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Research article

Do meteorological variables impact air quality differently across urbanization gradients? A case study of Kaohsiung, Taiwan, China

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ABSTRACT

Air pollution has become a major challenge to global urban sustainable development, necessitating urgent solutions. Meteorological variables are key determinants of air quality; however, research on their impact across different urban gradients remains limited, and their mechanisms are largely unexplored. This study investigates the dynamic effects of meteorological variables on air quality under varying levels of urbanization using Kaohsiung City, Taiwan, as a case study. Meteorological and air pollutant data from monitoring stations in Kaohsiung, Taiwan, for the year 2023 were collected and analyzed. The Air Quality Index (AQI) was used to quantify air quality levels, and Granger causality tests and Vector Autoregression (VAR) models were employed to analyze the dynamic relationships between meteorological variables and AQI. The results revealed that: (1) Suburban areas exhibited significantly better air quality than urban and near-urban areas, with annual AQI values of 59.58 in Meinong (outskirts), 67.86 in Renwu (suburbs area), and 76.73 in Qianjin (urban area), showing a progressive improvement in air quality from urban to suburban areas, primarily due to lower levels of urbanization and abundant forest resources; (2) Temperature and relative humidity emerged as key meteorological variables influencing AQI, with Granger causality tests indicating that temperature significantly affects AQI, especially in urban areas. Impulse response analysis revealed that temperature had a notable positive and negative correlation effect on AQI over lagged periods, while wind speed showed a negative correlation with AQI in suburban areas, gradually shifting to a positive correlation over time; (3) Variance decomposition indicated that temperature had the largest impact on AQI in urban areas, particularly with cumulative lag effects, while wind speed was the main variables influencing air quality in suburban areas. This study provides scientific evidence for future urban planning and environmental management, supporting the development of more effective air quality improvement strategies to promote sustainable urban development.

1. Introduction

Air pollution is a major challenge to global sustainable development. According to the World Health Organization (WHO) and the United Nations Environment Programme (UNEP), air pollution causes millions of premature deaths annually [1,2], significantly increasing the risk of acute and chronic health problems, particularly respiratory diseases [3–5]. Air pollutants not only reduce

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atmospheric visibility but also negatively impact biodiversity, ecological quality, and urban aesthetics [6,7]. With global economic growth, greenhouse gas emissions and vehicle exhaust have become major sources of urban air pollution, hindering sustainable urban development and severely affecting the health and quality of life of residents [8].

Meteorological variables are considered important variables influencing air pollution. Extensive research has explored the relationship between meteorological variables and air quality, yielding significant findings. Studies show that variables such as temperature, humidity, wind speed, and precipitation can alleviate or exacerbate urban air pollution by affecting the transport and dispersion of pollutants [9–12]. For instance, rising temperatures have been shown to significantly increase PM2.5 concentrations [13], while wind speed plays a key role in dispersing pollutants in coastal cities [14]. Additionally, high humidity levels increase ground-level ozone concentrations [15], while changes in atmospheric pressure influence the accumulation and dispersion of pollutants [16]. Solar radiation intensity is closely related to air quality, as high solar radiation promotes photochemical reactions, increasing ozone and other secondary pollutants [17]. Precipitation improves air quality by removing particulate matter and gaseous pollutants through washout effects [18,19]. Regional studies also reveal unique impacts of meteorological variables on air quality under different climate conditions. For example, a study in Kabul found that temperature, humidity, wind speed, and solar radiation significantly influence aerosol optical depth (AOD), with AOD peaking in spring and summer, indicating that meteorological variables exacerbate urban air pollution in certain seasons [20]. Another study in eastern Myanmar found that seasonal variations significantly influence the sources of carbonaceous particles, with biomass burning as the main source in the dry season and vehicle emissions dominating in the wet season [21].

Moreover, the effects of meteorological variables on air quality vary significantly across urban spaces. Urban centers and suburban areas are affected differently by meteorological variables due to differences in building density and green coverage. For example, in Beijing, high-density buildings and heavy traffic contribute to elevated PM2.5 concentrations in urban areas, while pollutant concentrations are significantly lower in suburban areas [22]. The high density of buildings in city centers limits the effectiveness of wind speed, reducing the dispersion and dilution of pollutants, leading to higher pollutant concentrations. Additionally, the urban heat island effect intensifies pollutant accumulation in city centers [23]. In contrast, suburban areas, with more open space and green coverage, are influenced by meteorological variables differently. Green spaces absorb carbon dioxide and other pollutants through photosynthesis, while transpiration increases air humidity and lowers ground temperatures, thereby improving overall air quality [24,25]. Open spaces facilitate airflow, allowing pollutants to disperse and dilute more easily. The interaction between urban morphology and meteorological variables creates distinct air pollution characteristics in different regions. For instance, a study in Atlanta showed that the spatial arrangement of roads and vegetation, combined with wind speed and other meteorological variables, jointly affect PM2.5 concentrations, highlighting that the interplay between urban form and meteorological conditions can either exacerbate or mitigate pollutant dispersion [26]. Additionally, research in China revealed that severe winter PM2.5 pollution exhibits meteorological threshold variations across regions, closely associated with the periodic changes in the East Asian Trough, suggesting that regional meteorological conditions are of significant reference value in pollution control [27].

In recent years, advancements in deep learning and machine learning have significantly enhanced the accuracy and practicality of air quality prediction methods. For example, hybrid models that combine convolutional neural networks (CNN) and long short-term memory (LSTM) networks effectively capture the spatial and temporal dependencies of air pollutants, greatly improving prediction accuracy for PM2.5, NOx, and other pollutants [28]. The combination of residual networks (ResNet) with LSTM has demonstrated superior performance in multi-site air quality prediction compared to traditional models [29]. Another study showed that LSTM models outperform traditional ARIMA and decision tree models in predicting the air quality index (AQI) on an hourly basis, further validating the effectiveness of deep learning in air quality prediction [30]. Although deep learning models offer significant advantages in air quality forecasting, traditional time series models also exhibit strong applicability. For instance, a study in Abu Dhabi employed ARIMA models to predict NO2, PM10, and PM2.5 concentrations, revealing temporal variations in different pollutants [31]. Another study in a desert region combined ARIMA with kriging spatial analysis, identifying pollution hotspots affected by industrial activities and traffic, such as the Mussafah and Hamdan Street areas, underscoring the importance of combining time series and spatial models in urban air quality management [32].

Despite recent progress in air quality prediction and pollution control, the differential impacts of meteorological variables on air quality across diverse urban spaces remain underexplored. High-density urban areas are prone to pollutant accumulation due to dense buildings and traffic congestion, whereas open spaces with better airflow and green coverage facilitate pollutant dispersion. However, existing studies primarily focus on single urban environments, lacking comparative analyses between urban centers and suburban areas. In structurally diverse cities like Kaohsiung, Taiwan, understanding these spatial differences is crucial for developing targeted air quality management strategies. Based on this, this study introduces Granger causality tests and vector autoregression (VAR) models to systematically analyze the dynamic relationships between meteorological variables (e.g., temperature, humidity, wind speed, and precipitation) and air quality. Granger causality tests reveal causal mechanisms between variables, while VAR models capture interdependencies among multiple variables, providing a comprehensive framework for dynamic analysis [33–35]. Through impulse response and variance decomposition analyses, we assess both the short-term and long-term impacts of meteorological variables on air quality, thereby providing scientific evidence for air quality management under varying meteorological conditions.

Accordingly, this study utilizes meteorological and air pollution data from Kaohsiung's monitoring stations in 2023, employing Granger causality tests and VAR models to analyze the dynamic relationships between meteorological variables (temperature, humidity, wind speed, and precipitation) and air quality. Impulse response and variance decomposition analyses are conducted to assess the short-term and long-term impacts of these variables on air quality. Specifically, the objectives of this study are to: (1) analyze spatial differences in air quality between urban and suburban areas in Kaohsiung and identify the primary influencing variables; (2) determine the causal relationships between meteorological variables and AQI across different urban spaces; (3) assess the response patterns of meteorological variables on AQI in urban and suburban areas; and (4) quantify the contribution of meteorological variables to AQI fluctuations.By revealing the specific impacts of meteorological variables on air quality across different urban spaces, this study aims to provide a scientific basis for future urban planning and environmental management, supporting targeted air quality improvement strategies and promoting sustainable urban development.

2. Materials and methods

2.1. Overview of Kaohsiung City

Kaohsiung City, located in southwestern Taiwan, China, at 22°37′29″ N and 120°19′32″ E (Fig. 1a), spans 2947 km^2 and has a population of 2.78 million. As Taiwan's second-largest city and ranked 88th among the world's top 500 cities in 2023, Kaohsiung serves as a major industrial and port hub. Bordered by the Taiwan Strait to the west and mountains to the east, Kaohsiung's unique geography creates distinctive air circulation patterns. Coastal breezes interact with mountainous barriers, significantly influencing the dispersion and accumulation of pollutants. The city's subtropical monsoon climate, characterized by hot, humid summers and mild winters, further amplifies the impacts of meteorological variables on air quality. Kaohsiung faces serious air pollution challenges from sources such as petrochemical industries, steel manufacturing, power plants, vehicular emissions, and port activities. Its urban zones exhibit varying pollution profiles: industrial areas contribute high emissions, residential zones are impacted by secondary pollution, while suburban green spaces enhance air quality through pollutant absorption and improved airflow.

To analyze the differences in air quality between urban and suburban areas, we selected ten monitoring stations. Five are located in urban areas (Nanzi, Qianzhen, Qianjin, Xiaogang, Zuoying) and five in suburban areas (Daliao, Fengshan, Linyuan, Qiaotou, Renwu), as shown in Fig. 1b.

2.2. Data source and analysis

2.2.1. Data source

We collected the data of meteorological variables and air pollutants from monitoring stations of Kaohsiung in 2023 (https://airtw.moenv.gov.tw/). In this study, we focused on six primary pollutants (PM2.5, PM10, SO_2, CO, O_3, and NO_2), which are recognized by agencies such as the World Health Organization (WHO) and the United States Environmental Protection Agency (EPA) as the main indicators of air quality and four meteorological variables (Average Temperature, Relative Humidity, Wind Speed and Rainfall). These data are publicly available through the official platform of the Kaohsiung Environmental Protection Bureau. We analyzed the concentration levels of these pollutants relative to established norms. Specifically,we compared our findings against the WHO (https://www.who.int/publications/i/item/9789240034228) and the EPA National Ambient Air Quality Standards (https://www.epa.gov/criteria-air-pollutants/naaqs-table).

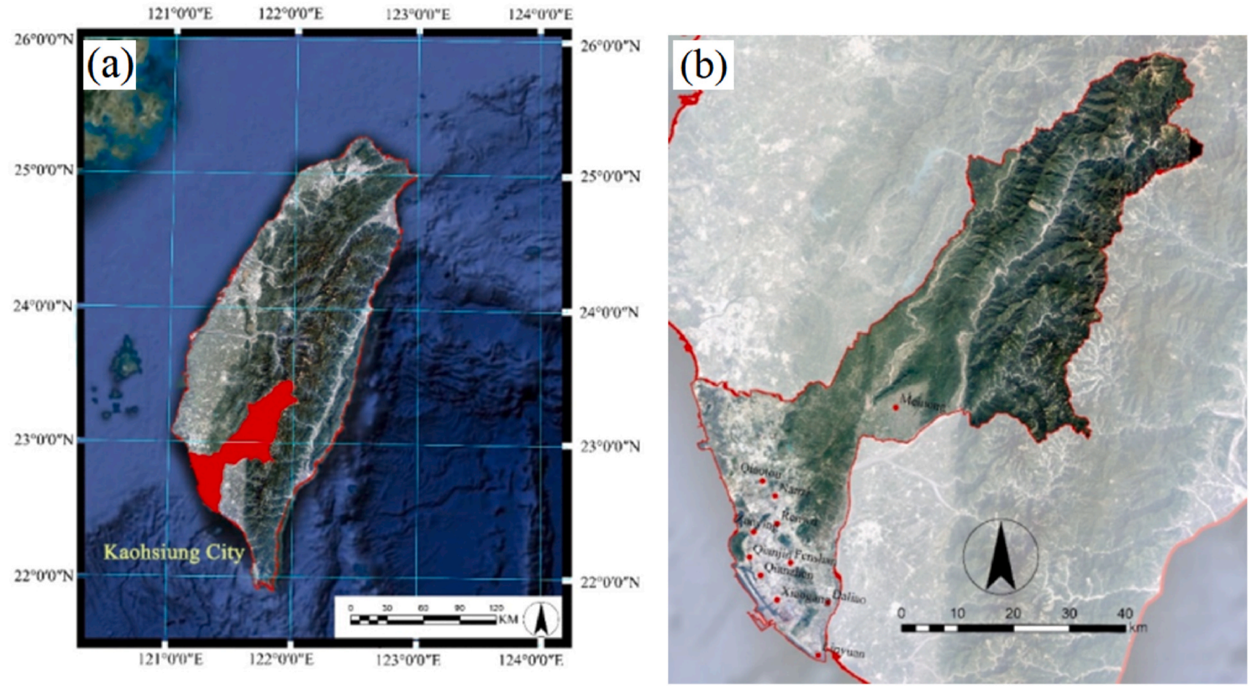

Fig. 1. Location of Kaohsiung in Taiwan, China (a); Location of ten weather stations in Kaohsiung (b).

2.2.2. Data analysis

(1) Air Quality Index (AQI)

AQI was a way to grade air quality levels, and is suitable for representing air environment in cities. The scientific of AQI has been recognized by the world. We classify the AQI of Kaohsiung by the U.S. National Ambient Air Quality Standards (NAAQS) (https://www.epa.gov/naaqs). The calculates method as equation (1).

$$AQI = \frac{(I_{high} - I_{low})}{(C_{high} - C_{low})}(C - C_{low}) + I_{low} \tag{1}$$

Where AQI represents Air Quality Index, I_{high} represents index breakpoint corresponding to C_{high}, I_{low} represents index breakpoint corresponding to C_{low}, C represents pollutant concentration, C_{high} represents concentration breakpoint that is $\geq$ C, C_{low} represents concentration breakpoint that is $\leq$ C.

(2) Granger causality test

First of all, we conduct Granger causality test analysis on meteorological variables and AQI to determine whether there is a causal relationship between the two. Then through VAR (Vector Automatic Regression Model) to analyze the interconnected time series system between the two, and analyze the dynamic impact of random interference on the variable system. Finally, we provide information about the relative importance of each random disturbance affecting the variables in VAR through variance decomposition. The calculation method is shown in equation (2) (3) (4) [36].

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + \varepsilon_t \tag{2}$$

$$y_t = \sum_{i=1}^{q} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j y_{t-j} + \varepsilon_{1t} \tag{3}$$

$$x_t = \sum_{i=1}^{s} \lambda_i x_{t-i} + \sum_{j=1}^{s} \sigma_j y_{t-j} + \varepsilon_{2t} \tag{4}$$

Where y_t is a k-dimensional endogenous variable, x_t is a d-dimensional exogenous variable. $A_1 \dots A_p$ and B are the matrix of coefficients to be estimated. ε_t is the perturbation vector, which can be correlated with each other simultaneously, but not with its own lag values and with the variable on the right of the equation.

3. Results

3.1. Characteristics of air environment changes

According to equation (1), we calculated the AQI of three monitoring stations in Kaohsiung. The days of different AQI standards in three weather stations as showed in Table 1. The number of days with “Good” level reached 129 days, “Moderate” level reached 221 days, and “Unhealthy to sensitive groups” level just 15 days in Meinong (outskirt). On the contrast, the number of days with “Unhealthy to sensitive groups” level reached 86 days in Qianjin (urban area), and 74 days in Renwu (suburbs area). The AQI showed great air conditions in Meinong (outskirts), while the air quality of Qianjin (urban area) and Renwu (suburbs area) is more general, and even more than 20 % of the days in the year showed “Unhealthy to sensitive groups”.

As showed in Fig. 2, the overall value of AQI is lower in summer and autumn than spring and winter in Kaohsiung. The AQI value in the Meinong region is the lowest among the three regions, especially in summer. The air quality of outskirts was significantly better than the suburbs and urban areas. The difference of AQI between the suburbs and the urban area was small, but the air quality in the suburbs area had showed a slightly better than the urban area. In winter, the AQI values in the three regions did not change much.

As seen in Table 2, from an air quality perspective, the annual AQI value of three weather stations showed Qianjin (urban area, 76.73) > Renwu (suburbs area, 67.86) > Meinong (outskirt, 59.58) in 2023. The quality of air decreased gradually from the urban area to the suburbs and then to the outskirts. Based on the average annual data, air quality in these three areas has a value of less than 100,

Table 1
The days of different AQI standards in three weather stations.

AQI standard	Number of days		
	Qianjin	Renwu	Meinong
Good	93	90	129
Moderate	186	201	221
Unhealthy to sensitive groups	86	74	15

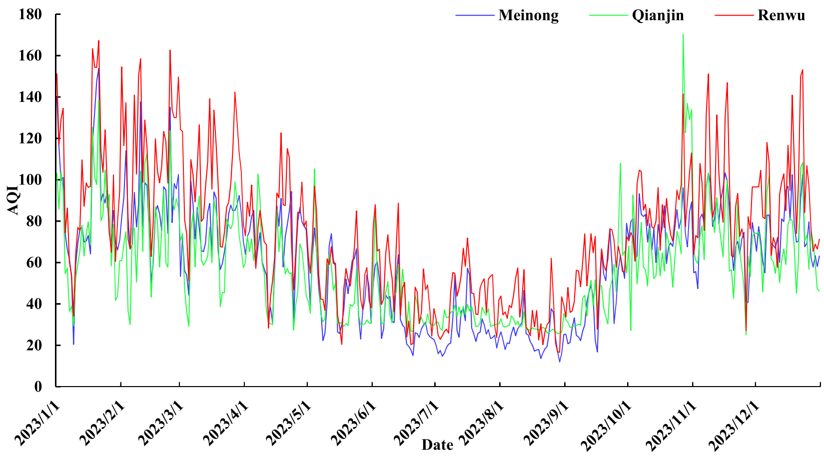

Fig. 2. The AQI of three weather stations in Kaohsiung.

so they have all reached "Moderate" level. It shows that the overall air quality of Kaohsiung City was great.

From a meteorological perspective, the temperature difference among the three regions is not significant. The average temperature of Qianjin (25.98 °C) in urban areas was the highest, then was Meinong (25.37 °C), and Renwu (25.28 °C) in the suburbs area was the lowest. Relative humidity appears as Qianjin (urban area, 73.14 %) < Renwu (suburbs area, 75.63 %) < Meinong (outskirt, 76.19 %), showing a gradient change from urban area to outskirts. In terms of rainfall, Meinong (outskirts) was significantly higher than that in Qianjin (urban area) and Renwu (suburbs area), and there showed not much difference between suburbs and urban areas. From our results, we can see a significant difference in meteorological conditions between the outskirts and urban area, while the difference between the suburbs and urban area was not significant.

3.2. Granger causality test between AQI and meteorological variables

As we can see from Table 3, the Granger causality relationship between temperature and AQI, whether it is urban area, suburbs area or outskirts area, temperature change was the Granger causality of AQI change in Kaohsiung. Judging from the Granger causality of humidity on AQI, in urban areas and suburbs area, the change of humidity was the Granger causality of AQI change, but the humidity in the outskirts area was not the Granger causality of AQI change. As wind speed on AQI, in urban areas and outskirts area, changes in wind speed was not the cause of AQI changes, but in the suburbs area, changes in wind speed was the causes of AQI changes. From the perspective of rainfall, whether it was in the urban, suburbs or outskirts area, the change in rainfall was not the Granger cause of AQI changes.

3.3. Impulse response and variance decomposition of meteorological variables on AQI

3.3.1. Impulse response of meteorological variables on AQI

The paper analyzed the impulse response function of AQI on meteorological variables, and the results were shown in Table 4. It can be seen from Table 4 that when lagging by first period, the temperature in the Meinong (outskirts area) had the largest impulse response, reaching 0.73, followed by Qianjin (0.28), and Renwu (0.04). At this time, temperature and AQI show a positive correlation. With the change of the lag period, at the second period of the urban and the suburbs area, and at the third period of the outskirts area, the impulse response value became negative correlation between meteorological variables and AQI. The range of temperature impulse response changes in the urban area (Qianjin) was more significant than suburbs (Renwu) and outskirts (Meinong), and the response amplitude began to ease after the lag fifth period. The impulse response value at this time reached −4.15, indicating that the AQI value declined the fastest with the accumulation of temperature at this time. In the suburbs area, the impulse response of temperature on AQI turns into a tortuous change, first falling to the trough at the lag third period (−2.21), rebounding at the lag fourth period, then continuing to decline, and then slowly rising after lag eighth period (−3.28). In the outskirts area, the impulse response had been on a

Table 2
The annual air environment average value of three weather stations.

Weather stations	AQI	Average Temperature (°C)	Relative Humidity (%)	Wind Speed (m/s)	Rainfall (mm)	Location
Qianjin	76.73	25.98	73.14	1.30	0.34	Urban area
Renwu	67.86	25.28	75.63	1.70	0.35	Suburbs area
Meinong	59.58	25.37	76.19	0.94	0.50	Outskirts area

Table 3
Granger Causality Tests between AQI and meteorological variables.

	Null hypothesis	Chi-sq	Prob.	Result
Qianjin	Temperature does not Granger Cause AQI	12.65	0.00	Reject
	Relative Humidity does not Granger Cause AQI	3.18	0.04	Reject
	Wind speed does not Granger Cause AQI	2.48	0.09	Accept
	Rainfall does not Granger Cause AQI	0.09	0.91	Accept
Renwu	Temperature does not Granger Cause AQI	11.63	0.00	Reject
	Relative Humidity does not Granger Cause AQI	4.53	0.01	Reject
	Wind speed does not Granger Cause AQI	5.32	0.01	Reject
	Rainfall does not Granger Cause AQI	1.07	0.34	Accept
Meinong	Temperature does not Granger Cause AQI	5.47	0.01	Reject
	Relative Humidity does not Granger Cause AQI	2.40	0.09	Accept
	Wind speed does not Granger Cause AQI	2.42	0.09	Accept
	Rainfall does not Granger Cause AQI	1.94	0.15	Accept

Note: The significance level is 5 %.

Table 4
Impulse response function of meteorological variables on AQI in Kaohsiung.

Period	Urban area (Qianjin)		Suburbs area (Renwu)			Outskirts area (Meinong)
	Temperature	Relative Humidity	Temperature	Relative Humidity	Wind speed	Temperature
1	0.28	1.1	0.04	0.05	−4.45	0.73
2	−1.33	−0.48	−0.41	−1.89	−4.25	0.29
3	−2.68	−1.02	−2.21	−1.51	−1.02	−0.8
4	−3.61	−1	−0.87	−1.59	0.28	−1.52
5	−4.15	−0.74	−1.95	−2.52	−0.69	−2.04
6	−4.41	−0.4	−2.83	−2.5	−0.48	−2.35
7	−4.48	−0.08	−3.26	−2.06	0.14	−2.5
8	−4.42	0.19	−3.28	−1.6	0.79	−2.55
9	−4.29	0.39	−3.25	−1.1	0.98	−2.53
10	−4.12	0.54	−3.07	−0.74	1	−2.49
11	−3.94	0.63	−2.87	−0.43	0.95	−2.44
12	−3.74	0.7	−2.73	−0.14	0.93	−2.37

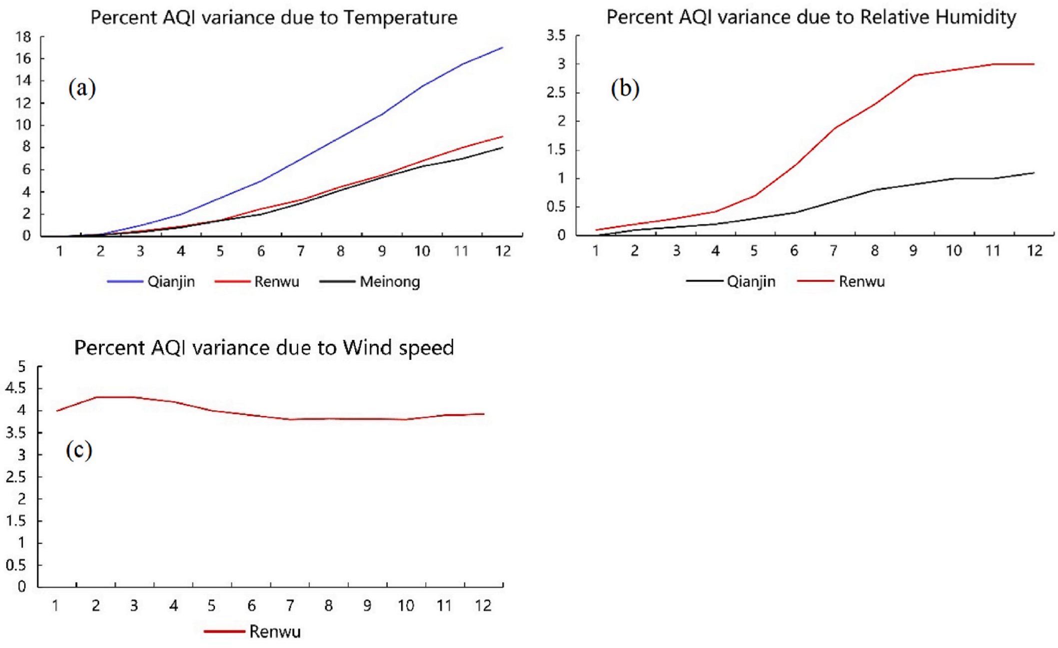

Fig. 3. Variance decomposition of meteorological variables on AQI. (a) represents the percentage contribution of temperature to AQI variance, (b) represents the percentage contribution of relative humidity to AQI variance, and (c) represents the percentage contribution of wind speed to AQI variance.

downward trend, with the most significant decline at the third period, followed by a slow decline.

When the relative humidity lags first period, both the urban and the suburbs area showed a positive correlation impulse response, and the highest impulse response value was in the urban area (1.10). By the lag second period, the urban area showed a negative correlation response. Until lag third period, the negative correlation response value reached a maximum of −1.02, and then showed a slowly rebounded, until the lag eighth period, it became a positive correlation response again, and showed a slowly rising trend. In the suburbs area (Renwu), it also began to show a negative correlation response at the lag second period, but the value of the negative correlation impulse response at the lag seventh period was the highest, reaching −2.06. Then it slowly declined and remained negatively correlated. As the lag period is postponed, it eventually extends in the direction of positive correlation.

Compared with the other three meteorological variables, the wind speed had the greatest impact on AQI in the suburbs area (Renwu). The negative correlation response at the lag first period reached −4.45. Due to the unstable variables of wind speed, the wind speed change fluctuated greatly in the previous six lag periods. Starting from the lag seventh period, the wind speed changed to a stable positive correlation response.

3.3.2. Variance decomposition

In this study, the meteorological variables and AQI were decomposed with 12 lag periods according to the research needs. As can be seen from Fig. 3, the effect of temperature on the AQI in urban, suburbs, or outskirts area became more and more significant as the lag period accumulates, especially in urban areas. It showed that the effect of urban area on temperature was more sensitive than that in suburbs and outskirts area. The influence of temperature on AQI in the suburbs and outskirts area was similar. Since relative humidity had no Granger causality in the far suburbs, this study only analyzed the impact of relative humidity on AQI in urban and suburbs areas. It can be seen that the relative humidity had a higher impact on suburbs area (Renwu) than that on urban area (Qianjin). The influence of humidity on AQI was relatively lower in urban and suburbs area. Wind speed is the most significant meteorological variables affecting AQI in the suburbs area. The variance decomposition of the wind speed on the AQI showed that the effect reached its peak at the lag second period (7.41 %). With the accumulation of the lag period, the effect on AQI had not changed much and had showed a slowly downward trend, but it was still at a relatively high level of influence on AQI.

4. Discussion

4.1. Characteristics of air quality changes

From the results of our analysis, it can be concluded that the overall air quality of Kaohsiung City was above average in the region. Among the study areas, the air quality in the outskirts area was better than urban and suburbs area, whether it was the average annual value or the number of days when the AQI standard reaches "good" in Kaohsiung. The reason for this result was mainly due to the low urbanization level of the Meinong in the outskirts area and the abundant forest resources as well. Abundant forest resources have alleviated the impact of air pollutant emissions brought by urban industrialization to a certain extent, so that more than 95.89 % of the days still have air quality above "Moderate". This result aligns with the findings of [9]. The favorable ecological environment in suburban areas aids in the absorption and purification of air pollutants, thereby maintaining better local air quality [37].

The air quality in suburban and urban areas is relatively similar, primarily due to the effects of urban sprawl [38]. The rapid increase in urbanization levels in suburban areas and the relocation of industrial factories to these regions contributed to this similarity. Some studies have even indicated that, based on the trends of suburban industrialization and urbanization, air quality in suburban areas may deteriorate to levels worse than those in urban areas in the near future [39].

Kaohsiung's coastal location does introduce unique meteorological influences, such as increased humidity, variable wind patterns, and specific temperature modulations due to sea breezes. These factors can contribute to the dispersion and dilution of pollutants, potentially impacting air quality in distinct ways compared to inland regions.

In our study, we acknowledged the coastal influence, especially when analyzing wind speed and relative humidity, as these variables can be affected by the proximity to the sea. While we did not specifically isolate the seashore factor, our findings provide insights into how these coastal characteristics may influence air quality dynamics across different urbanization gradients.

4.2. Granger causality test between AQI and meteorological variables

Granger causality test in Table 3 indicates that temperature was the only meteorological variable that has Granger causality under different urbanization gradients. With rising global temperature, the ground temperature rises, while the upper-air temperature was lower. The effect of the troposphere was conducive to the diffusion of pollutants. Many studies had confirmed the importance of temperature in affecting the air quality in urban areas. From the results of impulse response, we can also see that temperature has a greater impact than other meteorological variables on the three regions we chosen. With the temperature lags accumulate, the negative correlation response with AQI is significantly enhanced. This phenomenon was consistent with the results of the annual change trend of the AQI value we obtained in Kaohsiung. As showed in Fig. 2, when the time comes to summer, the AQI value at this time comes to the lowest valley, while in the spring and winter, the AQI value reaches the highest peak in three regions. In addition, in the variance decomposition (Fig. 3a), as temperature lags accumulate, its effect also shows an upward trend, confirming the significant effect of temperature on AQI. It was consistent with the findings of missing content [40].

Relative humidity has a Granger causality relationship with the suburban and urban areas, but it can be seen from the variance decomposition (Fig. 3b) analysis that the humidity has a lower response to the suburbs and urban area. From Table 2, we can see that the value of relative humidity exceeds 70 % in urban areas, suburbs, and outskirts, which was at a relatively high level. From the impulse response analysis, we also get an interesting result. In the urban area, when the relative humidity lags to the eighth period, the negative correlation response relationship changes to a positive correlation response relationship. This indicates that the accumulation of humidity will increase the AQI and reduce the air quality. This is consistent with the research results of [41]. When the relative humidity reaches a high value, it will cause the hygroscopicity of particles, especially fine particles (such as PM2.5), to increase the concentration of particles. Our AQI calculation results also show that the main air pollutant in Kaohsiung is PM2.5, so the accumulation of relative humidity will cause the concentration of PMs to increase. There was no Granger causality between AQI and relative humidity in the outskirts area, mainly because the vegetation also has the function of adsorbing fine particles [42]. The rich forest vegetation resources in the outskirts make the function of relative humidity adsorption and purification of fine particles decreased. This was the reason why there was no Granger causality relationship between relative humidity and AQI in the outskirts.

4.3. Impulse response and variance decomposition of meteorological variables on AQI

Vegetation also has the function of adsorbing fine particles. The rich vegetation resources in the outer suburbs make the effect of adsorbing and purifying fine particles of humidity less obvious. This is why there is no causal relationship between relative humidity and AQI in the outer suburbs. From the impulse response analysis, we also get an interesting result. In urban areas, when the relative humidity lags to the eighth period, the negative correlation response relationship changes to a positive correlation response relationship, indicating that the accumulation of humidity will increase the AQI and reduce the air quality. This is consistent with the research results of [43,44]. When the humidity reaches a high value, it will cause the hygroscopicity of particulate matter, especially fine particulate matter (such as PM2.5) to increase, resulting in an increase in particulate matter concentration. The pollutant is AQI, so with the accumulation of relative humidity, it will cause the concentration of PMs to increase.

Except for the temperature, the wind speed was also a major variable that affects the air environment in the suburbs area. Related studies have indicated that wind speed can transport and disperse air pollutants [45]. Due to the large number of industries in the suburbs area and the serious accumulation of air pollutants, there was an urgent need to channel and diffuse these air pollutants to reduce air pollution [46]. Compared with the urban area, the building density and floor height of the suburbs area were lower, and the ventilation effect of the suburbs area was doing better than that urban area. Therefore, the wind speed in the suburbs can effectively play its role in the dilution and diffusion of PM2.5. This was the reason for the Granger causality between wind speed and AQI in the suburbs area. In addition, from our impulse response analysis and variance decomposition, these two values have been maintained at a relatively high level (Table 4 and Fig. 3c), it can be seen that wind speed plays an important role in mitigating AQI in suburban areas. This result was also consistent with the study of Zhu et al. (2020). The reason for the absence of Granger causality between the wind speed and AQI in the urban area was mainly due to the high building density and height of the urban area. This makes the wind speed unable to exert its function of channeling and diffusing air, so there showed no Granger causality between them. Related studies have shown that in areas with high-density vegetation, the dilution effect of wind speed may also be weakened [47]. In the outskirts, although there was no high-density building complex, dense forest vegetation will also weaken the dilution effect of wind speed on pollutants, so that there was no Granger causality between them.

4.4. Practical implications for urban planning

This study provides actionable recommendations for improving air quality based on the identified relationships between meteorological variables and urbanization gradients.

1) Enhancing Air Circulation in Suburban Areas

Wind speed significantly improves air quality in suburban areas. Preserving open spaces and designing wind corridors can enhance airflow and pollutant dispersion, while limiting dense industrial or residential development reduces emissions.

2) Temperature Management in Urban Areas

Higher temperatures aid pollutant dispersion but can increase ozone levels during warm seasons. Urban greening initiatives, such as planting trees and creating green roofs, can mitigate heat island effects, lower temperatures, and improve air quality.

3) Humidity Control Strategies

High humidity exacerbates particulate matter and ozone levels, especially in urban areas. Improved ventilation and localized dehumidifying systems can help reduce pollutant accumulation in densely populated zones.

4) Seasonal Air Quality Strategies

Seasonal variations in air quality require adaptive measures. For instance, targeting emissions reductions during winter, when AQI levels peak, can effectively mitigate seasonal pollution.

These strategies highlight the importance of integrating meteorological data into urban planning to develop effective and region-specific air quality management solutions.

4.5. Limitations

This study focuses on the impact of meteorological variables on air quality across different urbanization gradients in Kaohsiung, highlighting the differences in air quality between urban and suburban areas. However, as the research was conducted solely in Kaohsiung, the results may be influenced by the city's specific climatic and geographical conditions, limiting their generalizability to other regions. Furthermore, the scope of this study is constrained by the data coverage, which is based on observations from a single year and may not fully capture the long-term effects of meteorological variables on air quality. Therefore, the applicability of these findings to different regions or climatic contexts should be interpreted with caution. Future studies are recommended to conduct similar research in more diverse communities or regions to compare results across different environments, providing a broader scientific basis for air quality management under various climatic conditions.

We recognize that our findings may be influenced by specific local conditions in Kaohsiung, such as its unique climate, geographical characteristics, and urbanization patterns. However, we believe that the trends identified in this study, such as the impact of temperature, wind speed, and humidity across urbanization gradients, are consistent with findings from similar urban studies and thus may be generalizable to some extent. To improve the applicability and robustness of these findings, future studies could extend the observation period to cover multiple years and include diverse urban settings to validate and refine the observed patterns. This would help in assessing whether these relationships hold over time and across different environmental contexts.

5. Conclusion

This study analyzed the dynamic relationship between meteorological variables and air quality across different levels of urbanization in Kaohsiung City in 2023, revealing the diverse impacts of these variables on air quality in different areas. The results indicate that suburban areas exhibit significantly better air quality compared to urban and near-urban areas, primarily due to lower urbanization levels and abundant forest resources, highlighting the positive role of suburban ecological environments in mitigating air pollution. Specifically, temperature was found to have a significant Granger causality relationship with the Air Quality Index (AQI) across all regions, with rising temperatures promoting pollutant dispersion and thus significantly reducing AQI values, especially in summer. Wind speed showed a substantial effect on improving air quality in suburban areas, whereas its impact was weaker in densely built urban areas, indicating that the effect of wind speed on air quality varies across different spatial environments. Furthermore, relative humidity significantly affected AQI in urban and near-urban areas, where higher humidity levels increased particulate matter concentrations, thereby reducing air quality. However, in suburban areas with substantial vegetation cover, the influence of relative humidity on AQI was diminished due to vegetation's strong adsorption and purification effect on fine particles, explaining why no significant causality relationship was observed between relative humidity and AQI in suburban areas.

Our study further demonstrates that the mechanisms by which meteorological variables impact air quality differ across urbanization gradients, providing a scientific basis for future urban planning and environmental management. Notably, our findings offer practical insights for developing targeted air quality improvement strategies tailored to urban and suburban areas under varying meteorological conditions. For example, urban and near-urban areas should focus on the impact of temperature and humidity variations on air pollution, whereas suburban areas can benefit from utilizing wind speed to enhance pollutant dispersion and improve air quality. Future studies could extend this research to diverse climatic and environmental contexts to compare and validate results, thereby offering a broader scientific foundation for air quality management under varied climate conditions.

These conclusions reveal the multidimensional mechanisms by which meteorological variables affect air quality across different levels of urbanization, enhancing the practical applicability of our findings and providing theoretical support for promoting sustainable urban development.

CRediT authorship contribution statement

Bohan Wu: Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **Shuang Zhao:** Writing – review & editing. **Yuxiang Liu:** Writing – review & editing. **Chunyan Zhang:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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