MACAO AIR QUALITY FORECAST USING STATISTICAL METHODS

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ABSTRACT
The levels of air pollution in the cities of Greater Bay Area in Southern China, including Macao, are extremely high and often exceeded the levels recommended by World Health Organization Air Quality Guidelines. In order for the population to take precautionary measures and avoid further health risks under high pollutant exposure, it is important to develop a reliable air quality forecast. Statistical models based on multiple regression analysis were developed successfully for Macao to predict the next-day concentrations of particulate matter (PM$_{10}$ and PM$_{2.5}$) for Taipa Ambient, a background representative station located within the area of Macao (32.9 km$^2$), at Taipa Grande, the headquarter of Macao Meteorological and Geophysical Bureau. The two developed models were statistically significantly valid, with a 95% confidence level with high coefficients of determination. A wide range of meteorological and air quality variables were identified, and only some were selected as significant dependent variables. The meteorological variables such as geopotential height and relative humidity at different vertical levels were selected from an extensive list of variables. The air quality variables that translate the resilience of the recent past concentrations of each pollutant were the ones selected. The models were based in meteorological and air quality variables with five years of historical data, from 2013 to 2017. The data from 2013 to 2016 were used to develop the statistical models and data from 2017 were used for validation purposes, with high coefficients of determination between predicted and observed daily average concentrations (0.92 and 0.89 for PM$_{10}$ and PM$_{2.5}$, respectively). The results are expected to be the basis for an operational air quality forecast for the region.

Keywords: air pollutants, air quality forecast, management, modelling, monitoring.

1 INTRODUCTION
Macao is located in Southern China and one of the cities within the Greater Bay Area. The historical center of Macao has been awarded ‘World Cultural Heritage’ status by the United Nations Educational, Scientific and Cultural Organizations (UNESCO) in 2005. Nevertheless, the land area of Macao is extremely limited due to rapid growth of population and lack of land resources, and thus, the United Nations World Prospects Report had listed Macao as the number one most densely populated region in the world [1]. Macao has a land area of 30.8 square kilometers with a population of 653,100, which leads to a population density of 21,100 per square kilometers [2]. Due to the high population density, the health impact of air pollution is significant in Macao. The levels of particulate matter (PM) in Macao and its neighboring cities in the Greater Bay Area are extremely high and often exceeding the established limit values recommended by World Health Organization (WHO) Air Quality Guidelines (AQG). Therefore, it is important to develop a reliable prediction methodology for the concentration of PM, which can provide alert for health hazards in advance. Small particles less than 10 micrometers in diameter pose the greatest problems, specifically due to the fine particles below 2.5 micrometers that can get deep into the respiratory system, and some may even get into the bloodstream. Exposure to such PM can affect cardiovascular system. People with heart or lung diseases, older adults and children are considered at greater
Risk from the exposure to PM. Numerous studies showed that exposure to PM has increased hospital admissions and emergency room visits and leading even to death from heart or lung diseases [3]. The exposure to PM would increase the chance of hospital admissions for cardiovascular and respiratory disease and mortality in the world [4].

The Macao Meteorological and Geophysical Bureau (SMG) adopted the WHO interim target-1 (IT-1) for the threshold of pollutants, which has a less strict standard on the pollutants compared to the WHO AQG. Table 1 shows the WHO Air Quality Standards and different limit values for air pollutants for the regions across the world. Figure 1 shows the locations of air quality monitoring stations in Macao. Taipa Ambient is an ambient station in Macao, which is also the background representative station. It is located at Taipa Grande, the headquarter of Macao Meteorological and Geophysical Bureau (SMG).

PM levels are usually measured higher during the winter season, from December to February due to the northern wind bringing the air pollutants to the region, lowering mixing height, fewer amount of rainfall and lower frequency of rainfall. In contrast, the levels of PM are usually measured lower during the summer season, from June to August due to the southern winds from the China sea, higher mixing height and higher frequency of rainfall and amount, which allowed for a better air pollution dispersion and deposition conditions [12], [13]. Figures 2 and 3 show the monthly levels of PM in Macao. The months from June to August recorded the lowest concentration of PM10 and PM2.5 in Macao. In contrast, the months from December to February recorded the highest concentration of PM10 and PM2.5 in Macao.

Figures 4 and 5 show the hourly levels of PM in Macao. The hours from 10:00 to 12:00 and from 15:00 to 18:00 recorded the highest concentration of PM10 in Macao. The hours from 8:00 to 11:00 recorded the highest concentration of PM2.5 in Macao. In addition, Macao has a typical tropical oceanic climate which is hot and humid, with an annual average temperature of 22.3°C and an annual average wind speed of 3.5 m/s, with northwestern wind dominant in winter and southeastern wind dominant in summer [14].

The forecasting of air pollutant concentrations is very important for areas with air quality problems. The forecasting can be developed through the integration of physicochemical relationships from both meteorology and pollutant behavior or by using stochastic methods
Figure 1: Map of Macao air quality monitoring station network [11].

Figure 2: Monthly levels of PM$_{10}$ in the Macao air quality monitoring stations from 2013 to 2017.

Based on data series analysis. A combination of standard statistical methods was the selected process described in this paper. Statistical models based on multiple regression (MR) analysis were developed to forecast the average daily concentration for PM (PM$_{10}$ and PM$_{2.5}$, coarse and fine particles, respectively) for the next day, for the air quality monitoring station of Taipa Ambient.
Figure 3: Monthly levels of PM$_{2.5}$ in the Macao air quality monitoring stations from 2013 to 2017.

Figure 4: Hourly levels of PM$_{10}$ in the Macao air quality monitoring stations from 2013 to 2017.

Figure 5: Hourly levels of PM$_{2.5}$ in the Macao air quality monitoring stations from 2013 to 2017.
2 METHODS

Using past information on studies to understand the variability of PM$_{10}$ and PM$_{2.5}$ \cite{15--19} was the first step to start to build a highly detailed database using all the air quality and meteorological existing data from the years of 2013 to 2017. Data from the years between 2013 and 2016 were used to develop the models, and each of the models was validated using the data of 2017. There were a total of 35 variables to forecast each pollutant, which include 30 meteorological variables and 5 air quality variables. Some of the meteorological variables that were considered included H$_{1000}$, H$_{850}$, H$_{700}$ (the height of geopotential at 1,000, 850 and 700 hPa, respectively), HRMD, HRMN and HRMX (relative humidity of mean, minimum and maximum daily values). Some of the air quality variables that were considered included PM$_{10-16D1}$, PM$_{2.5-16D1}$ (PM$_{10}$ and PM$_{2.5}$ from the 16:00 of yesterday to 15:00 of today, respectively) and PM$_{10-23D1}$ and PM$_{2.5-23D1}$ (PM$_{10}$ and PM$_{2.5}$ average from the previous day, respectively). Table 2 shows the list of meteorological variables that were selected as significant independent variables for the best-fitted MR models, and Table 3 shows the list of air quality variables also incorporated as independent variables in each of the models, for daily next-day average PM$_{10}$ and for daily next-day average PM$_{2.5}$, respectively.

Air quality data were obtained from the Macao Meteorological and Geophysical Bureau (SMG). Surface meteorological parameters such as relative humidity were collected from the Taipa Ambient station. Geopotential heights were also collected from the daily soundings of Hong Kong King’s Park meteorological station. The European Centre for Medium-Range Weather Forecasting would issue the meteorological forecast at GMT+8 16:00 (local time) daily, and these data are used to feed the forecasting model \cite{20}. In addition, the use of MR can determine the meteorological comparability between the measurement days \cite{21}. Following the precedent experiences \cite{22--25}, the statistical models were initially created using forward MR analysis with a significance level of 0.05. The MR analysis was performed with SPSS version 25.

<table>
<thead>
<tr>
<th>Meteorological variables</th>
<th>Description (units)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H$_{850}$</td>
<td>Height of geopotential at 850 hPa (m)</td>
</tr>
<tr>
<td>HRMD</td>
<td>Average relative air humidity (%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Air quality variables</th>
<th>Description (units)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PM$_{10-16D1}$</td>
<td>Average of the hourly values between 16:00 of yesterday and 15:00 of today for PM$_{10}$ (µg/m$^3$)</td>
</tr>
<tr>
<td>PM$_{2.5-16D1}$</td>
<td>Average of the hourly values between 16:00 of yesterday and 15:00 of today for PM$_{2.5}$ (µg/m$^3$)</td>
</tr>
</tbody>
</table>
3 RESULTS AND DISCUSSION

Table 4 shows the variables used in each of the statistical models to predict next-day daily average of PM$_{10}$ and PM$_{2.5}$. In the case of relative humidity, the decrease in humidity will imply intensification of the northern or western flow with transport of continental dryer air over Macao increasing the concentrations of PM. In the case of the geopotential height at 850 hPa, the influence is less relevant and more difficult to explain because the variability of geopotential height is small at the latitude of Macao. One of the possible explanations for the influence of geopotential height is related to the atmospheric circulation and air mass characteristics of Macao.

Data from 2013 to 2017 were used in this study. In particular, the data from 2013 to 2016 were used to build the statistical models, while the data of 2017 were used to validate the models. The statistical models were built for Taipa Ambient air quality monitoring station of Macao. The corresponding ANOVA tables for the regression models for the selected MR models are presented in Tables 5 and 6 for PM$_{10}$ and in Tables 7 and 8 for PM$_{2.5}$, respectively. The equation for next-day 24-h average PM$_{10}$ at Taipa Ambient is presented as follows:

$$\text{PM}_{10} = (0.891 \times \text{PM}_{10-16D1}) + (0.018 \times \text{H}_{850}) - (0.261 \times \text{HRMD}_{TG})$$  \hspace{1cm} (1)

The equation for next-day 24-h average PM$_{2.5}$ at Taipa Ambient is presented as follows:

$$\text{PM}_{2.5} = (0.918 \times \text{PM}_{25-16D1}) + (0.009 \times \text{H}_{850}) - (0.128 \times \text{HRMD}_{TG})$$  \hspace{1cm} (2)

Table 4: Variables used in statistical models.

<table>
<thead>
<tr>
<th>Station</th>
<th>Dependent variables (daily next-day average)</th>
<th>Independent variables used in the best-fit multiple regression model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taipa Ambient</td>
<td>PM10</td>
<td>PM10$<em>{16D1}$, H$</em>{850}$, HRMD</td>
</tr>
<tr>
<td></td>
<td>PM2.5</td>
<td>PM25$<em>{16D1}$, H$</em>{850}$, HRMD</td>
</tr>
</tbody>
</table>

Table 5: ANOVA for PM$_{10}$ at Taipa Ambient.

<table>
<thead>
<tr>
<th>Model</th>
<th>Sum of squares</th>
<th>Df</th>
<th>Mean square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Regression</td>
<td>4,826,913.618</td>
<td>3</td>
<td>1,608,971.206</td>
<td>20,087.037</td>
</tr>
<tr>
<td></td>
<td>Residual</td>
<td>112,940.966</td>
<td>1,410</td>
<td>80.100</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>4,939,854.584$^a$</td>
<td>1,413</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Model summary for PM$_{10}$ at Taipa Ambient.

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R square$^b$</th>
<th>Adjusted R Square</th>
<th>Std. error of the estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.989$^a$</td>
<td>0.977</td>
<td>0.977</td>
<td>8.950</td>
</tr>
</tbody>
</table>
The models were tested with collected data from 2017 to perform a model validation. The results show a high correlation (with an $R^2$ of 0.98 and 0.97, for PM$_{10}$ and PM$_{2.5}$, respectively), statistically significant at a 95% confidence level. The selected models allow a better understanding of each synoptic situation and its relationship with air quality, leading to a forecast with considerable certainty for the majority of the identified scenarios. Figures 6 and 7 show an example of the test for the year of 2017 and the results of model validation for PM$_{10}$ and PM$_{2.5}$.

Table 7: ANOVA for PM$_{2.5}$ at Taipa Ambient.

<table>
<thead>
<tr>
<th>Model</th>
<th>Sum of squares</th>
<th>Df</th>
<th>Mean square</th>
<th>$F$</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>1,805,650.479</td>
<td>3</td>
<td>601,883.493</td>
<td>14,496.557</td>
<td>0.000c</td>
</tr>
<tr>
<td>Residual</td>
<td>58,085.172</td>
<td>1,399</td>
<td>41.519</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>1,863,735.651d</td>
<td>1,402</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 8: Model summary for PM$_{2.5}$ at Taipa Ambient.

<table>
<thead>
<tr>
<th>Model</th>
<th>$R$</th>
<th>$R$ square$^b$</th>
<th>Adjusted $R$ square</th>
<th>Std. error of the estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.984$^a$</td>
<td>0.969</td>
<td>0.969</td>
<td>6.444</td>
</tr>
</tbody>
</table>

The models were tested with collected data from 2017 to perform a model validation. The results show a high correlation (with an $R^2$ of 0.98 and 0.97, for PM$_{10}$ and PM$_{2.5}$, respectively), statistically significant at a 95% confidence level. The selected models allow a better understanding of each synoptic situation and its relationship with air quality, leading to a forecast with considerable certainty for the majority of the identified scenarios. Figures 6 and 7 show an example of the test for the year of 2017 and the results of model validation for PM$_{10}$ and PM$_{2.5}$.

Table 9 shows the model performance indicators for PM in Taipa Ambient station. The Root Mean Square Error (RMSE) is used to measure the disagreement between the regression model and the observations, and it is particularly sensible to large deviations. Since the BIAS is positive, it means that the model is overestimating on average by 1.1 μg/m$^3$. In addition, the Absolute Error (MAE) values of 4.5 and 3.2 μg/m$^3$ correspond to a relative error around 10% of the mean observed concentrations. The small differences between MAE and RMSE do not indicate the presence of large deviations. The $R^2$ of around 0.9 means that the predictors explain 90% of variance.

Figure 6: Observed and predicted PM$_{10}$ concentration values using MR models in Taipa Ambient (2017).
CONCLUSION

The work presented here is a statistical attempt to forecast air pollutant concentrations, based on a detailed analysis of both historical and expert knowledge involving meteorology and air quality aspects concerning PM. The final objective was to develop a daily air quality forecast using statistical methods to predict the next-day daily average of PM$_{10}$ and PM$_{2.5}$ for the Macao region for the most relevant background location, namely Taipa Ambient. Both models of PM$_{10}$ and PM$_{2.5}$ used independent variables including the average of the hourly values between 16:00 of yesterday and 15:00 of today for PM$_{10}$ and PM$_{2.5}$ respectively, geopotential height at 850 hPa and average relative air humidity. A four-year period (2013–2016) was selected as the fitness period for the models, while another period (2017) was selected for the validation of the model. The use of statistical models based on MR analysis was successful in forecasting the average daily concentrations for PM for next day for this particular location in the region of Macao. The models developed also allow for a better understanding of different variables and the relationship between them. The variables that explained most of the variability for PM are geopotential height and average relative air humidity.

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