APPENDIX XII

MATES V

FINAL REPORT

Biomass Burning Contribution to PM2.5 (Levoglucosan Data Analysis)

Appendix XII

Biomass Burning Contribution to PM2.5 (Levoglucosan Data Analysis)

XII.1. Introduction

MATES is a study that focuses on the measurement and modeling of ambient air toxics for the primary purpose of evaluating health risks due to air pollution. As part of MATES V, levoglucosan, a key tracer of wood smoke, was measured alongside other particulate species at all ten fixed monitoring sites. The addition of levoglucosan measurements provided insight into pollution sources that influence both basin-wide and localized health risks and also allowed for improvement to pollution forecast models to help residents minimize their exposures to air pollution.

Wood smoke from residential wood burning is an important source of wintertime fine particulate matter (PM2.5) in the South Coast Air Basin (South Coast Air Quality Management District, 2008) and concentrations are influenced by both meteorology and human behavior. Levoglucosan is a component of PM2.5 produced during wood burning (Fine, et al., 2001) and was measured in the months leading up to and throughout the MATES V campaign from January 2018 to April 2019. The acquisition of levoglucosan data provided staff with the opportunity to create a forecasting tool specifically tailored to residential wood burning patterns in the Basin. Machine learning techniques were used to create a forecasting model for residential wood smoke based on levoglucosan observations during the MATES V period. The levoglucosan observations are referred to as the 'training data' for the model. The influence of meteorology on wood smoke concentrations is represented in the model by meteorological forecast data from the North American Mesoscale (NAM) model (National Centers for Environmental Information, 2020). The influence of human behavior on wood smoke concentrations is represented in the model by calendar-based patterns such as day of week and holidays. Levoglucosan concentrations are modeled with these predictor variables and then conversion factors are used to estimate the PM2.5 concentrations due to wood smoke.

This forecast tool can be used to both estimate wood smoke concentrations on days without MATES V measurements and to predict concentrations on any day with NAM meteorological forecast data—up to three days into the future. South Coast AQMD staff issue a daily air quality forecast for the entirety of Los Angeles, Orange, San Bernardino, and Riverside counties, which takes into account forecasted concentrations of ozone, PM2.5, PM10, carbon monoxide, and nitrogen dioxide. Air quality forecasting models used by South Coast AQMD staff to issue the daily forecast do not completely account for the strong dependence of wood smoke PM2.5 on calendar and meteorological parameters. However, the levoglucosan model can be used to improve PM2.5 predictions during the winter months in the Basin as part of the daily air quality forecast.

XII.2. Background

Levoglucosan (1,6-anhydro-β-D-glucopyranose), a thermal degradation product of cellulose and hemicellulose, is a widely used tracer of biomass burning contributions to atmospheric particulate loading (Simoneit, 2002). Levoglucosan has been shown to be present at very high concentrations in fine particulate (PM2.5) emissions from both residential wood combustion (Schauer, et al., 2001; Fine, et al., 2002) and wildland biomass combustion (Sullivan, et al., 2008; Hosseini, et al., 2013), making it a robust indicator for key biomass burning processes in the Basin. Although particulate levoglucosan concentrations may be reduced by photochemical oxidation (Hennigan, et al., 2010; Hennigan, et al., 2011; Hoffmann, et al., 2010), this effect is mitigated by the dominance of local pollution sources and relatively short distances between monitors within the Basin (South Coast Air Quality Management District, 2016). Additionally, levoglucosan is more stable at cooler temperatures observed in winter (Pratap, et al., 2019) when residential wood burning is most common (South Coast Air Quality Management District, 2008). To date, several studies have incorporated levoglucosan into receptor modeling studies to better characterize the contribution of biomass burning/wood smoke to total PM2.5 mass or PM2.5 organic carbon in the Basin (South Coast Air Quality Management District, 2008; Heo, et al., 2013; Shirmohammadi, et al., 2016).

In addition to levoglucosan, other minor monosaccharide anhydrides produced during hemicellulose pyrolysis can provide further insight into the predominant biomass fuel type. The relative yields of levoglucosan and its isomers mannosan (1,6-anhydro-β-D-mannopyranose) and galactosan (1,6-anhydro-β-D-galactopyranose) have been shown to be characteristic of burns of different vegetation types (e.g., hardwood, softwood, grass, etc.) (Sullivan, et al., 2008; Fine, et al., 2004). Metrics such as the levoglucsoan/mannosan ratio in particulates can thus be used to distinguish different biomass burning sources provided sources are derived from sufficiently distinct vegetation types.

XII.3. Levoglucosan Measurement Methods

Levoglucosan and other monosaccharide anhydrides were analyzed using a method adapted from procedures described in (California Air Resources Board, 2015; Cordell, et al., 2014; Schauer & Sioutas, 2012). Fine particulate matter (PM2.5) for levoglucosan analysis was collected by ambient air filtration onto quartz fiber filters on a dedicated channel of a speciated air sampling system (SASS) PM2.5 sampler at each site. Samples were collected on a 1-in-6 day schedule at all ten fixed MATES V sites except for Central L.A. and Rubidoux, where sampling frequency was increased to a 1-in-3 day schedule to better characterize temporal variability. Prior to analysis, filters were spiked with an internal standard ($^{13}C_6$-levoglucosan) and extracted by ultrasonication in acetonitrile. Extracts were then derivatized with a silanizing reagent to convert monosaccharide anhydrides to trimethylsilyl (TMS) derivatives suitable for gas chromatography-mass spectrometry (GC-MS) analysis. Samples were analyzed by GC-MS using a simultaneous selective ion monitoring (SIM)/full scan method and quantified by comparison to authenticated standards for each compound of interest. Further sampling and analytical details can be found in Appendix III.

XII.4. Levoglucosan Observations

Average levoglucosan concentrations measured at each station over the MATES V analysis period (May 2018-April 2019) are shown in Figure XII-1. With the exception of Compton, average MATES V levoglucosan concentrations at all sites were generally comparable to site averages of 45-60 ng/m^3 measured during the second year of MATES III from May 2005 – April 2006 (South Coast Air Quality Management District, 2008).[1] As expected, levoglucosan concentrations at all sites were much higher during late fall/winter due to increased residential wood burning during cooler months (Figure XII-2). Late fall/winter levoglucosan concentrations at Compton were generally higher than concentrations measured at other sites, which could reflect increased wood burning in this area or closer proximity to a local biomass burning source. Average winter (December-February) mannosan/levoglucosan ratios ranged from 5.5 to 6.3 across the basin, which is consistent with softwood-dominated or mixed hardwood/softwood burning based on reported ranges in the literature ((Fabbri, et al., 2009) and references therein).

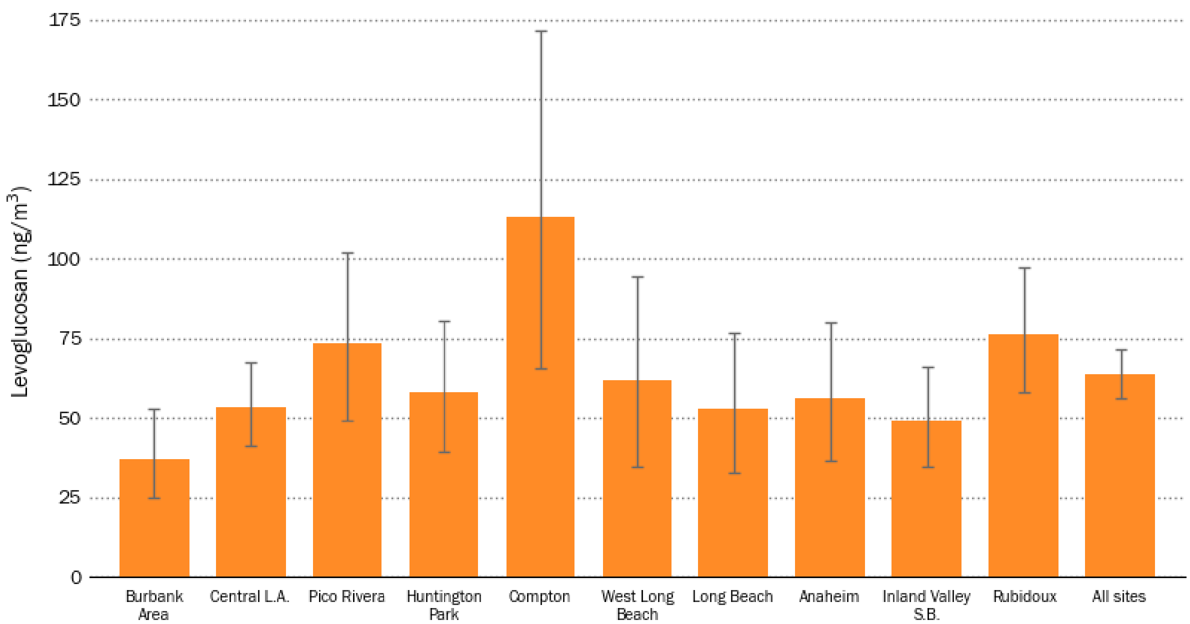


Figure XII-1. Kaplan-Meier mean levoglucosan concentrations measured at MATES V sites from May 2018 to April 2019. Error bars represent 95% confidence intervals of averages. The station name Inland Valley San Bernardino is abbreviated as Inland Valley S.B.

[1] Results from three sites (Huntington Park, Long Beach, and Pico Rivera) with incomplete levoglucosan MATES III Year 2 datasets are not included in this range.

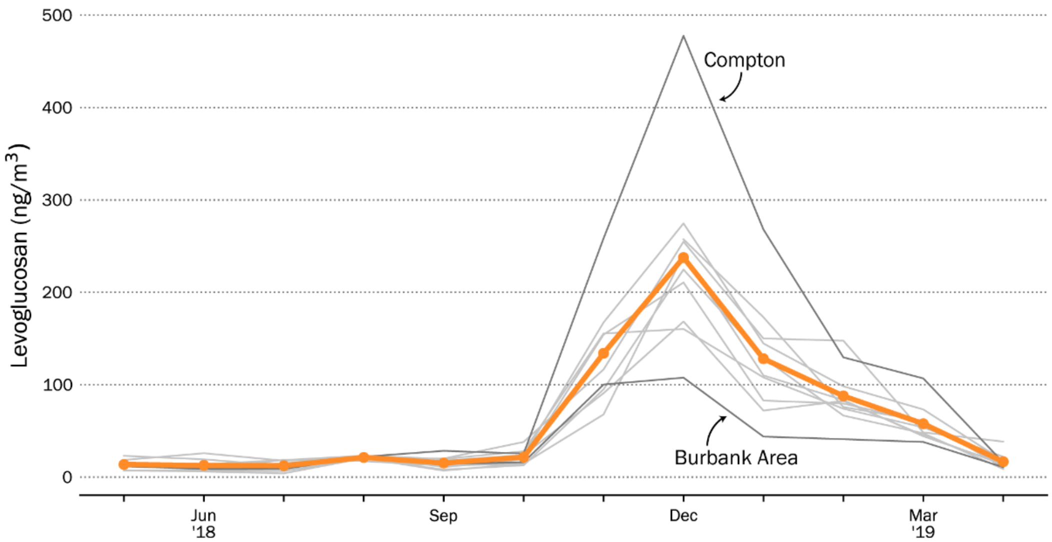


Figure XII-2. Monthly average levoglucosan concentrations during MATES V monitoring period. Gray lines show monthly averages at individual sites, and bold orange line shows Basin (ten site) average.

Outside of the winter wood burning season, several peaks in levoglucosan concentrations coincided with local wildfires or smoke plumes from wildfires outside the Basin, although the magnitude of these peaks was variable. These events included transport of smoke into the basin from northern California wildfires on August 24, 2018 and from the Woolsey/Hill Fires in Ventura County and western Los Angeles County on November 10, 2018. Both events were marked by higher levoglucosan concentrations at sites in the western and coastal portions of the Basin, consistent with westerly transport of smoke into the SCAB. The Euclid Fire south of Chino also may have contributed to an elevated levoglucosan concentration of 108 ng/m^3 at Rubidoux on June 13, 2018 compared to a summer station average of 21 ng/m^3.

XII.5. Conversion Factors

Observed and model forecasted levoglucosan concentrations at each station were scaled by a conversion factor, defined as the ratio of wood smoke PM2.5 to levoglucosan, to estimate total PM2.5 mass due to wood smoke. This conversion factor is a major source of uncertainty for wood smoke PM2.5 estimates since it depends on the fuel burned, the characteristics of the burn (e.g., combustion temperature, combustion efficiency), the age of the smoke, ambient temperature, and actinic flux (Fine, et al., 2001; Fine, et al., 2002; Fine, et al., 2004; Schauer, et al., 2001; Sullivan, et al., 2008; Kuo, et al., 2011; Hennigan, et al., 2011; Hoffmann, et al., 2010; Sang, et al., 2016; Pratap, et al., 2019). This uncertainty is represented in the variety of conversion factors ranging from 8.33 to 41.7 that were either reported in studies or calculated from several studies, see Table XII-1. To empirically constrain the wide range of conversion factors found in the literature, levoglucosan observations with co-located speciated PM2.5 data were analyzed. Several conversion factors reported in the literature produced calculated wood smoke PM2.5 concentrations that were larger than the measured total PM2.5. A maximum empirical conversion factor could be determined by assuming that all of the PM2.5 mass with the exception of soil, ammonium nitrate, and ammonium sulfate was wood smoke PM2.5. The smallest of these empirical conversion factors was used as the new upper-bound estimate of the conversion factors. The lowest conversion factor from the literature (Table XII-1) was used as a lower-bound estimate of the PM2.5 due to wood smoke. The levoglucosan forecast model outputs a lower-bound estimate of the PM2.5 due to wood smoke using the smallest conversion factor from the literature (8.33, see Table XII-1) and an upper-bound estimate of PM2.5 due to wood smoke using the smallest empirical conversion factor (16.39).

Applying this conversion factor range to measured winter levoglucosan concentrations illustrates the potential significance of wood smoke contributions to total PM2.5 mass in the SCAB. From December 2018-February 2019, the period during MATES V when residential wood burning would be expected to reach peak levels, levoglucosan alone constituted an average of 0.8-1.9% of total PM2.5 mass measured at each site (Table XII-1). Winter levoglucosan/PM2.5 mass ratios did not show any clear spatial trend, with average levoglucosan concentrations remaining relatively close to 1% of total mass at most sites. The only exception was at Compton, where levoglucosan represented a larger fraction of average winter PM2.5 mass (1.9%). After applying the range of conversion factors determined above, observed levoglucosan concentrations would translate to wood burning contributions ranging from 7-32% (0.5-4.8 $\mu g/m^3$) of total winter PM2.5 mass at individual sites, with a basin average of 11-21% (1.3-2.5 $\mu g/m^3$). These levoglucosan-based estimates are somewhat higher than estimated winter biomass burning contributions at Central L.A. and Rubidoux from 2002-2007 determined using a Positive Factorization Matrix (PMF) receptor model (Central L.A.: 1.7 $\mu g/m^3$/8.3% PM2.5 mass, Rubidoux: 1.0 $\mu g/m^3$/5.0% PM2.5 mass (Hasheminassab, et al., 2014)). However, this finding is consistent with a decrease in emissions from non-wood smoke PM2.5 sources relative to wood smoke PM2.5 sources.

Table XII-1: Conversion factors derived from literature for use in wood smoke model.

Conversion Factor	Citation	Notes
8.3333	(Fine, et al., 2001)	Calculated from numbers in the paper: "The results in Table 3 also indicate that almost all of the emitted fine particulate mass consists of organic compounds. Organic carbon contributes over 80% of the fine particle mass in the emissions from every wood species studied." "Between 3% and 12% of the fine particulate organic compound emissions are accounted for by levoglucosan"
9.01	(Busby, et al., 2016)	"We used a combination of the experimental and published values for L_A, L_B and L_S to establish a low and a high estimate of the conversion factor. Using only the most relevant published results (Fine et al., 2004a) gives a [conversion factor] = 9.01, which is used here as a lower limit" "L_A, L_B, and L_S are the levoglucosan mass fractions for aspen, birch, and spruce woodsmoke respectively."
10.4	(Busby, et al., 2016) (citations therein)	"Piazzalunga et al. (2011) generated conversion factors of 10.4 using literature values and 16.9 using [positive matrix factorization] in Italy."
10.4167	(Fine, et al., 2001)	Calculated from numbers in the paper: "The results in Table 3 also indicate that almost all of the emitted fine particulate mass consists of organic compounds. Organic carbon contributes over 80% of the fine particle mass in the emissions from every wood species studied." "Between 3% and 12% of the fine particle organic compound emissions are accounted for by levoglucosan"
10.7	(Busby, et al., 2016) (citations therein)	"Schmidl et al. (2008) and Caseiro et al. (2009) measured, reported and used a conversion factor of 10.7 to calculate wood smoke particulate from levoglucosan."
10.7	(Busby, et al., 2016) (citations therein)	"Herich et al. (2014) compared results for multiple studies in alpine regions of Europe and found that wood smoke PM to levoglucosan ratios varied from 10.7 to 25.2."
10.72	(Busby, et al., 2016)	"Using all data and the minimum and maximum wood smoke PM2.5 estimates from the [carbon-14 analysis methods] data yielded [conversion factor] = 10.72 ± 0.61 and 12.91 ± 0.74, respectively."
11.31	(Busby, et al., 2016)	slope of [carbon-14 analysis methods] vs levoglucosan, removing the highest point
11.45	(Busby, et al., 2016)	"Another approach is to calculate and average the ratios of wood smoke PM2.5 to levoglucosan for each sample. Using minimum and maximum estimates for wood smoke PM2.5 from the

		[carbon-14 analysis methods] data yielded mean [conversion factor] values of 11.45 ± 0.89 and 13.8 ± 1.1, respectively."
11.46	(Busby, et al., 2016)	slope of [carbon-14 analysis methods] vs levoglucosan, removing the 4 highest points
11.82	(Busby, et al., 2016)	"analyses. Fig. 2(b) demonstrates a high correlation between the levoglucosan and [carbon-14 analysis methods] measures with a slope ([conversion factor]) of 11.82 ± 0.67 (r2 = 0.97, F = 1257, n = 40)."
12.2	(Busby, et al., 2016)	"device type data by zip code was utilized together with wood species survey data to generate site-specific [conversion factor] values weighted for both wood species and device type. These conversion factors, calculated using LB and LS from Table 3 and the published value for LA, ranged from 12.2–12.4. There was significant concern about these site-specific results because of the combined uncertainties in L values, wood species usage, and stove type usage. Because of this, and because they are bracketed by [lower and upper bound conversion factors], they were not used for additional calculations."
12.4	(Busby, et al., 2016)	"device type data by zip code was utilized together with wood species survey data to generate site-specific [conversion factor] values weighted for both wood species and device type. These conversion factors, calculated using LB and LS from Table 3 and the published value for LA, ranged from 12.2–12.4. There was significant concern about these site-specific results because of the combined uncertainties in L values, wood species usage, and stove type usage. Because of this, and because they are bracketed by [lower and upper bound conversion factors], they were not used for additional calculations."
12.91	(Busby, et al., 2016)	"Using all data and the minimum and maximum wood smoke PM2.5 estimates from the [carbon-14 analysis methods] data yielded [conversion factor] = 10.72 ± 0.61 and 12.91 ± 0.74, respectively."
13.3	(Busby, et al., 2016)	"An upper limit [conversion factor] was calculated using the average experimental values for LB and LS from Table 3 over all burn conditions and the published value of LA. The resulting [conversion factor] = 13.3 is strongly influenced (43%) by the published value for aspen."
13.8	(Busby, et al., 2016)	"Another approach is to calculate and average the ratios of wood smoke PM2.5 to levoglucosan for each sample. Using minimum and maximum estimates for wood smoke PM2.5 from the [carbon-14 analysis methods] data yielded mean [conversion factor] values of 11.45 ± 0.89 and 13.8 ± 1.1, respectively."
15.12	(Busby, et al., 2016)	"wood smoke PM2.5 concentration estimated from [chemical mass balance] is plotted vs the measured levoglucosan levels …"

		"Separate regression of the results at the three sites yields slopes of 15.12 ± 0.39 (r2 = 0.96, F = 1470, n = 57), 23.3 ± 2.2 (r2 = 0.89, F = 464, n = 58) and 19.8 ± 2.5 (r2 = 0.84, F = 245, n = 46) at the North Pole, Peger Rd., and State Building sites, respectively. The slopes are estimates of the [conversion factor] values assuming that [chemical mass balance] modeling provides an accurate estimate of wood smoke PM2.5."
16.9	(Busby, et al., 2016) (citations therein)	"Piazzalunga et al. (2011) generated conversion factors of 10.4 using literature values and 16.9 using [positive matrix factorization] in Italy."
18.3	(Busby, et al., 2016) (citations therein)	"Zhang et al. (2010a) used [positive matrix factorization] to obtain a conversion factor of 18.3 for the southeastern US"
19.8	(Busby, et al., 2016)	"wood smoke PM2.5 concentration estimated from [chemical mass balance] is plotted vs the measured levoglucosan levels … "Separate regression of the results at the three sites yields slopes of 15.12 ± 0.39 (r2 = 0.96, F = 1470, n = 57), 23.3 ± 2.2 (r2 = 0.89, F = 464, n = 58) and 19.8 ± 2.5 (r2 = 0.84, F = 245, n = 46) at the North Pole, Peger Rd., and State Building sites, respectively. The slopes are estimates of the [conversion factor] values assuming that [chemical mass balance] modeling provides an accurate estimate of wood smoke PM2.5."
23.3	(Busby, et al., 2016)	"wood smoke PM2.5 concentration estimated from [chemical mass balance] is plotted vs the measured levoglucosan levels … "Separate regression of the results at the three sites yields slopes of 15.12 ± 0.39 (r2 = 0.96, F = 1470, n = 57), 23.3 ± 2.2 (r2 = 0.89, F = 464, n = 58) and 19.8 ± 2.5 (r2 = 0.84, F = 245, n = 46) at the North Pole, Peger Rd., and State Building sites, respectively. The slopes are estimates of the [conversion factor] values assuming that [chemical mass balance] modeling provides an accurate estimate of wood smoke PM2.5."
25.2	(Busby, et al., 2016) (citations therein)	"Herich et al. (2014) compared results for multiple studies in alpine regions of Europe and found that wood smoke PM to levoglucosan ratios varied from 10.7 to 25.2."
33.3333	(Fine, et al., 2001)	Calculated from numbers in the paper: "The results in Table 3 also indicate that almost all of the emitted fine particulate mass consists of organic compounds. Organic carbon contributes over 80% of the fine particle mass in the emissions from every wood species studied." "Between 3% and 12% of the fine particulate organic compound emissions are accounted for by levoglucosan"

35.25	(Villalobos, et al., 2017)	Calculated from numbers in the paper: "wood burning is responsible for 84.6%", "The mean levoglucosan/PM2.5 ratio (0.021) is similar to the ratio found in Santiago (0.024)". Lev/PM2.5_tot = 0.024, PM2.5_wood/PM2.5_tot = 0.846, solve for PM2.5_wood, which gives a conversion factor of 0.846/0.024 = 35.25
40.29	(Villalobos, et al., 2017)	Calculated from numbers in the paper: "wood burning is responsible for 84.6%", "The mean levoglucosan/PM2.5 ratio (0.021) is similar to the ratio found in Santiago (0.024)". Lev/PM2.5_tot = 0.021, PM2.5_wood/PM2.5_tot = 0.846, solve for PM2.5_wood, which gives a conversion factor of 0.846/0.021 = 40.29
41.6667	(Fine, et al., 2001)	Calculated from numbers in the paper: "The results in Table 3 also indicate that almost all of the emitted fine particulate mass consists of organic compounds. Organic carbon contributes over 80% of the fine particle mass in the emissions from every wood species studied." "Between 3% and 12% of the fine particulate organic compound emissions are accounted for by levoglucosan"

Table XII-2. Average winter (December 2018-February 2019) PM2.5 and levoglucosan concentrations and estimated biomass burning contributions to total PM2.5 at MATES V sites. Low and high estimates were calculated with levoglucosan-PM2.5 conversion factors of 8.33 and 16.4, respectively.

Station	$PM_{2.5}$ mass ($\mu g/m^3$)	Levoglucosan (ng/m^3)	Levoglucosan/$PM_{2.5}$ (%)	Estimated biomass burning $PM_{2.5}$ ($\mu g/m^3$)		Estimated biomass burning contribution to total $PM_{2.5}$ (%)	
				Low	High	Low	High
Burbank Area	7.76	64	0.83	0.53	1.1	6.9	14
Central L.A.	10.71	127	1.18	1.1	2.1	9.8	19
Pico Rivera	13.53	178	1.31	1.5	2.9	11	22
Huntington Park	12.55	124	0.99	1.0	2.0	8.3	16
Compton	15.10	292	1.93	2.4	4.8	16	32
West Long Beach	13.82	168	1.22	1.4	2.8	10	20
Long Beach	11.94	140	1.17	1.2	2.3	9.8	19
Anaheim	12.48	145	1.16	1.2	2.4	9.6	19
Inland Valley S.B.	10.82	108	0.99	0.90	1.8	8.3	16
Rubidoux	12.66	188	1.48	1.6	3.1	12	24
Basin Average	12.14	153	1.26	1.3	2.5	11	21

XII.6. Model Training Data

Levoglucosan observations included the measurements made at 10 stations from May 2018 through April 2019, and additional measurements during the lead-up period to MATES V (January-April 2018). All of these measurements were incorporated into a training set for a new wood smoke forecasting model. Four levoglucosan observations were removed from the training set because they were impacted by smoke according to Hazard Mapping System (HMS) smoke plume data (National Oceanic and Atmospheric Administration Office of Satellite and Product Operations, 2020; NOAA OSEPO, 2020), and thus not representative of residential wood burning. Three additional observations were removed due to missing data from the NAM weather model (National Centers for Environmental Information, 2020). The data for 9% of randomly-selected dates with observations were separated as a held-out data set to be used for model verification. The held-out data set contained 57 observations. The final training data set contained 854 observations. Figure XII-3 shows the time series of levoglucosan measurements by station.

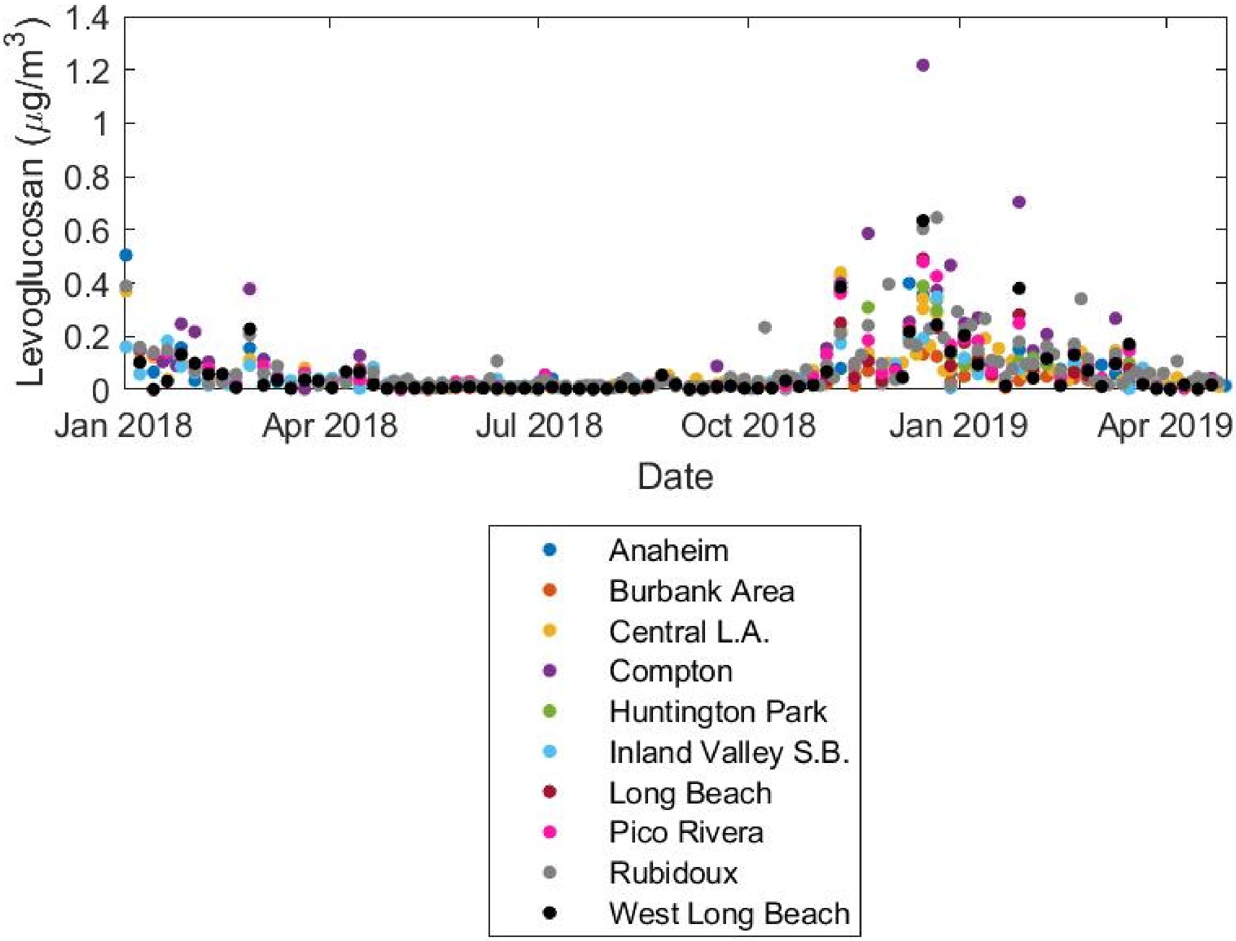


Figure XII-3: Time series of levoglucosan measurements by station.[2] The station name Inland Valley San Bernardino is abbreviated as Inland Valley S.B.

XII.7. Model Configuration

Matlab's Regression Learner® software (MathWorks, 2020) was used to train the model. First, several built-in algorithms were implemented with all predictor variables to help identify the best performing algorithm. The exponential Gaussian Process Regression (Exponential GPR) algorithm had the lowest root mean squared error (RMSE). After determining the best performing algorithm, the number of predictor variables was reduced empirically from an initial list of 33 predictor variables by removing one at a time and re-training the Exponential GPR algorithm. Removing variables can improve model performance due to collinearities among predictor variables or predictor variables not being strongly related to levoglucosan concentrations. If the RMSE improved without a variable, that variable was permanently left out

[2] One data point (Rubidoux on 10/8/2018) was invalidated after the model was operational for the 2019-2020 winter season. The invalidation of one data point in the training data is likely to cause only a minor change in the model.

of the training and the next variable was tried. This process led to a final list of 21 predictor variables included in the training (see Table XII-3).

XII.8. Predictor Variables

The model is trained to create forecasts for the 10 stations that were in the training data using 21 predictor variables, see Table XII-3 and Figure XII-4 - Figure XII-5. Station is a categorical variable indicating the name of the monitoring station, and the levoglucosan forecasts are made only at the stations with levoglucosan measurements. This variable serves as a proxy for characteristics and emission patterns of the area around each monitor. The remaining predictor variables are either calendar-based (determined by day of week, proximity to holiday, etc.) or meteorologically-driven, based on the North American Mesoscale Forecast System at a resolution of 12 km (12 km NAM) (National Centers for Environmental Information, 2020). Since the 12 km NAM model provides a forecast out to 84 hours, the levoglucosan model can be used to create a 3-day forecast.

The meteorological forecast data for the station locations were extracted by using data in the grid cell in which each monitor is located. The naming convention for the meteorological variables is that “TodayEve” variables describe a summary of the weather during 4 PM – 11 PM of the evening before the forecasted date. This is because the weather variables that promote an accumulation of PM2.5 (such as low planetary boundary height and calm winds) the evening before the forecasted date will promote higher PM2.5 concentrations the next day. “Tomorrow” in variable names indicates that the variable is a summary of the forecasted weather for the date of the forecast.

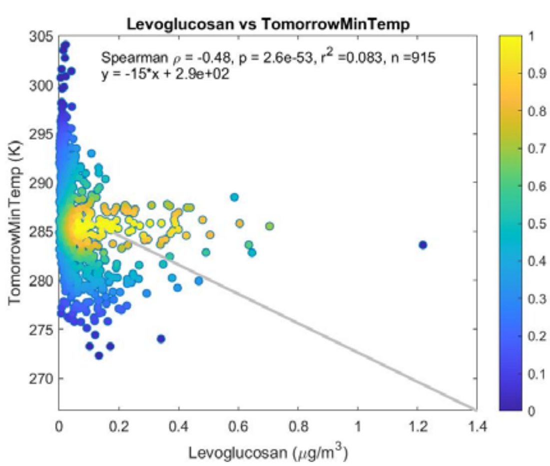
The variables used in the final version of the model and their descriptions are presented in Table XII-3. The following variables were empirically removed as predictor variables for the levoglucosan model: DayOfWeekName, Eve, TodayEveMinTemp, TodayEveMaxTemp, TodayEveRH, TodayEveUwind, TodayEveVent, TomorrowDSWRF, TomorrowMaxTemp, TomorrowPBH, TomorrowPrecip, and CumulativePM25Factors. These variables follow the naming conventions established in Table XII-3. The variable “Eve” is a categorical (binary) variable indicating if the date to be forecasted was December 24 or December 31 (‘Yes’) or any other day (‘No’). “CumulativePM25Factors” is analogous to “CumulativeFactors,” except that it is based on PM2.5 instead of levoglucosan.

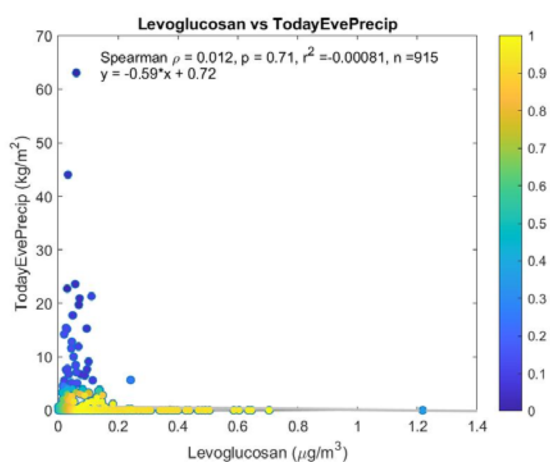
Table XII-3: Predictor Variables for Levoglucosan Forecast Model.

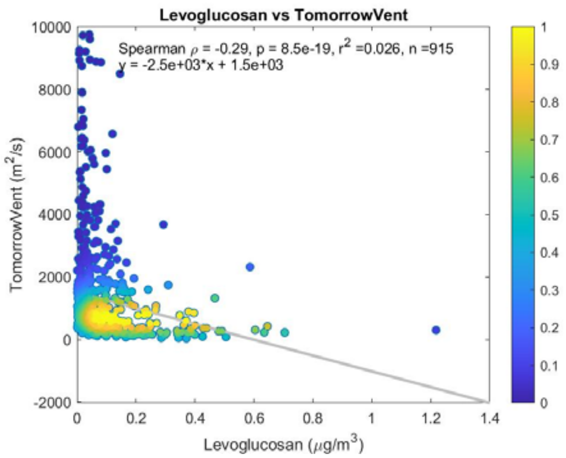
Variable	**Description**
Station	Station is a categorical variable indicating the name of the monitoring station. This variable serves as a proxy for characteristics and emission patterns of the area around each monitor.
TomorrowMinTemp	TomorrowMinTemp indicates the minimum temperature at 2 m above ground forecasted during the day of the forecast in the NAM 12 km model grid cell containing the station.
TodayEvePrecip	TodayEvePrecip is a summation of forecasted precipitation during 4 PM – 11 PM on the day before the forecast.
TomorrowVent	TomorrowVent is the average ventilation rate of the planetary boundary layer for the forecasted date.
TodayEvePBH	TodayEvePBH is the maximum planetary boundary height during 4 PM – 11 PM the day before the forecasted date.
TomorrowUwind	TomorrowUwind is the average of the east/west component of the wind at a height of 10 m above ground level for the forecasted date.
TodayEveVwind	TodayEveVwind is the average of the north/south component of the wind at height of 10 m above ground level during 4 PM – 11 PM the day before the forecasted date.
TomorrowVwind	TomorrowVwind is the average of the north/south component of the wind at a height of 10 m above ground level for the forecasted date.
TomorrowRH	TomorrowRH is the average relative humidity at a height of 2 m above ground level for the forecasted date.
TodayEveDSWRF	TodayEveDSWRF is the average downwelling shortwave radiation flux (i.e., sunlight) during 4 PM – 11 PM the day before the forecasted date.
TodayEveVwind850mb	TodayEveVwind850mb is the average north/south component of the wind at an altitude of 850 mb during 4 PM – 11 PM the day before the forecasted date.
TomorrowVwind850mb	TomorrowVwind850mb is the average north/south component of the wind at an altitude of 850 mb for the forecasted date.
TodayEveUwind850mb	TodayEveUwind850mb is the average east/west component of the wind at an altitude of 850 mb during 4 PM – 11 PM the day before the forecasted date.
TomorrowUwind850mb	TomorrowUwind850mb is the average east/west component of the wind at an altitude of 850 mb for the forecasted date.
TodayEveMinTempCat	TodayEveTempCat is a categorical variable with value ‘cold’ if TodayEveMinTemp is at or below 288 K and warm otherwise.
TomorrowMaxTempCat	TomorrowMaxTempCat is a categorical variable with value ‘cold’ if TomorrowMaxTemp is at or below 297 K and warm otherwise.

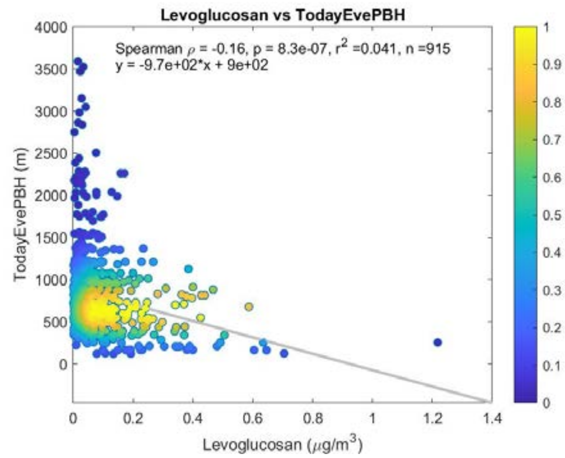
MonthName	MonthName is a categorical variable indicating the month.
Weekend	Weekend is a categorical variable indicating if a day is a weekday or part of the weekend.
HolidayType	HolidayType is a categorical variable indicating if a day was a major holiday, minor holiday, or not a holiday.
ProximityToMajorHoliday	ProximityToMajorHoliday is 0 on major holidays, -1 the day before and after a major holiday, -2 two days before or after a major holiday, or -3 three days before or after a major holiday. All other days are -4 with the assumption that holiday-related activities only influence residential wood burning patterns within three days before or after a holiday.
CumulativeFactors	CumulativeFactors is an integer variable that indicates how closely the meteorological conditions resemble aggregate descriptions of the weather conditions corresponding to the highest 10% levoglucosan concentrations. For example, if TomorrowMinTemp for a date of interest was less than the highest TomorrowMinTemp corresponding to the highest 10% of levglucosan measurements, CumulativeFactors would be increased by 1. CumulativeFactors is increased by 1 if ProximityToMajorHolidays is greater than -4. CumulativeFactors is also increased by 1 for weekends. The maximum value for CumulativeFactors would be 22.

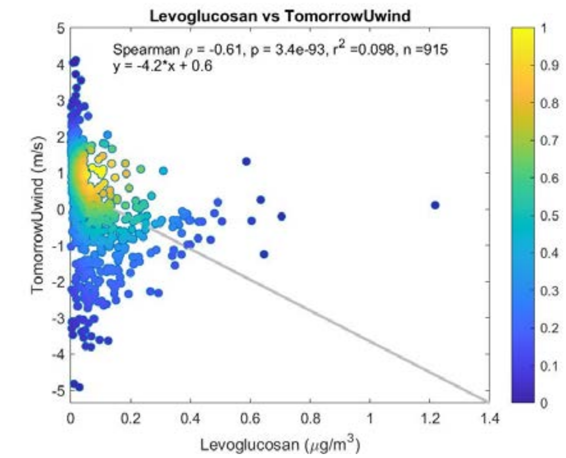
Figure XII-4 illustrates how each of the non-categorical predictors vary with levoglucosan concentration. Figure XII-5 shows the time series of levoglucosan concentration and the ProximityToMajorHoliday variable.

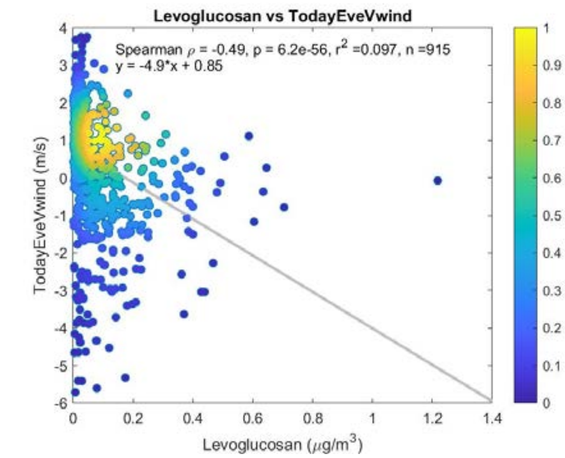


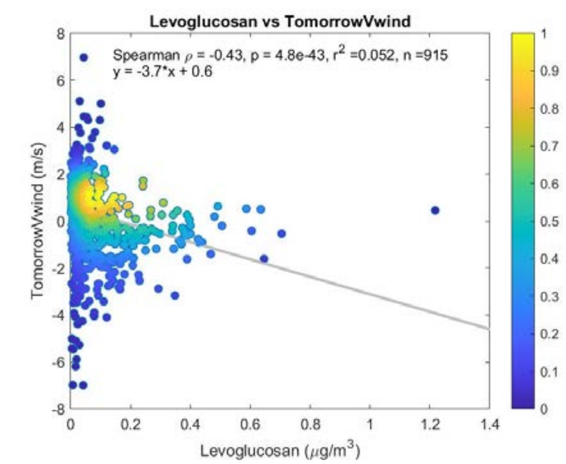


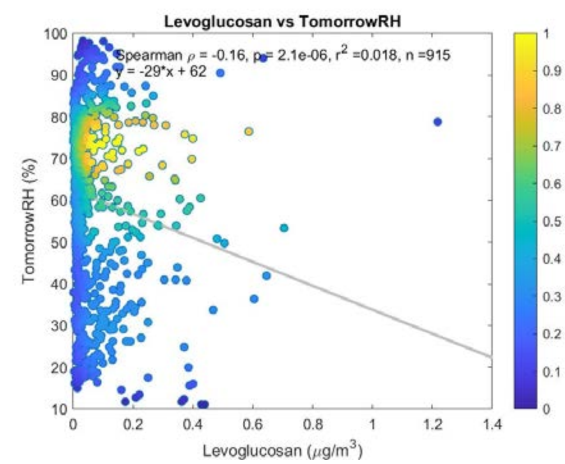

Levoglucosan vs TomorrowVent
Spearman ρ = -0.29, p = 8.5e-19, r^2 =0.026, n =915
y = -2.5e+03*x + 1.5e+03
TomorrowVent (m^2/s)
Levoglucosan (μg/m^3)


Levoglucosan vs TodayEvePBH
Spearman ρ = -0.16, p = 8.3e-07, r^2 =0.041, n =915
y = -9.7e+02*x + 9e+02
TodayEvePBH (m)
Levoglucosan (μg/m^3)


Levoglucosan vs TomorrowUwind
Spearman ρ = -0.61, p = 3.4e-93, r^2 =0.098, n =915
y = -4.2*x + 0.6
TomorrowUwind (m/s)
Levoglucosan (μg/m^3)


Levoglucosan vs TodayEveVwind
Spearman ρ = -0.49, p = 6.2e-56, r^2 =0.097, n =915
y = -4.9*x + 0.85
TodayEveVwind (m/s)
Levoglucosan (μg/m^3)


Levoglucosan vs TomorrowVwind
Spearman ρ = -0.43, p = 4.8e-43, r^2 =0.052, n =915
y = -3.7*x + 0.6
TomorrowVwind (m/s)
Levoglucosan (μg/m^3)


Levoglucosan vs TomorrowRH
Spearman ρ = -0.16, p = 2.1e-06, r^2 =0.018, n =915
y = -29*x + 62
TomorrowRH (%)
Levoglucosan (μg/m^3)

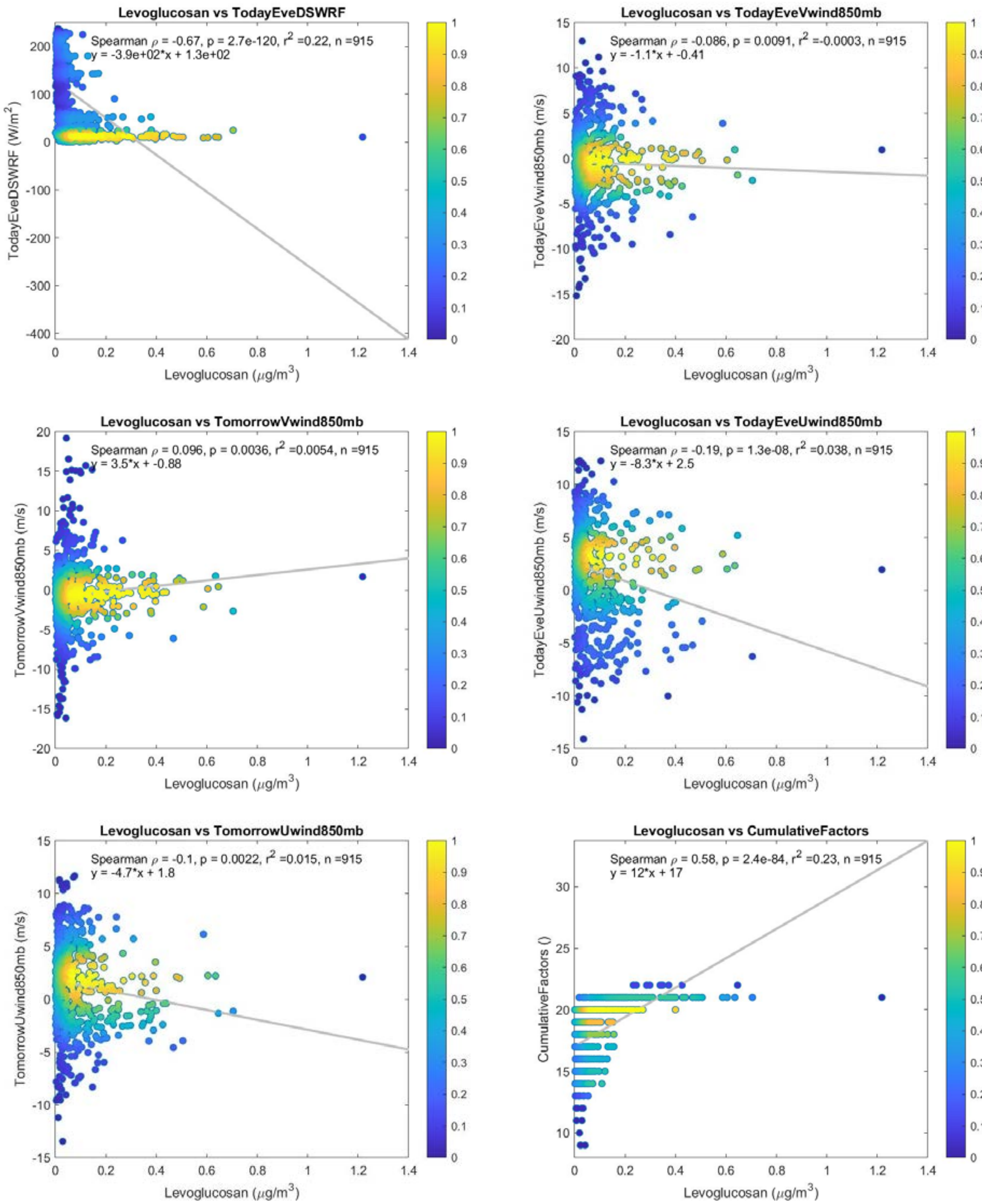


Figure XII-4: Density scatter plots of levoglucosan and the weather variables in Table XII-3. The color bars indicate the relative density of data points next to each other, as data can be plotted on top of each other in scatter plots.

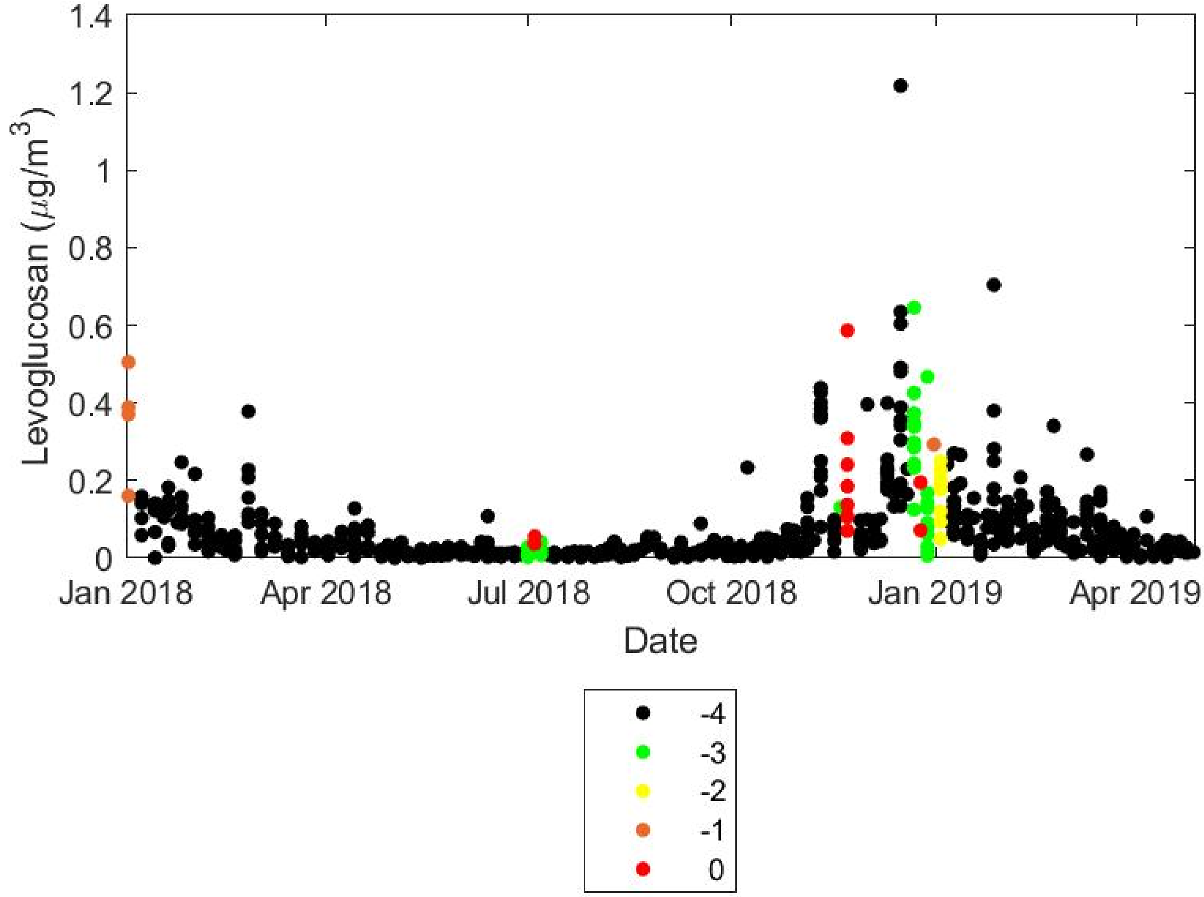


Figure XII-5: Time series of Proximity to Major Holiday variable. The different colored dots represent the number of days before or after a major holiday, with 0 being the holiday date, -1, -2, and -3 being one, two, or three days before or after a major holiday, respectively. All other days are considered "-4", with the assumption that holiday-related activities only influence residential wood burning patterns within three days before or after a holiday.

XII.9. Model Performance

The training used 10-fold cross validation, and the Regression Learner application calculated an RMSE of 0.049 ug/m3 and an R-squared of 0.73. Figure XII-6 shows the scatter plot of the 57 held-out data points and the corresponding prediction from the model (hindcast). The RMSE and R-squared for the held-out data set are 0.0554 and 0.85, respectively.

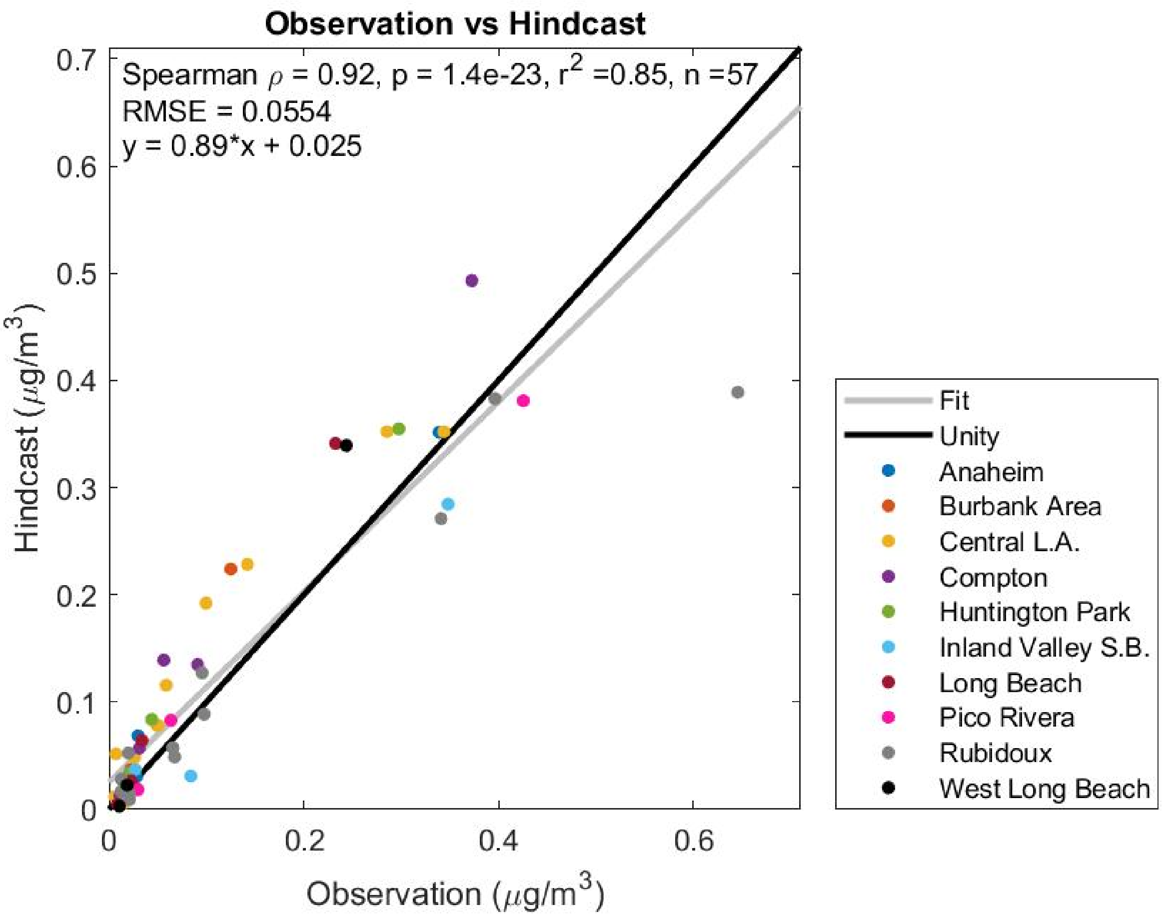


Figure XII-6: Scatter plot of held-out observations and corresponding predictions (hindcast). The station name Inland Valley San Bernardino is abbreviated as Inland Valley S.B.

XII.10. Application to Daily Air Quality Forecasts

While residential wood smoke may contribute significantly to PM2.5 concentrations on certain days in the winter months, emission inventories for PM2.5 chemical transport forecasting models apportion wood smoke based on a static temporal profile that is not dependent on meteorology. Wood smoke PM2.5 predictions from other forecasting models used by South Coast AQMD staff to issue daily forecasts also have high levels of uncertainty because of their inability to capture the human behavioral influence on burning patterns. In order to improve winter-time predictions of total PM2.5, the midpoint of the upper- and lower-bound estimates of wood smoke PM2.5 from the levoglucosan model is used in a weighted ensemble of PM2.5 forecast models to improve predictions of total PM2.5 when widespread residential wood burning occurs.

XII.11. Multi-Year Time Series

The levoglucosan model predictions can be generated for any day for which the predictor variables can be calculated, i.e., any day for which the NAM data is available. Residential wood burning patterns may gradually change over the course of several years, which means that the model will need to be trained with new levoglucosan measurement data. However, residential wood burning patterns are unlikely to change substantially over the course of a few years. As such, staff has run the levoglucosan model backward in time to create retrospective forecasts starting on January 1, 2017 through the start of the on-going operational model runs, resulting in a time series from January 1, 2017 through January 1, 2021.

This multi-year time series of levoglucosan model predictions has been used to help guide outreach efforts for the Check Before You Burn Initiative related to Rule 445 (South Coast Air Quality Management District, 2013; South Coast Air Quality Management District, 2020). To achieve this goal, we used levoglucosan model wood smoke PM2.5 predictions during the 2020-2021 and 2019-2020 Check Before You Burn seasons (November to February) to estimate the impact of wood burning on the annual mean PM2.5 concentration and the 98th percentile of daily PM2.5 concentrations—two important statistics for the PM2.5 federal standards. Outreach was prioritized in communities with higher PM2.5 concentrations along with a larger contribution from residential wood smoke.

XII.12. Conclusion

Analysis of measured levoglucosan concentrations has provided critical insight into the spatial and temporal trends of wood smoke throughout the South Coast Air Basin. Development of a machine learning model with the levoglucosan measurements has improved the accuracy of wintertime forecasts and allowed for prioritization of outreach for the Check Before You Burn program in communities most impacted by residential wood smoke.

XII.13. References

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