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PM2.5 forecasting in Coyhaique, the most polluted city in the Americas

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ABSTRACT

Coyhaique is a southern Chilean city with a population of approximately 64,000 habitants. In spite of its small size, Coyhaique has been identified as the city with highest annual PM2.5 concentrations of the Americas (including south America, central America and north America). Episodes of high pollution are concentrated on the fall- winter season when meteorological conditions do not favor atmospheric particle dispersion and extended use of wood stoves is responsible for more than 99% of the emissions. In Chile, the 24 h average of PM2.5 concentration is classified in four ranges: fair, bad, very bad and critical. We have developed a neural network model and a linear model aimed to forecast the maximum of the 24 h moving average one day in advance. Input variables for the models are hourly values of PM2.5 at 18 h and 19 h of the present day, measured and forecasted temperature, wind speed and precipitation and measured values of NO_2, CO and O_3 concentrations. The neural network model is slightly more accurate than the linear model. We are able to anticipate the observed range in 75% of the cases, and critical days in 84% of the cases.

1. Introduction

Chile is a long and narrow country that expands along longitude 70° west between parallels 17° 30′ and 56° 30′ south. Continental region (without considering Eastern island and the Antartic zone) has a length of 4329 km and an average width of 180 km. The limits are naturally defined by the Andes mountains to the east and the Pacific ocean to de west (see Fig. 1). The northern part, between 17° and 28° south is known as the driest desert in the world. Here, the most important cities are located along the coast and in spite of the absence of rain, good ventilation favors air pollutant dispersion. In the center- south region, between Santiago (33°) and Puerto Montt (41°), most of significantly populated cities are located in valleys between the Andes mountains and a coastal range with a typical distance of 50 km between them. During fall and winter seasons (cold season), these cities have a poor ventilation, and emissions from transportation, industry and heating systems generate frequent episodes of high concentrations of fine particulate mater PM2.5. Coyhaique (45°) is located in the continental part of a southern region dominated by islands of different size, in a flat area at 310 m over sea level, has 64,000 habitants. In.

Fig. 2 we have an aerial view of the city where we can verify the presence of surrounding mounts. The city is located inside a canyon 4 km wide. Average temperatures are 12 °C in summer and 7 °C in winter. Annual precipitation is 800 mm, distributed evenly along the year. During the cold season, rain is concentrated in a relatively small fraction of days. In the absence of precipitation,

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Fig. 1. Map of South America showing location of Santiago (the capital of Chile) and Coyhaique.

Fig. 2. The city of Coyhaique. Circle indicates location of monitoring station.

anticyclone conditions prevail, thermal inversions are frequent and dispersion of pollutants becomes difficult. Due to low temperatures, residential heating, based on wood stoves, is widely and intensively used. Most of these stoves do not have an efficient control system for emissions of PM2.5 and this implies that according to the ministry of the environment 99.7% of the emissions in the city are produced by them. Transportation is responsible for 0.2% of the emissions and industry for 0.1% (planesy-normas.mma.gob.cl/archivos/2017/proyectos/Folio_155_a_164.pdf, 2017).

Recently, the World Health Organization (WHO Global Urban Ambient Air Pollution Database, 2016) has published a report with measured PM2.5 concentrations in cities with reliable data around the world. Ordering from more to less polluted, Coyhaique with an annual average of 66 μg/m^3 is in place 143 (behind cities mainly in Africa and Asia) but it appears as the most polluted city in the Americas (including north, central and south America). The high concentrations observed in the cold season create the necessity that environmental authorities take actions to protect the health of the population. While there is no significant replacement of the heating devices in homes, a plan of warnings and restrictions for the most critical days is a possibility.

According to Chilean legislation air quality on a given day, on the basis of 24 h moving average of PM2.5, is classified in four levels (www.leychile.cl).

Level A (fair): maximum of 24-h average of PM2.5 is less than 80 μg/m^3.

Level B (bad): maximum of 24 h average is between 80 μg/m^3 and 110 μg/m^3.

Level C (very bad): maximum of 24 h average is between 110 μg/m^3 and 170 μg/m^3.

Level D (critical): 24 h average is greater than 170 μg/m^3.

Restrictions to emissions apply when air quality is on level B or higher. These restrictions are mostly in the form of recommendations in order to avoid the use of wet wood in stoves and do not use more than one stove per house. Suspension of outdoor sports especially in schools is also suggested. Warnings are oriented to inform to the habitants that exposure to open air may have impact on their health, whether in the short term or long term. It is convenient that these warnings are made with an anticipation of at least 24 h, so people can plan their activities. For this reason, it is important to have at hand an operational air quality forecasting model.

There are two main approaches in order to build an air quality forecasting model. One, based on first principles, requires the use of equations for the interaction between pollutants and meteorology and information about topography and spatial and temporal distribution of emissions (Rouïl et al., 2009, Mc Keen et al., 2007, Baldasano et al. Baldasano et al., 2008). From the other hand we have the statistical models, which are based on the intelligent usage of historical data of pollutants and meteorology (Shahraiyni and Sodoudi, 2016 is a review that shows many recent air quality statistical forecasting models developed around the world). In general, to get an accurate forecasting with a first principles model, a detailed information is necessary to feed and significant computation resources are required. Usually, statistical models may be run on a portable laptop.

In this paper we show the results of two PM2.5 statistical forecasting models applied to the city of Coyhaique. One is a feed forward artificial neural network model and the other is a linear model. The variable to forecast is the maximum of the 24 h moving average for the next day, based on data measured up to 7 pm of the present day.

2. Mechanisms for the generation of air pollution in Coyhaique

We may ask why this relatively small city shows worst air quality than other more populated Chilean cities that have similar emission sources and also have unfavorable conditions for pollutant dispersion. One reason is that Coyhaique is closer to the south pole and then average temperature is lower. This implies a more intensive use of wood stoves which are the means of heating for more than 90% of the residents. Secondly, Coyhaique is not in a valley between chains of mountains but in a small flat area surrounded by elevations (Fig. 2). The longest straight path you can follow before intercepting a mount is 10 km. The other Chilean cities with significant air pollution are located in valleys that are typically 50 km wide.

Episodes of high pollution are usually associated to a decrease in local circulation, generating a situation of atmospheric stagnation in the surface layer, which inhibits the dispersion of air pollutants. The most intense episodes occur at night under clear skies, which favor the heat loss from the surface, giving rise to a surface or radiation inversion (De Nevers, 2010), trapping the emitted pollutants bellow few hundred meters of altitude over local terrain (airecoyhaique.mma.gob.cl/wp-content/uploads/2017/docs/Estudio-Factor-Meteorologico-Coyhaique.pdf, 2017). This type of inversion has been found relevant for the explanation of air pollution episodes in Beijing (Wang et al., 2019), Hanoi (Trinh et al., 2019), Granada and Malaga (Lyamani et al., 2012). Wagner and Schaefer (2017) have shown that a decreasing mixing layer height is strongly correlated with an increase on air particulate matter concentrations. Under these conditions, average wind speed in Coyhaique during the cold season is 2.4 m/s and this city shows the strongest anti correlation between particulate matter concentrations and wind speed as compared to other Chilean cities. From the other side, wind direction does not seem to be a relevant predictor for high PM2.5 concentrations. From Fig. 3 we observe that wind rose for days with episodes does not differ significantly from the general annual pattern (Molina et al., 2017).

The majority of the stoves used in the city have a PM2.5 emission factor of the order of 5 g/kg (under optimal operation). However, according to a study solicited by the Chilean ministry of the environment, maloperation in terms of ignition, preheating, loading and humidity content in wood can increase emissions by a factor of 6 (airecoyhaique.cl/wp-content/uploads/2018/11/Presentacion-Evaluacion-Programas-Recambio-2018.pdf, 2018). This is consistent with the evidence that particulate matter emission factors strongly depend on operating conditions (Klauser et al., 2018).

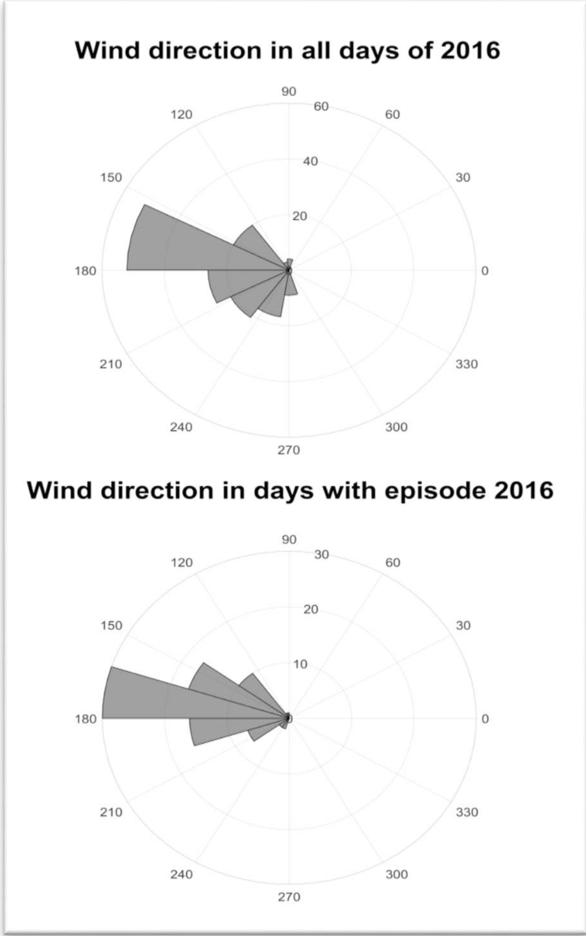

Fig. 3. Wind direction for 2016 in Coyhaique. Upper figure is for all days of the year and lower figure is for days with episode (24 h average PM2.5 concentration greater than 80 μg/m^3).

3. Data

Data for this study was obtained from station Coyhaique II which is part of the national network of monitoring stations and which are of public access in sinca.mma.gob.cl. The station reports hourly values of PM2.5, PM10, NOX, O3, CO, NO2, NO and SO2. Besides, at the site meteorological data is also measured: atmospheric pressure, relative humidity, ambient temperature, wind direction and wind speed. Rain information was extracted from explorador.cr2.cl which is a web site developed by the Center for Climate and Resilience (CR)[2], belonging to Universidad de Chile.

We have focused on information from 2014 to 2016. Fig. 4 shows hourly averages of PM2.5 for the cold period of years 2014, 2015 and 2016. As was mentioned in the Introduction, more than 90% of PM2.5 in Coyhaique is generated by the use of wood stoves. Then we can interpret the shape of the curve at the light of this information. Highest concentrations occur around 9 PM, which is a time when low temperatures are observed and most of the people is at home for dinner time, so they have at least one stove in use. Furthermore, if no rain is present, atmosphere is rather stable at this time. Decrease of PM2.5 towards dawn occurs because an important amount of stoves is turned off during sleeping time. The peak around 9 AM may be explained by the fact that at breakfast time, many stoves are turned on again. Decrease of pollution in afternoon time may be related to the possibility of vertical and horizontal dispersion because of the increase of solar radiation and wind speed. During this cold season, the average PM2.5 for 2014 was 111.6 μg/m^3 and exceedences to the 80 μg/m^3 were 111, while for 2015 average PM2.5 was 74.2 μg/m^3 and exceedences were 91. For 2016, fine particulate matter average was 114.6 μg/m^3 and 118 cases over the limit of 80 μg/m^3 were observed.

In Fig. 5 we observe hourly averages for NO_2 and CO concentrations. For NO_2 we can verify a behavior that is qualitatively similar to PM2.5, but here the afternoon minimum is not as deep as in the case of particles, which may be related to the formation of Nitrogen dioxide upon the increase of solar radiation. More NO_2 present will facilitate the formation of Nitrate particles. The curve for CO is also very similar to that of PM2.5. This is not surprising because of the known strong correlation between both pollutants (Saide et al., 2016). In the next section we verify that including CO information as input improves the accuracy of PM2.5 forecasting.

In Table 1 we show information about precipitation in Coyhaique and its relation to PM2.5 concentrations during the cold season

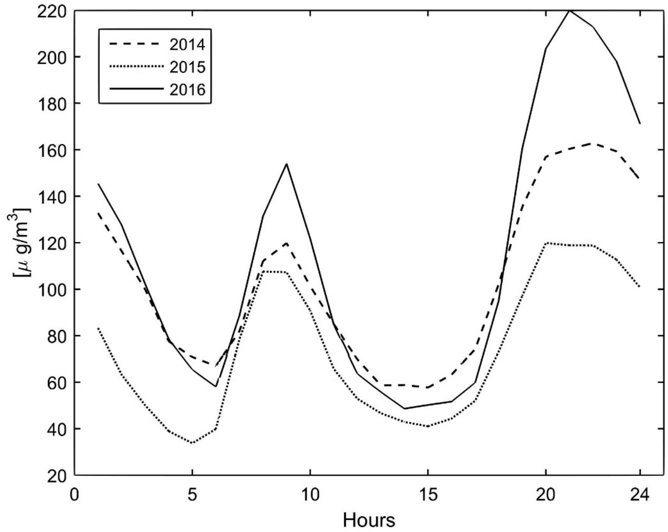

Fig. 4. Average hourly PM2.5 concentrations during the day in Coyhaique during cold season for years 2014, 2015 and 2016.

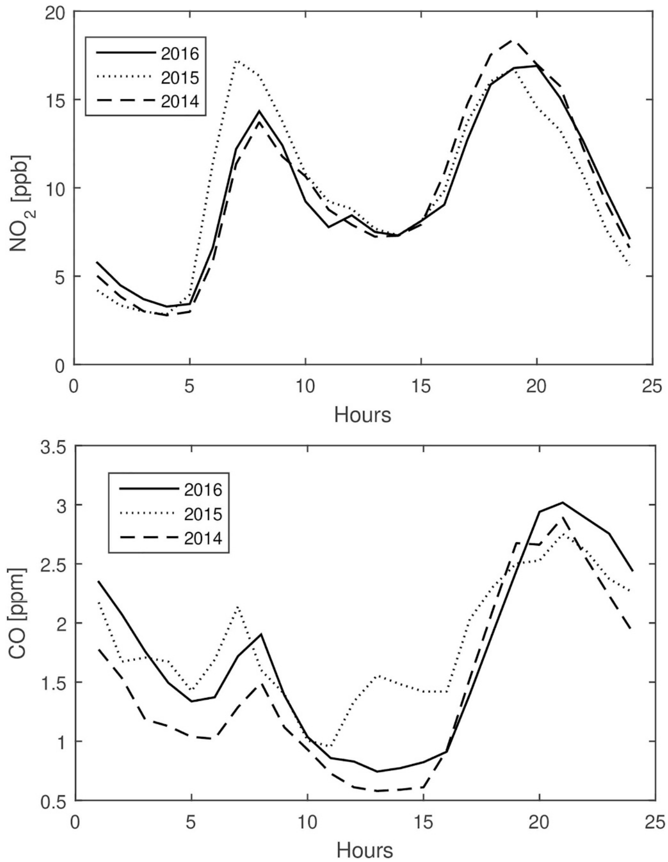

Fig. 5. Average hourly NO_2 and CO concentrations during the day in Coyhaique during cold season for years 2014, 2015 and 2016.

for years 2014, 2015 and 2016. The left column displays the accumulated precipitation in mm on a given day. It is evident that in the absence of rain and given the prevailing meteorological conditions during fall and winter, there is a high probability that the city becomes heavily polluted.

Searching for input variables for a PM2.5 forecasting model, we have verified that O_3 has a significant anti- correlation with particle concentration, especially between 10 am and 3 pm. This may be explained by the fact that for times when solar radiation

Table 1
Relation between accumulated rain in a day and daily average of PM2.5 concentration in Coyhaique. Period considered is cold season of years 2014, 2015 and 2016.

Precipitation per day (mm)	Average $PM_{2.5}$	N° Days
= 0	142.69 μg/m^3	264
]0,1]	112.49 μg/m^3	109
]1,4]	99.30 μg/m^3	79
]4,10]	98.92 μg/m^3	57
]10,20]	98.78 μg/m^3	23
> 20	68.65 μg/m^3	12

increases, O_3 formation increases but at the same time the probability of particle dispersion is greater.

4. Forecasting with a linear model and a multilayer neural network

Our goal is to forecast the maximum of the 24 h moving average of PM2.5 (MM24PM25) with an anticipation that facilitates the announcement of restrictions to emissions to the population. In our case we collect data until 7 pm of the present day in order to estimate MM24PM25 for the following day. We have implemented two statistical forecasting models: one is linear and the other is a non linear neural network. After a preliminary selection of input variables we ended with the set listed bellow. We discarded non relevant variables by means of a stripping scheme (Bahat and Mc Avoy, 1992). The reference model for this analysis was the neural network, and we used the same following final set of input variables for the linear model:

1) Hourly PM2.5 concentration at 6 PM of present day
2) Hourly PM2.5 concentration at 7 PM of present day
3) Average temperature between 7 PM of present day and 7 AM of following day
4) Average wind speed between 7 PM of present day and 7 AM of following day
5) Thermal amplitude during present day
6) Accumulated precipitation for following day
7) NO_2 average between 6 AM and 7 PM of present day
8) CO average between 6 AM and 7 PM of present day
9) O_3 average between 6 AM and 7 PM of present day
10) Maximum temperature during present day
11) Minimum temperature during present day.

Our plan is to build a model with which we could generate a report for the estimated value of MM24PM25 for the following day. This report should be delivered around 8 PM of present day. Reasons to include some of these 11 variables as input have been already given in the previous section. Hourly PM2.5 concentrations at 6 PM and 7 PM indicate the tendency of the variable to forecast, considering that some persistence is expected after afternoon wind has decreased (Perez and Gramsch, 2016). Minimum and maximum temperature are indicators of the willingness of the people to use heating. Large thermal amplitudes are usually present in days when thermal inversions are significant. Variables 3) and 4) are obtained from independent meteorological forecasts performed by the National Weather Office. These forecasted values show have an average accuracy over 90%. Best results were obtained using 7 neurons in one hidden layer. Training was performed with data from the cold season for years 2014 and 2015. 20% of the data was left out for validation. Training algorithm used was the Leung version of Backpropagation (Leung and Haykin, 1991).

We use some statistical indicators in order to evaluate the performance of the implemented PM2.5 forecasting models:

Pearson Correlation

$$CORR = \frac{\langle (y_{tp} - \langle y_{tp} \rangle)(y_{ta} - \langle y_{ta} \rangle) \rangle}{\sqrt{\langle y_{tp} - \langle y_{tp} \rangle \rangle \langle y_{ta} - \langle y_{ta} \rangle \rangle}} \tag{1}$$

Normalized Mean Percent Error

$$NPE = \frac{\langle |y_{tp} - y_{ta}| \rangle}{\langle y_{ta} \rangle} \tag{2}$$

Triangular brackets represent averages over the test set (2016 cold season data) the sample, y_{ta} is observed value and y_{tp} is the forecasted quantity. Pearson correlation varies between 1 and − 1 and is a measure of the strength of the linear relationship between paired data. The normalized Mean Error has been recommended for evaluation of operational model predictions because the average in the denominator tends to avoid the dominance of low observational values (Zhang et al., 2012).

We also consider the probability of detection (POD) and the probability of false detection (FAR):

$$POD = \frac{H}{O} \tag{3}$$

Table 2
Statistical indicators for PM2.5 forecasting models used.

PM2.5 Model	NPE	R	POD	FAR
Neural	0.18	0.95	0.77	0.18
Linear	0.29	0.86	0.74	0.21

$$FAR = \frac{F-H}{N-O} \tag{4}$$

These parameters are useful to evaluate if the forecasted value falls in the same range than the observed value. H is the amount of correctly forecasted cases in a given range. O is the amount of observed cases in the same range. F is the amount of cases forecasted to be in the range and N is the total amount of cases in a given range.

Results are displayed in Table 2.

In Fig. 6 we can see observed and forecasted values of MM24PM25 for the test data, 2016 cold season using the neural network model. Pearson correlation is 0.95 and average normalized mean error NPE is 0.18. In this graph, dotted horizontal lines indicate the limits defining classes B, C and D. The model seems to capture reasonably well the high concentrations, which is very important for the implementation of an operational model. The performance of the neural network forecasting model in estimating the class of MM24PM25 is summarized in Table 3 which represents what is known as a contingency table.

Here columns from A to D show the amount of forecasted cases in those classes and rows from A to D display the amount of observed cases per class. The values of the diagonal in the matrix correspond to the correct forecasted cases. The last column corresponds to the ratio between the value in the diagonal and the amount of observed cases for each class and coincides with what is defined as probability of detection in eq. (3) times one hundred. We notice that 84% of the 53 class D cases (when MM24PM25 is greater than 170 μg/m^3) are captured by the model. In Fig. 6 se observe the dispersion of modeled data. They seem to be evenly distributed around the identity straight line with $R^2 = 0.95$.

In order to compare the results of the neural network model with those obtained with a simpler model, we have also implemented a linear forecasting model for which the predictor variables are the same as the input variable of the neural model. From the results of this model we have built the respective contingency table (Table 4). We can verify that the probability of detection of class D days is the same than the neural model (which is an indication of the importance of the selection of input variables), but the neural network has better performance on class B and class C cases. For this linear model we find $R^2 = 0.86$.

5. PM10 forecasting in Coyhaique

Although in practice, warnings to the population in situations of bad air quality are formulated on the basis of PM2.5 concentrations, for legal reasons (because of the availability of historical data) the official plan to control particulate matter pollution is based on PM10 concentrations. The reason for this is that ranges for national PM10 episodes are established from the observation that in larger cities PM2.5 is of the order of 50% of PM10. Instead, in Coyhaique PM10 is more than 90% PM2.5, given that wood stoves emit mostly fine particulate matter.

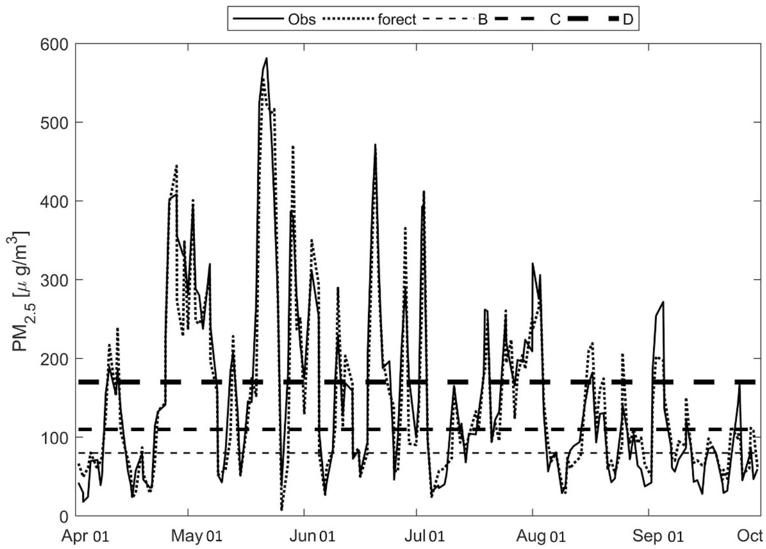

Fig. 6. Comparison between observed and forecasted values of maximum of the 24 h moving average of PM2.5 (MM24PM25) using three layer neural network for the cold period 2016. Doted lines are limit values for levels B (80 μg/m^3), C (110 μg/m^3), D (170 μg/m^3).

Table 3
Contingency table for observed and forecasted values of MM24PM25 for 2016 cold season using neural network model.

Class	A	B	C	D	Total	%O
A	**51**	9	2	0	62	82
B	7	**15**	3	0	25	60
C	2	7	**19**	5	33	58
D	1	2	7	**53**	63	84
Total	61	33	31	58	**183**	75
%P	84	45	61	91		

Bold means correct class forecasting.

Table 4
Contingency table for 2016 MM24PM25 data (cold season) using linear model.

Class	A	B	C	D	Total	%O
A	**51**	9	2	0	61	82
B	8	**12**	5	0	25	48
C	1	10	**17**	5	33	52
D	0	3	8	**52**	63	83
Total	61	34	32	57	**183**	72
%P	85	35	53	91		

Bold means correct class forecasting.

According to Chilean ruling levels of increasing awareness based on PM10 concentrations are:

Level A (fair): maximum of 24-h average of PM10 is less than 195 μg/m^3.

Level B (bad): maximum of 24 h average is between 195 μg/m^3 and 240 μg/m^3.

Level C (very bad): maximum of 24 h average is between 240 μg/m^3 and 330 μg/m^3.

Level D (critical): 24 h average is greater than 330 μg/m^3.

According to these ranges, between 2015 and 2017, 66 days in level B or higher according to PM10 were observed. However,

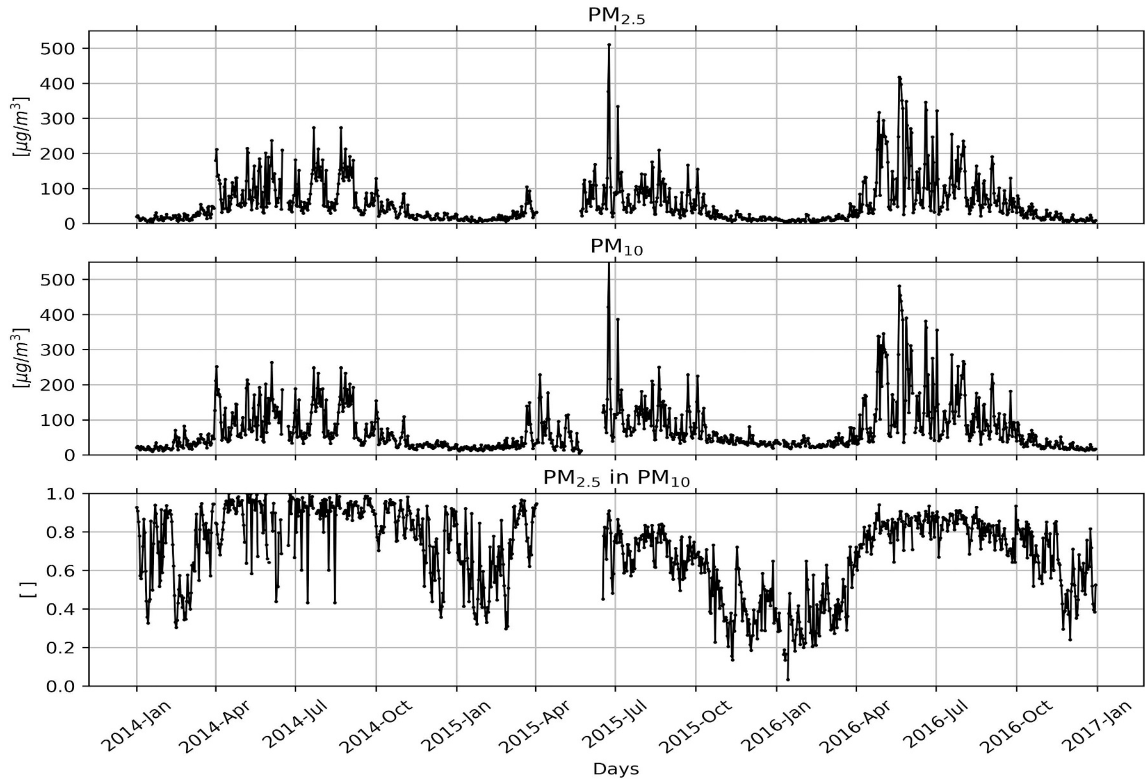

Fig. 7. Observed values of daily averages of PM2.5 and PM10 for years 2015, 2016 and 2017. Graph of the bottom represents the ratio between PM10 and PM2.5.

Table 5
Contingency table for 2016 MM24PM10 data (cold season) using PM2.5 neural model.

Class	A	B	C	D	Total	%O
A	**122**	5	0	0	127	96
B	5	**6**	3	0	14	43
C	5	5	**9**	2	21	43
D	0	2	6	**13**	21	62
Total	132	18	18	15	**183**	82
%P	92	33	50	87		

Bold means correct class forecasting.

based on PM2.5 concentrations, 223 cases in class B or higher occurred.

Fig. 7: shows the daily averages of PM10 and PM2.5 for years 2015–2017 and the ratio between the later and the former. We can verify that during cold season the ratio is close to one (except for 2015, when an important amount of missing data is observed). Under these conditions, it appears as a good approximation, that our PM2.5 developed model could be also used for PM10 forecasting during cold season. This is useful in order to fulfill the legal requirements of having a forecasting model for air pollution control based on PM10. Nevertheless, the warnings about danger to exposure of pollutants may be delivered based on the forecasted PM2.5 level.

Given this situation, we proceeded to build a contingency table that gives information about the performance of the PM2.5 model presented in the previous section in estimating PM10 levels.

We observe from Table 5 that with this model, the quality of PM10 forecasting for Levels A (96% agreement) and global (82%) is good. For level D, the highest concentrations, is acceptable (62% agreement).

6. Discussion

We have described the remarkable unfavorable air quality conditions experienced by the population of a small southern Chilean city during the cold season that extends from April to September. Emissions of PM2.5 are dominated by the combustion of wood stoves used as means of heating in the majority of homes. In the absence of rain very stable atmospheric conditions prevail especially at night. This combined with the topography of the area signify a very poor dispersion of pollutants. High concentrations observed in Coyhaique are surpassed only by levels registered in some cities in Asia and Africa.

We have developed a forecasting model which can anticipate the maximum of the 24 h moving average of PM2.5 concentration for the following day with 18% average error in the numerical value and with the capacity to predict 84% of the days falling in the class with the most toxic air. These results are possible by the use of an efficient neural network algorithm and the choice of appropriate input variables which include past concentrations of PM2.5 and gases that can contribute to the formation of secondary particles. Also relevant meteorological variables like temperature, wind speed and precipitation are used as input to the model.

Being able to report an accurate air quality forecast in a critically polluted city like Coyhaique is of significant help for the population. With this information, persons may plan their activities in order to avoid exposure to dangerous levels of PM2.5. Actions of individual responsibility may be to avoid areas with high pollution and decrease he intensity of physical efforts, check the efficiency of the combustion of heating devices or shift to cleaner fuels. Authorities may decide to ban or at least recommend the replacement of wood stoves. Taking into account the limited economical resources of the habitants of the city and considering that wood is by far the cheapest fuel available in the area, it is not possible to impose an obligation to change the means of heating, but is important that environmental and health authorities transmit strongly the message that expectancy of life will be significantly affected until this replacement is achieved in every house.

The results of this study may motivate the interest to analyze in more detail the air quality of small cities that have unfavorable conditions but are not the main focus of environmental policies.

CRediT author statement

Patricio Perez: Conceptualization, Methodology, Writing- Original draft preparation Camilo Menares.: Data processing, Software, Camilo Ramirez: Data processing, Software.

Declaration of Competing Interest

The authors of this manuscript declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.uclim.2020.100608.

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