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# Assessing the trend of ozone concentration and its key influences at a monitoring station in Hanoi, Vietnam, in 2018–2020

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**Abstract.** Ozone ($O_3$) is an air pollutant problem in Hanoi, indicating photochemical smog and posing health risks. The current $O_3$ problem remains relatively underexplored. This study aims to evaluate the temporal trend of $O_3$ formation over the period from 2018 to 2020 at a monitoring station in Hanoi and the relationship among $O_3$ levels, the precursor, and meteorological factors. Multiple linear regression (MLR) and Boosted regression trees (BRTs) models were applied to analyse and quantify the influence of meteorological factors and precursor pollutants on $O_3$ concentrations. The de-weather package was used to estimate $O_3$ concentration after removing the meteorological effects. The monthly $O_3$ concentration decreased in the winter season and rose in the summer season. The peak of hourly $O_3$ levels was consistently observed between 12:00 and 15:00 across all seasons, corresponding to peak photochemical activity. Both MLR and BRTs show that temperature and solar radiation were the dominant drivers of $O_3$ variability. Results from the BRTs model indicate that the de-weathering $O_3$ concentrations exhibited much less variation than the observed values.

**Keywords:** $O_3$, boosted regression trees, meteorological factors, temporal variation, de-weather package

## 1 Introduction

Ozone ($O_3$), a triatomic molecule of oxygen, constitutes the stratospheric ozone layer that protects life on Earth from harmful ultraviolet (UV) radiation. In contrast, $O_3$ in the troposphere is a harmful air pollutant that poses risks to both human health and ecosystems. While a small fraction originates from stratospheric transport, most of it is produced through photochemical reactions involving nitrogen oxides ($NO_x$) and volatile organic compounds (VOCs) in the presence of sunlight [1].

$O_3$ exposure poses significant health risks, including pneumonia and chronic obstructive pulmonary disease (COPD), with impacts dependent on concentration and exposure time [2–5]. WHO also showed that the daily mortality rate increases from 0.3% to 0.5% for each 10 μg/m³ (8-hour mean $O_3$ concentration) increase in $O_3$ concentration in the ambient air from the background concentration threshold of 70 μg/m³ [6]. Luong et al. [7] found that every 10 μg/m³ increase in the overall cumulative lag effect of 5 days exposure to $O_3$ in Hanoi was associated with a 0.7% rise in respiratory hospital admissions, with children under five most affected in winter. In addition to health impacts, elevated ground-level $O_3$ damages crops and man-made materials, and structures. Studies have shown significant yield losses in rice, wheat, and beans with an increase in $O_3$ concentrations [8–12], with effects, including reduced biomass, leaf damage, and smaller grain production. $O_3$ also accelerates the degradation of man-made materials and heritage structures through its strong oxidative properties, especially when interacting with other pollutants [13, 14].

Several studies have addressed $O_3$ pollution in Hanoi, which described a picture of considerable variability in the trends and magnitude of $O_3$ pollution across time and seasons [15–18]. They reflected differences in observation periods as well as the influence of meteorological factors. Especially, Chu et al. reported a steady decline in annual $O_3$ concentration from 41 to 14 μg/m$^3$ between 2002 and 2010, and June and October experienced the highest $O_3$ concentration [15]. Dam et al. found that the monthly $O_3$ level reached a peak from January to March in 2003 [16]. Sakamoto et al. observed that the annual average $O_3$ level reached 37 μg/m$^3$ from May to August, 2016, witnessing a higher monthly concentration [17]. Duong et al. recorded an annual average of 53 μg/m$^3$ in 2016, with higher concentrations during summer months, generally from May to November [18]. Across studies, $O_3$ concentration typically peaked around 14:00 and dropped to its lowest around 6:00.

Multiple linear regression (MLR) has been widely applied to quantify the influences of meteorological conditions and precursor substances on the $O_3$ ground level. Studies across Asia—including in China, Thailand, India, and Japan—demonstrate that MLR effectively quantifies the relative influence of variables such as temperature, solar radiation, wind speed, and relative humidity [20–25]. A research applying MLR was conducted in Hanoi in 2017 and 2018 [19]. Consistently, temperature and solar radiation indicated positive associations with $O_3$ formation through accelerating photochemical reactions [20–25]. While useful, MLR is limited in capturing nonlinear interactions. Boosted regression trees (BRTs) based "de-weathering" technique further normalises meteorological influences on $O_3$ concentrations by normalising meteorological effects. This allows for a more accurate assessment of precursor-driven variability and provides clearer insights into $O_3$ pollution dynamics. To the best of our knowledge, there has been a lack of comprehensive investigations into the influence of meteorological conditions and precursor substances on $O_3$ formation and concentration levels in Hanoi. Therefore, this study aims to determine the current $O_3$ levels and to investigate the influences of meteorological factors and their precursors on $O_3$ concentration. The results can support further understanding of the temporal trend and potential mitigation policy towards $O_3$ pollution.

## 2 Materials and methods

### 2.1 Monitoring sites, measuring instruments, and monitoring data

This study was conducted in Hanoi, a metropolitan city in Northern Vietnam with about 8 million inhabitants [26]. An automatic air quality monitoring station is located in Cau Giay District. The station is characterised as an urban station, about 27 m from the residential road and 335 m from the main road. The monitoring site was not affected by any obstacles in the surrounding area and is presented in Fig. 1.

The measurement instrument of the urban station was an O342e UV photometric ozone analyser (Envea Company, France). This analyser was a standard one and located on the rooftop of the DONRE's building. The measurement principle of O342e is based on the direct absorption of ultraviolet light, specifically utilising the property that $O_3$ molecules absorb UV radiation at a wavelength of 255 nm. The degree of UV absorption is directly related to the $O_3$ concentration, as described by the Beer-Lambert law [27].

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Other data, including meteorological parameters (pressure, temperature, relative humidity (RH), solar radiation, wind speed, and rainfall) and precursors (NO, $NO_2$, and CO) were also collected from the station as one-hour averages.

All instruments were operated, calibrated by the Hanoi Natural Resources & Environment Department.

## 2.2 Data analysis

### Multiple linear regression

Multivariate regression analysis was established as follows (Eq. (1)):

$$Y = \alpha + \sum_{j=1}^{k} \beta_j \times X_j + \varepsilon \quad (1)$$

where $Y$ is the dependent variable ($O_3$ concentration); $X_j$ is the independent variable encompassing meteorological factors; $\alpha$ is the intercept value; $\beta_j$ is estimated as the regression coefficients of respective independent variables; $\varepsilon$ is the model error; $k$ is the number of meteorological variables.

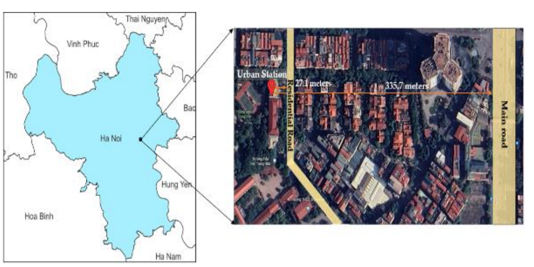


**Fig. 1.** Map of monitoring site

The meteorological factors considered in this study, including daily wind speed, temperature, RH, pressure, solar radiation, rainfall, and those from the previous day, were also incorporated into the correlation analysis to determine the lag effect.

Daily $O_3$ concentration was used accordingly. The Bayesian model average (BMA) package was utilised to identify the optimal MLR model. BMA allows the creation of the $2^n$ models ($n$ is the number of independent factors), and then five models were selected with the highest posterior probability. Parameters are selected in the five models in order to calculate the adjusted $R^2$. The model with the highest adjusted $R^2$ was selected as optimal. The statistical significance of each parameter was evaluated by using a stringent threshold ($p < 0.01$).

For obtaining the representative seasonal pattern, the data were split into dry winter (October to December), humid winter (January to April), and summer (May to August) periods for MLR analysis. Detailed information about seasonal patterns of meteorological conditions in Hanoi can be found in Ly et al. [28].

### Boosted regression trees algorithm and weather-normalised O3 concentration

The Boosted regression trees from the 'de-weather' package in R were employed. BRTs are recognised as a powerful tool for analysing air quality data, adept at capturing intricate interactions and non-linear relationships between variables.

Predictor variables include temporal factors (week and weekday) and the current meteorological variables, as in MLR, in daily averages. Besides, the precursors of $O_3$ (NO, $NO_2$, and CO) in daily average were included. The BRTs model employs 80% of the data for training and the remaining 20% for validation, ensuring robust model performance evaluation. The model is subsequently trained on the designated training dataset.

The testMod function within the 'de-weather' package identified the optimal number of regression trees, corresponding to the number of individual BRTs models that are iteratively constructed and evaluated based on the training dataset. Then, the buildMod function selected the most appropriate completed BRTs model, which was used for the input of the second step – weather normalisation.

Several parameters were used to validate the performance of the BRTs model, such as RMSE (root mean square error) and *r* (correlation factor). RMSE serves to quantify the model's error, and the correlation factor (*r*) determines the goodness-of-fit of the BRTs model's results; the values of *r* closer to 1 signify better performance. The formula for calculating RMSE is as follows (Eq. (2)) [29]:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i^{'} - y_i\right)^2} \quad (2)$$

where $n$ is the number of values; $y_i^{'}$ is the prediction; $y_i$ is the observation.

For evaluating the meteorological effect on $O_3$ concentration, daily data from one year were used.

Once the model was built, the meteorological averaging procedure was applied by predicting multiple times with the random sampling of weather conditions. This sampling was carried out by the "metSim" function. This random process was repeated a thousand times. As a result, the final predicted $O_3$ level (called weather-normalised level or de-weather level) was estimated by aggregating the thousand predictions obtained from the second step above. For obtaining the de-weather $O_3$ level, daily data from 2018–2020 were used.

# 3 Results and discussion

## 3.1 Variation of $O_3$ concentration

### Monthly and annual O3 concentration

Fig. 2 shows the daily $O_3$ concentration from 2018 to 2020. The annual average $O_3$ concentration was 15.0, 10.7, and 12.2 μg/m$^3$ for 2018, 2019, and 2020, respectively. The data exhibit notable seasonal and interannual variation. The $O_3$ levels peaked more frequently in 2018, declined in 2019, and rose again in 2020. This pattern suggests that the episodes of enhanced $O_3$ formation occurred more often or more intensely in 2018 and 2020 than in 2019. However, these short-term data do not support a definitive conclusion regarding long-term $O_3$ trends because of short observation time (only 3 years) and substantial variation in meteorological conditions. The averages of $O_3$ concentration in 2018–2020 were lower than those reported by Chu et al., who found a steady decline in the annual $O_3$ concentration from 41 μg/m$^3$ to 14 μg/m$^3$ between 2002 and 2010 [15] and those reported by Duong et al. (53 μg/m$^3$) in 2016 [18].

Fig. 3 presents the monthly mean $O_3$ concentrations from 2018 to 2020. They were generally higher in summer (May – September) and lower in autumn and winter (October – April). The highest monthly averages occurred in May 2018 and 2020 and September 2019, with peak values of 27.5 μg/m$^3$ (2018), 22.1 μg/m$^3$ (2020), and 17.3 μg/m$^3$ (2019). In other words, the $O_3$ concentrations tended to peak in warmer months, especially from May to September each year. The lowest values recorded were 1.6 μg/m$^3$ in 2018, 5.3 μg/m$^3$ in 2019, and 3.8 μg/m$^3$ in 2020, occurring in January, February, and December, respectively. Elevated summer $O_3$ levels were associated with higher temperatures (27–32 °C) and increased solar radiation, both of which favour $O_3$ formation. These seasonal patterns are consistent with previous studies conducted in Hanoi; for example, Duong et al. reported an annual mean of 53 μg/m$^3$ in 2016, with higher concentrations from May to November [18].

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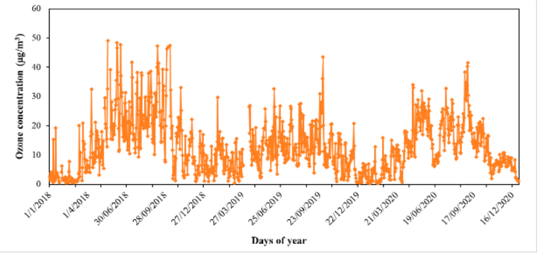


**Fig. 2.** Daily $O_3$ concentrations from 2018 to 2020

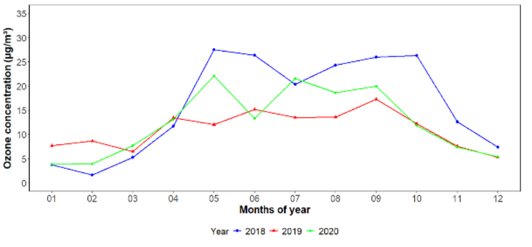


**Fig. 3.** Monthly $O_3$ concentration from 2018 to 2020

**Diurnal O3 concentrations**

Fig. 4 illustrates the diurnal variation of $O_3$ concentrations at the station. During the study, the hourly $O_3$ concentration remained below the threshold set according to the Vietnam standard – QCVN 05:2023/BTNMT (200 μg/m$^3$). Diurnal variation in the $O_3$ levels in 2018 was higher than that in other years. A distinct diurnal pattern in $O_3$ concentration is observed. The $O_3$ level remained low from midnight and 7:00 the following day, with a gradual reduction to the end of this period, because of the lack of sunlight, minimal photochemical activity, and potential reactions with NO. Then, the $O_3$ level rose quickly and reached a peak around midday, typically between 13:00 and 15:00, depending on the year, as a result of increasing solar radiation, which enhances photochemical processes involving $O_3$ precursors like $NO_2$ and VOCs. Then, the $O_3$ level quickly declined until 21:00 and more slowly through the night until 7:00 the following day. This diurnal pattern reflects the influence of photochemical processes and atmospheric dynamics on $O_3$ formation. The ratio between the highest and lowest daily $O_3$ value was approximately 4 times. This observed daily trend of $O_3$ variation shows considerable similarity to findings from previous studies conducted in Hanoi City [15, 17, 18] and to broader global observations [20], suggesting that consistent photochemical processes drive the patterns of $O_3$ formation and depletion.

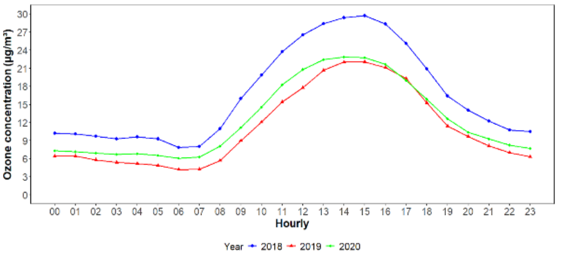


**Fig. 4.** Diurnal variation of $O_3$ from 2018 to 2020

### 3.2 Influence of meteorological conditions on $O_3$ concentration across seasons

The impact of meteorological conditions on $O_3$ concentration was analysed across three distinct seasons in Hanoi: the dry winter (October to December), the humid winter (January to April), and the summer (June to August). Table 1 presents the correlation results in the period of 2018–2019 from the multivariate linear regression model across seasons. In general, meteorological factors explained 56%–82% of $O_3$ variability, with strong influences from current temperature, rainfall, RH, and wind speed and lagged effects of the previous-day conditions (previous temperature, RH, rainfall, solar radiation, and wind speed) in winter, whereas the explained variance dropped to 24%–43% in summer, with solar radiation, RH, and lagged temperature, and wind speed, showing significant correlations in summer. This indicates that $O_3$ formation is more strongly influenced by precursor emissions and enhanced photochemical processes than meteorological effects in summer, whereas in winter it was largely controlled by meteorological conditions. Meanwhile, solar radiation emerges as a crucial factor influencing $O_3$ concentration, as photochemical $O_3$ formation is fundamentally dependent on sunlight. A positive correlation between current and previous solar radiation and $O_3$ concentration across almost all seasons was also observed, and this finding aligns with previous studies in the Bangkok region, Thailand [23], and Agra, India [24]. In addition, atmospheric pressure showed a positive correlation with $O_3$ concentration during the humid winter of 2019, likely because of high-pressure systems fostering conditions—clear skies, calm winds, and higher temperatures—that promote $O_3$ formation, while low-pressure systems enhanced pollutant dispersion. On the other hand, both current and previous wind speeds generally exhibited an inverse relationship with $O_3$ concentration throughout the study period, suggesting that stronger winds enhanced the dispersion and dilution of $O_3$ and its precursors. Similar findings were reported in Zhuzhou, China [20]. Overall, meteorological factors, such as temperature, humidity, and solar radiation, are consistently influential on $O_3$ formation across the seasons.

### 3.3 Partial influences of meteorological parameters on $O_3$ concentration

The boosted regression trees model, applied alongside the 'de-weather' package (or equivalent methodology for meteorological adjustment), demonstrated good performance based on the evaluated error and accuracy metrics. Specifically, the root mean square error of the validation dataset of 8.3, 14.2, and 5.6 μg/m³ and the correlation factor (*r*) of 0.96, 0.93, and 0.95 for 2018, 2019, and 2020, respectively, indicate satisfactory model accuracy. The partial effect of current meteorological factors on $O_3$ concentration is displayed in Table 2. The partial effects of precursors and temporal components were not presented.

Temperature consistently emerged as the most influential meteorological parameter in the years 2018–2020, accounting for 41.9%, 33.8%, and 36.6% of the $O_3$ variation, respectively (Table 2). The high contribution of temperature aligns with the result in the seasonal multivariate regression presented in Section 3.2 that temperature statistically significantly affected $O_3$ concentration in almost all investigated seasons. Solar radiation generally exhibited a positive influence on $O_3$ levels, with a notable contribution of 4.1% in 2018, 24.1% in 2019, and 14.4% in 2020. In 2018–2019, the atmospheric pressure, exceeding 1000 hPa, was associated with increased $O_3$ concentration, but a clear trend was not observed in 2020. This suggests that high-pressure conditions, often characterised with clear skies, calm winds, and higher temperatures, promote $O_3$ formation and accumulation. RH showed a consistent inverse relationship with $O_3$ concentration across all the three years, indicating that elevated RH, often concurrent with rainfall events, contributed to reductions in $O_3$ levels. However, in this study, the rainfall contributed to a minor influence (0.6%–1.6%) on $O_3$ variation. The wind speeds above 1 m/s showed an inverse correlation with $O_3$ concentration, likely because of the stagnation of pollutants in areas with very low wind speeds. In conclusion, this study employed MLR to examine the linear influence of meteorological factors on $O_3$ variability, while BRTs were applied to improve predictive performance and assess the relative importance of variables. On the basis of the BRTs model, weather normalisation was conducted to obtain $O_3$ concentrations adjusted for meteorology, yielding a time series that more accurately reflects underlying trends and emission-driven changes. By integrating both approaches, the analysis ensures scientific transparency and enhances the reliability of predictions and trend evaluations of $O_3$ pollution in Hanoi.

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**Table 1.** Correlation between meteorological factors and $O_3$ concentration

| Seasons of year | Year | $R^2$ | Adjusted –$R^2$ | Meteorological factors ($p < 0.01$) |
|---|---|---|---|---|
| Wet winter season (Jan. to Apr.) | 2018 | 0.82 | 0.7 | WS<br>Temp<br>RH<br>SR-pre<br>RH-pre<br>Rain-pre<br>WS-pre |
| | 2019 | 0.56 | 0.46 | WS<br>P<br>WS-pre |
| | 2020 | 0.64 | 0.58 | Temp<br>RH |
| Summer season (Jun. to Aug.) | 2018 | 0.324 | 0.27 | SR<br>RH-pre<br>Temp-pre |
| | 2019 | 0.43 | 0.38 | RH<br>Temp-pre |
| | 2020 | 0.24 | 0.18 | Temp-pre<br>WS-pre |
| Dry winter season (Oct. to Dec.) | 2018 | 0.58 | 0.5 | Rainfall<br>SR-pre |
| | 2019 | 0.79 | 0.73 | SR<br>Temp<br>RH-pre |
| | 2020 | 0.72 | 0.66 | SR<br>P-pre |

*Note: WS: Wind speed; WS-pre: Wind speed in previous day; Temp: Temperature; Temp-pre, Temperature in previous day, RH: relative humidity; RH-pre: relative humidity in previous day; SR: solar radiation; SR-pre: Solar radiation in previous day; P: Pressure; P-pre: Pressure in previous day; R: Rainfall; R-pre: Rainfall in previous day.*

**Table 2.** Partial effect of meteorological factors on $O_3$ concentration in 2018–2020

| Partial effect of meteorological factors | 2018, % | 2019, % | 2020, % |
|---|---|---|---|
| Temperature | 41.9 | 33.8 | 36.6 |
| Solar radiation | 4.1 | 24.1 | 14.4 |
| Relative humidity | 9.1 | 6.6 | 5 |

| Partial effect of meteorological factors | 2018, % | 2019, % | 2020, % |
|---|---|---|---|
| Pressure | 4.4 | 4.3 | 4.1 |
| Wind speed | 6.5 | 3.3 | 2.9 |
| Rainfall | 1.6 | 0.6 | 1.2 |

### 3.4 Weather-normalised levels of $O_3$

Fig. 5 illustrates the daily average $O_3$ concentration during the study and compares the observed values (orange line) with weather-normalised values derived by using the 'de-weather' package (blue line). In this research, a weather-normalisation technique was applied to eliminate the effects of weather on $O_3$ levels, a method widely used in previous studies [29, 30]. The results show that the weather-normalised levels of $O_3$ were more stable than the monitored $O_3$ levels. It may be explained by removing meteorological variability, thereby providing a clearer representation of baseline pollutant contributions and clarifying long-term air pollution trends. In 2018–2020, the differences between the minimum and the peak values of observed $O_3$ levels were from 27.7 to 48.6 μg/m³, whereas those of normalised $O_3$ levels were from 16.7 to 32.9 μg/m³. These findings are consistent with those reported by Ly et al. [31], who found strong impacts of meteorological conditions on daily averaged levels of $PM_{2.5}$ in Hanoi. However, the annual averages of normalised values in the observed period have no statistically significant differences from the observed values.

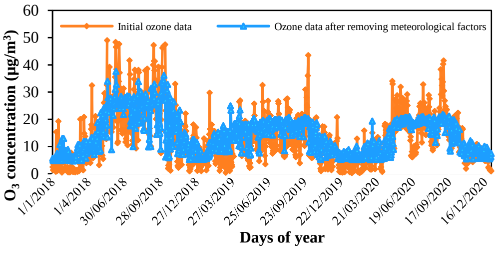


**Fig. 5.** Observed and weather-normalised levels of $O_3$ in the researched period

## 4 Conclusions

This study examined the temporal variation of $O_3$ concentrations by using data from an automatic air quality monitoring station in Hanoi from 2018 to 2020. The results show a decreasing trend in annual average $O_3$ concentrations, from approximately 15.0 μg/m³ in 2018 to 10.7 μg/m³ in 2019, with a slight increase to 12.2 μg/m³ in 2020. Throughout the study period, one-hour average $O_3$ concentrations remained below the limits specified by the Vietnam standard (QCVN 05:2023/BTNMT). Diurnal patterns were consistent across the years, with peak $O_3$ levels occurring between 12:00 and 15:00, and the lowest levels between midnight and 7:00 the following day. Seasonally, higher concentrations were observed during summer.

A multiple linear regression model implemented in R explained 56%–82% of winter $O_3$ variability and 24%–43% in summer, with significant contributions from temperature, rainfall, relative humidity, solar radiation, wind speed, and lagged effects from the previous day. Utilising BRTs and the 'deweather' package approach enabled to quantify the percentage influence of each factor on $O_3$ concentrations and the removal of meteorological confounding effects when examining inter-annual $O_3$ trends. The results show that air temperature and solar radiation consistently accounted for a high percentage of influence, while the impact of other factors varied depending on the specific year.

The weather-normalised levels of $O_3$ were of lesser variation than the monitoring $O_3$ levels, suggesting the significant effects of meteorological

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conditions. These findings underline the importance of meteorological effects when evaluating $O_3$ pollution and formulating effective air quality management strategies.

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