AN EMPIRICAL MODEL FOR ASSESSING DAILY BUSHFIRE COMMUNITY SMOKE EXPOSURE OVER LARGE GEOGRAPHIC AREAS



Part of: Smoke impacts on community health and social perceptions

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The Smoke Impacts project has three major streams.

- Assessing direct health impacts of exposure to bushfire smoke in clinical studies;
- Evaluating community perceptions of planned burn and bushfire smoke: and
- Evaluating novel ways of measuring smoke exposure over wide geographic areas for use in epidemiological studies.

Parts (1) and (2) have been presented previously. Here we present results from part (3).

BACKGROUND

Many existing epidemiological studies into the health effects of bushfire smoke have relied on the limited available monitor data, which provide a relatively crude estimation of population exposure, with little geographic resolution.

In 2012, the British Columbia Centre for Disease Control (BCCDC) developed an empirical model for PM_{2.5} exposure that combined monitored and remotely sensed data with meteorological information to improve the spatial resolution of exposure estimates and increased the power to detect relatively small health effect associations.

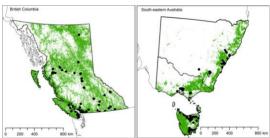


Figure 1. Study areas in British Columbia, Canada, and south-eastern Australia.

We took the model developed for British Columbia and applied it in south-eastern Australia, a region with similar seasonal forest fire events in proximity to population centres.

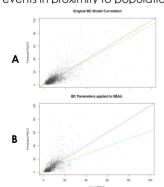


Figure 2A and B. Predicted vs measured PM 2.5.

Australia (B).

The original model applied in British Columbia (A) and SE

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1) Using the same variables and coefficients in

We applied the model in three forms;

- as in British Columbia. (Figure 2b)
- 2) Using the same variables, but retraining the model with data from PM2.5 monitors in SE Australia.
- 3) Improving the model by introducing new variables and trying novel non-linear modelling methods (RandomForest).

METHODS

The model operates on a 5km grid, and is trained on data for the summer half-year using data with the top 5th-percentile of FRP values. The basic model is a linear regression model, with regressions performed using reduced variable sets used for a given prediction point if data was missing.

Variables included in the original model:

- Lagged PM2.5 for the nearest monitor
- aerosol optical depth (AOD) derived from the MODIS platform
- summed fire radiative power (FRP) within
- venting index (VI), a measure of the ability for smoke to disperse in the lower atmospheric layer

The improved model also included:

- Atmospheric total column ozone (O3) concentration.
- C-Haines index of atmospheric stability
- An automated process called a RandomForest machine learning model was used in place of linear regression.

RESULTS

Applying the BC model to Tasmania directly retained some power in predicting PM2.5 values, but was not as good as when originally applied in BC.

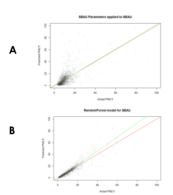
Training the data on south-eastern Australian monitor data did little to improve the model, nor did including additional variables, although the slope was closer to 1:1 when trained on Australian data.

The biggest improvement came from using RandomForest modelling, which achieved an excellent correlation.

with the British Columbia Centre for Disease Control, the Victorian Department of Environment, Land, Water and

Table 1. Correlation coefficients for the original model applied in British Columbia, and Australian iterations of the method.

Model	Pearson's	Normalized
	Correlation	root mean
	Coefficient	squared error.
Original BC Model	0.82	64.5
BC Model applied to SEAU	0.64	81
SEAU-trained model	0.66	117.8
SEAU with new variables	0.66	118.3
SEAU RandomForest	0.90	60.0



Figures 3A and B. Predicted vs measured PM

2.5. Model trained on Australian data (A) and the final Australian RandomForest model (B).

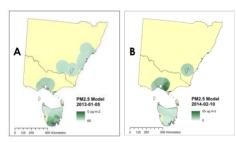


Figure 4. RandomForest model PM2.5 estimates. During the Dunalley fire in Tasmania, January 2013 (A), and the Hazelwood fire in Victoria, February 2014 (B).

OUTCOMES

This approach shows promise in being able to provide PM2.5 exposure estimates across a broad geographic area in south-eastern Australia.

Next we will use the estimates produced by this method to evaluate the impact of bushfire and planned burn smoke exposure on ambulance callouts in south eastern Australia.