Re-analysis of ARTC Data on Particulate Emissions from Coal Trains

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1. SUMMARY

This report describes a re-analysis of ARTC's data on particle emissions from coal and other trains in the Hunter rail corridor. Our analysis was based on regression modelling, as recommended in a previous critique by the first author of an analysis of those same data by Katestone Environmental Pty Ltd.

The data analysis was challenging, complicated by the large volume of data available, as well as the strong levels of serial correlation. We found clear evidence that particulate levels were elevated when trains passed by the monitoring station. Effects were strongest and of a similar magnitude (approximately 10% increase above background levels) and highly statistically significant for freight and coal trains, both loaded and empty. Effects for passenger trains were mostly statistically significant, but of a smaller magnitude. The effect for passenger trains became non-significant when we excluded times when multiple trains were passing simultaneously. There was no evidence that loaded coal trains produce more dust than empty coal trains. In fact, while differences were not statistically significant, particulate levels associated with the passing of unloaded coal trains were higher than those associated with loaded coal trains and freight trains.

The effects were apparent for all available particulate measures, including TSP, PM10, PM2.5 and PM1, especially for freight and coal trains (loaded and empty). Passenger train effects were non-significant for PM1 and only marginally significant for PM2.5. Since coal dust is likely to be reflected in the larger particle counts (TSP and PM10), this finding suggests that other contaminants such as diesel may be of more concern than coal dust. This conclusion is further supported by the fact that effect sizes were similar for freight, loaded and unloaded coal trains, all of which are pulled by diesel locomotives.

The report concludes with suggestions about further analysis that would help understand the nature of particulate exposure in the Hunter Valley.

2. INTRODUCTION AND BACKGROUND

Katestone Environmental Pty Ltd (referred to hereafter as Katestone) was commissioned by Australian Rail Track Corporation to conduct a monitoring study of particulate matter, with a view to determining

1. Whether trains operating on the Hunter Valley rail network are associated with elevated particulate matter concentrations; and
2. Whether trains loaded with coal have a stronger association compared with unloaded coal trains or other trains on the network.

To address these questions, a continuous particulate monitoring station was installed to measure particulate levels in the rail corridor adjacent to tracks carrying different types of trains. Specific details of the monitoring design were informed by a previously conducted pilot study. In addition to continuous monitoring of particulate levels, the time of each train pass-by was recorded, along with other details about each corresponding train. Additional data were available regarding wind speed and direction, as well as rainfall.

After the final report was submitted, a number of independent reviews were undertaken to evaluate the reliability of the results. Several of the reviews raised concerns regarding the statistical methods used to analyse the data. Professor Louise Ryan was engaged as an independent, expert statistical reviewer, to assess the suitability and reliability of the statistical methods used to analyse the study data. Her report discussed several concerns:

- Use of only a single monitoring site made it difficult to generalize the results
- Katestone's approach of treating the outcome of interest as the average particulate levels associated with various kinds of train passings.

Professor Ryan argued that while multiple monitoring stations would have been helpful, a continuous time series at this single site should still provide useful insight into the questions of interest. She recommended that the study be reanalysed using regression analysis methodologies, taking into consideration the likelihood of serial correlation due to the time-series nature of the data. She suggested that the outcome variable for the analysis should be the individual particulate measurements (that is, without any averaging). Such an analysis would allow for incorporation of covariates indicating train type, wind speed, precipitation, as well as additional variables reflecting time of day, day of week and other temporal effects. She also recommended that preliminary exploratory analysis be conducted to see if a log transformation of the data would improve the modelling process. Such an approach would more appropriately address the questions of interest, whilst accounting for possible confounding effects. The purpose of this present report is to describe such an analysis.

3. THE DATA

We obtained all 61 days of monitoring, weather and train passing data from Katestone.

Particulate data: The monitoring system was set up to measure particulate levels every 6 seconds throughout each day over a 61 day period, yielding a maximum total number of 24*60*60/6 = 14,400 sets of measurements each day. As described in Katestone's final report, many of the days collected substantially less than this amount of data. Two days (December 2nd and 16th) had no measurements while an additional three days (December 5th, December 15th and January 1st) had less than 1000 data points (100 minutes of data). Our analysis reports on the subset of 56 days that had at least 1000 monitoring measurements. On these days, the mean number of observations was 10,990 (approximately 18 hours). 48% of the days had at least 22 hours of monitoring data.

Wind data: Data on concurrent wind speed and direction were available for approximately 75% of the particulate observations. These observations were spread over 45 days, with an average of 17.5 hours of wind speed and direction data concurrent with particulate data monitoring, per day. The first day of observation (November 30th) had only 867 concurrent wind observations. Thus, we restricted our analyses involving wind speed and direction to the subset of 44 days with at least 1000 data points.

Train data: Over the course of the study period, a total of 7,315 trains passed by the monitoring station, with a median of 137 trains per day. Table 1 shows the breakdown by different train types, along with the duration (in seconds) of each passing and its speed. Table entries show medians, along with lower and upper quartiles.

As expected, there is a tendency towards a lower frequency of trains on weekends and in the middle of the night. This is especially so for passenger trains. Table 1 shows that passenger trains are the most frequent type of train, that they pass by very quickly (around 2 seconds) and at a relatively fast speed. Empty coal trains are the next most common. These pass by at a medium speed (median 19.8 m/sec) for a longish duration (median 73 seconds). Freight trains are less common (a median of 6 per day), but they show a similar pattern to unloaded coal trains in terms of their speed and duration of passing. There are generally just a couple of unknown train types each day.

Figure 1 shows some of the data on TSP from a typical day (January 8th). Both panels of the Figure show time (24 hour clock) on the horizontal axis. The top panel shows TSP levels measured on the original scale (ug/m^3) while the bottom panel uses a log transformation. A value of 1 is added to each TSP value to avoid problems associated with taking logs of zero. Data are shown for the time period between 10am and 4pm. The presence of various train types is represented using different colours, as indicated in the legend.

Figure 1 reveals a number of interesting and important features. First of all, we see that the data are quite skewed on the original scale, with a number of extreme values. In contrast, the log-transformed data are much more symmetrically distributed around the overall trend. Consequently, statistical analyses based on log-transformed data are likely to be more reliable and stable. All subsequent analyses were thus done on log-transformed data. The Figure also shows that the data tend to reflect a changing trend as time progresses. This may be explainable by changes in wind patterns or perhaps other unmeasured factors. Thus it will be important for our analyses to either directly account for wind and time of day, or build in the likelihood that there might be significant serial in the data. The plots suggest that some of the observed train passings are associated with a strong spike in TSP levels, while others are not. This observed variability underscores the importance of using reliable statistical methods that can help to sort out the patterns. While an eye-ball assessment of the plot might suggest that TSP levels might be slightly higher when a coal train (loaded or unloaded) or freight trains pass, it is also clear that the effects are moderate in magnitude relative to background levels. The plots also suggest that TSP levels associated with empty coal trains are as high as, if not higher than TSP levels associated with loaded coal trains. This observation will be born out with our subsequent statistical modelling.

Figure 2 shows plots of TSP, PM10, PM2.5 and PM1.0, all on the log scale, for a four hour period (4am to 8am) on another typical day, January 5th 2013. Note that constants of 1, 2 and 5, respectively, were added to the PM10, PM2.5 and PM1 levels in order to avoid the problem of taking logs of negative numbers. The Figure shows that TSP and PM10 levels have fairly similar patterns, though PM10 levels are less noisy than TSP. In contrast, the plots for PM2.5 and PM1.0 suggest that levels are generally relatively low, except during train passings. It is likely that these small particles correspond to diesel particles, not coal dust particles, which are more likely to be reflected in PM10 and TSP. In general, it appears that the spikes observed in the PM2.5 and PM1 plots are also reflected in the TSP and PM10 plots, though with more noise generally added in. This reflects the fact that there are likely to be a number of different sources reflected in the measurements of the larger particles, including coal dust and general dust.

4. STATISTICAL MODELLING STRATEGY

We analysed the data using a variant of linear regression, with outcome variable corresponding to one of the four particulate measures (PM1, PM2.5, PM10 or TSP) transformed to the log scale, as described above. The advantage of regression analysis is that it allows for simultaneous adjustment with respect to various confounding factors that may otherwise bias or distort the analysis. For example, loaded and unloaded coal trains were more commonly seen during the early morning and evening hours, compared with passenger trains which tended to be more frequent in daytime hours. Since particulate levels are likely to be generally higher in the daytime hours, a naïve comparison of particle levels associated with the different train types would be biased. A regression model that includes appropriate terms corresponding to time of day and day of study provides an adjustment that puts train type comparisons on an equal footing. We used an advanced version of linear regression analysis, the so-called generalized additive model, which allows for the flexible modelling of continuous functions using splines and other kinds of functions[1]. All statistical analysis was conducted in the statistical package *R*[2], using a function called *gam()*, which is part of the package *mgcv* developed by Wood[1]. One of the variables included in the model was a smooth spline function of *time of day*. Inclusion of this term in the model allowed for the likelihood that there might be a diurnal pattern in the data. Similarly, we included another smooth spline function of *day of observation*. Inclusion of this term allowed for the possibility that there might be a longer term pattern, for example associated with rainfall or temperature changes over time. Our model also included day of week indicators. We first conducted analyses excluding the wind speed and wind direction variables, since these data were not available on all study days.

Exploratory analysis of the residuals from our regression models suggested the presence of strong autocorrelation. This is to be expected in data such as these which represent a long time series of observations measured closely together in time. While there is a variation of the *gam()* function available that allows for autocorrelation, we found that because of the magnitude of our analysis datasets, the models were extremely slow to run or did not run at all. Consequently we used a bootstrap [3] to adjust the standard errors computed in our models for autocorrelation. In particular, we used a specific variant, the so called *blocked bootstrap*[4], which has been developed for use with serially correlated data. In our setting, a particularly simple implementation of the blocked bootstrap was achieved by resampling days. Standard errors were computed based a total of 50 bootstrap samples.

The large size of the analysis dataset meant that each model took several minutes to run and the bootstrap several hours. In order to explore the data and to identify suitable models, we first ran analyses using ordinary linear regression with polynomial terms in time of day and day of study. Our final analyses were then repeated using the more computationally intensive but accurate bootstrapped *gam*() function. In general, we found that linear regression models gave qualitatively similar results to the *gam*() analyses and hence they provided a useful practical approach to exploratory analysis.

The main variables of interest in all our analysis related to the various occurrences of train passings. For each of the 5 different kinds of train types, we created three different variables for inclusion in our model:

1. An indicator that took the value 1 while a particular train type was passing, 0 otherwise;
2. An indicator that took the value 1 for a period of T_{before} seconds before a particular train type arrived;
3. An indicator that took the value 1 for a period of T_{after} seconds after a particular train type had passed.

For these second and third variables, we considered a range of different values for T_{before} and T_{after}, ranging from 0 up to 70 seconds. The concept here was to allow the models to capture the likely effect whereby air disturbances just prior to and just after a train passing would be likely to stir up dust and other particles. As discussed presently, these variables turned out to be quite important. To select appropriate values of T_{before} and T_{after}, we reran our models over a range of feasible values and picked the values that gave us the best fit to the data according to the Akaike Information Criterion (AIC)[5] . We found that the optimal value of T_{before} was 3 minutes, while the optimal value of T_{after} was 5 minutes. As discussed in the conclusions section, there are some more sophisticated approaches that would be useful to explore, given more time. However, it is unlikely that these would lead to any substantial changes to our conclusions from a qualitative perspective.

5. RESULTS

Table 2 shows geometric means of all four particulate types corresponding to the periods when different types of trains are passing. Geometric means simply correspond to the exponent of the mean of the logged variables. Geometric means are commonly used when analysing environmental exposure data which often tend to highly skewed, just as we have found in the current context. In addition to showing particle levels while trains are passing, the Table also shows the geometric means corresponding to different periods of time prior to each train arrival, as well as after it has passed. For comparison, the last column ("No Train") shows particulate levels during periods where there is at least 3 minutes before the next train arrival and 5 minutes after the most recent train passing. A comparison of the columns labelled "During Train Passing" and "No Train" suggests that all particle types are elevated when the various trains pass by. The pattern persists if we consider "Any Train Type" (the first block of numbers in the table), or each of the 5 specific train types (Passenger, Freight, Loaded Coal, Empty Coal and Unknown). The "Any Train Type" variable was computed by ignoring the specific train types. Differences between the "During Train Passing" and "No Train" columns are quite small for passenger trains, but of a similar magnitude (approximately 10% to 15%) for freight, loaded coal, empty coal and unknown train types.

Table 2 reveals some interesting patterns corresponding to particle concentrations in the periods before trains arrive and after they have passed. For all train types and all particle types, we see that concentrations are elevated in the few minutes before and the few minutes after a train has passed. These elevations are apparent whether we look at 1, 2 or 3 minute periods prior to train arrival or 1, 2, 3, 4 or 5 minute periods after train passings. Our approach was a little different than the Katestone approach: they considered an entrainment period corresponding to the period after the train passed and lasting for a period corresponding to 3 times each train's passing duration. We come back to this point in the discussion and conclusion section of the report.

We have purposely not included standard errors in Table 2 since a naïve comparison between these columns would be inappropriate due to presence of serial correlation (see discussion in the statistical modelling section above). Also, computation of standard errors is complicated by the presence of serial correlation in the data. Instead, we assign statistical significance to the observed differences on the basis of generalized additive regression modelling as described previously. Table 3 shows the estimated regression coefficients, standard errors and p-values associated with the various type train indicators, based on using a blocked bootstrap applied to the *gam()* models described earlier. The first column of the Table indicates train type. Information for the four available particulate measures (TSP, PM10, PM2.5 and PM1) are shown in the four vertical blocks. Within each block, the first column is the estimated regression coefficient from an analysis of the log transformed particulate measurement. The second column within each block shows the estimated standard error and the third block shows the estimated p-value. These p-values can be used to attach significance to the observed differences seen in Table 2. Small p-values (say <.001) can be considered highly significant. Values between .001 and .01 can be considered significant, while values between .05 and .01 could be considered marginally significant. Some readers may be used to considering any p-value <.05 as significant. In the current context, however, we recommend being slightly more conservative due to the large number of p-values that have been calculated. Larger p-values (>.05) should be considered as non-significant.

To illustrate how to interpret Table 2 and 3 together, consider TSP levels associated with the passing of a loaded coal train. From Table 3, the coefficient of "LoadedCoal" from the regression analysis on TSP is 0.078. The associated standard error is 0.0146, resulting in a standardized regression coefficient of .078/.0146=5.34. Comparing this value to the standard normal tables tells us that this is a highly significant value (p<.0001). In other words, the analysis tells us that TSP levels are significantly higher than background levels when a loaded coal train is passing. To understand the magnitude of the effect, we need to convert this coefficient computed from a regression analysis on the log scale, back to the original scale, relative to background. More precisely, suppose we take as background level the "No Train" average of 28.93ug/m^3 seen in Table 2. The regression results imply that the TSP levels will rise to *28.93*exp(.078)=31.33*ug/m^3 when a loaded coal train is passing. This in turn means that the passing of a loaded coal train is associated with an average increase of 31.33-28.93=2.4ug/m^3 in TSP levels. This number is smaller than the difference we observe in Table 2 (33.02-28.93=4.09) because of the concurrent adjustments for time of day, day of study etc. Going through the same calculations for passenger trains, we find an estimated coefficient from Table 3 of .32, a corresponding standard error of .012 and p-value of .007 (a significant effect). Again taking background levels as 28.93, the regression analysis implies that TSP levels rise to *28.93*exp(.032)=29.87* ug/m^3 when a passenger train passes. Thus, the passing of a passenger train is associated with an average increase of 29.87-28.93=0.94. This number is again slightly smaller than the difference in geometric means (1.06) seen in Table 2 because of adjustment for other factors.

From Table 3, we see that with the exception of unknown train types (which are relatively infrequent anyway), the train coming and train passed variables are all either highly significant or marginally significant. As discussed in our conclusions section, we believe this is an area worthy of further exploration.

We ran a variety of additional models to explore other possible important features. For example, we re-ran our analyses excluding the 2189 seconds where multiple trains were passing at the same time. In this scenario, we found that there was no significant difference in the level of particulate levels associated with the passing of a passenger train. We also re-ran models that included information on the *speed of each train* at the time of its passing. This did not have any significant effect in terms of predicting particle levels. This finding is consistent with the Katestone report.

We explored the impact of *wind speed* by including as a smooth, non-linear term in the model, as a linear term and finally as a binary indicator of high versus low wind speed. None of these variables had a significant impact in terms of predicting particulate levels. This finding is consistent with the Katestone report.

We explored the impact of *wind direction* by creating an indicator function that took the value 1 when wind was blowing from the rail tracks towards the monitoring station (wind directions between 150 and 300 degrees) and then including these terms in our models. As reported by Katestone, wind direction does have significant impact. For example, in the "No Train" periods discussed above in the context of Table 2, we found that a geometric mean of 33.41ug/m^3 in TSP levels when wind was blowing towards the monitor, compared with 26.28ug/m^3 when wind was blowing away from the monitor. To explore the effect of wind direction further, we reran our models for the subset of data where the wind was blowing towards the monitor and then again in the subset where the wind was blowing away from the monitor. We found that the magnitude of the effects associated with each different train type increased when the wind was blowing towards the monitor. However, qualitative conclusions were unchanged. That is the magnitudes of the effect of a train passing were similar for freight and coal trains both empty and loaded. Passenger train effects were statistically significant, but of a smaller magnitude than for the freight and coal trains. With the exception of some of the "coming" variables, all effects were statistically significant. When wind was blowing away from the monitor, all effects were dampened and some effects lost significance. However, even when wind was blowing away from the monitor, we found a statistically significant increase in particulate concentrations associated with the passing of loaded and unloaded coal trains. The magnitude of these two effects were very close, with the effect of unloaded coal slightly higher.

6. DISCUSSION AND CONCLUSION

Despite the limitation of having data at only a single monitoring site, this two month time series of data provides useful information that can be used to address the two questions of interest, namely

1) Are trains operating on the Hunter Valley rail network associated with elevated particulate matter concentrations? and

2) Do trains loaded with coal have a stronger association compared with unloaded coal trains or other trains on the network?

With regard to Question 1, our analysis shows that there are clear and statistically significant elevations in particulate concentrations when a train passes by the monitoring station. These concentration elevations are apparent for all four particle types, including TSP, PM10, PM2.5 and PM1. In answer to Question 2, there is no evidence that loaded coal trains have a stronger association compared with unloaded coal trains or freight trains. Our analysis suggests that the freight trains and coal trains (loaded and empty) all have similar profiles. The elevations are of modest magnitude, with an increase of approximately 2.4 to 2.8 ug/m^3 relative to background levels for freight and coal trains (loaded and empty) for TSP. Corresponding increases for PM10, PM2.5 and PM1 are approximately 2, 0.7 and 0.12, respectively. In other words, there is approximately a 10% increase in the various kinds of particulate measurements associated with freight and coal trains. The impact of passenger train passings is much smaller, though still mostly statistically significant. When we reran our analyses excluding cases where there were multiple trains passing at the same time, the effect of a passenger train passing became non-significant. Our interpretation is that passenger trains do not contribute by themselves to elevations in particulate levels, but that the air turbulence associated with their passing causes an observed increase with other kinds of trains are passing at the same time.

The effects were apparent and remained significant for all available particulate measures, including TSP, PM10, PM2.5 and PM1, especially for freight and coal trains (loaded or empty). Effects were non-significant or only marginally significant for the smaller particles when passenger trains were passing. Since coal dust is likely to be reflected in the large particle counts (TSP and PM10), the fact that the signal remains strong for the smaller particle counts suggests that contaminants such as diesel may be of more concern than coal dust. This conclusion is further supported by the fact that effects were similar for freight, loaded and unloaded coal trains, all of which are pulled by diesel locomotives.

There are a number of areas where further analysis would be useful. For example, it would be useful to obtain information from the ARTC on the number of locomotives on each train, as well as indications of whether the locomotives were diesel or electric. If particles levels, especially smaller ones, increase with the number of diesel locomotives, this would lend credence to the possibility that diesel exhaust is contributing to particulate exposure in the Hunter region.

Much more work could usefully be done on the exposure profile associated with the various kinds of train passings. Our analysis has achieved a fairly simple, first pass assessment, distinguishing three time segment associated with the passing of a train: train approaching, train actually passing and train recently passed. We found some intriguing patterns that suggest that particulate levels begin to rise prior to a train's passing and stay elevated for several minutes. To accurately quantify the overall exposure level associated with a train's passing would require a more precise characterization of the exposure profile corresponding to the various stages of a train's passing. This could be achieved with a combination of considering physical concepts such as aerodynamics as well as applying more sophisticated statistical modelling techniques to empirically capture and model the profiles. A more accurate characterization of the train passing profile would also allow computation of the total exposure increase associated with a passing, rather than simply reporting on the average increase in concentration. For example while our analysis has shown that the average air concentrations in particulate levels are fairly similar for both loaded and unloaded coal trains, the total aggregate exposure associated with a loaded coal train may be different than that for an unloaded coal train because the passing durations vary so much.

There are also some technical aspects of our statistical modelling approach that would be worth exploring in more detail. For example, we found that the data exhibited significant serial correlation, even after adjusting for diurnal effects and longer term time effects. We adjusted for serial correlation through the use of a blocked bootstrap. It would be worthwhile exploring the nature of the serial correlation in the data to determine if other approaches might be applicable.

Finally, it would be worthwhile assessing the accuracy and reliability of the ARTC's train passing data. In particularly, there appeared to be occasional spikes in the observed particulate counts where no train passing had been reported. It is likely that such spikes corresponded to the passing of vehicles other than trains, for example maintenance vehicles. Obtaining such information would be useful and would improve the overall accuracy of the modelling. It would also be useful to consider the incorporation of other sources of information about ambient particulate exposure levels in the Hunter region. It is clear from our analysis that the data are quite noisy and that they display fairly strong diurnal and daily patterns. Incorporating additional information pertaining to regional background levels would help to isolate contributions due to train traffic in the Hunter corridor.

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7. GRAPHS AND TABLES

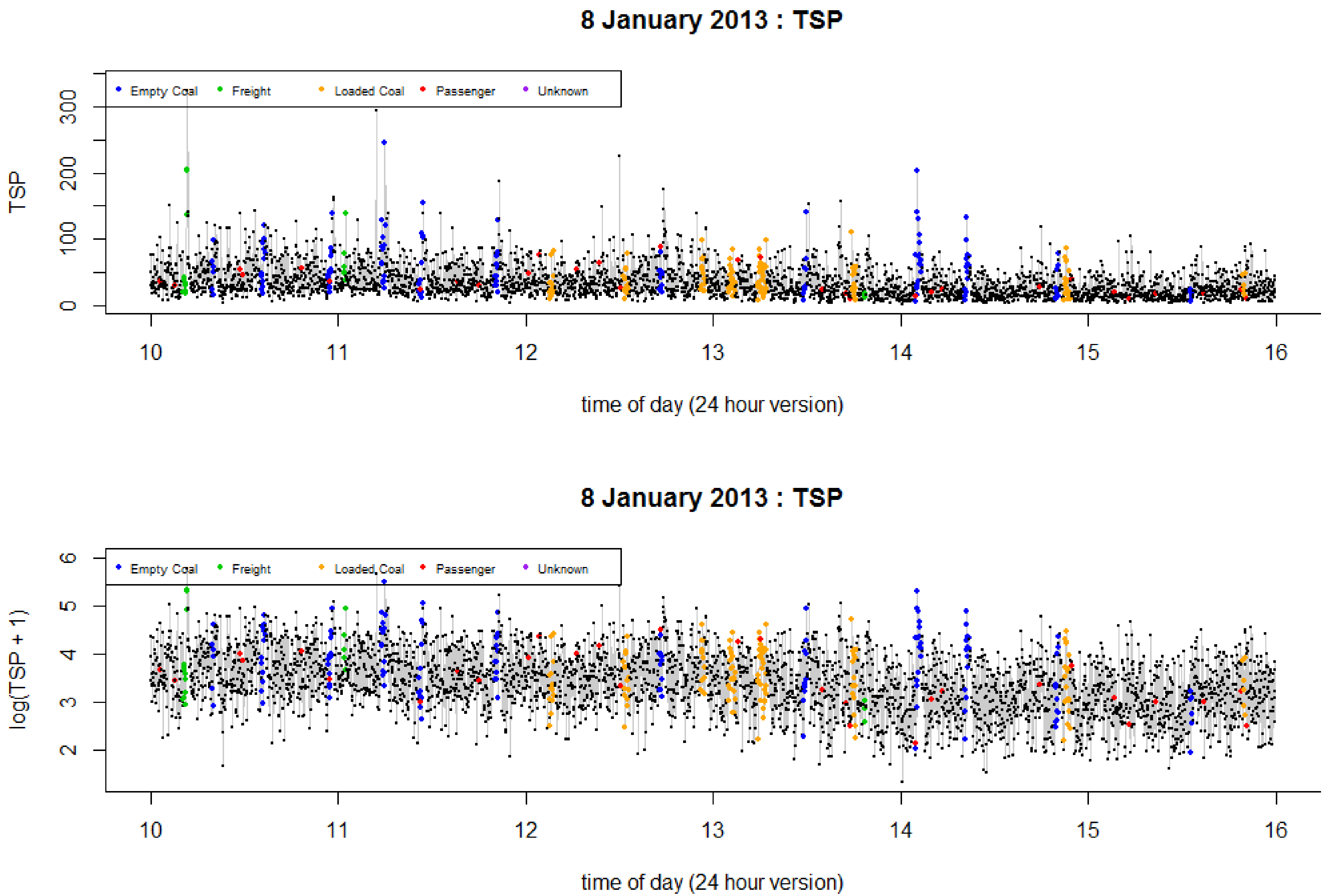

Figure 1: TSP and log(TSP+1) from 10am until 4pm on January 8th, 2013

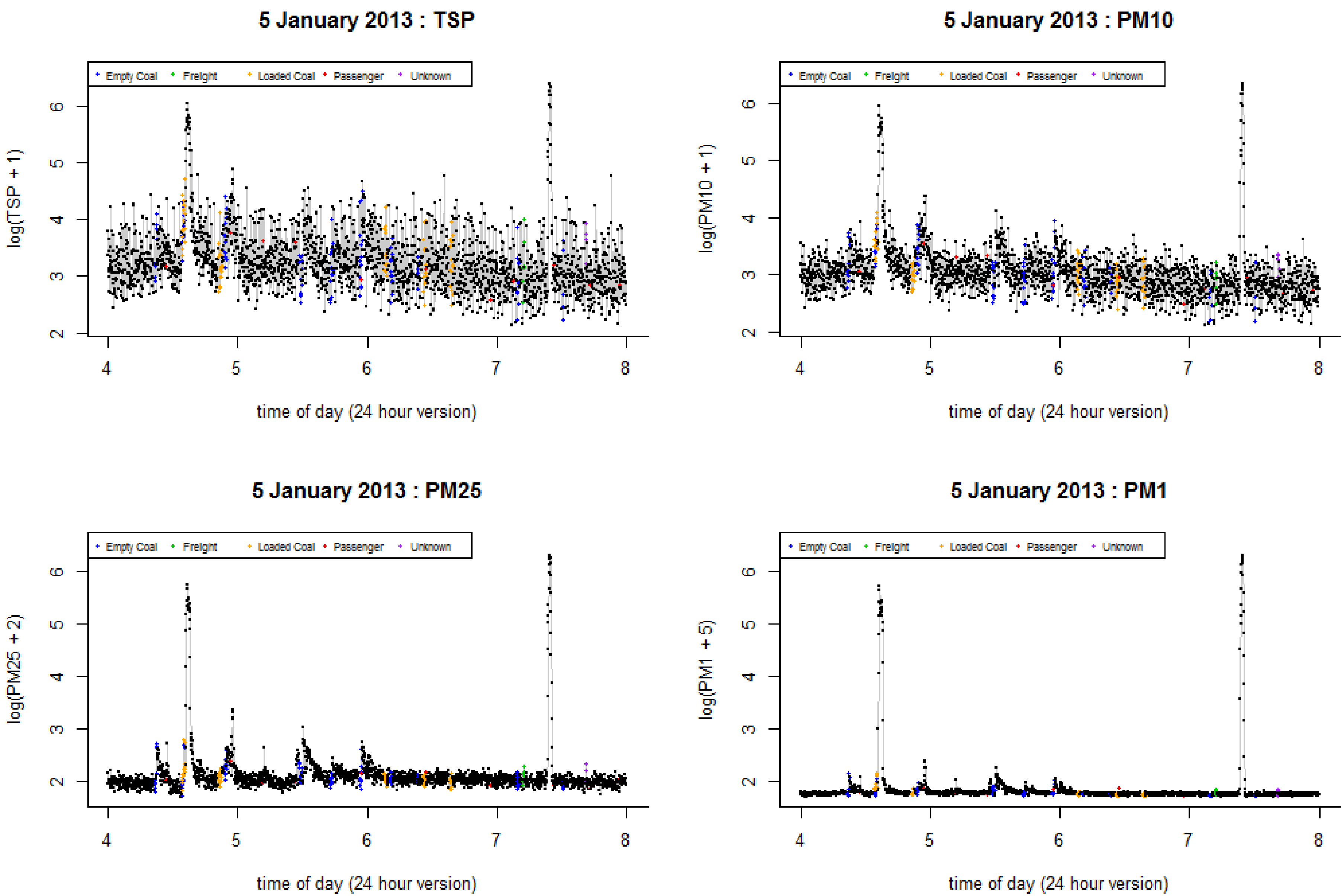

Figure 2: TSP, PM10, PM2.5 and PM1 from 4am until 8am on January 5th, 2013

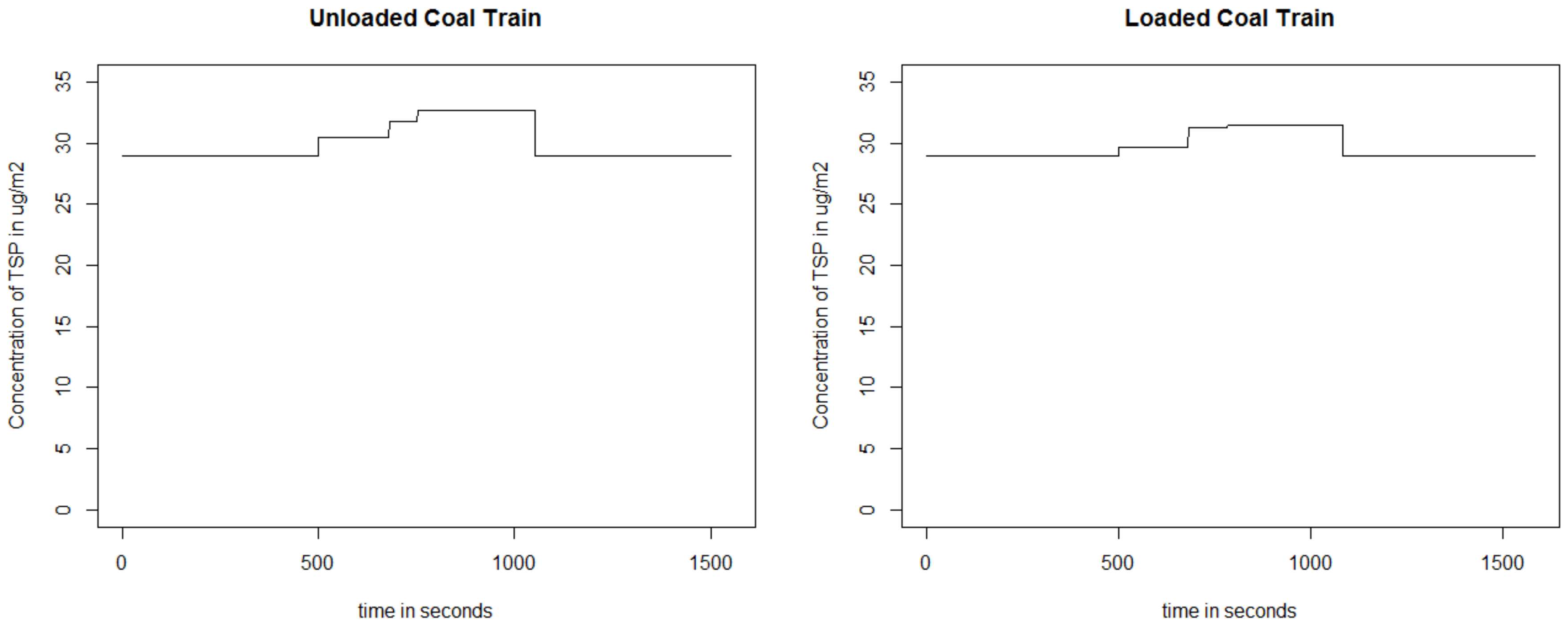

Figure 3: Estimated profiles of increases in TSP associated with an unloaded (left panel) and loaded (right Panel) coal train

Train type	Number per day Median (LQ,UQ)	Duration (secs) Mean (LQ,UQ)	Speed (m/sec) Mean (LQ,UQ)
Empty Coal	40 (27, 47)	72 (67, 78)	19.8 (18.5,20.7)
Freight	6 (2,8)	69 (40, 85)	18.7 (15.1, 20.5)
Loaded Coal	36 (24, 41)	103 (93, 117)	13.9 (11.8, 15.1)
Passenger	60 (55, 92)	2 (2,2)	24.9 (23.9, 28.8)
Unknown	3 (2, 3)	2 (2, 2)	24.6 (22.2, 27.6)

Table 1: Summary of daily train activity

Train Type	Particle Type	Period before train arrival			During train passing	Period after train has passed					No train
		3 min	2 min	1 min		1 min	2 min	3 min	4 min	5 min	
Any Train Type	TSP	30.81	30.99	31.16	33.01	32.23	32.48	32.36	32.01	31.75	28.93
	PM10	24.21	24.36	24.47	25.88	25.29	25.46	25.36	25.1	24.9	22.78
	PM2.5	10.04	10.1	10.14	10.54	10.43	10.47	10.43	10.34	10.26	9.35
	PM1	6.47	6.48	6.48	6.59	6.56	6.57	6.56	6.54	6.52	6.34
Passenger Train	TSP	29.92	30.02	30	29.99	30.14	30.33	30.42	30.4	30.33	28.93
	PM10	23.49	23.58	23.56	23.47	23.68	23.83	23.89	23.86	23.81	22.78
	PM2.5	9.86	9.9	9.89	9.88	9.98	10.04	10.05	10.03	10	9.35
	PM1	6.41	6.42	6.41	6.41	6.44	6.46	6.46	6.46	6.46	6.34
Freight Train	TSP	33.39	33.64	33.98	36.2	35.89	36.57	36.22	35.56	35.06	28.93
	PM10	25.89	26.04	26.2	28.13	27.85	28.24	28.02	27.51	27.16	22.78
	PM2.5	10.21	10.27	10.31	10.99	10.99	11.05	10.96	10.8	10.69	9.35
	PM1	6.45	6.46	6.5	6.65	6.64	6.65	6.63	6.6	6.59	6.34
Loaded Coal Train	TSP	31	31.33	31.62	33.02	33.7	34.08	33.77	33.23	32.71	28.93
	PM10	24.44	24.7	24.88	25.93	26.45	26.66	26.41	26.01	25.65	22.78
	PM2.5	10.11	10.19	10.22	10.55	10.74	10.79	10.7	10.58	10.46	9.35
	PM1	6.5	6.52	6.52	6.66	6.64	6.65	6.63	6.59	6.56	6.34
Empty Coal Train	TSP	31.61	32.02	32.51	33.19	34.64	35.03	34.74	34.15	33.7	28.93
	PM10	24.85	25.16	25.52	25.98	27.16	27.4	27.19	26.76	26.42	22.78
	PM2.5	10.23	10.36	10.48	10.58	10.99	11.07	10.99	10.85	10.73	9.35
	PM1	6.52	6.55	6.57	6.59	6.73	6.74	6.72	6.68	6.64	6.34
Unknown Train	TSP	32.77	32.93	33.91	37.25	35.94	35.41	35.1	34.29	33.85	28.93
	PM10	25.8	26	26.45	29.45	28.07	27.65	27.54	27.03	26.64	22.78
	PM2.5	10.52	10.63	10.73	11.73	11.32	11.15	11.1	10.92	10.78	9.35
	PM1	6.74	6.75	6.73	6.88	6.86	6.78	6.78	6.72	6.69	6.34

Table 2: Geometric means of particulate levels (TSP, PM10, PM2.5 and PM1) in ug/m^3 for different kinds of train passings and at duration durations before and after train arrival. The category "Any train type" refers to the presence of a passenger, freight, loaded coal, empty coal or unknown train type.

	Log(TSP+1)			Log(PM10+1)			Log(PM2.5+2)			Log(PM1+5)		
	Estimate	Std Error	p-Value	Estimate	Std Error	p-Value	Estimate	Std Error	p-Value	Estimate	Std Error	p-Value
Empty Coal Coming	0.053	0.0131	<0.001	0.050	0.0133	<0.001	0.045	0.0126	<0.001	0.017	0.0047	<0.001
Empty Coal	0.095	0.0158	<0.001	0.089	0.0155	<0.001	0.073	0.0138	<0.001	0.026	0.0047	<0.001
Empty Coal Passed	0.121	0.0151	<0.001	0.115	0.0155	<0.001	0.096	0.0150	<0.001	0.037	0.0056	<0.001
Freight Coming	0.043	0.0249	0.088	0.032	0.0238	0.167	0.008	0.0220	0.703	-0.001	0.0114	0.938
Freight	0.091	0.0258	<0.001	0.087	0.0260	<0.001	0.063	0.0231	0.006	0.023	0.0096	0.016
Freight Passed	0.099	0.0233	<0.000	0.089	0.0221	<0.001	0.061	0.0205	0.002	0.022	0.0102	0.029
Loaded Coal Coming	0.026	0.0132	0.053	0.027	0.0128	0.035	0.028	0.0118	0.014	0.009	0.0046	0.030
Loaded Coal	0.078	0.0146	<0.001	0.075	0.0141	<0.001	0.063	0.0111	<0.001	0.021	0.0040	<0.001
Loaded Coal Passed	0.086	0.0128	<0.001	0.082	0.0125	<0.001	0.067	0.0116	<0.001	0.020	0.0041	<0.001
Passenger Coming	0.024	0.0094	0.012	0.021	0.0091	0.016	0.018	0.0081	0.021	0.003	0.0027	0.229
Passenger	0.032	0.0120	0.007	0.025	0.0107	0.019	0.022	0.0112	0.047	0.004	0.0040	0.276
Passenger Passed	0.041	0.0109	<0.001	0.039	0.0102	<0.001	0.036	0.0096	<0.001	0.011	0.0034	0.001
Unknown Coming	0.039	0.0388	0.316	0.042	0.0381	0.265	0.049	0.0406	0.218	0.040	0.0234	0.085
Unknown	0.118	0.0549	0.031	0.126	0.0541	0.019	0.125	0.0574	0.028	0.043	0.0337	0.201
Unknown Passed	0.058	0.0376	0.119	0.050	0.0133	<0.001	0.062	0.0380	0.100	0.024	0.0179	0.174

Table 3: Coefficients of the train variables, their associated standard errors and p-values from gam() models that include smooth function of time since midnight, day of study and day of week.