Citizens' Surveillance Micro-network for the Mapping of PM$_{2.5}$ in the City of Concón, Chile

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ABSTRACT

A micro-network of low-cost sensors has been built and deployed in the city of Concón with the purpose of informing the community about the air quality in their neighborhood. Currently, 10 active stations, which are installed in resident-owned houses and public spaces, measure PM$_{10}$ and PM$_{2.5}$, rain, temperature, humidity, and wind speed and direction and display this information via a mobile application. The particulate matter is measured with a Dylos monitor, and the collected data has been calibrated using a Beta Attenuation Mass monitor for PM$_{2.5}$ located in the same city as where the low-cost monitors are deployed. The PM$_{2.5}$ concentration is obtained through a linear equation that uses small and large particle counts from the Dylos monitor. Additional calibration has been performed using neural networks, resulting in a noticeable improvement. The data also show that calibrations performed in other cities cannot be applied to measurements taken in Concón. As noted in many other studies, the relative humidity strongly influences the particle count. For the months of June, July, and August, the hourly profiles reveal a prominent evening peak in downtown Concón but a less obvious increase at the other sites, indicating that wood burning (or a similar source) mainly occurs in downtown. The nearby oil refinery, Enap, does not seem to increase the concentration of particulate matter on average, but short-term PM$_{2.5}$ events generated by the refinery have not yet been analyzed.

Keywords: PM$_{2.5}$; Low-cost sensor; Micro-network; Refinery.

INTRODUCTION

Air pollution is one of the main environmental problems in Chile, and it is also a source of public health problems. This phenomenon is widespread throughout the world, is greatly dependent on the economic status of a country and the number of inhabitants, but it is also very sensitive to the topographical and meteorological conditions. In most Chilean cities, the topography determines to a great extent the pollution levels observed (Gramsch *et al.*, 2006; Molina *et al.*, 2017).

It is standard practice and it is well known that the only way to measure and evaluate the impact generated by air pollution is through high-quality monitoring systems in controlled networks (EU, 2008; Snyder *et al.*, 2013). This is the case of several cities in Chile, which contain monitoring networks with characteristics that are adapted to the city. Together, these stations form the National Air Quality Information System (SINCA). It is also well known that these stations have a high purchasing and maintenance cost, with most monitors costing between USD 10,000 and 500,000 (Chong and Kumar, 2003; Osses *et al.*, 2013). The consequences of the high cost are that maintenance is often delayed, resulting in poor data quality. In other cases, equipment repairs may take several months, resulting in large gaps in the data.

In general, the number of air quality monitoring stations is insufficient to determine the spatial variability of air pollution within a city. In Concón there are 3 stations that measure criteria air pollutants (SINCA, 2019), but data for several contaminants suffer the problems mentioned above. The low number of monitors does not allow knowing what the air quality behavior is within a neighborhood or sector. The current number of stations only allows a general knowledge of the pollution in Concón, without information about large sectors in the periphery. This fact is counterproductive for the population, who every day is demanding more detailed

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information about pollution in their own neighborhood. The air quality stations in Concón are connected online to the National Air Quality Information System in Chile (SINCA, 2019). Any user can consult graphically those stations of interest and review the current values and historical data of air quality and meteorology. This capacity allows the community to be informed almost in real time on the quality of the air that they are breathing in the surroundings of the station. However, this same system also allows the user to detect gaps in the data, or calibration problems.

Citizen Networks

Citizens are concerned about pollution of the environment they live in, including the quality of the air they breathe. This concern manifests itself in different ways, but it has the greatest impact on public opinion when the citizens get organized. In fact, pollution problems have led to social organizations such as neighborhood associations, parent organizations, unions, etc. to organize many rallies and demonstrations which have had a very high impact on the social media and networks and have attracted considerable attention from politicians. At the same time, these organizations express high distrust of the official monitoring networks because they have seen the data gaps and calibration problems. They also see the stations as black boxes, on which they have no control and to which they have no access.

At the international level, the appearance of low-cost monitoring networks has been observed as a citizen's alternative for air quality monitoring. These low-cost networks can use a larger number of equipment for the same area, providing a spatial vision that allows the citizens to ask about the air quality in their immediate neighborhood. This spatial vision not only allows citizens to review the data and monitoring procedures, but also learn about the dynamics of pollutants, thereby identifying possible emission sources not considered in the local emissions inventory.

For example, a Canadian project that was implemented around Toronto and Hamilton shows how "citizen science," modern technology, and citizenship can generate unique initiatives that make a difference with state activities. The Initiative for Healthy Air and Local Economies project (INHALE, 2019) is directed by local agencies (Environment Hamilton and Toronto Environmental Alliance), whose objective is that ordinary people (citizens) can participate in the monitoring of air quality in their neighborhood. The initiative was generated because in Hamilton there are only 3 stationary air monitoring stations, which are grouped around the city. Although this information is reported on a map, it is totally insufficient for monitoring at the neighborhood level. From the viewpoint of its creators, INHALE is considered a relatively simple system, where a person (citizen) when walking or riding a bicycle, can carry a device that measures the concentration of particles in the air, along with a GPS to know the exact position of the measurement along the route taken. These data are collected and uploaded to a mobile application (Network, 2019), where a color scale shows the concentrations measured in the journey made by the citizen. For now, the INHALE initiative is only limited to certain neighborhoods of the city.

Another pioneering project, called Bicycle Air Monitoring, covers an even wider area, and since the sensors are linked to bicycles, if the users travel greater distances it is possible to cover larger areas. This type of approach (citizen science) is far from perfect, but it can provide us with background information that gives the spatial dimension of the problem of air pollution and air quality within cities. This approach has the main advantage of being able to be implemented in any city in the world.

We can mention another initiative which takes place in the city of Pittsburgh; it is the Group Against Smog and Pollution (GASP, 2019). This citizen's initiative is conceived in a similar way as the previous one, that is, the city has a few stationary air monitoring stations, which do not give citizens security on the air quality in their neighborhood. It is known that the spatial variability of air quality inside a city can change a lot depending on the location of the sources, wind pattern, street orientation, micro-topography, etc. In addition, the maximum concentration of particulate matter also depends on the time of day in the city. The above generates an additional problem; for example, if people live in a highly polluted area, but the closest air quality monitoring station is far away, they get the false impression that they live in a clean place. This leads citizens to have some level of distrust of the data shown by the stationary, official network. A comprehensive review of the different techniques used for low-cost monitoring is presented by Clements *et al.* (2017).

The city of Concón is very close to the Enap Oil Refinery and it suffers from many of the problems mentioned before. In the past, there have been many citizen protests related to air pollution. Several times the environmental authority has requested improvements in the refinery's management and has changed regulations; consequently, the refinery's operation has required adjustment.

This work aims to implement and assess a low-cost air quality monitoring system. These low-cost devices, relatively easy to operate and having some desirable technical features, such as their high time resolution, are suitable for citizen science in its collaborative aspect, considering the air pollution and related social concerns and distrust toward the authorities. A citizens' network was built for spatial surveillance (See map in Fig. 1) of air quality in the city of Concón. Data are presented to the public in real time via a mobile application (Network, 2019). An intuitive web system is being developed and implemented for citizen consultation at the neighborhood level from computers or cell phones. A network of this nature is the first implemented in Chile, setting a precedent and having an important impact, not only in the local community, but throughout the country. The network is being built through an association between two public universities and the Enap Oil Refinery. In this work, a description of the network is given, as well as the sensors and electronics used in all equipment. A discussion is presented about the important issue of sensor calibration according to the local environmental conditions, which, in the authors' opinion, is the main result of this work.
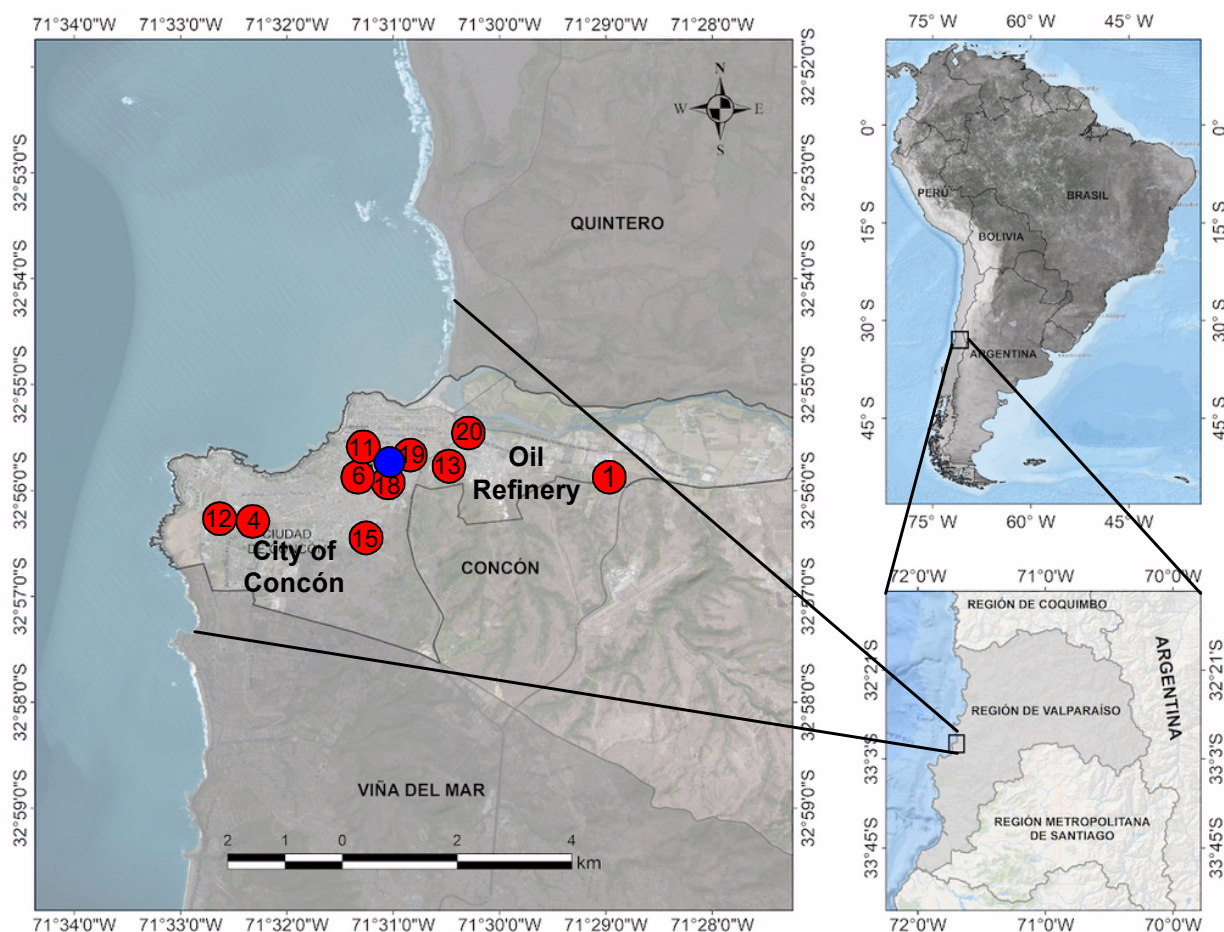
Fig. 1. Map of Concón with the location of the citizens' micro-network stations. The red circles are the stations of the micro-network; the blue circle shows the location of the Concón monitoring station from the SINCA network.

MEASUREMENTS AND METHODS

Study Area

The project is located in the Valparaíso Region, which has important industrial activity and three large ports (San Antonio, Valparaíso, and Quintero). In addition to the oil refinery, the study area has a copper smelter (Ventanas), a power plant with a total installed capacity of 272 MW (AES Gener), and several chemical companies. The citizens' air quality monitoring micro-network was implemented in the city of Concón because of the closeness to the oil refinery (see map in Fig. 1) and because citizens in this town are very sensitive to emissions from the refinery. The micro-network has 10 working stations that measure PM_{10} and $PM_{2.5}$, rain, temperature, humidity, and wind speed and direction and upload the mobile application (Network, 2019). Real-time data can be accessed through an application built for cell phones.

Concón has a temperate (Mediterranean) coastal climate, influenced by the cold Humboldt Current. The thermal behavior is characteristic of the coastal areas: During the summer the minimum temperatures oscillate between 12°C and 16°C (January), while the maximum temperatures are in the range between 20°C and 24°C. Very rarely, the temperature exceeds 28°C during the summer season, mainly because of

its mornings with cloud cover. In winter (July) the minimum temperatures vary between 6°C and 10°C, while the maximum temperatures are between 11°C and 15°C. Humidity in the area is also high, oscillating between 60% and 95% during the whole year. There is very little frost interference, rarely showing minimum temperatures below 5°C. Precipitation occurs mainly between autumn and winter, with July the rainiest month (with 107 mm on average), and an annual average of 480 mm. During winter this zone is often affected by the coastal trough (Garreaud *et al.*, 2002) increasing the air pollution problems; however, the wind regime tends to attenuate the maximum values, displacing during the day the air masses towards the north or towards the interior by canyons and valleys.

Sensor Development

A low-cost sensor station was designed and built in order to deploy it in Concón's network. It is equipped with an optical sensor (DC1100 Pro; Dylos Corp., Riverside, CA, USA) to count large and small particles and measure rain, temperature, humidity, and wind speed and direction. The particle count can be converted to PM_{10} or $PM_{2.5}$ by means of a suitable equation (see "Results" section). A Raspberry Pi micro-computer integrates the signal from all sensors and sends the data to the app (Network, 2019) through a GPRS

communications system. Fig. 2(a) shows a picture of the whole station with the particle counter and meteorological sensors. Fig. 2(b) shows a detail of the station with the Dylos sensor, Raspberry Pi, and interface. The station is also equipped with a battery that allows 2 hours of operation if there is a power outage. PM_{10} and $PM_{2.5}$ are measured with a Dylos DC1100 optical system (Dylos Corp., 2019). A window was built in the box so that users can review the particle count on the sensor and contrast it with the number displayed on the web site. This feature was built because one of the aims of the network was to improve citizens' trust of the network. The Dylos sensor has 2 channels for small and large particles which roughly correlate to $PM_{2.5}$ and PM_{10}. However, there have been many studies evaluating the performance of low-cost particle matter monitors (Williams *et al.*, 2014; Jovasevic *et al.*, 2015; Manikonda *et al.*, 2016; Feinberg *et al.*, 2018; Zheng *et al.*, 2018) and it is widely agreed that calibration of the equipment has to be performed for each site. The Dylos sensor gives the number of small and large particles with an average sampling time of 60 sec. Temperature and humidity are measured with an SHT30 sensor (Sensirion AG, Switzerland); meteorological parameters are measured with a Wind/Rain Sensor Assembly from Argent Data Systems (Santa Maria, CA, USA). The station was mounted on a tripod for easy installation on the participants' backyard.

Twenty stations were built and 10 are currently deployed in houses in Concón. A picture of the sensors during the inter-calibration procedure is shown in Fig. 3. The whole system is installed in the backyard of citizens' homes or in public places, such as fire stations and park entrances.

Neural Networks

As an alternative to calibrate $PM_{2.5}$ concentrations using particle counts from the Dylos, the capacity of a multi-layer neural network (MLP) has been analyzed. An MLP is an algorithm based on the activity of processing units or neurons. These neurons are organized in layers, and all neurons in one layer are connected to neurons in the next layer. Since the activation function for each neuron is non-linear, the global algorithm is also non-linear. Connection weights are calculated during a learning phase based on a sample of the data, where particle count and meteorology are inputs and $PM_{2.5}$ concentrations are known outputs (Rumelhart *et al.*, 1986; Salini and Pérez, 2015).

Intercomparison

An intercomparison of the instruments was performed to determine the variability among them. 10 instruments were located on top of one of the stations of SINCA 2019, and measurements were made for 1 month. A picture of the instruments while they were tested is shown in Fig. 3. The raw output from the Dylos monitor was averaged to obtain 1 point per hour. A plot of the small particle data from 8 stations is shown in Fig. 4. For clarity, not all the stations are shown in the plot. It is seen that they all show similar variations, with very high correlation. The highest correlation obtained was 0.9949 and the lowest was 0.7641. These values are consistent with Feinberg *et al.* (2018), who obtained correlations between 0.73 and 0.86 for the Dylos small
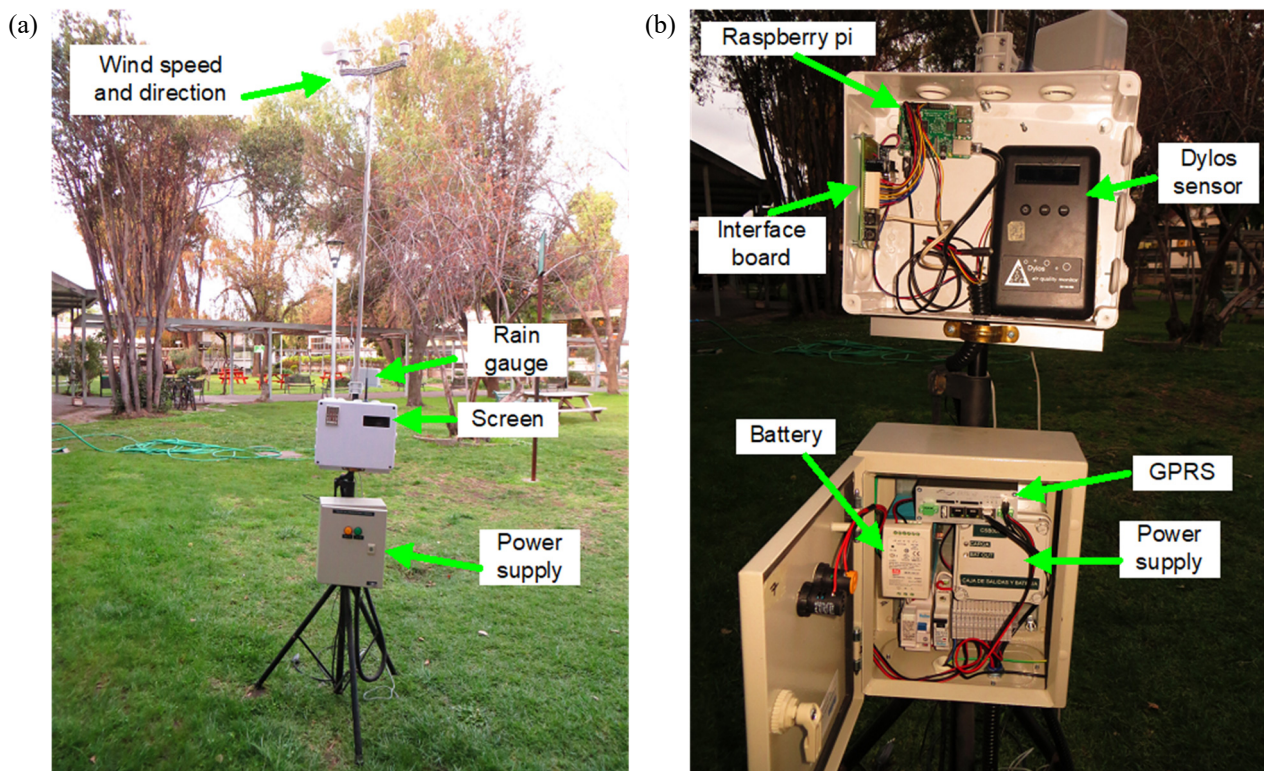
Fig. 2. (a) Picture of the station with power supply, wind and speed sensors, rain gauge, and screen to visualize particle counts from the Dylos. (b) Open station detailing the Dylos sensor, Raspberry Pi, and interface board.

Fig. 3. Low-cost sensors on top of a pollution monitoring station located inside the Enap Oil Refinery during calibration procedure.
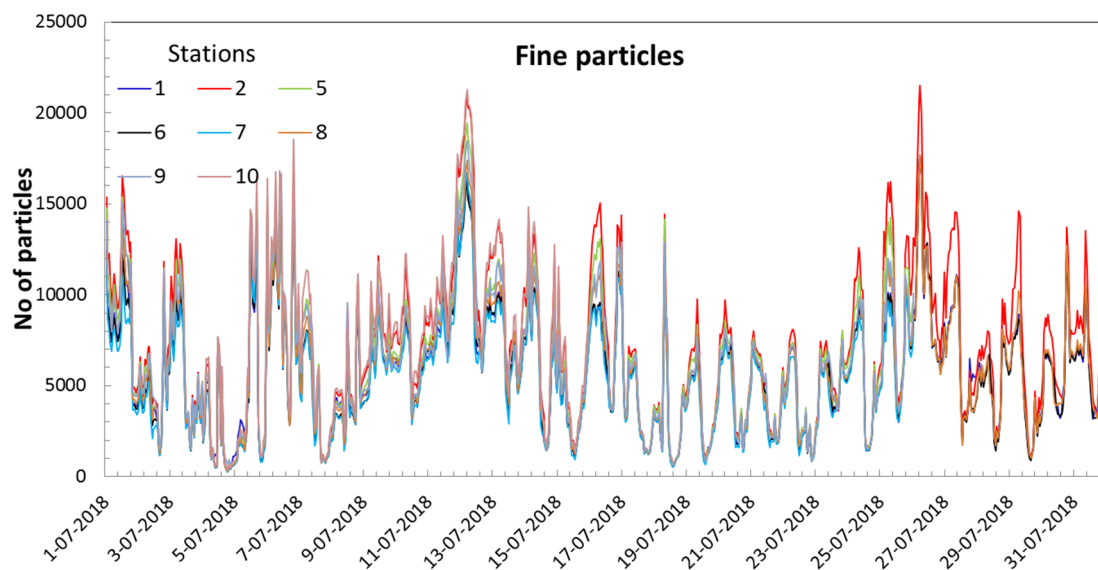
**Fig. 4.** Comparison of 8 stations during July 2018.

particle count. Our results also show very high correlation for large particles. For the 10 instruments, the average and standard deviation of the number of small and large particles is shown in Fig. 5 for the month of July 2018. A difference in the average result of up to 20% for small particles and 25% for large particles was measured for this month. However, since the correlation between instruments is very high, with proper calibration the difference can be reduced greatly (Manikonda *et al.*, 2016).

RESULTS

Linear-fit Calibration

Initial calibration of 1 low-cost monitor was performed in

Las Condes Air Pollution Station (Gramsch *et al.*, 2016), which belongs to the SINCA network (SINCA, 2019) and is located in Santiago, Chile, about 100 km south-east of Concón. Calibration was done in Las Condes because the site has been used in previous studies and it is well suited for an intercomparison between instruments (Gramsch *et al.*, 2006). Las Condes has a dry climate (low relative humidity (RH) most of the year) and is a receptor site for pollution coming from downtown Santiago. The low-cost monitor was co-located with a Beta Attenuation Mass monitor (BAM 1020; Met One, Grants Pass, OR, USA) for PM_{10} and $PM_{2.5}$ as well as a meteorological station. The BAM monitor has a U.S. EPA Federal Equivalent Method (FEM; U.S. EPA, 2019) designation for continuous $PM_{2.5}$ and PM_{10} monitoring; the
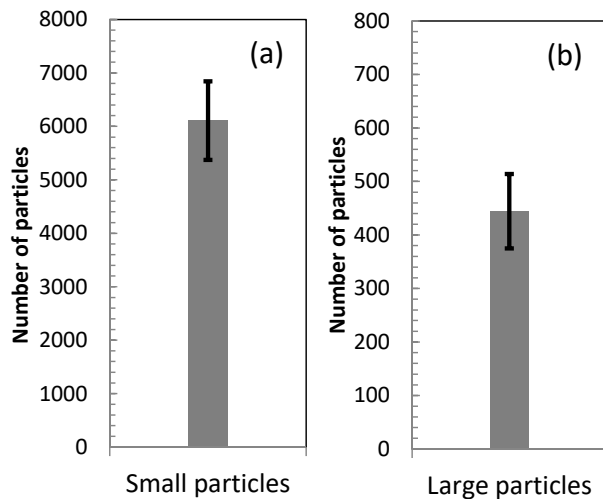
Fig. 5. Average and standard deviation for number of (a) small and (b) large particles of 12 stations during July 2018. Note the differences in scales between the small and large particles.

units used are [μg m^{-3}]. Measurements were performed continuously from March 27 until April 10, 2018. The basic statistics for the data (mean, standard deviation, max, min, and sample size) are shown in Table 1 As already mentioned, the number of small particles minus large particles is roughly proportional to PM$_{2.5}$ (Williams *et al.*, 2014; Manikonda *et al.*, 2016); thus a simple linear equation was constructed for the concentration obtained with the Dylos instrument, PM$_{2.5D}$:

$$PM_{2.5D} = (S - L)f_1 + Lf_2 \qquad [\mu g\ m^{-3}] \qquad (1)$$

where S is the number of small particle output from the Dylos, L is the number of large particles, f_1 and f_2 are calibration factors with units of [μg m^{-3}], and PM$_{2.5D}$ is the fine particle matter obtained from the Dylos in units of [μg m^{-3}]. f_1 and f_2 were obtained by optimizing the correlation with the BAM, the square of the differences, and the total average for the measuring period. The Pearson correlation for this period was R = 0.507. The precision was calculated using the normalized root mean square error (nRMSE; Manikonda *et al.*, 2016) and the result for the period was 0.415, which is very similar to the value obtained by Manikonda *et al.* (2016). A similar equation was constructed for PM$_{10D}$ in Las Condes. The correlation was R = 0.505, with nRMSE = 0.527. However, in this case the best result was obtained when $f_1 = 0$, i.e., only

the number of large particles is related to PM$_{10}$. There is also a small positive correlation (R = 0.418) between the number of small particles and relative humidity. When the relative humidity is higher than ~85%, a larger increase in the number of particles is seen, just as has been noted before (Williams *et al.*, 2014). However, no attempt has been made to correct for relative humidity, because there is a wide divergence with respect to the type of correction to be made (Zheng *et al.*, 2018). The f_1 and f_2 factors as well as R and nRMSE are shown in Table 2.

Using the calibration factors obtained in Las Condes, the particle count data from a station in Concón was adjusted to get PM$_{2.5}$ concentration. Data from a BAM monitor belonging to the Concón station of the SINCA network was used. The station is shown with a blue dot in Fig. 1. The BAM monitor was compared with Station 19 located about 100 m to the west. The average result for Station 19 (shown in Fig. 1) was 37% higher than the BAM monitor. Therefore, a second calibration was performed in the city of Concón, where the monitors are being used. As before, a linear equation was obtained by optimizing the correlation with the BAM monitor, minimizing the square of the differences and the difference between the averages for the measuring period. The measuring period was from April 12 to October 28, 2018. The correlation between the BAM monitor and the calculated PM$_{2.5D}$ from the Dylos was R = 0.683, with nRMSE = 0.538. As expected, the f_1 and f_2 factors were different from those in Las Condes. Interestingly, there was no long-term drift in the 7 month period, as shown in Fig. 6(a). Concón is a coastal city, with very high humidity during the whole year, so the air quality is highly influenced by wind coming from the sea. Thus, in this site it is expected that the humidity plays a larger role in the particle count from the Dylos. A correlation plot between humidity and number of small and large particles from the Dylos monitor is shown in Fig. 7. It is clearly seen that when the humidity increases, the number of particles increases. For small particles (Fig. 7(a)), even at low humidity, there is an effect on the number of particles. It can also be seen that for high humidity levels there is not always a high particle count, which indicates that a simple linear relationship between number of particles and humidity will not correct the effect. For large particles (Fig. 7(b)), the influence of humidity on the number of particles is mainly for RH > 80%.

Neural Network Calibration

In order to reduce the error between the BAM monitor and

Table 1. Basic statistics for the concentrations measured with the Dylos and BAM monitors in both sites. Units are [μg m^{-3}].

| Measurement	Mean	Std. deviation	Max.	Min.	Sample size
Las Condes					
Dylos PM$_{2.5}$	19.2	8.8	45.7	6.1	333
BAM PM$_{2.5}$	19.2	7.1	41	4	333
Dylos PM$_{10}$	61.4	29.5	157.7	22.2	333
BAM PM$_{10}$	61.9	34.7	218	16	331
Concón*					
Dylos PM$_{2.5}$	20.7	14.8	96.6	0.9	3922
BAM PM$_{2.5}$	20.1	11.7	95	1	4678

* no PM$_{10}$ data was available in Concón Air Pollution Station.

Table 2. Parameters used for the linear fit between the Dylos and BAM monitor as well as the correlation and nRMSE.

Measurement	f_1	f_2	R	nRMSE
Las Condes				
Dylos PM$_{2.5}$ linear fit	0.00197	0.0042	0.507	0.415
Dylos PM$_{10}$ linear fit	0	0.1938	0.505	0.527
Concón[*]				
Dylos PM$_{2.5}$ linear fit	0.00348	0.00084	0.683	0.538
Dylos PM$_{2.5}$ N.Net. fit			0.742	0.339

[*] no PM$_{10}$ data was available in Concón Air Pollution Station.
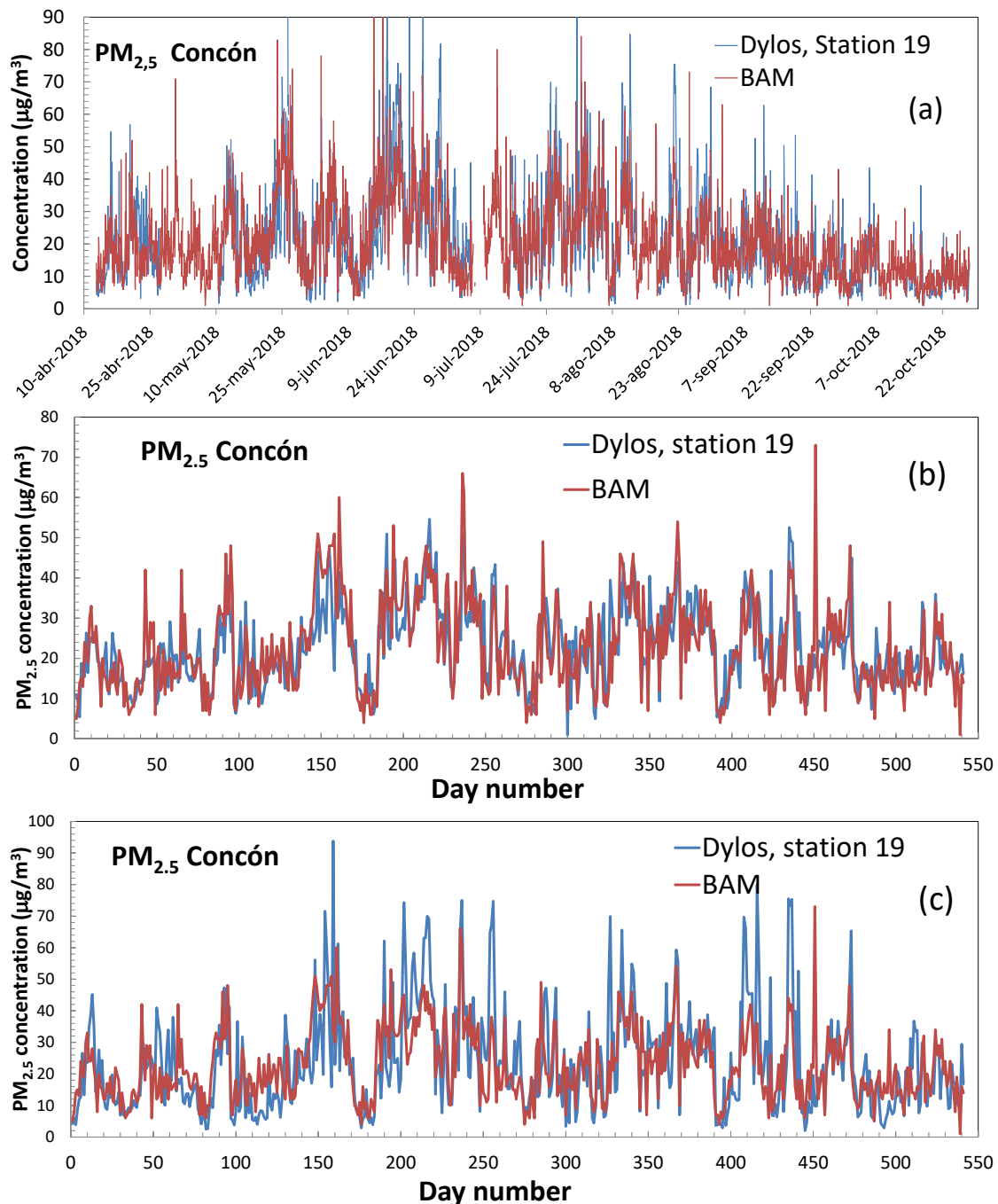
Fig. 6. (a) PM$_{2.5}$ in Concón with BAM monitor and Dylos data from Station 19, calibrated with the linear equation. (b) PM$_{2.5}$ with BAM monitor and Dylos data from Station 19 calibrated with the neural network (20% of the data). (c) PM$_{2.5}$ with BAM monitor and Dylos data from Station 19 calibrated with the linear equation (20% of the data).
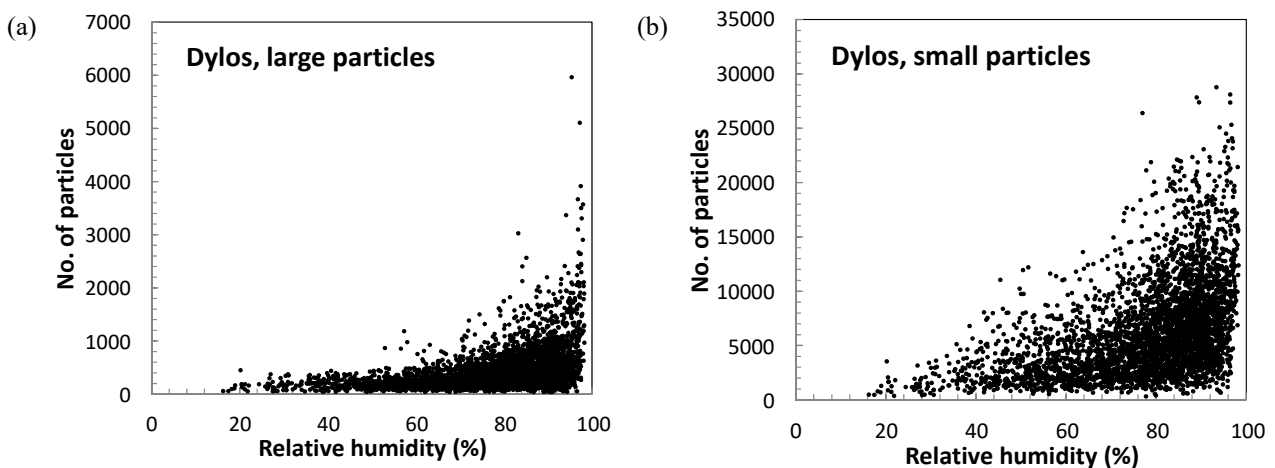
Fig. 7. Correlation plot between relative humidity and small particles (a) and large particles (b) measured at Station 19 in Concón for the April 12–October 28, 2018, period.

the stations, an MLP has been used for the calibration of PM$_{2.5}$. Based on the observed correlations between some meteorological variables and difference between large-particle and total particle count, the best results can be obtained using an MLP with the following properties: input layer with 7 neurons, hidden layer with 12 neurons, and output layer with 1 neuron.

The inputs are the total particle count, large particle count, difference between total and large particle count, temperature, relative humidity, wind speed, and solar radiation. Output is the predicted PM$_{2.5}$ concentration. Data considered are hourly values between April and September 2018. From this set, 80% of the data has been randomly extracted for training and 20% was used for testing. Based on the training set, weights are adjusted by minimizing the error between predicted and observed values. The test set of data is used for an independent estimation of PM$_{2.5}$ concentrations. Fig. 6(b) shows the quality of the calibration for the 20% of the data used for testing. A normalized percent error of 25% was obtained by comparing with BAM data, with the normalized percent error defined as:

$$NPE = \langle|obs - predicted|\rangle/\langle obs\rangle \qquad (2)$$

where triangular bracket means average over the test set values. The correlation between the BAM monitor and the calculated PM$_{2.5D}$ from the Dylos was R = 0.742 and nRMSE = 0.339. To make a fair comparison, the same 20% of the data was fitted to obtain PM$_{2.5D}$ using the linear equation and shown in Fig. 6(c). In this case, the normalized percent error was 38%, and the correlation between the BAM monitor and the calculated PM$_{2.5D}$ from the Dylos did not change by much (R = 0.638 and nRMSE = 0.532). The improvement using the neural network is evident from Figs. 6(b) and 6(c). Most of the overestimation and underestimation of the true value is reduced with the neural network calibration. The neural network results for Concón data are summarized in Table 2. Data in Las Condes (2 weeks) were not enough to use the neural network for calibration. In Las Condes there were only 333 data points compared to 4678 in Concón.

PM$_{2.5}$ Profile

Field deployment of the stations was done on houses of Enap's personnel and not all stations were installed at the same time. Data from April 2018 until November 2018 are available for the following stations: Station 1, which was installed in a sports field, downwind from the city and the oil refinery (see Fig. 1); Station 20, which was installed outside an office in the refinery; Station 19, which was installed in the backyard of a house in downtown Concón, about 100 m west of the SINCA station; and Station 12, which was installed on the western side of Concón. Fig. 8 shows a detailed picture of the measurement site. It can be seen that the sports field is not located near houses, while Station 19 is completely surrounded and Station 20 is very close to the river. These differences in the immediate surroundings make a difference in the total PM$_{2.5}$ and the profile of the site, in spite of the fact the longest distance between stations is only 5 km. The hourly profiles for the months of April–November are shown in Fig. 9. These averages have been used to see the trends in PM$_{2.5}$ in the city. It is very clear in all the sites that PM$_{2.5}$ increases from April (fall) to July (winter), and then decreases in September and October (spring). This trend is typical in most cities in Chile (Gramsch *et al.*, 2004; Gramsch *et al.*, 2006; Molina *et al.*, 2017). During winter, low wind speeds and strong inversion prevent the dispersion of contaminants, leading to high concentrations, especially at night. As a consequence, the highest concentrations are always seen in the months of May, June, and July. All plots in Fig. 9 show a rush-hour peak in the morning hours (7–10 a.m.) which is characteristic of any large city in the world (Molina *et al.*, 2012). Another peak occurs at night, and it is related to the evening rush hour traffic, emissions from heating appliances, restaurants, etc., and it is more pronounced during winter. At night, the wind speed is low and frequent thermal inversions keep contaminants close to the ground (Gramsch *et al.*, 2006; Gramsch *et al.*, 2014). Fig. 9 shows that the evening peak is more pronounced in downtown Concón (Fig. 9(a)) during the months of June, July, and August. The peak is less pronounced at the refinery (Fig. 9(b) and west Concón (Fig. 9(c)). In winter, the morning rush is very
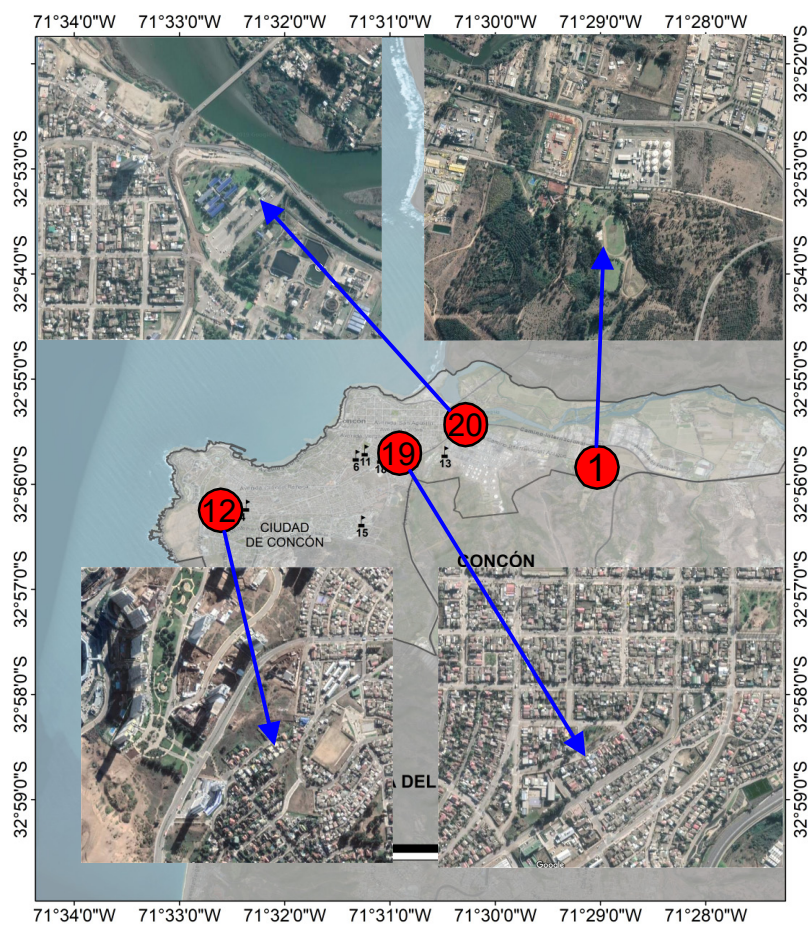
Fig. 8. Map for each of the 4 detailed locations discussed in the text and in Fig. 9.

similar in all the stations. The least pronounced peak during winter is the sports field station (Fig. 9(d)), probably due to the longer distances from the houses (Fig. 8). This is an indication that wood burning (or similar emissions) occur mainly in downtown Concón. In all the stations there is a clear concentration decrease during the afternoon (2:00–6:00 p.m.) which is due to higher wind speeds in the area, affecting all sites in the same way. An interesting feature is that the station at the refinery does not show higher $PM_{2.5}$ than the other stations, which indicates that, on average, the refinery does not seem to increase particulate matter pollution. Analysis of short-term events coming from the refinery that may increase $PM_{2.5}$ pollution has not been made yet. Another feature observed in the data that is not seen in other cities of Chile (Gramsch *et al.*, 2006; Molina *et al.*, 2017) is the fact that in the early morning (1:00–5:00 a.m.) $PM_{2.5}$ does not decrease despite the decrease in the city's activity. This may be due to the fact that at this time of the day there is high relative humidity which would increase the count in the Dylos detector.

PM₂.₅ Spatial Distribution

The spatial distribution of $PM_{2.5}$ can be used to teach people about pollution in their neighborhood and to determine possible sources of contamination. The spatial distribution in Concón has been calculated for the months of June, July,

and August 2018 (winter) and February and March 2019 (summer). The Dylos data was calibrated using Eq. (1); subsequently the hourly average was calculated and used to generate the interpolation. The program used was R (R Core Team, 2018) and the interpolation methodology was the inverse distance weighted interpolation (IDW). The maximum number of points for each station during winter 2018 was 2208 and the minimum was 1704. During summer, the maximum number of points for each station was 1280 and the minimum was 936. Fig. 10 shows the interpolation of $PM_{2.5}$ concentration for the winter of 2018 and summer of 2019. It can be seen that during summer the highest concentration is in the station close to the sea, indicating that particles from the sea are the main source of $PM_{2.5}$ in the area. In winter, the average concentration for the month of July is slightly higher in the refinery sector.

CONCLUSIONS

A micro-network of 10 low-cost Dylos sensors in Concón has been used to obtain the temporal and spatial profile of $PM_{2.5}$ in the city. Although this micro-network was deployed partly in houses belonging to residents of the community, the differences between its data and those obtained by the official network were not very large, with a correlation of R = 0.742 following neural network calibration. Although the
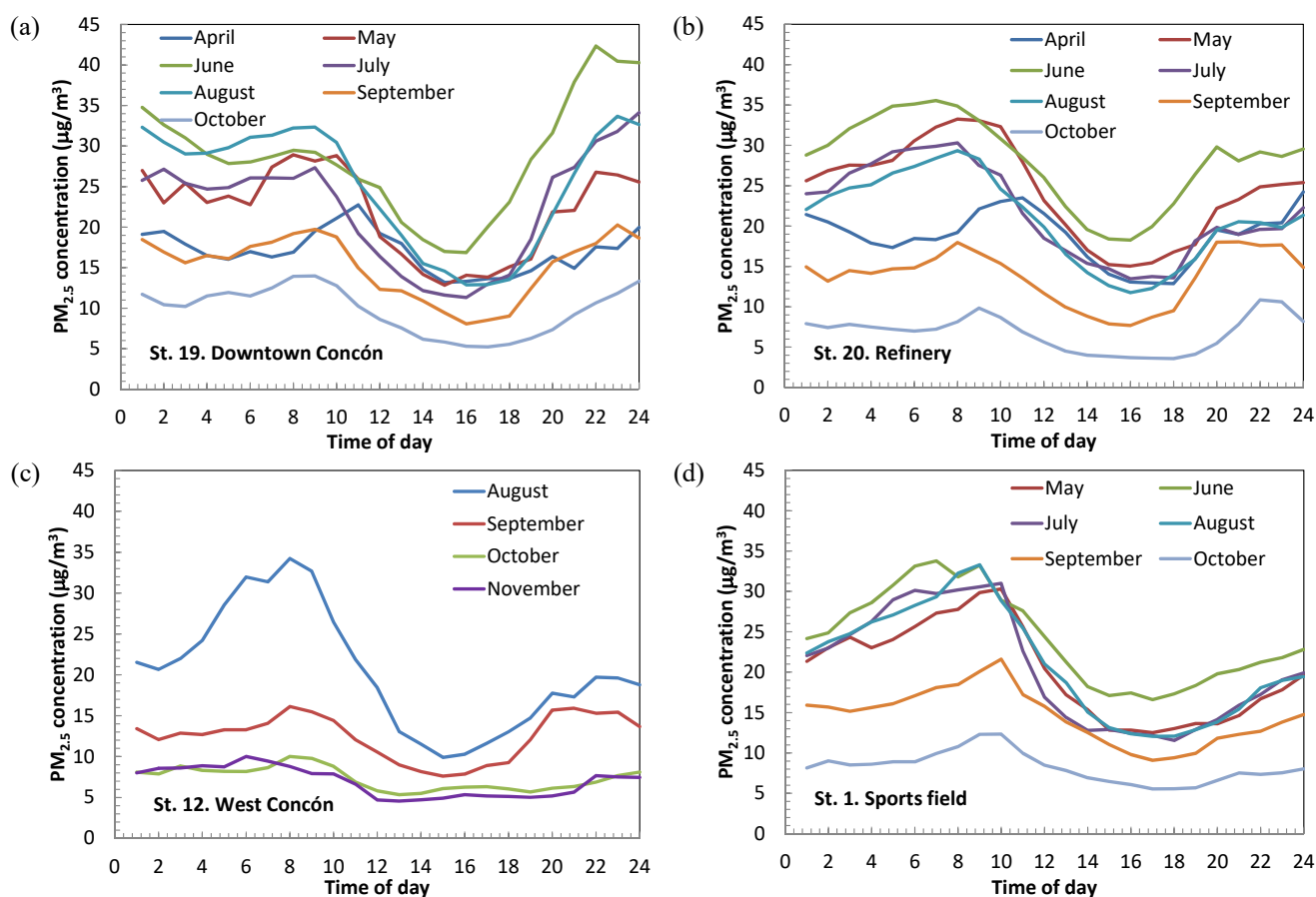
Fig. 9. PM$_{2.5}$ hourly profile for the months of April–November 2018 in 4 stations.
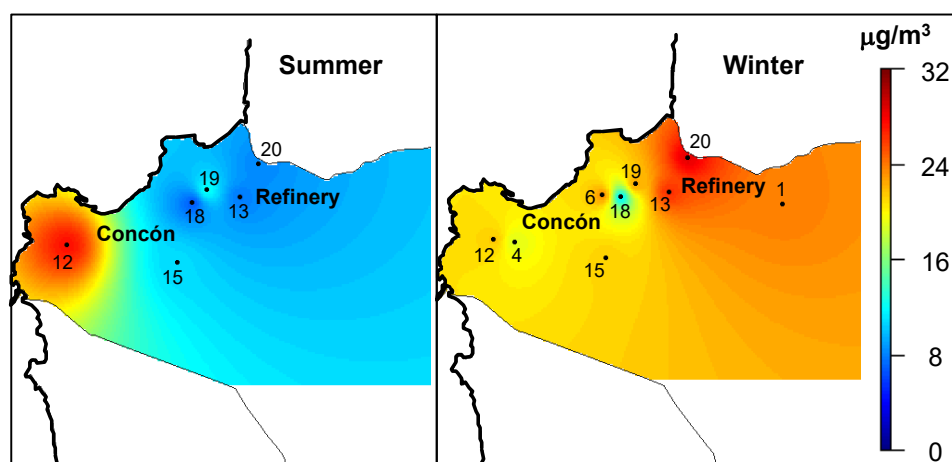
Fig. 10. Interpolated PM$_{2.5}$ concentration in summer (February–March 2019) and winter (June–August 2018) in Concón. The location of the monitoring stations is indicated with a dot and the corresponding number.

measurement area contains Enap, a large oil refinery, this facility does not seem to contribute significantly to the PM$_{2.5}$. Our results from calibrating the low-cost sensors with a BAM monitor indicate that conducting this process at the site where the sensors are to be installed is imperative, as a 37% difference in the PM$_{2.5}$ measurements between the BAM and the sensors arose following sensor calibration in a different location. Additionally, the correlation and the error between

the BAM monitor and the Dylos sensors noticeably improved when a neural network was employed for calibration, with the correlation increasing from 0.638 to 0.742 and the nRMSE decreasing from 0.532 to 0.339. The temporal profiles from all of the stations reveal a very strong influence from traffic emissions, which is typical of most cities around the world. Furthermore, relative humidity, which noticeably affected the particle count, was addressed in the neural network

calibration but not the linear calibration equations. Finally, downtown Concón displays a pronounced evening peak in the PM$_{2.5}$ during the winter, which is most likely related to emissions from wood burning. Sites that are located outside of downtown, however, exhibit a smaller peak.

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