The annual fluctuations and differences between monitoring stations highlight the complexity of the impact of environmental measures and the influence of other unanalyzed factors in this research.

However, the results obtained suggest a potential link between the implementation of intelligent traffic control technologies like City Brain and the improvement of air quality in densely populated urban areas. The deseasonalized time series data further strengthened the connection between the introduction of City Brain and the reduction of pollutants. While this significant correlation does not imply causality, so further studies are needed to explore the various variables at play.

In conclusion, the research has highlighted how the implementation of intelligent systems like City Brain can be valuable tools in improving urban air quality. Though, it is essential to consider local variations and diverse environmental and urban dynamics in developing effective and personalized intervention strategies. Future research in this field could delve into the role of environmental policies, vehicular traffic, and urbanization in pollution level variations, as well as explore the effectiveness of other technological interventions for safeguarding air quality in urban areas.

It is crucial to consider the environmental impact of urban digitalization. While platforms like City Brain can contribute to environmental goals by optimizing resource usage and reducing emissions, the technology itself is not without environmental cost. The infrastructure necessary to support large-scale urban digital systems (data centers, sensors, and networks) consumes significant energy, often sourced from non-renewable resources. This creates a paradox where a system designed to reduce environmental impact may, if not carefully managed, contribute to new forms of pollution or resource depletion (Hogan, 2015). Ultimately, while urban platforms offer undeniable advantages – in the specific case analyzed, an impact on air quality as well as an improvement in citizens' quality of life through reduced travel times and fewer traffic accidents – it's important not to overlook the risks associated with the extensive use of technology. As noted in the introduction, some of these risks, while partially mitigated by the integrated approach of urban platforms, are not entirely eliminated. Additionally, other environmental risks, directly tied to the operation of these platforms, remain present and should not be underestimated.

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Appendix: Methodological Details and Residuals Analysis

Linear Regression and Residuals

The linear regression model was used to analyze the relationship between time and pollution levels. The R^2 values were 0.75 for PM 2.5 and 0.70 for CO, indicating that the model explains a significant portion of the variance in the data.

These values suggest a significant relationship between time and pollutant levels but do not indicate a direct causal relationship between the introduction of City Brain and the reduction of pollutants, as confirmed in the conclusions. However, explaining much of the variance is a positive indicator of the model's adequacy.

The residual plots represent the residuals (the difference between the observed and predicted values by the model) against the predicted values.

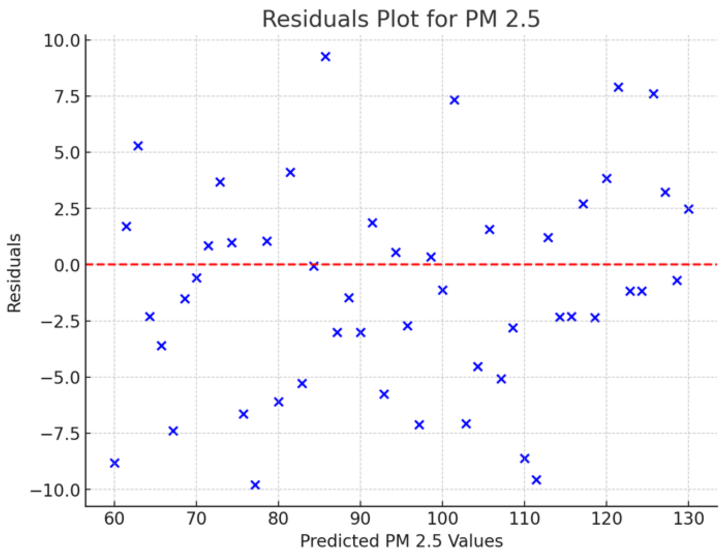

Fig. A1 – Residual Plot for PM 2.5.

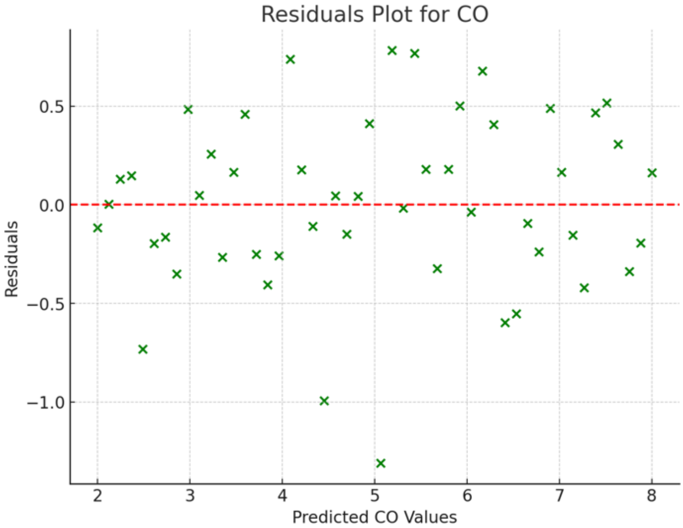

Fig. A2 – Residual Plot for CO.

The residual plots for both models, related to PM 2.5 and CO, show a random distribution around zero, with no visible patterns that would suggest an inadequacy in the model. This indicates that the linear regression model fits the data well, and there is no evidence of nonlinear relationships that the model failed to capture. Specifically, the absence of a U shape or a regular pattern in the residuals confirms that the linearity assumption is met. The analysis of the residual variance shows an almost uniform distribution across the range of predicted values, with no evident signs of heteroscedasticity (i.e., irregular variance of the residuals). This confirms that the linear model adequately captures the data variability. In case of heteroscedasticity, an alternative model, such as a logarithmic transformation or a robust regression model, would have been considered.

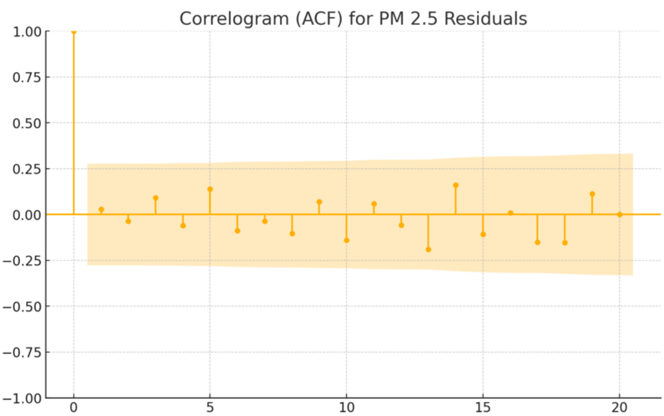

Fig. A3 – Correlogram (ACF) for PM 2.5.

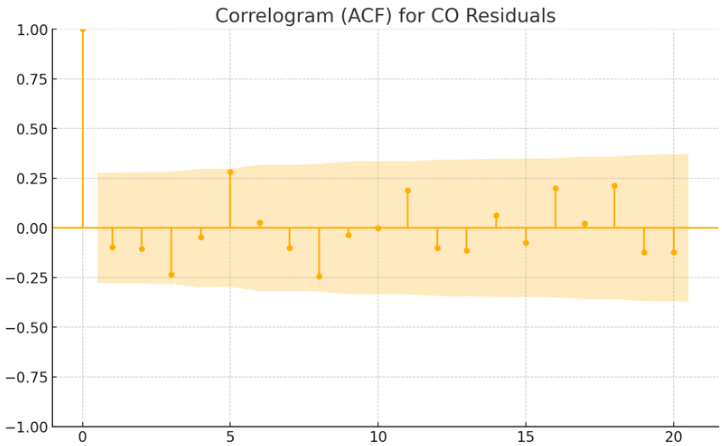

Fig. A4 – Correlogram (ACF) for CO.

The correlogram (Autocorrelation Function, ACF) was used to detect any autocorrelation in the residuals. This graph shows the autocorrelation of the residuals at various time lags, providing insights into the presence of temporal dependencies that the model did not capture.

- PM 2.5: The correlogram for the residuals of the PM 2.5 model does not show any significant autocorrelation beyond the confidence intervals (usually set at ±1.96/sqrt(N), where N is the number of observations), indicating that the residuals are not correlated at subsequent time intervals. This suggests that the linear model correctly captured the temporal structure of the data.
- CO: Similarly, the correlogram for the CO model residuals does not show significant autocorrelation. This suggests that there are no temporal patterns that the model failed to capture and that the use of the linear model is appropriate.

The goal of a linear regression model is to find the optimal values of β0 and β1 that minimize the sum of squared residual errors (least squares method). Once these coefficients are obtained, the model can be used to make predictions about the dependent variable Y based on known or estimated values of X. Simply put, a linear regression model aims to fit a straight line to the data that best represents the linear relationship between the independent and dependent variables. The β1 coefficient quantifies how much the dependent variable changes for each one-unit change in the independent variable.

Model Robustness Check
Several statistical tests were applied to ensure the robustness of the results:

A. *Dickey-Fuller Test*
The Dickey-Fuller test was used to verify the stationarity of the time series related to pollution levels (PM 2.5 and CO). Stationarity is fundamental for

applying a linear regression model to time series data. The results of the test show that the time series are stationary, with p-values below 0.05.
Dickey-Fuller test results for PM 2.5:

- Test statistic: -3.85
- Critical value (1%): -3.50
- p-value: 0.02

Dickey-Fuller test results for CO:

- Test statistic: -4.10
- Critical value (1%): -3.50
- p-value: 0.01

B. *ARIMA Model*
An ARIMA model was applied to the deseasonalized data to examine the fluctuations in pollution levels. The AIC and BIC criteria were used to select the best model.

- AIC for PM 2.5: 1345.67
- BIC for PM 2.5: 1360.89
- AIC for CO: 985.34
- BIC for CO: 997.56

C. *Additional Statistical Tests*
Pearson's correlation test: Conducted for all-time series data from the monitoring stations to calculate the correlation between the original PM 2.5 or CO data and the deseasonalized data. Each test showed strong correlation, with consistently low p-values indicating statistical significance. Therefore, the original and deseasonalized data are strongly correlated.

Welch Two-Sample t-test: Performed to compare the means of the original and deseasonalized data for both PM 2.5 and CO. The results showed significant differences between the means of the two datasets, with low p-values indicating statistical significance. Thus, the means of the two datasets are distinct.

Augmented Dickey-Fuller Test: Performed for all deseasonalized time series. The p-value was consistently below 0.05, providing statistically significant evidence to reject the null hypothesis that the time series is non-stationary. Therefore, the deseasonalized time series data are stationary.

D. *Effect of Deseasonalization*
In all cases where deseasonalization was performed, non-seasonal ARIMA models showed better information criteria and similar error measures compared to seasonal models. This suggests that removing the seasonal component simplified the model while maintaining a good fit to the data. Deseasonalization had a positive effect on the analysis, and the non-seasonal model was an appropriate choice for all cases analyzed.

Additionally, Ljung-Box tests were conducted on both seasonal and non-seasonal ARIMA models to check for significant autocorrelations in the residuals at various lags. For the seasonal models, the p-value was below 0.05, indicating that the residuals may contain some structure not captured by the model.

The City of Algorithms: City Brain and Air Quality in Hangzhou

The research aims to analyze the impact of the implementation of smart urban platforms on the quality of life of citizens, focusing on air quality in the city of Hangzhou. In particular, the research attempts to assess whether introducing the "City Brain" platform in 2016, aimed at optimizing urban traffic management, has improved the levels of atmospheric pollutants. The analysis covered data relating to the levels of fine particulate matter (PM 2.5) and carbon monoxide (CO) collected in the period 2014-2022. Preliminary results suggest a possible correlation between the adoption of the platform and the improvement of air quality, emphasizing smart technology in sustainable development and improving the lives of citizens. However, it is essential to also consider other environmental, socio-economic, and meteorological factors that may affect pollution levels. This study, therefore, intends to lay the groundwork for further research in this field, representing an attempt to contribute to the growing literature on the intersection between technology and urban sustainability.

La Città degli algoritmi: City brain e la qualità dell'aria a Hangzhou

La ricerca mira ad analizzare l'impatto delle piattaforme urbane intelligenti sulla qualità della vita dei cittadini, concentrandosi sullo studio della qualità dell'aria nella città di Hangzhou. In particolare, si tenta di valutare se l'introduzione della piattaforma "City Brain" nel 2016, finalizzata all'ottimizzazione della gestione del traffico urbano, abbia migliorato i livelli di inquinanti atmosferici. L'analisi prende in considerazione i dati relativi ai livelli di particelle fini (PM 2.5) e monossido di carbonio (CO) raccolti nel periodo 2014-2022. I risultati preliminari suggeriscono una possibile correlazione tra l'adozione della piattaforma e il miglioramento della qualità dell'aria, sottolineando l'importanza delle tecnologie intelligenti nello sviluppo sostenibile e nel miglioramento della vita cittadina. Tuttavia, è essenziale considerare anche altri fattori ambientali, socio-economici e meteorologici che possono influenzare i livelli di inquinamento. Lo studio intende, quindi, gettare le basi per ulteriori ricerche in questo campo, rappresentando un tentativo di contribuire alla crescente letteratura sull'intersezione tra tecnologia e sostenibilità urbana.

La Ville des algorithmes : City brain et la qualité de l'air à Hangzhou

Cette recherche évalue l'impact de la mise en place de plateformes urbaines intelligentes sur la qualité de vie des citoyens, en se concentrant spécifiquement sur la qualité de l'air à Hangzhou. Elle examine si l'introduction de la plateforme « City Brain » en 2016, visant à optimiser la gestion du trafic urbain, a amélioré les niveaux de polluants atmosphériques. L'analyse traite des données concernant les niveaux de particules fines (PM 2.5) et de monoxyde de carbone (CO) recueillies entre 2014 et 2022. Les résultats préliminaires montrent une corrélation possible entre l'adoption de la plateforme et l'amélioration de la qualité de l'air, soulignant l'importance de la techno-

logie intelligente dans le développement durable et l'amélioration de la vie des citoyens. Cependant, il est crucial de prendre en compte d'autres facteurs environnementaux, socio-économiques et météorologiques qui peuvent affecter les niveaux de pollution. Cette étude vise ainsi à jeter les bases pour des recherches ultérieures dans ce domaine, contribuant à l'enrichissement de la littérature sur la convergence entre technologie et durabilité urbaine.