Smoke Patterns around Prescribed Fires in Australian Eucalypt Forests, as Measured by Low-Cost Particulate Monitors

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Abstract: Prescribed burns produce smoke pollution, but little is known about the spatial and temporal pattern because smoke plumes are usually small and poorly captured by State air-quality networks. Here, we sampled smoke around 18 forested prescribed burns in the Sydney region of eastern Australia using up to 11 Nova SDS011 particulate sensors and developed a Generalised Linear Mixed Model to predict hourly PM\textsubscript{2.5} concentrations as a function of distance, fire size and weather conditions. During the day of the burn, PM\textsubscript{2.5} tended to show hourly exceedances (indicating poor air quality) up to ~2 km from the fire but only in the downwind direction. In the evening, this zone expanded to up to 5 km and included upwind areas. PM\textsubscript{2.5} concentrations were higher in still, cool weather and with an unstable atmosphere. PM\textsubscript{2.5} concentrations were also higher in larger fires. The statistical model confirmed these results, identifying the effects of distance, period of the day, wind angle, fire size, temperature and C-Haines (atmospheric instability). The model correctly identified 78% of hourly exceedance and 72% of non-exceedance values in retained test data. Applying the statistical model predicts that prescribed burns of 1000 ha can be expected to cause air quality exceedances over an area of ~3500 ha. Cool weather that reduces the risk of fire escape, has the highest potential for polluting nearby communities, and fires that burn into the night are particularly bad.

Keywords: smoke plume; smoke exposure; PM\textsubscript{2.5}; smoke dispersion; air quality; air pollution; prescribed burn

1. Introduction

Prescribed burning is a common strategy for reducing many aspects of wildfire risk, effects that have been quantified in many studies around the world. For example, in the south-eastern forests of Australia, which have experienced the most destructive fires in Australian history, the wildfire area is reduced by 1 ha for every 3 ha of treatment [1], and a recently burnt patch will reduce subsequent wildfire severity for approximately 7 years [2]. Smoke exposure is one aspect of risk that is poorly understood. It can be implied from other risk studies that prescribed burning reduces smoke emissions from wildfires, but prescribed fires produce smoke of their own. Thus, there is a need to understand the trade-off between the reduction of wildfire smoke and the deliberate introduction of smoke [3].

Wildfire smoke is known to affect human health in a variety of ways, increasing mortality, morbidity, chronic obstructive pulmonary disease (COPD), asthma and respiratory infection [4]. At its most basic, hundreds of thousands of deaths around the world are attributable to landscape fire smoke each year [5], and Australia contributes significantly to that total [6]. Landscape burning (both prescribed burning and wildfires) produces a variety of pollutants, including particulates, considered to pose a significant threat to human health [4,7]. Particulates less than 2.5 µm in diameter (PM\textsubscript{2.5}) are criteria pollutants...
in the regulatory systems for air quality, for example, in the USA National Ambient Air Quality Standards and Australian National Environment Protection (Ambient Air Quality) Measure.

Some of the important questions that remain about the impact of particulates from prescribed burning are how much particulates are produced, how far and in what spatial pattern they disperse, and how these factors compare to those related to wildfire particulates [3]. The need to understand the trade-off between smoke from prescribed fire and wildfire has been recognised for decades [8], but it is a difficult and multi-faceted problem. In theory, it would be possible to use atmospheric dispersion models, but these have proven to have low accuracy [9,10], especially at the local scales required for modelling community impacts from prescribed burning [11]. There is a need for an observational evidence base of the dispersion of prescribed burning smoke, but as yet, there have been few such studies. Indeed Navarro, Schweizer [12] reviewed observational studies in the USA and found only seven empirical studies of prescribed burning. These reported higher levels of particulates than studies of wildfire, but they were not directly comparable because the measurements were closer to the exposed communities.

While state air quality networks are often able to detect smoke from wildfires, they rarely detect prescribed burns because they are smaller and probably not dispersed so far as wildfires. There have been documented cases where prescribed burns have elevated particulate levels in air quality monitoring networks, such as those in May 2016 that caused poor air quality for four days in Sydney, Australia [13]. Also, the air quality network has occasionally been used for more systematic analyses of days with prescribed burns. Di Virgilio, Hart [14] identified days when prescribed burns occurred in the Sydney region and investigated the weather conditions that influenced whether those days had elevated PM$_{2.5}$ levels. They found that cool, stable conditions with light westerly winds were associated with smoke impacts in Sydney. However, they could not identify the effects of individual fires.

The scale mis-match between prescribed burning smoke and the air quality network means that a comprehensive quantification of smoke dispersion from individual prescribed fire is challenging [11]. It is more suited to a small-scale network of monitors deployed to each fire, and a few such studies have been conducted. Pearce, Rathbun [15] measured particulates around 55 burns in South Carolina (USA) savannah using a moveable grid of 19 devices with Teflon filters to collect samples. They found that particulates had fallen to background levels beyond 2 km of the burns and effects of wind angle and ignition type, but not of weather or atmospheric stability. In Australia, Price, Horsey [11] observed two prescribed burns using a single portable Dusttrak monitor and found a significant smoke impact in one of them up to 10 km from the fire due to an overnight collapse of the plume.

The proliferation of low-cost particulate monitors has greatly simplified the task of monitoring air quality around pollution events, including prescribed burns [16–18]. Here, we used 13 low-cost monitors deployed to 18 prescribed burns in eucalypt forests in the hinterlands of Sydney. We used the data to quantify the typical spatial and temporal patterns of particulates around the fires in the zone 100 m–20 km and the influence of weather conditions on those patterns. The objective was to identify weather conditions that are likely to cause greater smoke impact (so they can be avoided) and predict the distance that pollution will spread to improve the ability of fire authorities to manage risks to communities.

2. Materials and Methods
2.1. Data Collection

The study took place in the greater Sydney region of New South Wales (NSW), Australia (Figure 1). The study area consists of a coastal strip flanked by a mountain range rising to 1300 m. Our sampled burns were between 1 and 70 km from the ocean and 50 and 700 m of elevation. Downslope drainage of pollution from the mountains to the coast has been documented in the area. We sampled 18 prescribed burns that represented the range
of burns that occur in the region (Table 1), of which the majority (13) were conducted by the Department of Planning, Industry and Environment (DPIE), who manage the National Parks estate in NSW. Eleven of these were in 2019, and two in 2020. The other five burns consisted of two burns by the NSW Rural Fire Service in 2015, and three cultural burns conducted in 2019, one by the Mudjingaalbaraga Firesticks Program and one by the Koori Country Firesticks Aboriginal Corporation (Figure 1, Table 1). The fires ranged in size from <1 ha for the cultural burns to 1300 ha. All of the burns were in *Eucalyptus*-dominated dry sclerophyll forest [19]. A fuel consumption study undertaken in 11 of the burns has estimated that the mean fine fuel consumption was 10 t/ha (unpublished data), which is typical of prescribed burns in south-eastern Australian forests [20]. Fires were all ignited between 09:45 and 11:00 local time. Most of the fires were completed (crews reduced to ‘mop-up’) by 18:00 on the day of ignition, but for two of the fires, sections were burnt on different days, in which case we considered them as separate fires (Triplarina and Bowen Mtn).

Figure 1. A map of the 18 prescribed burns used in this study. The numbers refer to their entry in Table 1.
Table 1. Summary information for the 18 fires. Columns titled Pred. Max. refer to the maximum distance at which PM$_{2.5}$ exceeded 50 as predicted from a model of PM$_{2.5}$ v log (distance) for each fire (as used in the analysis by fire). Fires with * were cultural burns.

| Map Number | Fire Name   | Date          | Area (Ha) | Observations | Surface Pressure (hPa) | Inversion Temp. (°C) | Mixing Height (m) | Max Exceedance Distance (km) | Pred. Max. Exceed. Dist. (Day, m) | Pred. Max. Exceed. Dist. (Eve, m) |
|------------|-------------|---------------|-----------|--------------|------------------------|----------------------|------------------|-------------------------------|-----------------------------------|----------------------------------|
| 1          | Cataract 1  | 22 August 2015| 18.8      | 48           | 6.33                   | 1019                 | 2.2              | 5                             | 1.23                              | 2.00                             | 1.48                             |
| 2          | Cataract 2  | 9 October 2015| 300.1     | 49           | −0.95                  | 1033                | −2.7             | 934                           | 2.39                              | NA                               | NA                               |
| 3          | Woronora    | 10 March 2019 | 98.2      | 395          | 4.35                   | 1015                 | 0.3              | 5                             | 7.72                              | 4.02                             | 4.02                             |
| 4          | Back Run Creek | 28 March 2019 | 150.0     | 177          | −0.63                  | 1020                 | −0.9             | 177                           | 2.96                              | 0.00                             | NA                               |
| 5          | Coalcliff   | 13 April 2019 | 47.8      | 387          | 2.52                   | 1023                 | 1.9              | 73                            | 8.67                              | 0.08                             | 0.00                             |
| 6          | Wilson      | 17 April 2019 | 138.1     | 513          | 3.08                   | 1024                 | 2.7              | 20                            | 8.15                              | 0.00                             | 1.34                             |
| 7          | Dhalia      | 28 April 2019 | 204.5     | 344          | 10.35                  | 1020                | 4                | 5                             | 1.22                              | 2.70                             | NA                               |
| 8          | Waterfall West | 17 May 2019  | 70.7      | 413          | 3.63                   | 1026                | 3.4              | 73                            | 4.83                              | 0.00                             | 4.45                             |
| 9          | Lawson      | 19 May 2019   | 1298.0    | 698          | 0.07                   | 1029                | 2.6              | 5                             | 34.01                             | 6.00                             | 12.09                            |
| 10         | Avon        | 1 June 2019   | 926.5     | 223          | 0.52                   | 1025                | 3.4              | 21                            | 18.82                             | 8.96                             | NA                               |
| 11         | Triplarina 1 * | 15 July 2019 | 0.2       | 122          | −0.58                  | 1015                | −2               | 779                          | 0.37                              | 0.15                             | 0.02                             |
| 12         | Triplarina 2 * | 16 July 2019 | 1.0       | 94           | 9.52                   | 1016                | 1.8              | 21                           | 0.14                              | 0.54                             | 0.00                             |
| 13         | Yellomundee * | 27 July 2019 | 0.5       | 196          | 2.88                   | 1021                | 1.6              | 70                           | 0.00                              | 0.00                             | 0.00                             |
| 14         | Bowen Mtn   | 3 August 2019 | 177.3     | 375          | 7.45                   | 1027                | 3.4              | 103                          | 8.40                              | NA                               | 4.45                             |
| 15         | Heathcote   | 7 August 2019 | 97.1      | 394          | 10.72                  | 1014                | 5.6              | 13                           | 5.16                              | 3.64                             | 3.29                             |
| 16         | Bowen Mtn 2 | 13 August 2019| 174.4     | 417          | 3.18                   | 1023                | 0.8              | 5                            | 28.25                             | NA                               | 6.63                             |
| 17         | Woodfield   | 16 September 2020 | 15.6  | 180          | 8.4                    | 1024                | 1.4              | 5                            | 1.15                              | 0.00                             | 0.00                             |
| 18         | Abaroo      | 10 October 2020| 190.7     | 420          | 3.92                   | 1017                | 0.6              | 5                            | 6.51                              | 0.00                             | 0.05                             |
Smoke was sampled using low-cost particulate monitors housing a Nova SDS011 sensor, which measures PM$_{2.5}$ and PM$_{10}$ concentrations. The Nova sensor combines a fan and laser scatter sensor, and the output signal is converted into an estimated particulate concentration using a predetermined equation. Our monitors were built by the SMART (Simulation, Modelling, Analysis, Research and Teaching) Infrastructure Facility’s Digital Living Lab at the University of Wollongong, combining the sensor with an Arduino controller, clock, storage device and additional fan to ensure air flowed through the housing [21]. Forehead, Barthelemy [21] compared the performance of Nova sensor to two others commonly available and considered it to be the best. They also tested it against a reference monitor operated by the NSW DPIE (Beta Attenuation Method (BAM) TEI 5014i/TEI 5030) and found good correlation ($r^2 = 0.858$) and similar PM$_{2.5}$ values, even at concentrations below 10 µg m$^{-3}$. At each fire, between 7 and 11 Nova monitors were positioned at varying distances and directions, with the precise locations determined by accessibility and the forecast wind direction (more intense sampling downwind), sampling every minute. The median distance to the fire was 5.3 km from the perimeter, with 14% of deployments within 1 km and 10% greater than 20 km. At most of the fires, we also fixed a GPS-enabled version of the monitor to a vehicle and drove around the fire during the day, with median observation distance of 7.8 km and 3% of observations within 1 km and 15% greater than 20 km (Figure 2). The GPS was fixed to the front bumper of the vehicle, and testing indicated that the readings were not affected by the exhaust from the rear. The duration of the monitoring varied among the fires from 8 to 48 h depending on the fire duration.

![Distribution of monitor distances from the fires.](image)

Particulate concentrations from the stationary monitors were summarised to the nearest hour (mean value). The GPS observations were summarized to unique combinations of hour (time) and minute (location). There were a total of 5445 hourly PM$_{2.5}$ observations, comprising 3721 from stationary monitors and 1724 from mobile GPS monitors. We also classified observations into three time periods: daytime (from 10 a.m. until 4 p.m., while the fire was active), evening (4 p.m. until midnight, a period of smoke settling) and night-time (from midnight until 10 a.m., before the boundary layer lifted in the morning). The National Environment Protection (Ambient Air Quality) Measure defines standards for poor air quality, which currently is set at 25 µg m$^{-3}$ for daily PM$_{2.5}$ exposure, but there is no standard for hourly exposure. The Australian Health Protection Principal Committee (AHPPC) has agreed on a value of 50 µg m$^{-3}$ as an hourly threshold for issuing public
warnings of poor air quality. We used this threshold as a reference for interpreting our results and referred to values above the threshold as hourly exceedances.

Weather conditions for each of the hourly observations were estimated using an inverse distance weighted function of weather station data from the Bureau of Meteorology, recording the temperature, wind speed, wind direction and relative humidity. The mean distance to the closest weather station was 13.2 km. The weather data were used to calculate the wind angle (difference between the wind direction and the direction from the fire to the monitor). Wind angles <45° are considered as downwind and those >135° as upwind. In addition, daily values of several measures of atmospheric stability were calculated from 9 a.m. upper atmospheric observations (radiosonde data) at Sydney Airport (Bureau of Meteorology subscription service). The measures we used were C-Haines (mid-level atmospheric stability [22], mixing height, surface pressure and inversion temperature (the difference between the temperature at the warmest level and that at the surface).

2.2. Analysis

Graphical summaries of the effects of distance, wind angle and weather on PM$_{2.5}$ values were performed on the combined hourly data. For each fire, the maximum distance of hourly exceedance was also calculated.

A statistical model to predict PM$_{2.5}$ concentration as a function of distance, fire area, day period and weather was developed using generalised mixed modelling, with fire name as a random variable. The best model was determined in a two-step process: all combinations of the predictors were tested, and the best combination was selected based on AIC. Then all two-way interactions from the terms in the best model were tested to produce a final model. There were 11 predictors in total, as described in the previous paragraph. The main predictor of interest was distance (between fire and monitor), and to explore the form of this relationship, we compared linear, exponential and spline (using a generalised additive model) function and found the exponential to perform best (log of distance). Fire area (in hectares) was also log-transformed because this performed better than the untransformed area. To estimate the performance of the model, a random set of 20% of the data was withheld for testing. For these data, we compared the model predictions to the observed PM$_{2.5}$, reporting the mean percentage error (NMB, 100*(predicted-observed)/observed), root mean-square error (RMSE, sqrt(mean((observed-predicted)^2))) and the percentage of true positive and true negative exceedances (PM$_{2.5}$ values > 50). We also tested the degree of spatial autocorrelation in the model residuals using a Moran’s I test. The statistical modelling was conducted using the lme4 package [23] in r.

2.3. Estimating the Area Affected by Poor Air Quality

The area that can be expected to experience an hourly exceedance was estimated by applying the statistical model separately for daytime and evening conditions.

1. Apply the hourly model at different wind angles and a pre-determined fire area to predict the maximum distance from the fire perimeter of exceedance under median weather conditions.

2. Using the mean distance (R) across all angles, calculate the area of a circle $\pi R^2$. Notice, an adjustment was made for the radius of the fire (distances were measured from the fire boundary).

3. Repeat for fires of increasing area.
3. Results

Two of these fires were associated with 24 h exceedances for PM$_{2.5}$ in the state air quality network. The Lawson Ridge burn affected four monitors on the days after the fire (the furthest being Campbelltown, 52 km away), and the Bowen Mtn 2 burn affected Richmond, 12 km from the fire. Most of the hourly PM$_{2.5}$ observations using the low-cost monitors at the 18 fires were below 5.2 µg m$^{-3}$, and only 13% of the values were hourly exceedances (>50 µg m$^{-3}$). For reference, the average daily PM$_{2.5}$ concentration in NSW state air quality network in the Sydney region is 8.32 µg m$^{-3}$ [24] and the average weekly concentration has been reported as between 6 and 10 µg m$^{-3}$. For the majority of the fires, hourly exceedances were not observed beyond 5 km, and none of the three cultural fires recorded exceedances beyond 400 m (Table 1, Figure 3). However, three fires recorded exceedances beyond 15 km (Lawson, Bowen Mtn 2 and Avon). Although we attempted to sample all around and, particularly, downwind of the fire using the GPS sensor, it was not always possible to observe the absolute maximum exceedance distance.

![Maximum exceedance distance](image)

**Figure 3.** The maximum distance at which hourly PM$_{2.5}$ values > 50 µg m$^{-3}$ were recorded for each fire (usually from the GPS monitors). The three cultural burns are labelled with *.

3.1. Trends in Hourly Observations

Visual observations during the fires suggested that in most of the fires, smoke was aloft for most of the day (as shown in the photographs in Figure 4), but the plume started to descend from around 4 p.m.

The average PM$_{2.5}$ time trace for monitors within 5 km of any fire is shown in Figure 5, and the time trace for each individual monitor in the Bowen Mtn 2 fire is shown in Figure 6 as an example. While the studied fires were active (up to 6 p.m.), the PM$_{2.5}$ values tended to be below exceedance. From about 7 p.m., concentrations built up to reach a peak at 10 p.m. before gradually falling to exceedance levels at around 9 a.m. the following morning. Only the two Triplarina fires, which were both <1 ha in size, failed to show the evening increase. Fourteen of the 18 fires were still recording PM$_{2.5}$ concentrations above 10 µg m$^{-3}$ 28 h after ignition (Figure 5).
the evening, exceedances were predicted beyond 5 km for four of the fires (Woronora, Dhalia, Lawson and Bowen Mtn 2, Table 1).

During the day, PM2.5 concentrations were higher in stronger winds, but in the evening and night-time, they were higher under light winds (Figure 8). The temperature effects showed a similar split according to the time of day, with higher temperatures associated with higher PM2.5 concentrations in the daytime, but lower temperatures associated with high concentrations in the evening and night.

Figure 4. Three examples of the plumes generated by prescribed burns. Photographs were taken between 5.1 and 5.4 km from the fires.

Dhalia, 2019/04/28 2 pm, 205 ha

Waterfall, 2019/05/17 4 pm, 71 ha

Bowen Mtn, 2019/08/03 3 pm, 177 ha

Figure 5. Average time trace for the combined hourly observations (excluding those >5 km from the fires). The dashed line indicates the 50 µg m\(^{-3}\) hourly exceedance threshold.

Figure 5. Average time trace for the combined hourly observations (excluding those >5 km from the fires). The dashed line indicates the 50 µg m\(^{-3}\) hourly exceedance threshold.
Figure 6. The Bowen Mtn 2 fire as an example, showing the location of the fire, monitors (green) and smoke as observed from the MODIS Aqua satellite at ~2:30 p.m. on 13 August 2019 and the time trace of PM$_{2.5}$ at the monitors. The dashed line indicates the 50 µg m$^{-3}$ hourly exceedance threshold.

During the daytime and taking all fires together, downwind PM$_{2.5}$ concentrations were high near the fires but tended to drop below the exceedance level by 2 km from the fire (Figure 7a). Upwind concentrations were rarely above exceedance at any distance (Figure 7b). The fitted distance relationships for each fire predicted that only the Lawson fire exceeded the standard beyond 5 km during the day (Table 1). As the smoke concentrations began to increase in the evening, so did the distance that the smoke extended. Downwind, the evening concentrations tended to be above exceedance for 4 km from the fires, and there were many observations above exceedance at distances over 10 km from the fires (Figure 7c). In addition, the directionality of the smoke became less distinct in the evening, such that exceedances extended up to 4 km upwind from the fires (Figure 7d). In the evening, exceedances were predicted beyond 5 km for four of the fires (Woronora, Dhalia, Lawson and Bowen Mtn 2, Table 1).
During the day, PM$_{2.5}$ concentrations were higher in stronger winds, but in the evening and night-time, they were higher under light winds (Figure 8). The temperature effects showed a similar split according to the time of day, with higher temperatures associated with higher PM$_{2.5}$ concentrations in the day time, but lower temperatures associated with high concentrations in the evening and night.

3.2. Statistical Analysis

The statistical model of the hourly PM$_{2.5}$ concentrations revealed complex relationships (Table 2, Figure 9), with effects of distance, period (time of day), wind speed, wind angle, temperature and atmospheric stability (best represented by the C-Haines index), and eight two-way interactions. As expected, distance was the strongest predictor. During the day and under average weather conditions, PM$_{2.5}$ was predicted to fall below exceedance (50 µg m$^{-3}$) within 3 km from the fire downwind and within 1 km upwind. The model predicted that exceedance concentrations extend further in the evening than in the day, and night-time was similar to daytime (Figure 9). Exceedances extend further for large fires, lower temperatures and lower C-Haines values (more stable air). For small fires (~1 ha), the model predicted that exceedances would extend less than 1 km, while for large fires (~1000 ha), they extend to 5 km. Most of the interactions were subtle compared to the main effects. The most substantial interaction was the Fire area–Day period interaction, which predicted exceedances over 8 km for large fires in the evening (Figure 9C). According to this model, relative humidity, wind speed, mixing height and inversion height did not influence the PM$_{2.5}$ concentrations. There was a low degree of spatial autocorrelation in this model (Moran’s I for residuals = 0.145).

Figure 7. Mean and confidence intervals of the observed PM$_{2.5}$ concentration at increasing distance from the fire edge divided into downwind/upwind and daytime/evening combinations. Distances beyond 15 km are not shown in these graphs.
Figure 8. Mean and confidence intervals of the observed PM$_{2.5}$ concentration at increasing temperature (a) and wind speed (b) in daytime, evening and night-time periods. These data are for all fires but excluding observations >5 km from the fires. The dashed line indicates the 50 µg m$^{-3}$ hourly exceedance threshold.

Table 2. Estimate table for the best fixed terms of the Generalised Linear Mixed Model of hourly PM$_{2.5}$ observations ($n = 4224$). The full model formula was: PM$_{2.5} \sim \log\text{dist} \times \text{windangle} + \log\text{dist} \times \text{dayperiod} + \log\text{dist} \times \text{temp} + \log\text{dist} \times \log\text{area} + \log\text{dist} \times \text{C}_\text{haines} + \text{dayperiod} \times \text{temp} + \text{dayperiod} \times \log\text{area} + \text{dayperiod} \times \text{C}_\text{haines} + (1 | \text{firename})$, where firename is the random term, with a standard deviation of 42.3. Dayperiod is a factor with levels Daytime, Evening and Night, and with Daytime bound in the intercept. A colon (:) indicates an interaction.

| Variable   | Estimate | Std. Error | T Value | $p$   |
|------------|----------|------------|---------|-------|
| (Intercept)| 517.662  | 74.553     | 6.944   | <0.001|
| Logdist    | -57.215  | 8.398      | -6.813  | <0.001|
| Windangle  | -1.618   | 0.213      | -7.589  | <0.001|
| Evening    | 20.164   | 38.419     | 0.525   | ns    |
| Night      | -92.417  | 41.134     | -2.247  | <0.05 |
| Temperature| -27.923  | 3.012      | -9.271  | <0.001|
| Logarea    | 191.918  | 16.615     | 11.551  | <0.001|
| C_haines   | 19.470   | 3.861      | 5.042   | <0.001|
Table 2. Cont.

| Variable         | Estimate | Std. Error | T Value | p      |
|------------------|----------|------------|---------|--------|
| Logdist:Windangle | 0.176    | 0.026      | 6.887   | <0.001 |
| Logdist:Evening  | −1.603   | 3.545      | −0.452  | ns     |
| Logdist:Night    | 16.686   | 3.913      | 4.265   | <0.01  |
| Logdist:Temperature | 3.056 | 0.328      | 9.307   | <0.001 |
| Logdist:Logarea  | −20.060  | 1.713      | −11.711 | <0.001 |
| Logdist:C_haines | −2.121   | 0.460      | −4.612  | <0.001 |
| Temperature:Evening | −2.297 | 0.985      | −2.331  | <0.01  |
| Temperature:Night | −2.645   | 0.975      | −2.714  | <0.01  |
| Logarea:Evening  | 29.334   | 5.428      | 5.404   | <0.001 |
| Logarea:Night    | −0.787   | 5.475      | −0.144  | ns     |
| C_haines:Evening | −2.204   | 1.173      | −1.879  | <0.05  |
| C_haines:Night   | −2.543   | 1.295      | −1.965  | <0.05  |

Figure 9. Model predictions for the analysis of hourly PM$_{2.5}$ observations (see Table 2), exploring the relationships with distance and (A) wind angle and day period; (B) temperature and C-Haines atmospheric stability; (C) fire size and day period. For C-Haines, low = 2, high = 8. The bottom two graphs are for downwind only during the day. Variables not plotted are held at their median value. The dashed line indicates the 50 µg m$^{-3}$ hourly exceedance threshold.
The correlation between predicted and observed PM$_{2.5}$ concentrations in the test data was moderate ($r^2 = 0.222$, Figure 10). The overall bias in the model was low (NMB = 1.2%), but this was because it substantially over-predicted at predicted PM$_{2.5}$ below 50 µg m$^{-3}$ (NMB = 304%, RMSE = 48.1 µg m$^{-3}$) and under-predicted at predicted PM$_{2.5}$ above 200 µg m$^{-3}$ (NMB = 70.9%, RMSE = 337 µg m$^{-3}$). However, the model performed well for predicting hourly exceedances, with a true positive rate of 78.8% and a true negative rate of 71.8%.

![Figure 10](image_url)  
**Figure 10.** Plot of predicted vs. observed PM$_{2.5}$ in the test data (20% random selection). The mean bias and RMSE are shown for three portions of the data, with predicted PM$_{2.5}$ < 50, between 50 and 200 and >200 µg m$^{-3}$. The line of agreement (1:1) is added as a dashed line.

### 3.3. Estimating the Area Affected by Poor Air Quality

Applying model predictions to all wind angles at increasing fire areas, predicted a non-linear (asymptotic) relationship between fire area and smoke-affected area (Figure 11). The predicted area affected by hourly exceedance for a 500 ha prescribed burn will be approximately 2000 ha in the daytime and 5000 ha in the evening (Figure 11). A 3000 ha burn will affect 8000 ha in the daytime and almost 14,000 ha in the evening.

![Figure 11](image_url)  
**Figure 11.** Area affected by PM$_{2.5}$ exceedance according to fire area and time period, as predicted by the statistical model. Temperature and C-Haines are held at their median values (17 °C, 4, respectively).

### 4. Discussion

This analysis has identified several key patterns in smoke around prescribed burns. During the daytime, when most of the burning occurs, smoke impacts would not be expected to extend beyond 5 km from the fire. The raw data suggest this threshold to be
about 2 km, whereas the statistical model suggests it is about 3 km under average weather conditions. This is a similar outcome to the study by Pearce et al. [15] in USA savannas (2 km). Our modest threshold is, despite the fact that most of the fires had a large smoke plume, in many cases detected more than 20 km from the fire on MODIS satellite imagery (for example, 64 km for the Bowen Mtn 2 fire, Figure 6). During the day, the plumes are usually aloft, and only smoke blown laterally from the fire reaches the ground. This is consistent with a study that showed that PM$_{2.5}$ concentrations at air-quality stations under mappable smoke plumes across the USA are higher than for days without plumes, but 70% of them still rate air quality as ‘Good’ [25].

At about 6 p.m., after most of the burning was completed, the situation changed markedly, with a build-up of particulates several kilometres from the fires (exceedance >10 km in the raw and 5 km in the modelled results). Moreover, the smoke tended to spread up-wind as well during the evening. While we were not able to track smoke production from the fires, we noticed that the two fires that caused 24 h exceedances in the state air quality network continued to burn vigorously through the first night (Lawson and Bowen Mtn 2). We suspect that temperature inversion at night tends to trap night-time-generated smoke close to the ground. This tendency for concentrations to peak in the night and dissipate in the day is probably universal (e.g., [26]). The task of limiting the production and settling of smoke in the evening and overnight is a major challenge for fire managers.

There was a strong fire area effect in these results. This is to be expected (and was found by a previous study [15]) because the amount of pollution produced ought to be a linear function of fire area. The area effect at least partly explains why none of the three cultural burns caused PM$_{2.5}$ exceedances at any distance. The model suggests that the area affected by PM$_{2.5}$ exceedances increases asymptotically with fire area such that a 100 ha fire affects an area 5.6 times its size, but a 2000 ha fire affects an area only 3 times its size. The exact form of this relationship is highly dependent on the use of log transformations to measure the distance from the fire and fire area. In both cases, the transformations gave superior model fit, but that does not imply that they perfectly reflect the true nature of the functions. Some caution is needed in interpreting Figure 11.

Synoptic (broad-area) weather patterns are known to influence the air quality. In particular, in the Sydney Basin, the presence of a high-pressure system in the Tasman Sea (off the east coast) is associated with elevated ozone and particulate levels, irrespective of whether there are major point sources such as fires at the time [27]. Similarly, Di Virgilio, Hart [14] found that prescribed burn days with poor air quality in Sydney occurred under cool, stable air, which is associated with high pressure. In our study, we found that high levels of mid-level atmospheric stability (the C-Haines index) increased PM$_{2.5}$ dispersal. In addition, low temperatures tend to increase the impacts, and particularly so in the evening and night. In contrast, other measures of atmospheric conditions were not selected in the model, including inversion height, mixing height, surface pressure and wind speed. During the modelling process, each of these showed statistically significant effects, but the model with temperature and C-Haines was superior (as judged by AIC). We interpret our results to mean that unstable air (C-Haines) promotes fire activity (and, hence, smoke production), while cool temperatures facilitate the smoke collapsing to the ground. It is important to consider that particular measures of atmospheric conditions are associated with each other. For example, cool night air is associated with high pressure and temperature inversions. However, in our data, none of these measures was strongly correlated (in all cases, r < 0.2).

These results can contribute to decision making around the timing and placing of prescribed burning operations. For example, they suggest that limiting the size of the fire will reduce its impact, though knowledge is not yet sufficient to suggest a practical upper size. Avoiding periods of cold air will also reduce the magnitude of the evening build-up of pollution. Unfortunately, these conditions are ideal for conducting prescribed burning because they minimise the risk of fires escaping containment lines. Operational burning guidelines usually prescribe a suitable weather window, which includes a temperature range of 16–28 °C and maximum wind speed somewhere between 10 and 20 km$h^{-1}$ [28].
There are no minimum wind speed guidelines. The fires in this study followed these guidelines during the daytime, but nearly 40% of hourly observations were below 16 °C in the evening. Di Virgilio, Hart [14] recommended delaying the ignition of burns until the mixing height or planetary boundary layer has lifted (around midday) to allow smoke to ventilate away. The fact that particulates increase in the evening and our observation that the two most impactful fires were still burning well into the night, suggest that all efforts should be made to complete the burn well before sunset. Thus, there may be counterproductive outcomes by delaying a burn until midday if this causes it to burn later into the afternoon. An alternative might be to break the fires into smaller units that can be completed between midday and sunset. These are complex matters that need further research.

Should it not be possible to avoid adverse weather conditions, this study provides some guidance for predicting how far the smoke is likely to travel and hence which communities should be warned that a smoke event is likely. In the daytime, this zone is 2 to 7 km and only in the downwind direction. In cool, still conditions (10 °C and <5 kmh⁻¹), the evening risk zone is 20 km irrespective of wind angle, while in cool, windy conditions (10 °C and >15 kmh⁻¹), the evening zone is less than 3 km. In warm weather (>25 °C), the evening zone is intermediate, ~5–7 km.

While this study provides some useful information for managing prescribed burn smoke, there are some limitations. Our study has failed to clearly identify which aspect of the complex atmospheric dynamics is most influential. We have highlighted temperature and C-Haines in the statistical model, while wind speed was influential in the raw data. Other studies highlight the role of mixing height on smoke dynamics [14,29] and high pressure on air quality in general [27], and these measures are all interlinked. Due to the variable nature of smoke production and dispersal, we may not have adequately sampled the full range of outcomes, so we recommend that data collection such as this continues. The relatively strong accuracy of the model (72% for discriminating exceedances) provides some confidence in the study, though the systematic under-prediction at higher PM₂.₅ concentrations shows that improvement is needed. This is important because two of the fires (Lawson and Bowen 2) caused exceedances between 10 and 30 km away that were not well predicted by the model. Lastly, the study does not directly address the question of the trade-off between wildfire and prescribed burning smoke. That would require much additional information, including a similar study on wildfire smoke and the effects of prior prescribed burning on smoke production in wildfires. This is the subject of ongoing research.

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References

1. Price, O.F.; Bradstock, R.A. Quantifying the influence of fuel age and weather on the annual extent of unplanned fires in the Sydney region of Australia. Int. J. Wildland Fire 2011, 20, 142–151. [CrossRef]

2. Price, O.F.; Bradstock, R. The efficacy of fuel treatment in mitigating property loss during wildfires: Insights from analysis of the severity of the catastrophic fires in 2009 in Victoria, Australia. J. Environ. Manag. 2012, 113, 146–157. [CrossRef] [PubMed]

3. Williamson, G.; Bowman, D.; Price, O.; Henderson, S.; Johnston, F. A transdisciplinary approach to understanding the health effects of wildfire and prescribed smoke. Environ. Res. Lett. 2016, 11, 125009. [CrossRef]

4. Reid, C.E.; Brauer, M.; Johnston, F.H.; Jerrett, M.; Balmes, J.R.; Elliott, C.T. Critical Review of Health Impacts of Wildfire Smoke Exposure. Environ. Health Perspect. 2016, 124, 1334–1343. [CrossRef] [PubMed]

5. Johnston, F.H.; Henderson, S.B.; Chen, Y.; Randerson, J.T.; Marlier, M.; DeFries, R.S.; Kinney, P.; Bowman, D.; Brauer, M. Estimated Global Mortality Attributable to Smoke from Landscape Fires. Environ. Health Perspect. 2012, 120, 695–701. [CrossRef]

6. Johnston, F.; Hanigan, I.; Henderson, S.; Morgan, G.; Bowman, D. Extreme air pollution events from bushfires and dust storms and their association with mortality in Sydney, Australia 1994–2007. Environ. Res. 2011, 111, 811–816. [CrossRef] [PubMed]

7. Haikerwal, A.; Akram, M.; Sim, M.R.; Meyer, M.; Abramson, M.J.; Dennekamp, M. Fine particulate matter (PM2.5) exposure during a prolonged wildfire period and emergency department visits for asthma. Respirology 2016, 21, 88–94. [CrossRef]

8. Cooper, N. The trade-off between smoke from wild and prescribed forest fires. In Air Quality and Smoke from Urban and Forest Fires; National Academy of Science: Fort Collins, CO, USA, 1976.

9. Yao, J.; Brauer, M.; Henderson, S.B. Evaluation of a Wildfire Smoke Forecasting System as a Tool for Public Health Protection. Environ. Health Perspect. 2014, 121, 1142–1147. [CrossRef] [PubMed]

10. Saide, P.E.; Peterson, D.A.; da Silva, A.; Anderson, B.; Ziembia, L.D.; Diskin, G.; Sachse, G.; Hair, J.; Butler, C.; Fenn, M.; et al. Revealing important nocturnal and day-to-day variations in fire smoke emissions through a multiplatform inversion. Geophys. Res. Lett. 2015, 42, 3609–3618. [CrossRef]

11. Price, O.F.; Horsey, B.; Jiang, N. Local and regional smoke impacts from prescribed fires. Nat. Hazards Earth Syst. Sci. 2016, 16, 2247–2257. [CrossRef]

12. Navarro, K.M.; Schweizer, D.; Balmes, J.R.; Cisneros, R. A Review of Community Smoke Exposure from Wildfire Compared to Prescribed Fire in the United States. Atmosphere 2018, 9, 185. [CrossRef]

13. Broome, R.A.; Johnstone, F.H.; Horsley, J.; Morgan, G.G. A rapid assessment of the impact of hazard reduction burning around Sydney, NSW, Australia. Int. J. Wildland Fire 2010, 19, 607–611. [CrossRef] [PubMed]

14. Di Virgilio, D.; Hart, M.A.; Jiang, N. Meteorological controls on atmospheric particulate pollution during hazard reduction burns. Atmos. Chem. Phys. 2018, 18, 6585–6599. [CrossRef]

15. Pearce, J.L.; Rathbun, S.; Achtemeier, G.; Naeher, L.P. Effect of distance, meteorology, and burn attributes on ground-level particulate matter emissions from prescribed fires. Atmos. Environ. 2012, 56, 203–211. [CrossRef]

16. Kelleher, S.; Quinn, C.; Miller-Lionberg, D.; Volckens, J. A low-cost particulate matter (PM2.5) monitor for wildland fire smoke. Atmos. Meas. Tech. 2018, 11, 1087–1097. [CrossRef]

17. Adams, D.F.; Koppe, R.K.; Robinson, E. Air and surface measurement of constituents of prescribed forest slash smoke. In Air Quality and Smoke from Urban and Forest Fires; National Academy of Science: Fort Collins, CO, USA, 1976.

18. Durkin, A.; Gonzalez, R.; Isaksen, T.B.; Walker, E.; Errett, N.A. Establishing a Community Air Monitoring Network in a Wildfire Smoke-Prone Rural Community: The Motivations, Experiences, Challenges, and Ideas of Clean Air Methow’s Clean Air Ambassadors. Int. J. Environ. Res. Public Health 2020, 17, 8393. [CrossRef]

19. Keith, D.A. Ocean Shores to Desert Dunes: The Native Vegetation of New South Wales and the ACT; Department of Environment and Conservation: Hurstville, Australia, 2004.

20. Volkova, L.; Meyer, C.P.; Murphy, S.; Fairman, T.; Reisen, F.; Weston, C. Fuel reduction burning mitigates wildfire effects on forest carbon and greenhouse gas emission. Int. J. Wildland Fire 2014, 23, 771–780. [CrossRef]

21. Forehead, H.; Barthelemy, J.; Versaevel, N.; Price, O.; Perez, P. Traffic exhaust to wildfires: PM2.5 measurements with fixed and portable, low-cost LoRaWAN-connected sensors. PLoS ONE 2020, 15, e0231778. [CrossRef]

22. Mills, G.; McCaw, L. Atmospheric Stability Environments and Fire Weather in Australia—Extending the Haines Index; Centre for Australian Weather and Climate Research: Melbourne, Australia, 2010; p. 151.

23. Bates, D.; Maechler, M.; Bolker, B.; Walker, S. lme4: Linear mixed-effects models using Eigen and S4. R package version 1.1-7. [CrossRef]

24. Aryal, R. Kafley, D. Beecham, S. Morawski, L. Air Quality in the Sydney Metropolitan Region during the 2013 Blue Mountains Wildfire. Aerosol Air Qual. Res. 2018, 18, 2420–2432. [CrossRef]

25. Larsen, A.E.; Reich, B.J.; Ruminski, M.; Rappold, A.G. Impacts of fire smoke plumes on regional air quality, 2006-2013. J. Expo. Sci. Environ. Epidemiol. 2018, 28, 319–327. [CrossRef]

26. Strand, T.; Larkin, N.; Rorig, M.; Krull, C.; Moore, M. PM2.5 measurements in wildfire smoke plumes from fire seasons 2005–2008 in the Northwestern United States. J. Aerosol Sci. 2011, 42, 143–155. [CrossRef]

27. Hart, M.; De Dear, R.; Hyde, R. A synoptic climatology of tropospheric ozone episodes in Sydney, Australia. Int. J. Climatol. 2006, 26, 1635–1649. [CrossRef]
28. Clarke, H.; Tran, B.; Boer, M.; Price, O.; Kenny, B.; Bradstock, R. Climate change effects on the frequency, seasonality and interannual variability of suitable prescribed burning weather conditions in south-eastern Australia. *Agric. For. Meteorol.* 2020, 271, 148–157. [CrossRef]

29. Price, O.F.; Purdam, P.J.; Bowman, D.M.J.S.; Williamson, G. Comparing the height and area of wild and prescribed fire smoke particle plumes in southeast Australia using weather radar. *Int. J. Wildland Fire* 2018, 27, 525–537. [CrossRef]