

Development and Preliminary Results for a Model of Temporal Variability in Residential Wood Combustion Emissions

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ABSTRACT

Air quality modeling to support 24-hour $PM_{2.5}$ attainment demonstrations in regions of the U.S. where residential wood combustion (RWC) is a significant source of particle pollution requires a more accurate approach to the temporal distribution of emissions from these sources than is currently being used. This paper presents a statistical model of the daily temporal variability of RWC emissions as a function of simulated daily meteorology. The products of the model presented here are national county-specific temporal profiles for converting annual RWC inventories to daily emission estimates. These profiles can be developed as new simulated meteorology data become available and applied in the emissions modeling process to simulate the variability in RWC sources resulting from local weather conditions. This paper describes the model development process, including descriptions of both unsuccessful and successful experiments to (1) identify sites to use for developing the model and (2) identify the best predictors to use for simulating $PM_{2.5}$ from RWC sources. Comparisons are shown between the simulated temporal profiles using year 2006 meteorology data at several sites around the U.S. and the temporal profiles currently being used to simulate emissions from U.S. and Canadian RWC sources. While there are intuitive trends in the results from the RWC temporal variability model that appear to have validity, such as shorter burning seasons at lower latitudes than high latitudes, episodic burning periods associated with temperature anomalies, and changes in burning patterns across different years, there needs to be additional work to validate the model predictions.

INTRODUCTION

In 2006, USEPA tightened the 24-hour National Ambient Air Quality Standard (NAAQS) for fine particulate matter ($PM_{2.5}$, diameter $\leq 2.5 \mu m$) from 65 to 35 $\mu g/m^3$. The stricter $PM_{2.5}$ standard resulted in 31 areas of the United States consisting of 120 full or partial counties being designated as non-attainment of the annual or 24-hour $PM_{2.5}$ standards¹. States and Tribes with $PM_{2.5}$ non-attainment areas are now in the process of developing implementation plans, which are due in 2012, to demonstrate how they will reduce emissions to bring the areas under their jurisdiction into attainment of the NAAQS by the end of 2014. A component of the emissions reduction demonstration process required in the implementation plans involves using air quality modeling systems to test the impacts of different $PM_{2.5}$ emission reduction strategies. Given the relatively fine temporal resolution of the 24-hour standard, the effective use of air quality modeling systems for addressing $PM_{2.5}$ requires accurate representation of the day-to-day temporal variability in the major sources contributing to nonattainment in different regions of the country. Of the various sources of $PM_{2.5}$ contributing to the NAAQS violations, residential wood combustion (RWC), which consists of fireplaces and wood stoves for home heating and cooking, has a disproportionate impact on winter $PM_{2.5}$ concentrations in some parts of the U.S.^{2,3,4}. The U.S. EPA Technical Support Document⁵ for the most recent $PM_{2.5}$ non-attainment designations highlights several

areas where RWC is one of, if not the major emissions source of $PM_{2.5}$ contributing to violations of the 24-hour standard in the winter. Air quality modeling to support 24-hour $PM_{2.5}$ attainment demonstrations in the regions where RWC is a significant source of PM pollution requires a more accurate approach to the temporal distribution of these emissions than is currently being used.

With state and national emission inventories for RWC sources developed as annual totals, accurate emissions modeling processes that convert from annual to hourly estimates are critical for modeling these sources for 24-hour $PM_{2.5}$ NAAQS modeling applications. While the magnitude of the RWC emissions are captured as annual county totals in the emission inventory, the distribution of the annual inventories to the hourly estimates needed for air quality modeling uses temporal profiles that do not change from one year to the next. Herein referred to as static profiles, the current temporal profiles reflect neither the changes in the length of the heating season that occur at different latitudes nor episodic temperature changes (i.e., warm fronts or cold fronts). Using air quality models in the 24-hour $PM_{2.5}$ standard implementation plan process to develop emissions reduction strategies that include RWC sources requires realistic simulations of the daily variability in these important regional and seasonal sources of PM. To address the need for a more accurate estimate of the temporal patterns from RWC sources, this paper presents a statistical model of the daily temporal variability of RWC emissions as a function of simulated daily meteorology. The products of the model presented here are national county-specific temporal profiles for converting annual RWC inventories to daily emission estimates. These profiles can be developed as new simulated meteorology data become available and applied in the emissions modeling process to simulate the variability in RWC sources resulting from local weather conditions.

We developed a regression equation that relates ambient measurements of PM tracers of RWC sources to daily minimum temperatures to estimate daily temporal profiles for RWC emission sources. While the objective of this work was not to predict ambient $PM_{2.5}$, we used the model predictions of daily $PM_{2.5}$ to generate temporal profiles that can be applied to RWC emission sources. This paper describes the model development process, including descriptions of both unsuccessful and successful experiments to (1) identify sites to use for developing the model and (2) identify the best predictors to use for simulating $PM_{2.5}$ from RWC sources. The resulting regression equation can be easily implemented in the emissions processing sequence to replace the static national temporal profiles that are currently being used for $PM_{2.5}$ implementation plan modeling. In addition to discussing the model development process, this paper presents some preliminary results from the RWC temporal variability model through comparisons of the temporal profiles estimated by the model for different sites in the U.S. to the static temporal profiles that are currently being used to simulate emissions from RWC sources.

BODY

Methods

The conceptual model driving the development of a RWC emissions temporal variability model is that RWC emissions patterns are linked to temperatures, with a greater prevalence of households using RWC for heat during periods of cool temperatures. By relating measured ambient tracers of wood smoke at monitors that are strongly impacted by RWC emissions to observed meteorology variables, we hypothesize that we can develop a model that predicts the temporal variability of RWC emissions patterns given forecasted or simulated meteorology. In consideration that several factors, other than just ambient temperatures, influence both the concentrations of observed wood smoke tracers and behavioral patterns leading to RWC activities, we explored different regression-based statistical models in an attempt to develop an extensible model of RWC temporal patterns using a fairly limited amount of tracer data. We developed a model of RWC temporal variability in two phases. In the first phase, we sought ambient wood smoke tracer data that we could identify as being from RWC sources. In the second

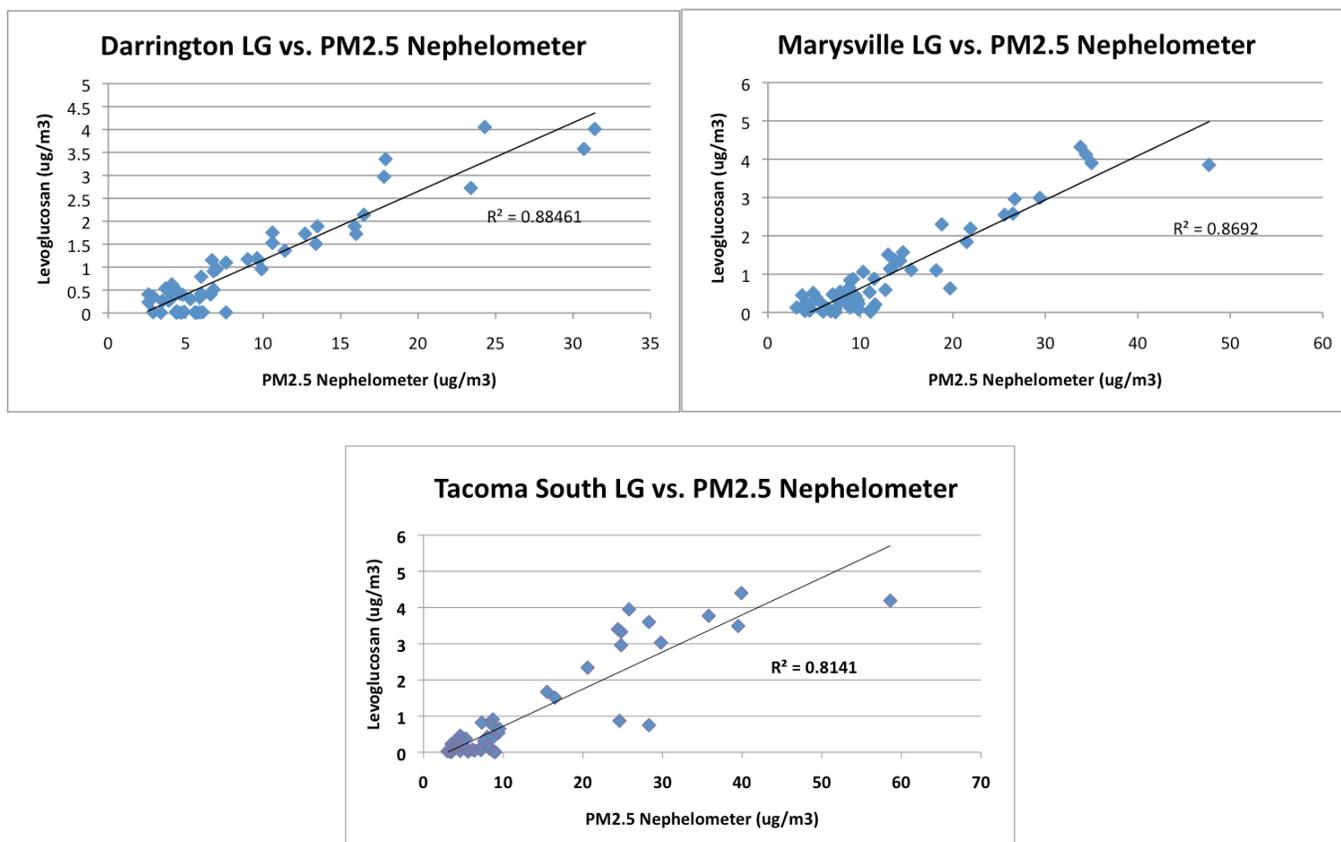
phase, after selecting the ambient data and monitors, we explored several different model formulations given the available data.

The objectives of the first phase of this research were to find an observed chemical tracer that could definitely identify wood combustion sources and to find monitoring locations that were dominated by RWC emissions. To satisfy the first objective, we initially focused on the particulate organic compound levoglucosan (LG) because it is widely cited in the literature as a conservative tracer of wood smoke emissions that has been used in several chemical mass balance studies to attribute observed PM_{2.5} concentrations to wood combustion^{6,2,3}. Although LG is collected on all PM filters impacted by wood combustion sources, observed LG concentrations are only available from monitoring campaigns that employed specific analytical techniques to extract it from the filters^{7,8}. We analyzed LG data collected in the Southeast U.S. in 2007⁹ and data collected in the Puget Sound region of Washington from 2005-2007⁶. To satisfy the second objective of this phase of our research, we sought monitoring sites and periods that were isolated from the impacts of non-RWC biomass burning, such as prescribed fires, agricultural fires, and wildfires. We employed an ad hoc assumption of using a 10° C (50° F) daily minimum temperature cutoff for filtering the analysis periods for the LG observations. With this assumption, we excluded the observations from all sites/days with daily minimum temperatures greater than 10° C. This was an arbitrary temperature cutoff that we used to exclude warm periods when we expected that either the likelihood of RWC use was low or when the likelihood of wildfires was high. We then compared the filtered LG measurements to the observed daily minimum temperatures at the monitoring locations to look for relationships in the data.

We also explored using more conventional ambient measurements, such as elemental carbon (EC), organic carbon (OC), and PM_{2.5} nephelometer (PM_{2.5}-neph) data to identify RWC monitors. We looked at OC/EC ratios from measurements in the Chemical Speciation Network (CSN) as an approach to select sites impacted by RWC sources. We calculated ratios of the CSN species OC (Oc Csn Unadjusted Pm2.5 Lc Tot) and EC (Ec Csn Pm2.5 Lc) based on evidence that higher OC/EC ratios indicate a biomass burning signal¹⁰. After reducing the year 2004 CSN data set to 16 sites by selecting the top 80th percentile of the OC/EC ratios and only using sites showing negative correlations between observed temperatures and OC concentrations, we explored the relationship between OC observations at these sites and different meteorology predictors. Similar to the LG analysis, we used a 10° C temperature cutoff before comparing the selected OC observations to simulated daily minimum temperatures, daily average wind speeds, and daily average planetary boundary layer (PBL) heights in 36-km and 12-km grid resolution meteorology data provided by the U.S. EPA. We chose to use simulated, rather than observed meteorology predictors for these analyses because we suspected that atmospheric stability, for which wind speeds and PBL heights can be a proxy, along with temperatures influence ambient PM concentrations. Only modeled data allowed the estimation of PBL heights and wind speeds at all of the monitoring locations in our analysis.

Finally, in addition to analyzing OC/EC ratios to select RWC monitoring locations, we focused on PM data collected at sites identified by Onstadt and Simpsons (2008) and the Puget Sound Clean Air Agency (PSCAA) as locations strongly influenced by RWC emissions. Three of the PSCAA monitors in particular, Darrington, Marysville, and Tacoma South, Washington were identified as locations with a high potential for influence from RWC sources. Since the number of LG observation points at these monitors was limited to only a short period (non-consecutive days over a 12-18 month period), we explored using other PM_{2.5} observations at these sites that were available for several years. The PSCAA has been collecting PM_{2.5}-neph data throughout its ambient monitoring network since 2004. While PM_{2.5}-neph is not specific to wood smoke sources, PM_{2.5}-neph collected at sites impacted by smoke sources will be proportional to PM from wood combustion. Figure 1 shows that there is a strong relationship between LG and PM_{2.5}-neph at the three PSCAA monitors identified above, indicating that these sites are strongly influenced by wood smoke sources and that PM_{2.5}-neph is a good alternative to LG as a wood smoke tracer at these locations.

Figure 1. Levoglucosan vs. PM_{2.5} nephelometer observations at the three PSCAA monitoring locations used to develop the RWC temporal variability model



For the second phase of our research, we explored both linear and conditional regression models to predict the concentrations of ambient PM tracers as a function of daily meteorology data. For the linear regressions we compared ambient wood smoke PM tracer concentrations to simulated daily minimum temperatures, daily average wind speeds, daily average PBL heights, and the daily ventilation index (PBL x 10-m wind speed) for model grid cells containing ambient monitors. For the conditional regressions, we compared ambient tracer concentrations to predicted daily minimum temperatures at different ventilation index values. The rationale for integrating ventilation index into the model was that while temperatures may influence when RWC sources are used, atmospheric stability influences the dilution rate of the emissions and hence the observed concentrations of the RWC tracers. For the OC-based models, which were based on a national monitoring network, we explored aggregating the observations spatially to increase the extensibility of the model. In addition to developing a series of monitor-specific models, we created state models, in which we aggregated the observations for all sites in a given state, and regional models, in which we divided the U.S. into quadrants and aggregated the observations for all sites in each region.

With none of the meteorology predictors providing statistically significant estimates of the PM tracers, we decided to simplify the model to use only daily minimum temperatures for estimating PM. As the objective of the model was to predict the temporal variability in RWC emissions and not ambient PM tracer concentrations, we were less concerned with the ability of the model to predict PM magnitudes as we were in its ability to capture day-to-day variability in the observations. We ultimately developed regression equations to calculate day-of-year, week-of-year, and month-of-year temporal profiles using daily minimum temperatures, weekly averaged temperatures, and monthly averaged

temperatures, respectively, using the PM_{2.5}-neph data available from the PSCAA monitors. We computed the temporal profiles as the ratio of the daily/weekly/monthly PM estimate to the annual total of all PM estimates. Equation 1 is an example of the day-of-year temporal profile calculation.

$$\text{Equation (1) } PE_{i,d} = \frac{(E_{i,d})}{\sum_{d=1}^{365} (E_{i,d})}$$

where,

$PE_{i,d}$ = Percentage of annual emissions at monitor i on day d .

$E_{i,d}$ = Daily average observation of RWC tracer at monitor i on day d .

As an initial evaluation of the modeled temporal profiles, we qualitatively compared the modeled temporal profiles at different monitor locations to the static temporal profiles currently being used to simulate RWC source emissions.

Results

Results are first presented for the site selection phase and then for the model development and validation phase of this research. Site selection involved the analysis of both observed LG data and OC/EC ratios to identify monitoring sites that were observing PM that was predominantly emitted by RWC sources. Figure 2 shows the locations of the Southeastern U.S. monitors analyzed for this study along with scatter plots comparing LG to daily minimum temperatures at these sites. Note that the plots in Figure 2 include all observations at these sites (i.e., these plots do not show the 10° C temperature cutoff). Figure 3 is a similar plot for the Puget Sound, Washington sites. Although the relationships between LG and temperatures at some of the monitoring sites (Darrington/Marysville/Tacoma, WA and Augusta/Macon, GA) appeared compelling, our site filtering approach left us with too few samples (number of LG-temperature pairs < 60) to develop a valid statistical model.

Figure 4 shows a time series of temperatures and PM_{2.5}-neph observations at eight PSCAA monitors from the year 2004 to the present. The pattern shows the intuitive inverse relationship between temperature and PM_{2.5}-neph observations that we would expect from RWC sources. Following from Figure 1, which illustrates that PM_{2.5}-neph can be used as a proxy tracer for wood combustion at sites that are dominated by wood smoke, we collected daily PM_{2.5}-neph observations for the Darrington, Marysville, and Tacoma South, WA sites to expand the sample size for developing a regression model to over 2000 PM-temperature data pairs.

Figure 2. Levoglucosan versus daily minimum temperatures for the Southeastern U.S. sites analyzed for this study.

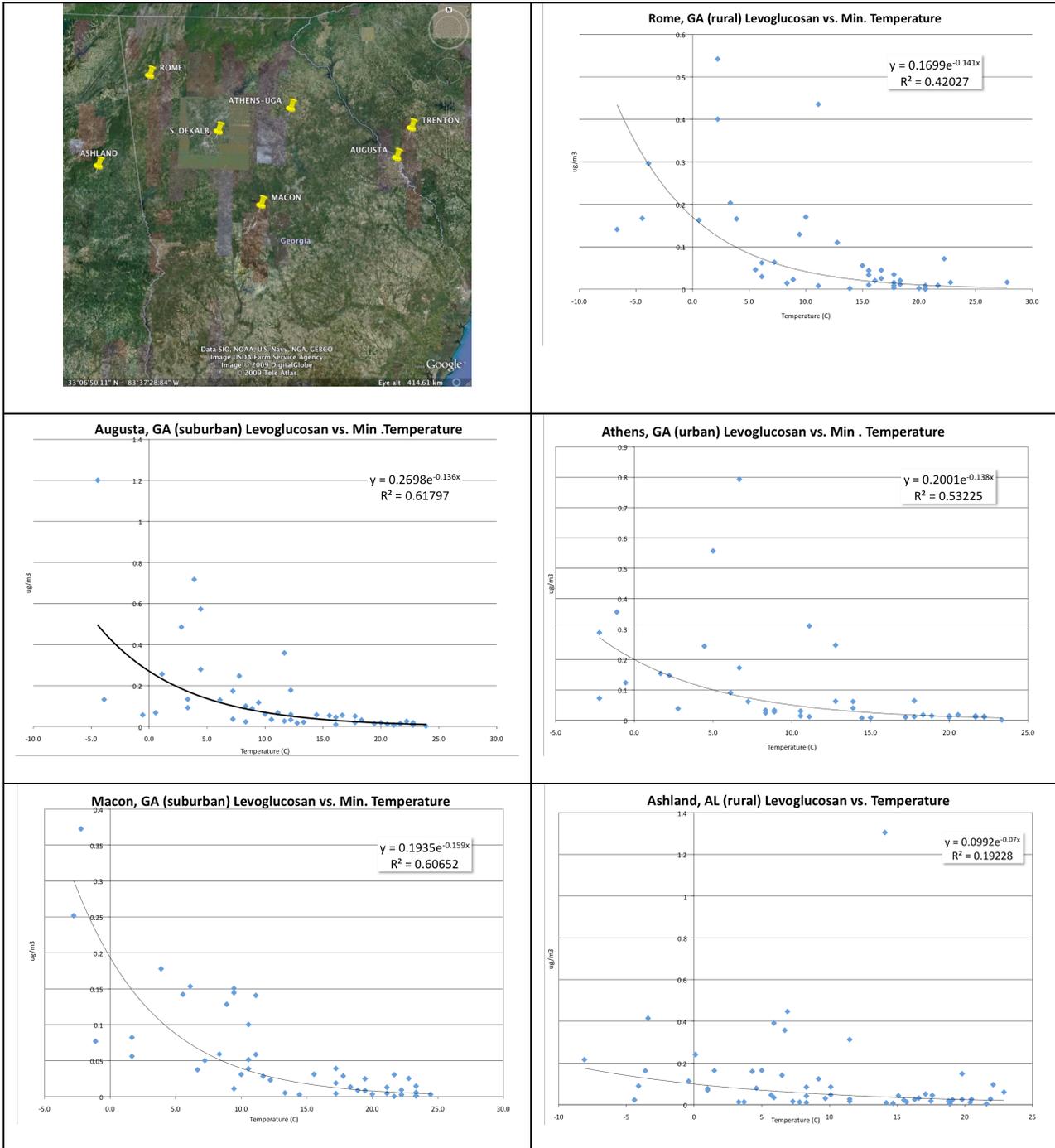


Figure 3. Levoglucosan versus daily minimum temperatures for the Puget Sound sites analyzed for this study.

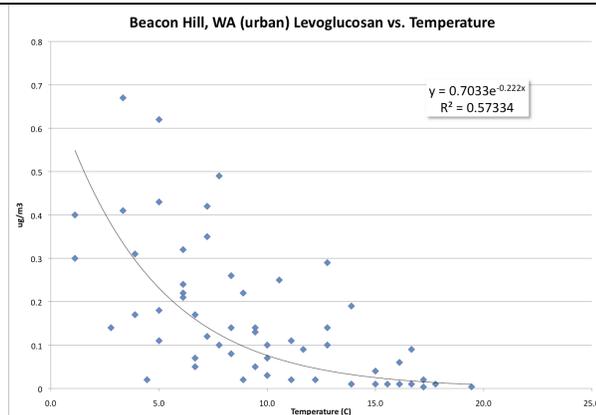
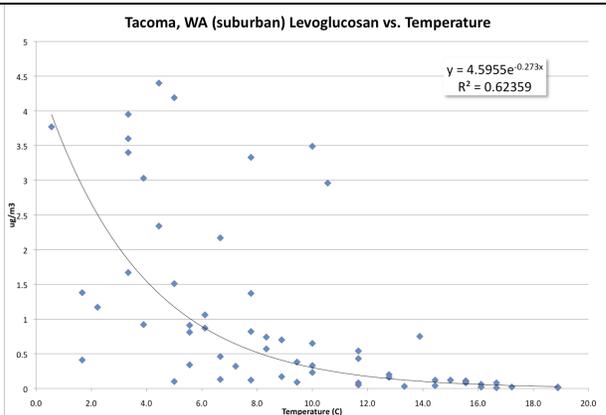
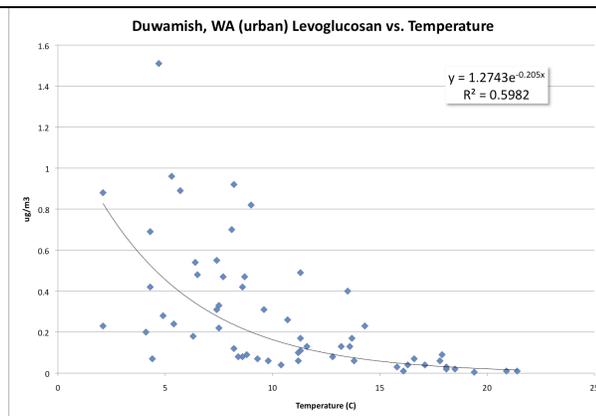
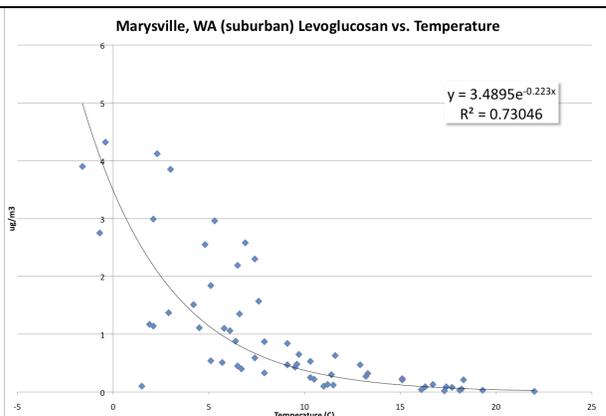
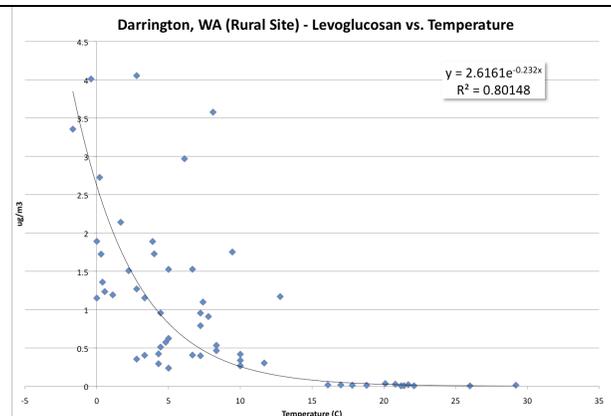
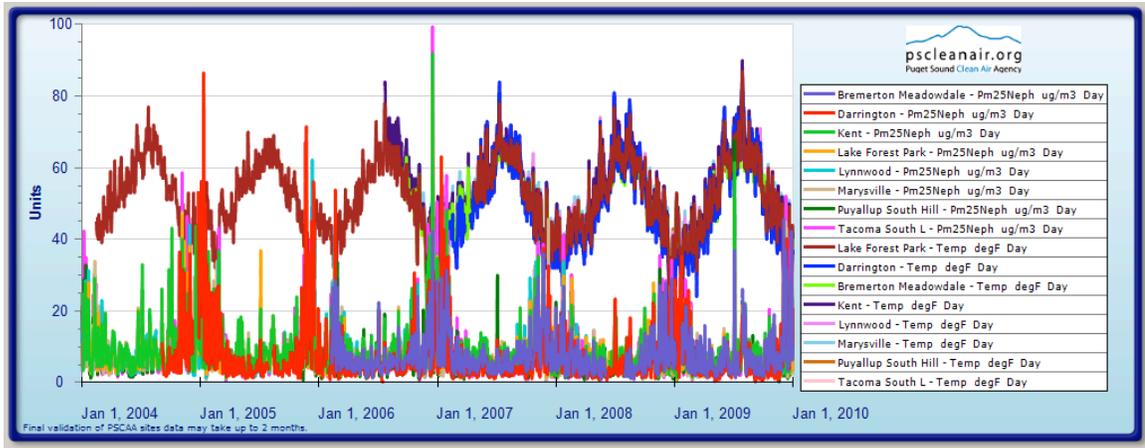


Figure 4. PM_{2.5}-neph and temperature time series at several sites in the PSCAA monitoring network



In addition to the LG data from the Puget Sound monitors, we explored the CSN as a potential monitoring network for developing a RWC temporal variability regression model. The CSN was appealing because it has national coverage, as opposed to the PSCAA sites, which are located in only a limited area around the Puget Sound. Table 1 shows the CSN monitors that we identified as RWC sites. These sites were identified by first excluding all days with daily minimum temperatures higher than 10° C, calculating the 80th percentile of the observed OC/EC ratio, and excluding all sites with a positive correlation between observed temperatures and OC. Table 1 also shows the rank of the counties that contain the selected monitors in terms of total RWC PM_{2.5} emissions in the 2005 National Emission Inventory.

Table 1. Top 80% percentile of CSN sites for OC/EC ratio; observations filtered by a 10° C temperature cutoff and negative correlations between temperatures and OC concentrations

Obs	State_name	County_name	Unique_ID	Mean	Median	No. of Obs	Corr	NEI05 Annual PM2.5 RWC, TPY (Rank)
1	California	Plumas Co	6-63-1009	16.4542	15.0000	58	-0.66155	680 (90)
2	Oregon	Lane Co	41-39-60	22.6467	8.4076	38	-0.65874	3068 (5)
3	California	Butte Co	6-7-2	12.9292	10.8000	36	-0.62111	967 (57)
4	Oregon	Jackson Co	41-29-133	14.6109	13.0085	41	-0.61450	2667 (7)
5	Montana	Lincoln Co	30-53-18	63.9475	12.5759	48	-0.41110	97 (866)
6	Idaho	Canyon Co	16-27-4	63.1415	9.9390	47	-0.39716	9 (2819)
7	Oregon	Union Co	41-61-119	15.3529	13.4674	43	-0.37476	469 (150)
8	North Carolina	Buncombe Co	37-21-34	11.2095	9.4103	33	-0.27715	168 (487)
9	Montana	Missoula Co	30-63-31	12.1630	9.0000	81	-0.18745	207 (397)
10	South Carolina	Greenville Co	45-45-9	44.5487	9.4490	48	-0.18711	696 (89)
11	Massachusetts	Hampden Co	25-13-8	14.2456	9.2365	34	-0.15018	801 (74)
12	Georgia	Floyd Co	13-115-5	19.9213	9.5082	30	-0.12476	49 (1575)
13	Virginia	Henrico Co	51-87-14	31.5479	8.7162	45	-0.08493	208 (394)
14	Indiana	Vanderburgh Co	18-163-12	17.6479	8.1405	34	-0.06512	24 (2776)
15	Minnesota	Hennepin Co	27-53-963	11.5916	8.1673	66	-0.04818	1036 (53)
16	Tennessee	Lawrence Co	47-99-2	32.6421	11.1330	31	-0.01946	114 (737)

Once we identified potential monitors for developing a regression model, we used the ambient data from the selected monitors to develop and test regression models of RWC emissions. Figure 5 shows the results of linear regressions between PM_{2.5}-neph and daily minimum temperatures at eight

PSCCA monitors. These sites include the three monitors that we identified as wood combustion sites through our comparisons between LG and PM_{2.5}-neph observations. Two sets of regressions are shown in Figure 5. The unrestricted results on the left show all PM_{2.5}-neph data available for the selected monitoring sites. The restricted results on the right exclude the top 10% of observations and include only days with minimum temperatures below 10° C. Table 2 summarizes the restricted results by displaying the R² values at selected PSCAA monitors.

Table 3 summarizes the results of regressions between OC observations at the selected CSN sites and various meteorology predictors. These results show that site location was the only significant predictor in the models developed from these data.

Figure 5. Regressions between PM_{2.5}-neph and temperatures at eight PSCAA monitoring locations; unrestricted (left) and with temperature and magnitude restrictions (right)

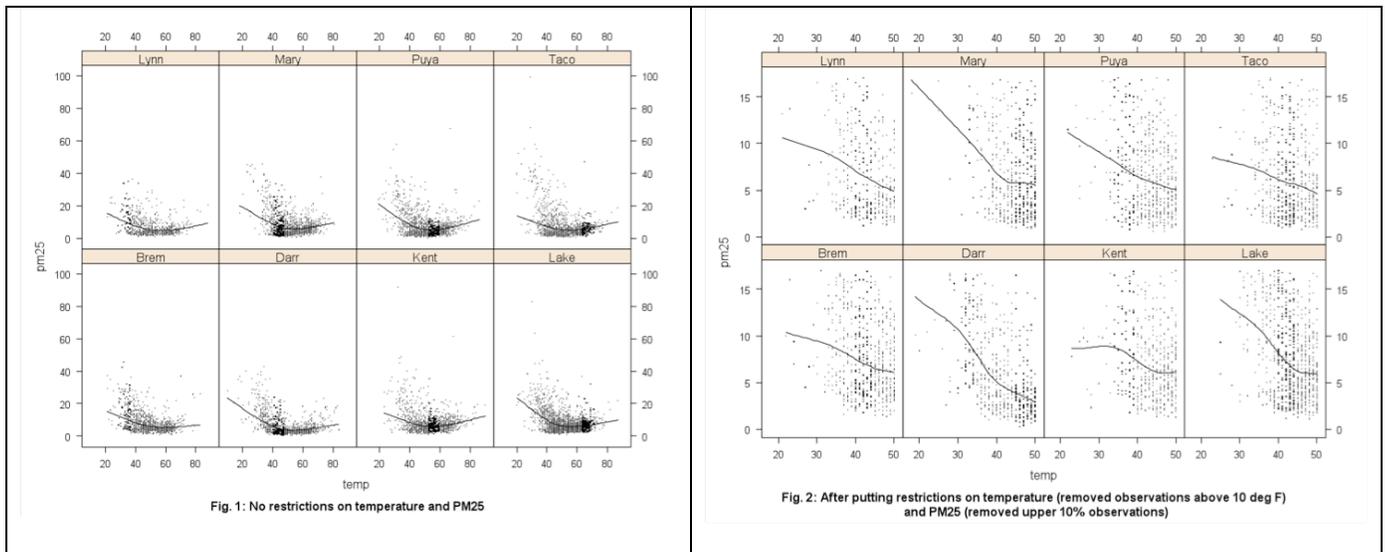


Table 2. PM_{2.5}-neph RWC model predictors and powers from three PSCAA sites

Site	Controlled Predictor	R ²
All 8 sites	Temperature, site, month, and weekday	0.20
All 8 sites	Temperature, site, year, month, and weekday	0.21
Darrington	Temperature and month	0.40
Marysville	Temperature and month	0.15
Tacoma	Temperature and month	0.15

Table 3. OC RWC model predictors and powers from sixteen CSN sites

Controlled Predictor	R ²
[1] Date, temperature, PBL height, wind speed and all possible interactions among these variables	0.15
[2] Same as [1] and control for month	0.16
[3] Same as [1] and control for site	0.35
[4] Same as [1] and control for location, where location is one of four quadrants used to subdivide the U.S.	0.20
[5] Same as [3] and all possible interactions with the site variable among the other predictors	0.51

Site location was the only statistically significant predictor of PM_{2.5} at all of the monitoring locations that we analyzed, indicating that any model developed from these data was only statistically significant at the site used to develop the model. In an attempt to develop a few extensible models, we explored grouping sites to develop regional or even state-specific models. The ability of these location-based models to predict the variance in the monitor groups was still not significant. The inability of the meteorology variables to predict the variability in the PM observations coupled to the strength of the site location as a predictor indicated that (1) there are other sources of variability in the PM data, such as human behavioral patterns, that we aren't capturing in the model and (2) that the combinations of the locations and chemical tracers we were using to develop the model were confounded by sources of PM_{2.5} other than RWC.

Given that there were sources of variability in the PM_{2.5} observations that would be difficult to parameterize in a model, like human behavioral patterns, we ultimately chose to simplify the RWC temporal variability model by developing it with data from monitors that we could definitively identify as being strongly impacted by wood smoke and to base it on only the relationship between temperatures and PM_{2.5}. Our rationale for this decision is that while the monitoring data that we analyzed could not be used to develop a geographically extensible model, by focusing on monitors that we know are observing wintertime wood smoke, we are using data that are representative of locations with high RWC emissions. The combination of LG observations and long-term PM_{2.5}-neph observations at the PSCAA sites, in our opinion, provided the best dataset for developing the RWC temporal variability model. The strong correlations between LG and PM_{2.5}-neph at the Darrington, Marysville, and Tacoma South monitors provided the best evidence of all of the data that we analyzed of monitors that were dominated by wood smoke PM. The availability of long-term PM_{2.5}-neph observations at these monitors provided a large number of data points for developing the RWC temporal variability model.

The three models that we developed using daily minimum temperatures, weekly averaged temperatures, and monthly average temperatures are shown in Equations 2 through 4, respectively. These equations were developed by combining all of the PM_{2.5}-neph observations at the Darrington, Marysville, and Tacoma South monitors for the period January 2004 – July 2010 into a single dataset, excluding all days with daily minimum temperatures above 10°C, and regressing between the temperatures and PM_{2.5}-neph observed at the monitors.

$$\text{Equation (2) } \text{PM}_{2.5} = 42.12 - 0.79T_d \text{ (n = 2008, } R^2 = 0.26)$$

$$\text{Equation (3) } \text{PM}_{2.5} = 38.03 - 0.68T_w \text{ (n = 305, } R^2 = 0.26)$$

$$\text{Equation (4) } \text{PM}_{2.5} = 36.52 - 0.64T_m \text{ (n = 71, } R^2 = 0.35)$$

where,

T_d = daily minimum temperature (°C)

T_w = weekly averaged temperature (°C)

T_m = monthly averaged temperature (°C)

Figures 6 through 8 compare simulated temporal profiles from these models using year 2006 meteorology data at several sites around the U.S. to the temporal profiles currently being used to simulate emissions from U.S. and Canadian RWC sources. The general trend of the simulated profiles is to allocate more emissions to the spring and fall seasons and less emissions to the winter season than the standard profiles. Figures 6 and 7, the plots of profiles from the daily and weekly models, show that for the sites in Montana the burning season runs later into the summer and starts earlier in the late summer than the standard profiles. Figure 7 illustrates that the Buncombe County, NC site, which is in the Southeastern U.S., has a much later start to the RWC burning season than the standard U.S. profile.

The simulated profiles from the daily and weekly models at all sites show an emissions spike in February that is also contained in the standard profiles. Another major difference between the simulated and standard profiles is the higher variability in the simulated profiles.

The simulated profiles contain more of both systematic and episodic variability than the standard profiles. The results of these two types of variability are seen in the daily and weekly profile plots in Figures 6 and 7, respectively. The variability in the simulated temperatures in the meteorology data produces the systemic variability, or noise, observed in the predicted profiles. In addition, the use of a 10° C temperature cut-off to effectively turn off RWC emissions on warm days causes the episodic variability in the predicted profiles. The daily profile plot in Figure 6 shows a one-day drop in the profile for Buncombe County, NC in the spring and a one-day increase in the profile for Lane County, OR in the summer. These spikes are the result of the temperature threshold application at these sites: an unseasonably warm spring day at the NC site and an unseasonably cool summer day at the OR site. The episodic variability in the profiles becomes more pronounced in the transition periods around the RWC off-season.

Figure 6. Daily temporal profiles from the PSCAA regression model and the standard profiles currently used for US and Canadian RWC sources.

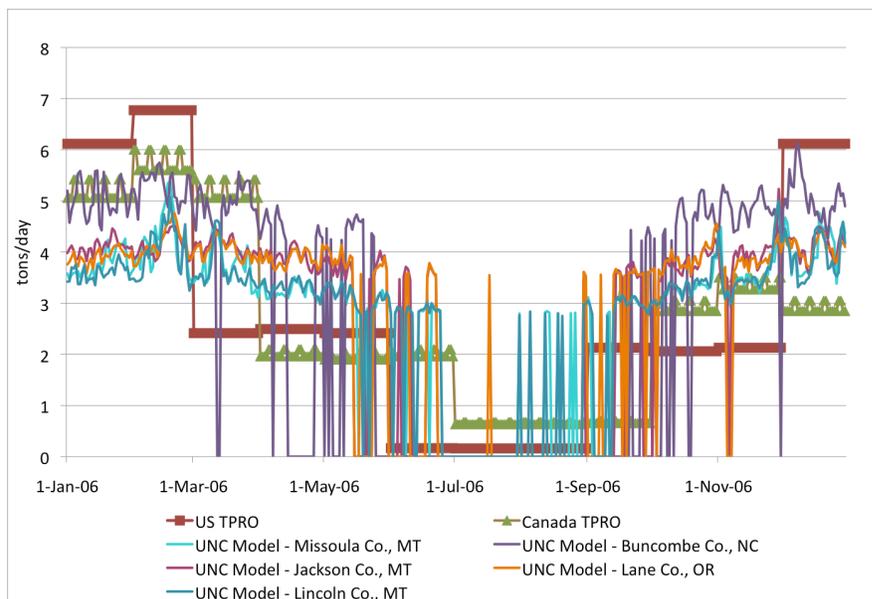


Figure 7. Weekly temporal profiles from the PSCAA regression model and the standard profiles currently used for US and Canadian RWC sources.

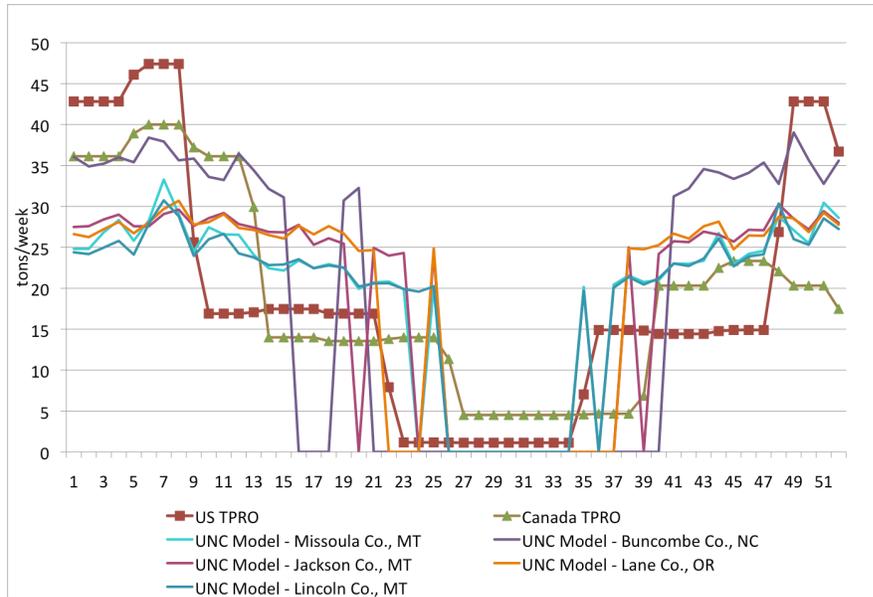
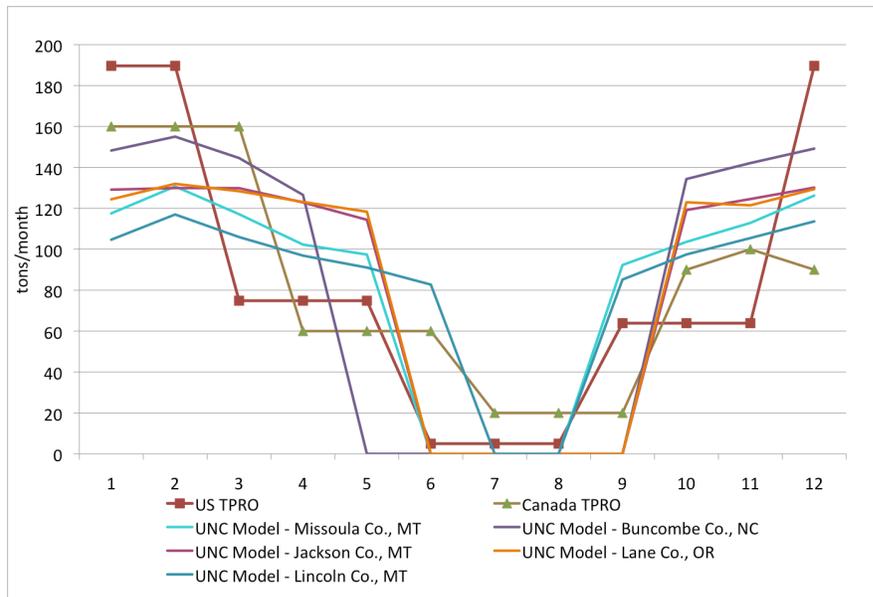


Figure 8. Monthly temporal profiles from the PSCAA regression model and the standard profiles currently used for US and Canadian RWC sources.



Discussion

The RWC temporal variability models developed in this project are based on the assumption that RWC use patterns are a function of temperature and that the three sites in the Puget Sound area of Washington are representative of national RWC use patterns. We chose these sites for developing the model because they were the only definitive locations that we could identify as being dominated by wintertime wood smoke PM that had a long record of proxy observational PM_{2.5}-neph data. We converged on a simple PM_{2.5} and temperature regression model because our experiments with trying to include meteorology indicators of atmospheric stability (i.e. wind speeds, PBL heights, and ventilation index) did not improve the performance of the model. Although these models show that temperature is a poor predictor of observed PM_{2.5}, because it cannot account for activity levels, such as the population of

wood stoves or the total amount of wood burned, they were not intended to simulate $PM_{2.5}$ directly, but rather the daily, weekly, and monthly variability in $PM_{2.5}$ from RWC sources.

While there are intuitive trends in the results from the RWC temporal variability models that appear to have validity, such as shorter burning seasons at lower latitudes than high latitudes, episodic burning periods associated with temperature anomalies, and changes in burning patterns across different years, there needs to be additional work to validate the model predictions. Known issues with the models and predicted temporal profiles that warrant further exploration include:

- The assumption that a daily minimum temperature of $10^{\circ}C$ is the point above which RWC ceases
- The assumption that RWC emissions go to zero above the temperature threshold
- Episodic spikes in the profiles are reflective of reality, i.e. does a single cold night in the summer initiate the use of RWC heating for one day?
- Does systematic variability, or noise, exist in the day-to-day use of RWC during cold months or is a flat profile more representative of use patterns?
- How well do the model predictions correlate with behavioral surveys of RWC use patterns?
- The model only considers temporal variability driven by temperatures and does not consider behavioral patterns. Different RWC use patterns during holidays, for example, are not captured by the model

As these models were developed to predict the temporal variability in wintertime RWC emissions, the resulting profiles should not be applied uniformly to all RWC sources. Charcoal and wood grilling sources are not valid applications of these profiles. It should be restated that the models presented here are predicting the temporal variability in RWC emissions. The actual magnitude of emissions, or annual tonnage of emitted pollutants, is reflected in the emission inventory used with these data.

CONCLUSIONS

The ability to predict the temporal variability in RWC emissions using local meteorology data represents a significant improvement over the current methods of using static temporal profiles for these sources. The use patterns of residential heating fuels will become less predictable with changes in climate. The ability to capture these changes along with the more basic simulation of differences in RWC use across years and latitudes is powerful new tool for air quality planners in regions where RWC is a threat to human health and the environment.

The Center for Environmental Modeling for Policy Development at the University of North Carolina is implementing the daily RWC temporal profile model in a profile generator preprocessor that will be distributed with the Sparse Matrix Operator Kernel Emission (SMOKE) model. The profile generator will read in hourly meteorology and Geographic Information System (GIS) spatial surrogate data to produce county-based temporal profiles for RWC sources. These profiles will be written in a format that can be directly read in by SMOKE for processing RWC emissions.

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