

Article

Simplifying Air Quality Forecasting: Logistic Regression for Predicting Particulate Matter in Chile

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Abstract

Widespread residential wood burning in southern Chile combined with cold climate conditions cause severe episodes of particulate matter (PM_{2.5} and PM₁₀) pollution. In this study, we used logistic regression to predict daily exceedances of fine (PM_{2.5}) and coarse (PM₁₀) particulate levels at multiple urban sites, assessing model performance under different air quality standards. Results showed a clear latitudinal gradient in air pollution, with communities further south experiencing significantly higher PM levels and more frequent threshold exceedances, likely due to higher per capita firewood use and cooler temperatures. The logistic models achieved their best predictive accuracy under the strictest European (ESP) air quality standards (F1-scores up to ~0.72 for PM₁₀ and ~0.59 for PM_{2.5}), while Chile's national (NCh) thresholds significantly underestimated pollution events. Additionally, annual per capita wood energy consumption in the far south was several times higher than in central Chile, contributing to disproportionately high emissions. These findings highlight the need to adopt more protective air quality standards and reduce wood-fueled emissions to improve early warning systems and decrease particulate exposure in southern Chile.

Keywords: biomass burning; prediction threshold level; residential wood combustion; air quality standards; southern Chile; cold regions



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1. Introduction

Air pollution is recognized as one of the most pressing environmental challenges globally, with well-documented impacts on human health, ecosystems, and the climate [1]. Epidemiological evidence indicates mortality rates several times higher than those associated with malaria or HIV (Human Immunodeficiency Virus), contributing to an estimated 5.5 million premature deaths worldwide each year [2–4]. Particulate matter (PM) is considered the most harmful air pollutant [5]. Smaller particle sizes are directly associated with increased adverse health effects [6], longer atmospheric lifetimes, and greater transport distances, collectively increasing the likelihood of exposure [7]. However, the chemical composition of PM is crucial for improving risk assessment [8]. Therefore, fine particles with an aerodynamic diameter less than 2.5 µm (PM_{2.5}) pose a greater health risk than larger particles with an aerodynamic diameter of 10 µm (PM₁₀) [9–11], since they can penetrate the lower respiratory tract and even enter the bloodstream [5,12].

Exposure to PM is associated with serious diseases, including stroke, heart disease, and respiratory infections, among others [10,13–16]. Increasing evidence from epidemiological

and toxicological studies suggests that particles from various sources can have different health effects. However, most research has concentrated on fine particles, which primarily originate from combustion processes [4,17,18]. In many regions, especially in low- and middle-income countries, households continue to burn solid fuels (biomass) to meet basic energy needs (cooking and heating). Unfortunately, this combustion releases pollutants that deteriorate indoor air quality and add to PM_{2.5} levels in the environment, leading to adverse health impacts [11,19–21]. This dependence has been reported from socioeconomic perspectives [22–24], from air-quality and wood-smoke tracer analyses [25,26], and through policy evaluations related to critical-episode management [27,28].

Emission factors and chemical profiles from wood combustion vary by species and combustion conditions, with higher moisture content and incomplete combustion increasing PM_{2.5} and toxic compounds, such as PAHs [29–31]. Biomass burning is the primary source of PM_{2.5} emissions in Chile, accounting for 92.7% of the national total in 2022, with 68% of this due to residential wood burning (40.8% urban and 27.2% rural). The rest is from forest fires [32]. For PM₁₀, the percentage is 93.2%, comprising 37% from urban wood burning, 24.9% from rural wood burning, and 30.9% from forest fires [32]. This is concentrated in the central and southern regions, where over 80% of urban households and nearly all rural households rely on firewood for heating due to its low cost, despite its harmful effects [25,33]. Reports from the Chilean Ministry of Energy [34] show that biomass consumption is concentrated in the south-central regions, with Biobío accounting for 40% of the national total, followed by Los Lagos (15%), La Araucanía (11%), and Maule (10%). Despite this regional distribution, national biomass consumption is almost evenly split between the industrial (52%) and residential (47%) sectors, a balance that becomes more significant in areas where household reliance on firewood is particularly high.

As a result, cities in the south experience recurrent critical episodes of air pollution, with PM_{2.5} and PM₁₀ concentrations that systematically exceed primary air quality standards [11,35], leading several municipalities in the center-south of the country to be officially designated as “saturated zones” [19,36]. In Chile, this legal classification is applied when municipalities record prolonged periods with pollutant concentrations above regulatory thresholds. The health burden caused by PM_{2.5} is significant, estimated to result in approximately 3000 hospitalizations and 4500 deaths each year [25]. To address this problem, decontamination plans in Chile aim to reduce PM emissions, especially PM_{2.5} and PM₁₀. These plans include measures such as thermal refurbishment, replacement of polluting heaters, promotion of dry firewood, and stricter regulation of emissions. The costs of implementing these plans vary by region and require substantial financial resources with medium-term implementation horizons [37].

Beyond high levels of atmospheric pollutants, adverse health effects are also influenced by the toxicological characteristics of particulate matter. Oxidative stress has been identified as a key mechanism, caused by an imbalance between reactive oxygen species (ROS) production and the body’s antioxidant defenses, which ultimately results in cellular and tissue damage [4,17,18]. This process is especially relevant for particles from wood combustion, which contain redox-active compounds like transition metals and polycyclic aromatic hydrocarbons that facilitate ROS formation [38]. The ability of particles to induce ROS production, known as oxidative potential (OP), has been extensively linked to biomass burning emissions [31,38,39]. Consequently, reliance on firewood for residential heating in southern Chile not only drives recurrent critical episodes in saturated areas but also poses a significant health risk due to the oxidative potential of emitted particles. Forecasting these episodes is therefore crucial to protect vulnerable populations [40,41]. These events are strongly modulated by meteorology and topography, a condition documented for the center-south of the country [42]. In this context, the Climate Science and Resilience

Center (CR2) recommends strengthening the information base for decision-making through simulations and projections that enable early warnings and ex-ante evaluation of measures.

In atmospheric forecasting of air quality events, numerical weather prediction (NWP) models are commonly used because they can simulate atmospheric dynamics based on physical equations [43]. However, their use has limitations, including high computational costs, strict latency requirements, and reliance on accurate initial conditions, which can impact the accuracy of the location, timing, and strength of the predicted events [43–45]. In addition, these models face constraints in computing capacity, data availability, and assimilation, as well as challenges in predicting rare events and communicating uncertainty [46,47]. In response, machine learning (ML) models have been adopted as an alternative because they reduce reliance on complete emissions inventories and enable direct analysis of observed data. However, they also face challenges such as limited availability and short climate record durations, which can hinder statistical prediction performance [48]. Despite these models having an advantage for a few to medium-sized datasets and the ability to reduce variance, they also pose a risk of overfitting, making it difficult to achieve a straightforward interpretation, and have a low ability to capture the full complexity of pollutant behavior [49–52].

Given these constraints, threshold-based prediction provides an alternative that combines efficiency and clarity in interpretation. This method relies on models like logistic regression (Logit), which allow for estimating the probability of exceeding a critical concentration level using a binary response. This maintains accuracy while providing straightforward explanations of each predictor variable's impact [52–54]. Logit offers flexibility and simplicity, making it suitable even for users without advanced knowledge of atmospheric science [55], and it delivers dependable daily predictions along with a transparent view of the key influencing factors [51]. Therefore, this study aims to develop and evaluate a logistic regression model based on concentration thresholds to predict daily air quality categories in southern Chile.

2. Materials and Methods

2.1. Study Area

Chile extends between 17°30' S and 56°30' S in the extreme southwest of South America. This study focuses on seven communes located between Curicó (approximately 34.98° S) and Coyhaique (approximately 45.57° S), spanning the central and southern regions of the country (Figure 1). These localities represent diverse geographic, climatic, and demographic conditions. Yet, all have been officially designated as saturated zones for particulate matter (PM₁₀ and/or PM_{2.5}) by the Ministry of the Environment, where residential wood burning is the dominant pollution source, particularly in central and southern Chile [56,57]. According to Chilean regulations, a saturated zone is declared when long-term PM_{2.5} or PM₁₀ levels exceed national thresholds, either by surpassing annual or multi-year averages or by frequent exceedances of 24 h concentration limits [58,59]. The geographic, demographic, and meteorological characteristics of the selected communes, along with their legal classification as saturated zones, are summarized in Table 1.

2.2. Database

The data used in this study were obtained from SINCA, the National Air Quality Information System of Chile (<https://sinca.mma.gob.cl/>, accessed 10 January 2025). The selected stations are located in central–southern Chile, in communes officially designated as saturated zones due to residential wood burning as the primary energy source for heating. All seven stations are automatic beta attenuation monitors (Met One BAM-1020, Met One Instruments Inc., Grants Pass, OR, USA) that provide daily concentrations of

PM₁₀ and PM_{2.5}, along with meteorological variables including maximum and minimum temperature (Tmax, Tmin), precipitation (pp), relative humidity (HR), and wind speed (WS). For rainfall, additional lagged variables (1-, 2-, and 3-day delays) were derived to account for its role in atmospheric cleansing processes. All data used in this study originate from stations validated by the Chilean Ministry of the Environment and meet national quality assurance criteria, in accordance with the methodologies and reference standards established by the United States Environmental Protection Agency (U.S. EPA) for particulate matter and meteorological monitoring. Each station provides at least ten years of valid data, with annual completeness above 75%. Across the study area, maximum temperatures range from 21 °C in the north to 13 °C in the south, while minimum temperatures vary from 8.6 °C to 4.2 °C. Precipitation shows a strong north–south gradient, ranging from ~260 mm/year to ~1280 mm/year, and relative humidity ranges from 37% to 80%.

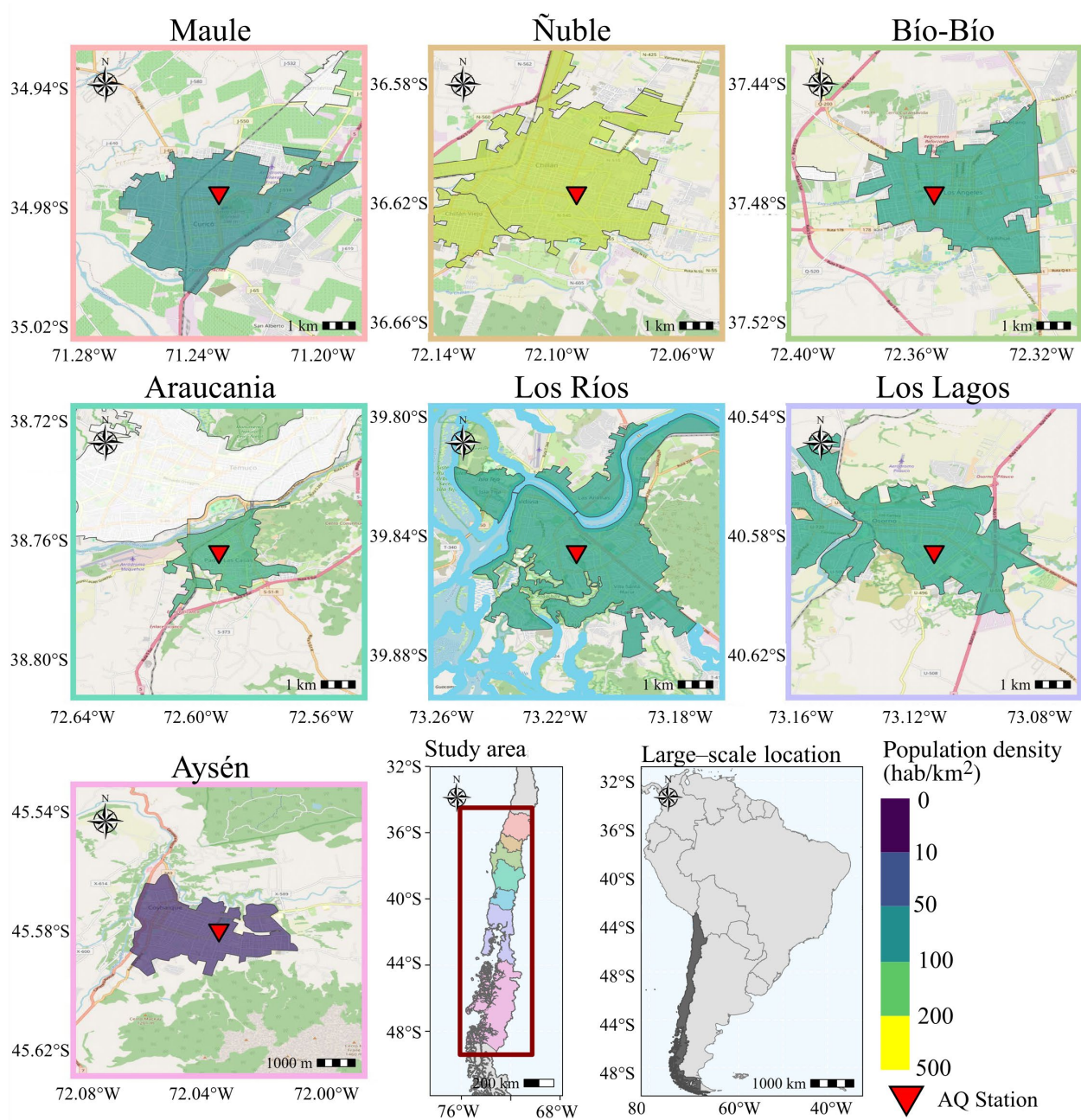


Figure 1. Macro-, meso-, and micro-scale location of the monitoring stations representing air quality in saturated zones affected by biomass burning in central–southern Chile.

Table 1. Geographic, demographic, air quality, and meteorological characteristics of the selected communes, together with their legal classification as saturated zones.

Geographical Characteristics			Monitoring Network										Saturate Zone Information		
			Air Quality				Meteorological Condition								
Region	Station	Population	Coordinates	Period	%Data (PM ₁₀)	%Data (PM ₂₅)	Valid Years	Tmin (° C)	Tmax (° C)	Prec (mm)	HR (%)	DS * N°	DS Year	Pollutant	
Maule	Curico—CRC	159,968	34° 59' S, 71° 14' W	2014—2024	98.5	97.2	11	8.6	21.7	365.7	68.2	8	2011	PM ₁₀	
Ñuble	Puren—PEN	190,382	36° 36' S, 72° 06' W	2013—2024	98.4	97.8	12	7.7	20.8	563.1	70.2	36	2013	PM ₁₀ , PM _{2.5}	
Biobío	21 de mayo —MAY	219,441	37° 28' S, 72° 21' W	2013—2024	98.6	97.9	12	8.6	20.3	620.9	66.9	11	2015	PM ₁₀ , PM _{2.5}	
La Araucanía	Padre casas II—PLC	80,656	38° 46' S, 72° 36' W	2014—2024	79.8	88.7	10	8.2	15.4	258.5	79.2	2	2013	PM _{2.5}	
Los Ríos	Valdivia—VAL	170,043	39° 48' S, 73° 14' W	2008—2024	84.1	72.8	15	7.6	17.5	1276.5	74.1	17	2014	PM ₁₀ , PM _{2.5}	
Los Lagos	Osorno—OSO	166,455	40° 34' S, 73° 08' W	2009—2024	78.4	78.5	13	6.4	17	1051.9	74	27	2012	PM ₁₀ , PM _{2.5}	
Aysen	Coyhaique II—COY	57,823	45° 34' S, 72° 04' W	2014—2024	97.6	98.1	11	4.2	13.7	473.2	37.1	33/15	2012/2016	PM ₁₀ , PM _{2.5}	

Tmin: Minimum temperature. Tmax: Maximum temperature. Prec: Precipitation. HR: Relative humidity. DS: Supreme decree. * Supreme Decree issued by the Chilean Ministry of the Environment that officially declares an area as having air-quality problems. The year corresponds to the formal notification of the saturated zone status, which is one of the inclusion criteria described in the Methods section.

2.3. Threshold Forecast Design

Daily exceedance forecasts for particulate matter (PM₁₀ and PM_{2.5}) were generated using logistic regression. Three sets of concentration thresholds were evaluated: (i) NCh, corresponding to the values defined in the Chilean Primary Air Quality Standard for Respirable Particulate Matter; (ii) INT, based on the ranges of the U.S. Environmental Protection Agency (EPA) Air Quality Index (AQI); (iii) ESP, based on the European Air Quality Index established by the European Environment Agency (EEA). All thresholds were analyzed under the same logistic regression framework (Table 2).

Table 2. Daily average concentration thresholds for PM₁₀ and PM_{2.5} used to classify air quality according to the Chilean Standard (NCh), the U.S. EPA/International guideline (Int), and the Spanish Standard (Esp).

Standard	Pollutants	Good	Regular	Alert	Pre-Emergency	Emergency
NCh	PM ₁₀	0–149	150–194	195–239	240–329	≥330
	PM _{2.5}	0–50	51–79	80–109	110–169	≥170
Int	PM ₁₀	0–54	55–154	155–354	355–424	≥425
	PM _{2.5}	0–9	10–35.4	35.5–125.4	125.5–225.4	≥225.5
Esp	PM ₁₀	0–20	21–40	41–50	51–99	≥100
	PM _{2.5}	0–10	19–20	21–25	26–49	≥50

The concentration ranges are in µg/m³ for PM₁₀ and PM_{2.5} were maintained according to the values defined by each reference agency. The qualitative categories selected were preserved from the Chilean regulatory framework, and their consistency with international standards was verified.

The predictor variables included the daily meteorological observations previously described. Logistic regression was implemented as a binary classifier that estimates the probability that pollutant concentrations on a given day exceed the established threshold. To define the critical probability of exceedance, the cut-off values were adjusted according to the observed frequency of threshold exceedances in the historical database, rather than fixing the standard value of 0.5. This approach avoids systematic overestimation in cases where exceedances are relatively infrequent, and is consistent with previous studies highlighting the importance of presence/absence proportions in the success of binary models [53,60]. The general formulation is expressed as:

$$f(x) = \log \left[\frac{p}{1-p} \right] = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n \quad (1)$$

where $x_1, \dots, x_n$ represent the predictors or explanatory variables, and p corresponds to the probability of exceeding the concentration threshold on a given day. From a mathemat-

ical perspective, the logistic model is a parametric, additive, and flexible model with an easy-to-interpret binary response. The sign of the parameter β (coefficient of the predictor) indicates the direction of the effect (positive or negative), and its magnitude indicates the weight of the predictor in the equation [53]. All models were trained using data prior to 31 December 2022 and tested with the two most recent years of data, from 1 January 2023 onward.

The effectiveness of the model was assessed by contrasting its classification results with actual observed data different to training. During the training phase, three different metrics were employed to measure how well the model performed. Sensitivity (percentage of true positives to total observed positives) is defined as:

$$\text{Sensitivity (SEN)} = \frac{TP}{TP + FN} \quad (2)$$

Specificity (percentage of true negatives to total observed negatives) defined as:

$$\text{Specificity (SPC)} = \frac{TN}{TN + FP} \quad (3)$$

where TP: true positives, FN: false negatives, TN: true negatives, and FP: false positives.

F1-score is a combination of the harmonic mean of precision and recovery; that is, it helps to balance recovery and precision. Its range is [0, 1]. It punishes extreme values and indicates the accuracy and robustness of the classification model. The higher the F1-score, the better the model. It is an effective metric that considers the unbalanced distribution of classes in the data [61,62]. All analyses were performed using R version 4.3.3 (R Foundation for Statistical Computing, Vienna, Austria) in RStudio version 2023.06.02+561 (Posit Software, Boston, MA, USA).

$$\text{F1 Score} = \frac{2 TP}{2 TP + FP + FN} \quad (4)$$

3. Results

Table 3 shows PM concentrations during the period and the areas of study. In the case of PM₁₀, the CRC station (located in the Maule region), the furthest north, recorded the lowest mean, maximum, and minimum values. Moving southward, PM₁₀ concentrations progressively increased, reaching their highest levels at the COY station (Aysén region), and a similar north–south gradient was observed for PM_{2.5}. At CRC, the lowest values were noted for all parameters, whereas COY exhibited the highest. This pattern is corroborated by 98% percentile on both size of PM; increasing southward, which indicate more days with a critical episode, as shown in the daily and annual exceedances in Table 3. Notably, despite being among the southernmost and least populated regions (with 91,492 inhabitants), Aysén exhibits the highest PM concentrations for both pollutants (Figure 2). Conversely, Maule, located further north and with a population of over ten times larger (908,097 inhabitants), consistently presented the lowest concentration. The observed variation suggests a higher per capita consumption of firewood in the southern regions, resulting in greater particulate emissions per inhabitant. The trend is likely related to increased energy demand for residential heating, driven by the temperature decline observed along the latitudinal gradient, which decreases between -0.38 and -0.70 °C per 100 km.

Table 3. Descriptive statistics and frequency of annual and daily exceedances of PM₁₀ and PM_{2.5} by season.

Pollutant	Station	Minimum ± SD	Mean ± SD	Maximum ± SD	Absolute Maximum	Peak Date (dd-mm-yy)	P _{98%}	CV	% of National Standard Daily	% of National Exceedance Annual
PM ₁₀	CRC	9.95 ± 1.76	44.36 ± 5.25	165.82 ± 28.56	225.00	24-Apr-15	120.5	0.12	1.3	18.2
	PEN	9.92 ± 2.18	47.33 ± 4.58	262.16 ± 40.18	330.00	28-Apr-15	168.0	0.10	4.8	33.3
	MAY	7.42 ± 2.64	48.53 ± 6.67	301.20 ± 79.40	480.00	04-Feb-23	174.0	0.14	4.4	50.0
	PLC	8.48 ± 2.96	50.50 ± 8.32	252.30 ± 56.83	339.00	22-May-18	186.1	0.17	6.8	33.3
	VAL	6.49 ± 1.84	44.54 ± 10.73	218.30 ± 48.21	300.35	27-May-16	168.8	0.24	4.7	23.1
	OSO	7.12 ± 3.13	53.98 ± 19.00	347.92 ± 101.11	628.00	30-Jul-12	252.3	0.35	8.5	46.2
	COY	9.27 ± 4.18	62.41 ± 14.06	420.91 ± 99.02	562.00	02-Jun-18	283.5	0.23	11.1	72.7
	CRC	2.82 ± 1.19	24.54 ± 1.90	133.65 ± 16.61	155.00	16-Jun-18	92.0	0.08	13.2	100.0
PM _{2.5}	PEN	2.25 ± 0.72	30.61 ± 3.46	231.71 ± 40.31	289.00	17-May-13	148.3	0.11	19.2	100.0
	MAY	2.15 ± 0.91	28.70 ± 2.88	257.63 ± 69.17	434.00	04-Feb-23	143.6	0.10	15.9	100.0
	PLC	1.72 ± 0.65	39.18 ± 6.89	239.35 ± 60.58	319.00	22-May-18	176.0	0.18	26.0	100.0
	VAL	2.81 ± 1.86	32.48 ± 5.50	187.43 ± 42.48	277.28	24-Jul-09	131.2	0.17	22.2	100.0
	OSO	2.88 ± 2.56	38.29 ± 8.53	310.08 ± 78.78	474.00	16-Jul-12	192.6	0.22	22.9	100.0
	COY	2.34 ± 1.18	46.20 ± 10.14	390.55 ± 98.78	543.00	02-Jun-18	248.0	0.22	27.7	100.0

CV: coefficient of variation. SD: standard deviation.

Both PM₁₀ and PM_{2.5} levels exhibited a clear seasonality, with concentrations peaking during the colder months. At the northernmost station (CRC), a marked increase was observed between April and October, followed by an abrupt decline. As latitude increases, the seasonal gradient becomes less steep, likely reflecting lower maximum and minimum temperatures in southern regions (Supplementary Material Figures S1–S7). This effect is more pronounced for PM_{2.5} than for PM₁₀, as indicated by the stronger negative correlation between temperature and particulate matter concentrations; colder conditions are consistently associated with higher pollutant levels, particularly in the southern stations during autumn and winter (Supplementary Material Figures S1–S7). Heatmaps for all stations further support this pattern, confirming that the highest PM₁₀ and PM_{2.5} concentrations occur during the cold season. However, a decline in the number of extreme events (pre-emergency and emergency days) has been observed in recent years (Supplementary Material Figures S1–S7).

Table 4 summarizes the percentage distribution of days by categorical air quality thresholds under the Chilean (NCh), U.S. (INT), and European (ESP) standards. For PM₁₀, the NCh thresholds classified almost all days as Good quality (94–99%), with only a small fraction (<6%) falling into Regular or Alert categories. Under the INT standard, the proportion of Good days decreased markedly (72–81%), while Regular conditions increased to 19–28%. The ESP thresholds, being considerably more stringent, reclassified most days as Regular or worse: Good quality accounted for only 14–31% of the records and Regular levels dominated (66–84%). Episodes categorized as Alert, Pre-emergency, or Emergency were also more frequent under the ESP standard, reflecting a higher sensitivity to exceedances.

For PM_{2.5}, a similar but more pronounced trend was observed. The NCh standard labeled 75–87% of the days as Good quality, while INT reduced this proportion to 29–40%, increasing the share of Regular conditions to 54–68%. Under the ESP thresholds, the stricter limits further shifted the classification: only 32–45% of the days were considered Good, while 51–66% were Regular, and up to 49% fell within Alert or more severe categories. This comparison highlights that the application of international and European air quality criteria substantially increases the number of days classified in poorer air quality categories, particularly for PM_{2.5}, emphasizing the relative leniency of the national standard (NCh) in evaluating exposure risk. The observed differences arise mainly from the stricter concentration limits defined by the European and U.S. standards (e.g., 50 µg/m³ for 24 h PM₁₀ in the EU vs. 150 µg/m³ in Chile). Consequently, adopting international thresholds would substantially increase the number of alert and pre-emergency days, par-

ticularly for PM_{2.5}, implying a greater perceived health risk and the need for more frequent mitigation measures.

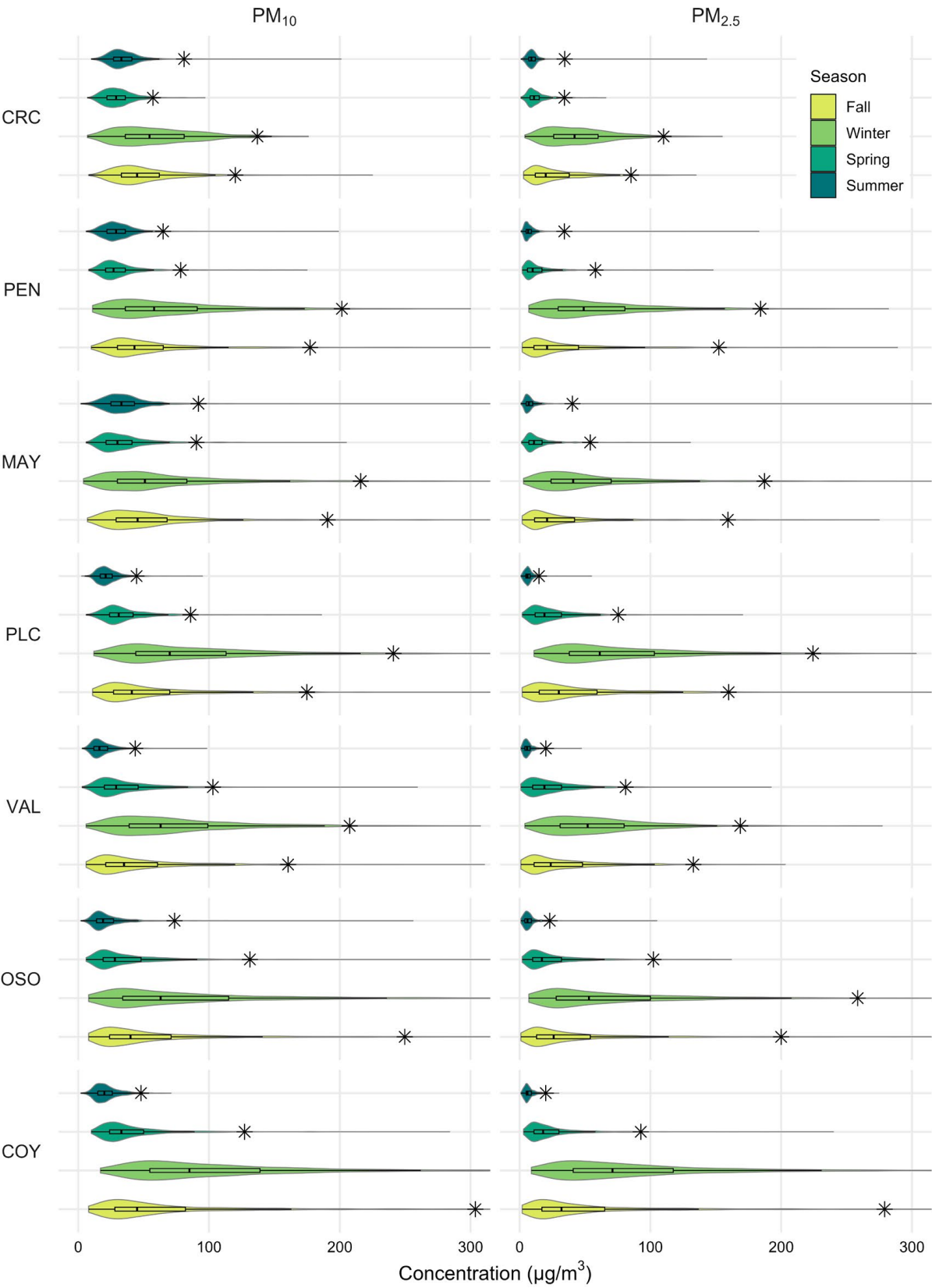


Figure 2. Seasonal variation in daily mean PM₁₀ and PM_{2.5} concentrations at stations from central to southern Chile (2013–2024). * is the 98th percentile.

Table 4. Percentage of data by categorical air quality threshold according to the different standards applied.

Pollutant	Category ¹	NCh				INT				ESP			
		CRC	PEN	MAY	COY	CRC	PEN	MAY	COY	CRC	PEN	MAY	COY
PM ₁₀	Good	99.4	97.3	97.4	94.6	80.3	76.9	81.0	71.8	15.6	13.7	22.4	31.0
	Regular	0.6	2.7	2.6	5.3	18.7	22.5	18.6	27.5	81.4	84.2	75.3	66.3
	Alert	0.1	0.3	0.7	2.2	0.6	2.3	1.9	1.0	33.8	37.6	30.8	36.7
	Pre-emergency	0.0	0.0	0.1	1.0	0.0	0.0	0.1	0.3	21.9	25.8	22.8	30.4
	Emergency	0.0	0.0	0.1	0.3	0.0	0.0	0.1	0.0	3.2	7.6	6.8	13.3
PM _{2.5}	Good	87.4	84.4	86.1	75.2	36.0	40.3	40.0	29.4	41.3	44.0	45.6	32.3
	Regular	11.6	15.5	13.5	24.5	58.7	56.0	54.4	67.7	54.2	53.1	50.6	65.5
	Alert	3.9	8.9	8.4	14.3	19.6	24.3	20.9	32.8	32.6	36.4	32.6	48.8
	Pre-emergency	0.7	3.9	4.0	8.1	0.4	2.7	2.7	6.0	27.9	32.9	28.5	41.7
	Emergency	0.0	0.4	0.8	2.4	0.0	0.0	0.1	1.3	13.5	16.3	14.1	25.2

NCh: Chilean Air Quality Standard; INT: Air Quality Index; ESP: European Environment Agency; CRC: Curicó; PEN: Pemuco; MAY: 21 de Mayo; COY: Coyhaique. ¹ Qualitative air quality categories were taken from Chilean legislation and harmonized with the corresponding international (EPA) and European (EEA) standards.

Figure 3 shows the type of relationships (positive or negative) and statistical significance of meteorological predictors on logistic regression models, disaggregated by regulatory thresholds (ESP, INT, NCh), PM fractions (PM₁₀ and PM_{2.5}), and monitoring stations (COY, CRC, MAY, PEN). Predictors include maximum and minimum temperature (Tmax, Tmin), wind speed (ws), relative humidity (HR), precipitation (pp), and lagged precipitation variables (l1.pp, l2.pp, l3.pp). Bar colours indicate significance levels (red: $p \leq 0.01$, blue: $0.01 < p \leq 0.05$, green: $0.05 < p \leq 0.1$), and the position above or below the zero line reflects the direction of the effect.

Under ESP thresholds for PM₁₀, Tmin and ws generally exhibit a significant negative association, while HR consistently shows a positive influence. Tmax displays a significant positive association only in CRC and PEN stations. INT thresholds show similar patterns, with minor differences in significance levels. In NCh thresholds, Tmin and Ws maintain significant negative associations across most stations and air quality categories, although Ws shows weaker effects under Moderate to Very Poor conditions. HR remains positively associated at the COY station across all thresholds, with reduced significance in MAY in the Fair, Good, and Moderate categories.

For PM_{2.5}, ESP thresholds show a consistent negative influence of Tmax, Tmin, and Ws across most categories, except for MAY under Good air quality, where significance is lower. HR exhibits a strong and positive association across nearly all thresholds and stations. Under INT thresholds, Tmin and Ws remain negatively associated, although significance decreases under Poor and Very Poor levels in MAY and PEN. Tmax also shows a significant negative effect in most stations under Fair and Good air quality. HR shows positive effects throughout in COY, with reduced significance in Moderate to Very Poor categories. NCh thresholds confirm these trends, with Tmin and Ws consistently showing significant negative effects across all air quality levels, and Tmax showing significant influence in Fair to Moderate levels. HR maintains a positive and significant association across most thresholds and stations. Precipitation variables (PP and its lagged terms) show more heterogeneous patterns, with fewer significant associations. These effects tend to be sporadic and station-specific, with occasional positive influences at higher pollution levels, though no consistent trend is observed across thresholds or PM fractions.

Overall, results indicate a predominance of negative associations for Tmin and Ws and positive associations for HR, highlighting their importance in modulating PM concentrations. Spatial variability is notable, with stations like COY and CRC exhibiting more consistent significant effects, particularly under the local NCh threshold. These findings suggest that both the regulatory framework and meteorological dynamics play a key role in shaping air pollution episodes (Supplementary Material Tables S1–S10).

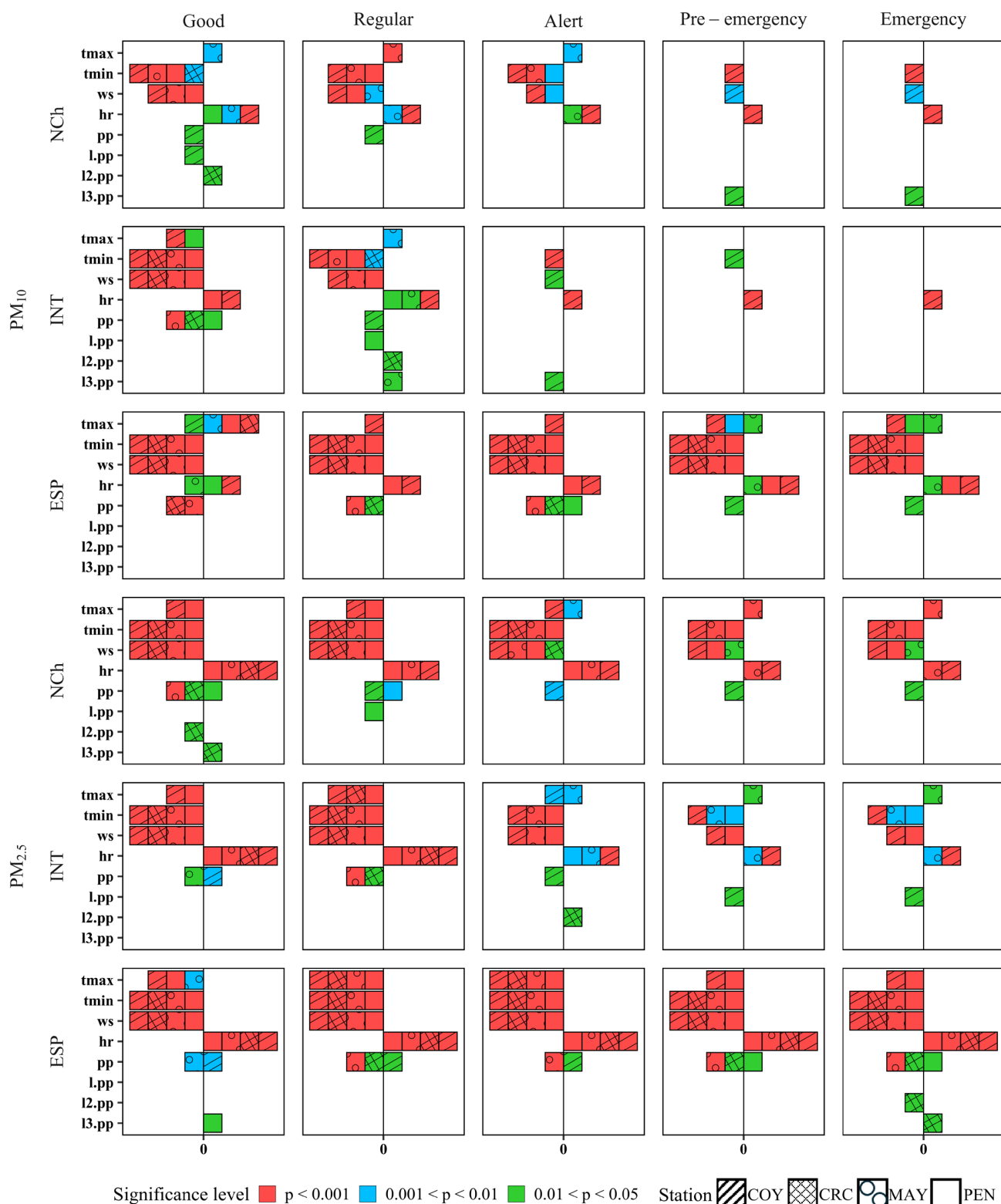


Figure 3. Frequency and significance level of meteorological predictors for each particulate matter type (PM₁₀ and PM_{2.5}) and regulatory concentration threshold (ESP: European Environment Agency, INT: International, NCh: Chilean) based on logistic regression models. Predictors include: tmax (maximum temperature), tmin (minimum temperature), ws (wind speed), hr (relative humidity), pp (precipitation on the day of measurement), l1.pp (precipitation one day before), l2.pp (precipitation two days before), and l3.pp (precipitation three days before). Bar colours represent the level of statistical significance (red: $p \leq 0.01$, blue: $0.01 < p \leq 0.05$, green: $0.05 < p \leq 0.1$), and direction (positive or negative) is indicated by position above or below the zero line.

Figure 4 summarizes the predictive performance of the logistic regression models for PM_{10} and $PM_{2.5}$ according to the sensitivity, specificity, and F1-Score metrics across the three regulatory standards (NCh, INT, ESP) and concentration thresholds (Good, Regular, Alert, Pre-emergency, Emergency). Sensitivity represents the model's ability to correctly predict exceedances, whereas specificity indicates its ability to correctly identify non-exceedances. The F1-Score provides a balanced indicator of model performance, integrating both sensitivity and precision into a single metric for comparison among stations, thresholds, and standards.

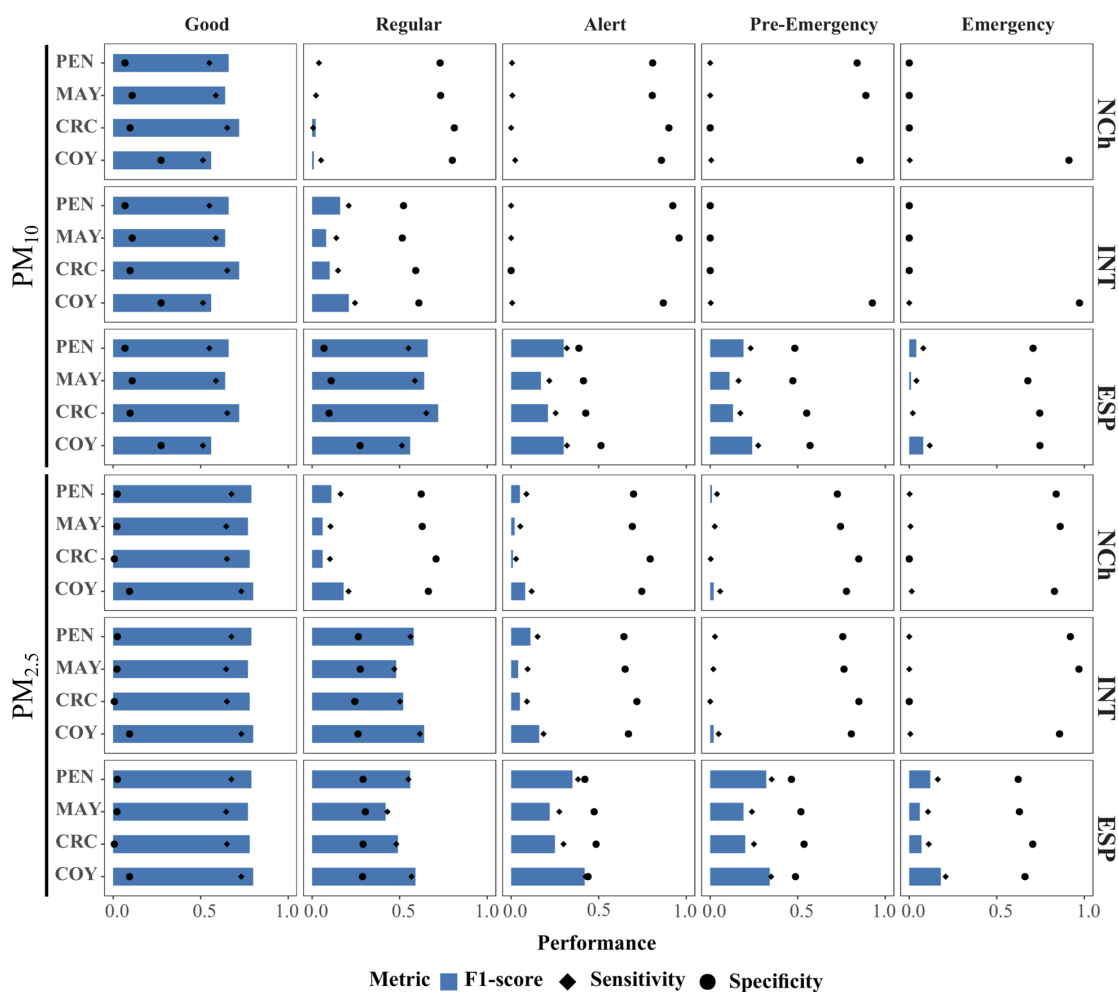


Figure 4. Performance of logistic regression models for PM_{10} and $PM_{2.5}$ prediction under air quality standards using Sensitivity, Specificity, and F1-Score across concentration thresholds and monitoring stations.

For PM_{10} , the results show that under the NCh standard, sensitivity values are extremely low across all stations and thresholds (generally below 5%), indicating a limited capacity to detect exceedances. Specificity, however, remains consistently high—often exceeding 80%, reflecting that the model reliably predicts non-exceedance conditions. The resulting F1-Scores are therefore close to zero, revealing an imbalance between the two metrics. Under the INT thresholds, sensitivity improves slightly (up to 24.5% at COY), particularly at the Regular category, while specificity declines moderately. The model becomes more reactive to exceedances, but still misses a large proportion of critical days. In contrast, the ESP thresholds, which are more restrictive, yield a substantial increase in sensitivity (reaching 65.2% at CRC) and higher F1-Scores (up to 0.72), although specificity drops markedly (as low as 10%). This indicates that while the model better detects exceedances

under stricter criteria, it also generates more false alarms. Across stations, COY exhibits the highest specificity at the Emergency threshold (74.6%), whereas CRC achieves the best overall balance between sensitivity and accuracy under the Regular ESP threshold.

For PM_{2.5}, the general behavior is similar but with slightly better overall performance. Under NCh, sensitivity values remain low (typically $\leq 20\%$), while specificity is higher (70–86%), again producing low F1-Scores (≤ 0.18). The INT thresholds markedly enhance model responsiveness, with sensitivity reaching 61.5% and F1-Score 0.64 at COY, though specificity decreases, particularly at lower thresholds. The ESP thresholds maintain high sensitivity (up to 56.7% at COY) and moderate F1-Scores (0.59), with specificity values around 30–70%. The consistency of results between COY and CRC suggests that southern and northern stations perform differently depending on the standard applied, but both yield their highest combined accuracy under the ESP Regular threshold.

When comparing pollutants and standards, PM_{2.5} shows overall higher F1-Scores than PM₁₀, indicating that the model better captures exceedances of fine particles. The NCh thresholds are associated with the most conservative performance, high specificity and very low sensitivity, whereas ESP thresholds provide the best trade-off between detection and accuracy. In both pollutants, the highest sensitivity and F1-Scores are found at the Regular ESP thresholds, while maximum specificity occurs at the Emergency thresholds under INT and NCh. This pattern reflects a systematic shift: as thresholds become more restrictive, the model's capacity to detect exceedances improves, but its precision in identifying non-exceedances declines.

4. Discussion

In high-latitude regions with prolonged cold seasons, residential wood combustion remains a major source of domestic heating. Recent studies highlight its relevance for particulate pollution through improved emission inventories [63], long-term trend analyses [64], quantified contributions to PM_{2.5} concentrations [65], and dispersion modelling under different meteorological scenarios [66]. This broader evidence helps contextualize our findings, particularly the behavior of CRC and PEN, where our logistic models showed a higher probability of exceeding the Regular and Alert thresholds during periods of reduced atmospheric ventilation. Such patterns are consistent with the accumulation dynamics described in previous studies, in which limited dispersion enhances the impact of local heating emissions [67,68].

However, the magnitude of contributions reported elsewhere, such as the 0.5–2 $\mu\text{g}/\text{m}^3$ annual averages attributed to wood combustion in major Finnish cities [69], does not translate directly to the communes analyzed here. Instead, our results suggest that the exceedance behavior is driven less by heating-related demand and more by structural and meteorological factors specific to each station. For example, the markedly lower exceedance probabilities in COY indicate more efficient dispersion conditions, consistent with its urban configuration and exposure to better ventilation.

In contrast, the communes analyzed in southern Chile show considerably higher values (Table 3 and Supplementary Material Table S11). Previous studies have demonstrated that residential wood burning accounts for 80–90% of total PM_{2.5} emissions during winter in southern Chile [26,70–72]. Based on data from Chile's National Energy Balance [73], annual per capita firewood consumption ranges from 9.3 GJ person^{−1} year^{−1} in Maule to 46.1 GJ person^{−1} year^{−1} in Aysén, increasing southward with decreasing temperature. These values are two to five times higher than those reported for European countries, typically varies between 1.6 and 8.6 GJ person^{−1} year^{−1} [74]. Such high per capita consumption underscores the strong reliance on biomass for residential heating in southern Chile and helps explain the persistently elevated PM_{2.5} concentrations observed during

winter months (Supplementary Material Figure S8). Furthermore, these markedly elevated concentrations likely could be attributed by weaker appliance regulation, the widespread use of inefficient heating technologies, and lower urban density.

Several studies have demonstrated that stricter appliance standards and improved combustion technologies substantially reduce particulate emissions from residential wood burning. Kukkonen et al. [68] reviewed PM_{2.5} emissions in four Nordic cities and detailed how the Ecodesign Directive (EU 2015/1185) and the Ambient Air Quality Directive (2008/50/EC) have established emission ceilings for solid-fuel appliances, achieving significant reductions despite the persistence of older, unregulated installations. Skreiberg et al. [75] reported that modern certified stoves can emit over 80% less particulate matter than older models, mainly due to improved combustion efficiency and fuel quality. Conversely, in Chile, regulatory progress has been slower. Farías et al. [76] found that before Supreme Decrees 39/2011 and 46/2013, domestic heaters emitted 4–20 g h^{−1} of PM, whereas certified models now achieve <3.5 g h^{−1}. Furthermore, fuel quality remains a major factor; an increasing wood moisture to 25% can double PM_{2.5} emissions per kg of wood and significantly raise particle numbers and PAH content from incomplete combustion [30].

Differences in PM levels are driven not only by emission intensity and heating technology but also by land-use configuration and atmospheric ventilation capacity. Urban areas located in valleys or topographic depressions are particularly vulnerable due to the combination of high local emissions and unfavorable meteorological conditions for dispersion [77]. During clear, cold nights, surface cooling generates strong thermal inversions that restrict vertical mixing and trap pollutants near the ground [78,79]. This mechanism has been repeatedly observed in mountainous regions [77] and extensively documented across Chilean cities in the central and southern zones [27,28,33,42,80]. Overall, low temperatures, weak winds, and frequent inversions act as natural amplifiers of residential emissions, explaining the persistence of critical pollution episodes in saturated areas where wood burning remains the dominant energy source.

The combined effect of emission intensity, fuel characteristics, and atmospheric stability defines the conditions under which pollution events develop. To further explore how these environmental factors interact, the following analysis evaluates the role of meteorological predictors in determining exceedance probabilities for PM₁₀ and PM_{2.5} concentrations across stations. Previous research confirms that particulate matter concentrations systematically increase under conditions of low temperature, poor ventilation, and elevated relative humidity. In particular, inverse relationships with low minimum and maximum temperatures and wind speed suggest that cold, stagnant air limits dispersion. By contrast, relative humidity often shows a positive association, likely due to the hygroscopic growth of fine particles (PM₁₀/PM_{2.5}), which increases their mass and lowers their residence time in humid conditions [81,82]. Concha & Rivera [28] confirm the findings, highlighting the synergy between atmospheric stability and domestic combustion sources as the main determinant of winter pollution in topographically restricted urban contexts. In the case of precipitation, no statistically significant effect on PM concentrations was observed; consistent with Mardones & Cornejo [27], who indicate that increased use of heating can counteract the natural removal of particles during rainy events. Similarly, a direct relation between high PM concentrations and precipitation suggests that rainfall is not always a mitigating factor [8,33,55]. The reason is that the rainy season in central-south Chile typically features lightning, with isolated heavy precipitation concentrated during the winter months [83].

This coupling between meteorology and emissions explains the recurrence of critical episodes in saturated areas of Chile. It underscores the need to incorporate meteorological

variables into air quality forecasting and planning systems, as recent records from the Ministry of the Environment (MMA) and SINCA show that critical episodes involving PM₁₀ and PM_{2.5} remain highly frequent and recurrent in the central and southern parts of the country. During the period April–September 2024, Coyhaique recorded 27 critical episodes, including 10 pre-emergencies and 2 emergencies, followed by Osorno with 14, Los Ángeles with 10, and Chillán with 11. These are consistent with the historical patterns reported by REMA 2021, where the 98th percentile of PM₁₀ and PM_{2.5} concentrations in these same municipalities greatly exceeded regulatory values, reaching averages close to or above 150 µg/m³.

Beyond meteorological controls, our results indicate that local emission patterns strongly modulate the probability of exceeding particulate thresholds. In the studied communes, residential wood combustion remains a dominant source of primary PM emissions [84,85], and its influence becomes particularly evident under conditions of limited dispersion. The higher exceedance probabilities observed in CRC and PEN are consistent with areas where firewood remains the primary heating fuel and where combustion inefficiencies, especially the burning of wet or “green” wood, significantly increase PM emission factors [86]. These characteristics amplify the sensitivity of air quality to periods of atmospheric stability, explaining why our models show sharp increases in predicted exceedances under shallow boundary-layer depths.

The contrast with neighboring countries such as Argentina, Peru, and Bolivia, where natural gas availability reduces emissions from solid fuels [87], highlights that the magnitude of threshold transitions in southern Chile is determined less by regional climate and more by the intensity and persistence of local combustion sources. The limited public awareness of the air-quality impacts of wood burning reported in previous studies [88,89] further contributes to sustained emission levels, which, in turn, increase the likelihood that episodes of low ventilation will trigger higher regulatory categories in our classification models.

Estimates based on national surveys and regional studies confirm the extent of firewood use as an energy source in southern Chile. According to the 2013 CASEN Survey (Encuesta de Caracterización Socioeconómica Nacional), 81.8% of households in the south-central regions reported using firewood for heating or cooking, underscoring its dominant role in the country’s residential energy matrix [90]. Even more strikingly, a study conducted in the city of Osorno found that 95.5% of households purchased firewood for domestic use, revealing the profound dependence on this fuel in colder southern regions [89]. Consequently, the results of this study should be interpreted within this broader socio-environmental framework, where effective air quality management demands integrated policies that combine energy efficiency, environmental education, and social equity; simultaneously addressing the economic accessibility, thermal culture, and energy vulnerability that characterize southern Chile. International experience indicates that community education campaigns and household stove modernization programs could help substantially mitigate this burden, potentially reducing emissions from wood burning by up to 60% by 2030 [68,69].

Model validation results (Figure 4) reveal that the best performance was obtained under the ESP thresholds, where the model achieved the highest sensitivities and F1-scores, particularly for the Regular category. For instance, at CRC, PM₁₀ reached a sensitivity of 65.2% and an F1-score of 0.72, while at COY, PM_{2.5} achieved 56.7% and 0.59, respectively. These values indicate that, when the thresholds are less restrictive, the model achieves a better balance between sensitivity and accuracy, effectively identifying polluted days. In contrast, under the NCh and INT standards, performance declined markedly, especially for the Pre-emergency and Emergency categories, where both sensitivity and F1-score were

near zero. This indicates that the model behaves conservatively, avoiding false alarms but failing to detect most critical pollution events.

Station-specific validation highlights clear spatial contrasts. COY, located in the southernmost region with the highest exceedance frequency, showed the greatest predictive consistency under the ESP framework. Superior performance likely stems from the greater frequency and persistence of critical episodes, which provide the model with a larger sample of positive cases and, consequently, a stronger learning base. This behavior aligns with observations by Vélez-Pereira et al. [51], who reported that logistic regression models perform better in areas with frequent exceedances. At the same time, sensitivity decreases in cleaner environments with fewer high-pollution days.

This relationship between model performance and threshold severity also reflects a structural and political dimension. Although the World Health Organization (WHO) recommends stricter guideline values for PM_{10} and $PM_{2.5}$, Chile maintains comparatively lenient national standards due to the socioeconomic implications of adopting more stringent limits—particularly in the south, where residential heating depends heavily on firewood. Studies by Schueftan and Sommerhoff [56] and Vergara-Vásquez et al. [8] emphasize that energy vulnerability and the high costs of transitioning to cleaner heating systems constrain the implementation of rigorous air-quality policies. Consequently, higher sensitivities under ESP thresholds do not merely reflect better statistical performance but also mirror the reality of more frequent exceedances relative to international benchmarks. In that sense, the model's predictive response captures both the regulatory context and the energy dependence that shape southern Chile's air-quality dynamics, where achieving WHO-level standards would require substantial socioeconomic transformation.

When compared with other modeling strategies, logistic regression achieved a satisfactory balance between sensitivity and precision, yielding competitive F1-scores relative to multiple linear models [91,92]. While advanced nonlinear or machine learning methods, such as Random Forest, Support Vector Machines, or Neural Networks, often deliver higher predictive accuracy [49,93–95], yet they also demand greater computational resources and often sacrifice interpretability. In contrast, logistic regression preserves clarity and transparency, relying on interpretable coefficients and modest data requirements, features that make it particularly suitable for local-scale applications and institutional contexts with limited technical capacity.

Although the model developed in this study does not match the precision of high-resolution numerical forecasts or complex data-driven approaches, logistic regression offers an accessible and transparent framework for supporting air quality management. The method identifies probabilistic risk scenarios by integrating meteorological and socio-environmental variables that explain threshold exceedances. Within the framework of Chile's Atmospheric Decontamination Plans (PDA); for example, DS No. 7/2019 for Coyhaique; such modeling can complement operational systems by identifying periods and locations with a higher likelihood of standard exceedance, guiding preventive and adaptive management actions. In summary, logistic regression represents a pragmatic, interpretable, and low-cost analytical tool that complements more sophisticated prediction models. Beyond forecasting, the approach strengthens understanding of how meteorological, regulatory, and social drivers converge to shape air pollution patterns, providing a sound empirical foundation for advancing air-quality governance in southern Chile.

5. Conclusions

This study shows that logistic regression effectively models the relationship between weather conditions and the chances of surpassing PM_{10} and $PM_{2.5}$ concentration limits in various urban areas of southern Chile. Instead of aiming for long-term predictions, the

model offers a clear, quantitative way to estimate the likelihood of exceedance using easily accessible weather data, making it a straightforward and efficient tool for short-term risk assessment. The differences seen between stations emphasize the significant role of local dispersion and emission patterns in the model's predictions. Thresholds linked to poor air circulation showed the greatest sensitivity to weather changes, aligning with patterns seen in areas impacted by residential burning. Comparing different regulatory standards shows that the probabilities of exceeding limits vary greatly depending on how these thresholds are defined—highlighting the need to consider these definitions carefully when analyzing pollution episodes. Overall, our results suggest that logistic models are a valuable part of early warning systems for particulate matter pollution, especially where detailed emission data is lacking but weather data is regularly available. Future research should explore building on this approach with validation metrics that account for uncertainty, alternative machine learning methods, and combining these models with dispersion or chemical transport models to improve the reliability and usefulness of exceedance forecasts in complex terrains and diverse emission settings.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/atmos16121377/s1>, Figure S1: Daily, monthly, and weekly behavior of PM₁₀ and PM_{2.5} concentrations in Curicó (CRC), Maule Region; Figure S2: Daily, monthly, and weekly behavior of PM₁₀ and PM_{2.5} concentrations in Puren (PEN), Ñuble Region; Figure S3: Daily, monthly, and weekly behavior of PM₁₀ and PM_{2.5} concentrations in 21 de Mayo (MAY), Biobío Region; Figure S4: Daily, monthly, and weekly behavior of PM₁₀ and PM_{2.5} concentrations in Padre Las Casas (PLC), Araucanía Region; Figure S5: Daily, monthly, and weekly behavior of PM₁₀ and PM_{2.5} concentrations in Valdivia (VAL), Los Ríos Region; Figure S6: Daily, monthly, and weekly behavior of PM₁₀ and PM_{2.5} concentrations in Osorno (OSO), Los Lagos Region; Figure S7: Daily, monthly, and weekly behavior of PM₁₀ and PM_{2.5} concentrations in Coyhaique (COY), Aysén Region; Figure S8: Seasonal cycle of daily mean concentrations of PM₁₀ and PM_{2.5} for all stations included in the study; Table S1: Logistic regression coefficients for the Good category according to the Chilean, International, and European thresholds for PM₁₀; Table S2: Logistic regression coefficients for the Regular category according to the Chilean, International, and European thresholds for PM₁₀; Table S3: Logistic regression coefficients for the Alert category according to the Chilean, International, and European thresholds for PM₁₀; Table S4: Logistic regression coefficients for the Pre-emergency category according to the Chilean, International, and European thresholds for PM₁₀; Table S5: Logistic regression coefficients for the Emergency category according to the Chilean, International, and European thresholds for PM₁₀; Table S6: Logistic regression coefficients for the Good category according to the Chilean, International, and European thresholds for PM_{2.5}; Table S7: Logistic regression coefficients for the Regular category according to the Chilean, International, and European thresholds for PM_{2.5}; Table S8: Logistic regression coefficients for the Alert category according to the Chilean, International, and European thresholds for PM_{2.5}; Table S9: Logistic regression coefficients for the Pre-emergency category according to the Chilean, International, and European thresholds for PM_{2.5}; Table S10: Logistic regression coefficients for the Emergency category according to the Chilean, International, and European thresholds for PM_{2.5}; Table S11: Comparative summary of annual PM concentrations and per capita emissions in wood-burning-dependent cities from Europe and Chile. References [96–104] are cited in the supplementary materials.

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Abbreviations

The following abbreviations are used in this manuscript:

AQI	Air Quality Index
COY	Coyhaique monitoring station
CRC	Curicó monitoring station
CR2	Climate Science and Resilience Center (Centro de Ciencia del Clima y la Resiliencia, Chile)
EEA	European Environment Agency
EPA	Environmental Protection Agency
ESP	European Air Quality Standard
HR	Relative Humidity
INT	International Air Quality Index (U.S. EPA)
Logit	Logistic Regression Model
l1.pp	Precipitation with a one-day lag
l2.pp	Precipitation with a two-day lag
l3.pp	Precipitation with a three-day lag
MAY	21 de Mayo monitoring station
ML	Machine Learning
NCh	Chilean Primary Air Quality Standard
OP	Oxidative Potential
OSO	Osorno monitoring station
PAHs	Polycyclic Aromatic Hydrocarbons
PEN	Pemuco monitoring station
PM	Particulate Matter
PM _{2.5}	Particulate Matter with aerodynamic diameter $\leq 2.5 \mu\text{m}$
PM ₁₀	Particulate Matter with aerodynamic diameter $\leq 10 \mu\text{m}$
PP	Precipitation
SINCA	National Air Quality Information System of Chile (Sistema de Información Nacional de Calidad del Aire)
ws	Wind speed

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