



Curtin University

WHO COLLABORATING CENTRE FOR CLIMATE
CHANGE AND HEALTH IMPACT ASSESSMENT



Spatiotemporal machine learning modelling with season-trend decomposition to capture and quantify extreme particulate matter air pollution (PM_{2.5}) attributable to bushfire, dust and woodheater inversion layer events for health research

Ivan Hanigan PhD^{1,2} and “CAR/CSA” Bushfire smoke exposure team

¹ WHO Collaborating Centre for Climate Change & HIA Curtin University:

<https://research.curtin.edu.au/whocc-cchia/>

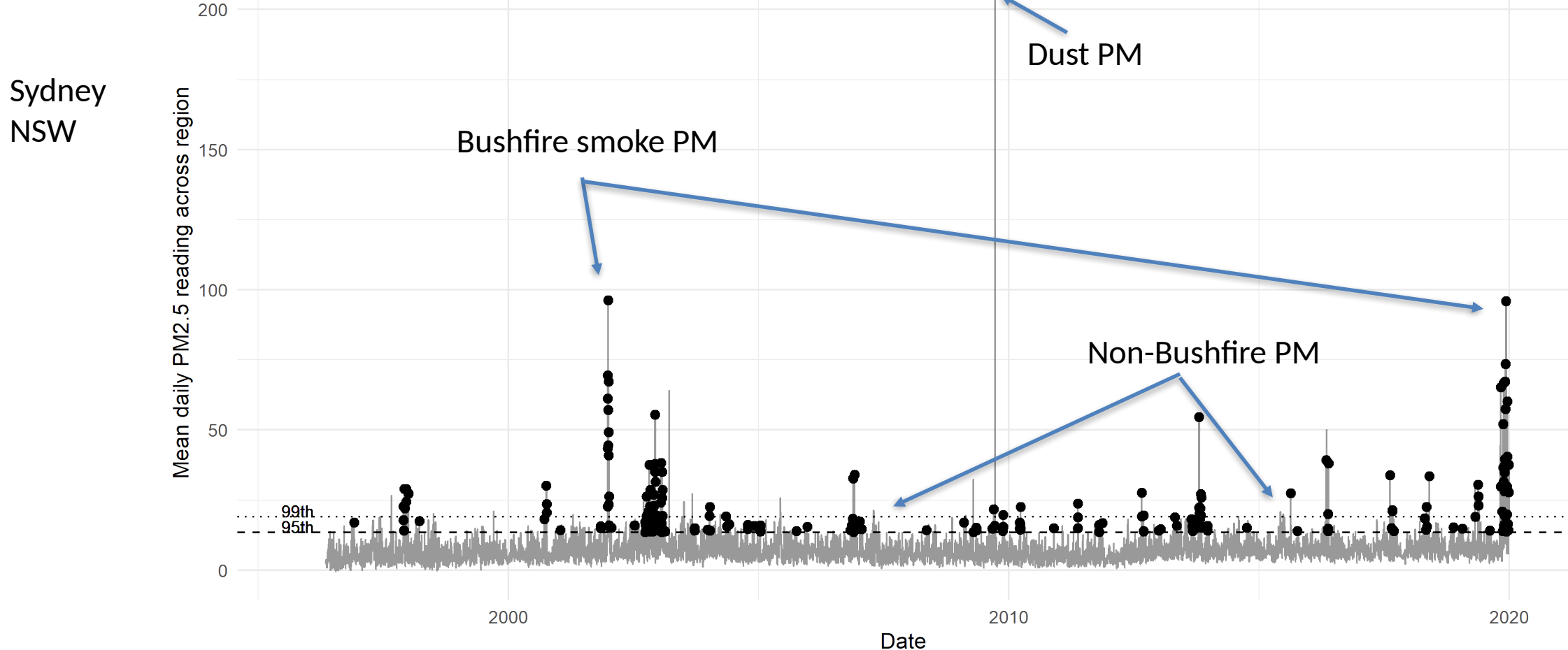
² Healthy Environments And Lives (HEAL) National Research Network, Australia



Centre for
Safe Air

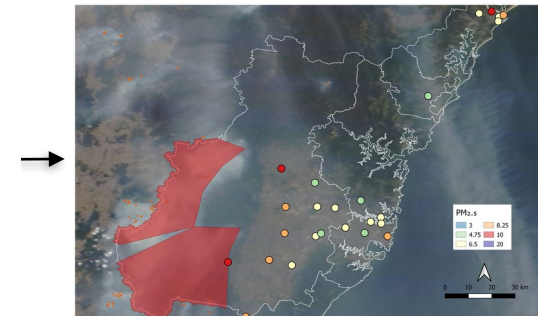
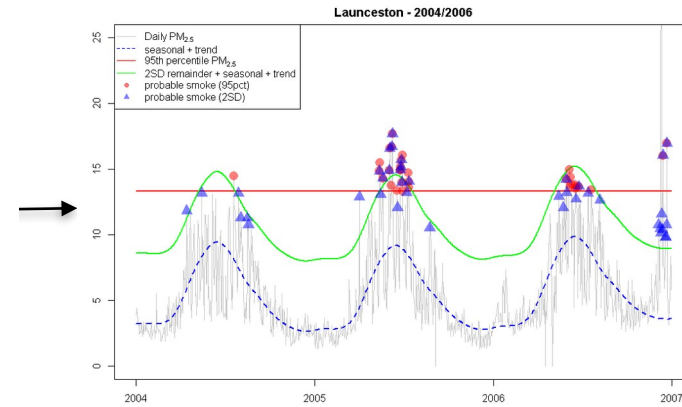
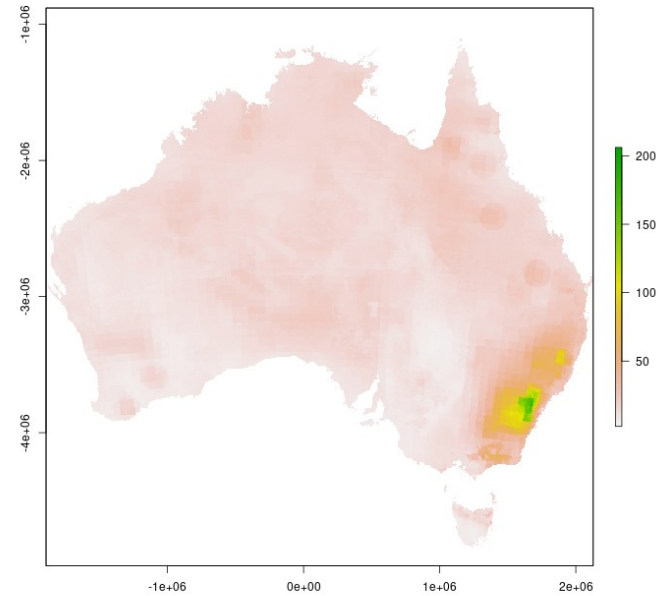
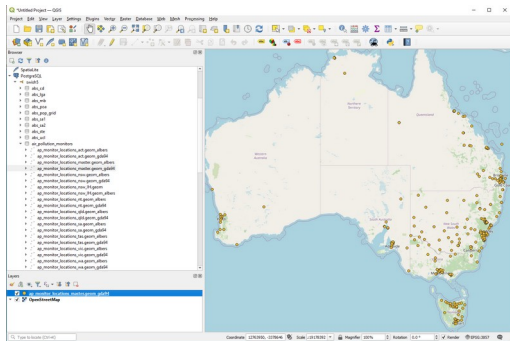
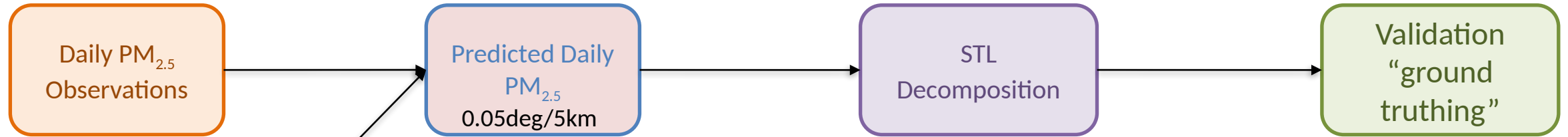
Not all PM2.5 is bushfire events= relevant to public health

- E.g. Valid Fire Events of Airborne Particles (PM2.5) used in health studies for Sydney (Published in multiple Epidemiology Journals)



Hanigan, Morgan, Williamson et al (2018). Extensible Database of Validated Biomass Smoke Events for Health Research. MDPI Fire, 1, 50; <http://doi.org/10.3390/fire1030050>

Statistical and machine learning methods GIS Air Quality Modelling



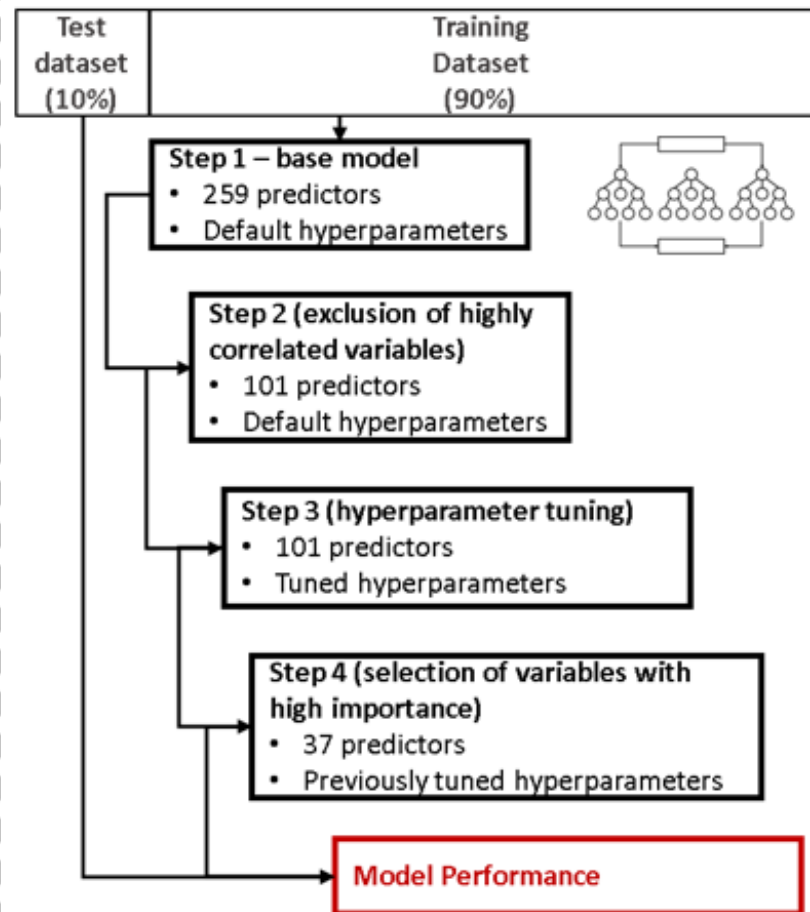
Statistical and machine learning methods

PM_{2.5} (Random Forest Machine Learning)

- 1) Geospatial predictors collected on CARDAT's data platform:
E.g. temperature, rainfall, drought, fires, burned, AOT, elevation, landcover

Clean Air Research
Data and Analysis Technology
(CARDAT)

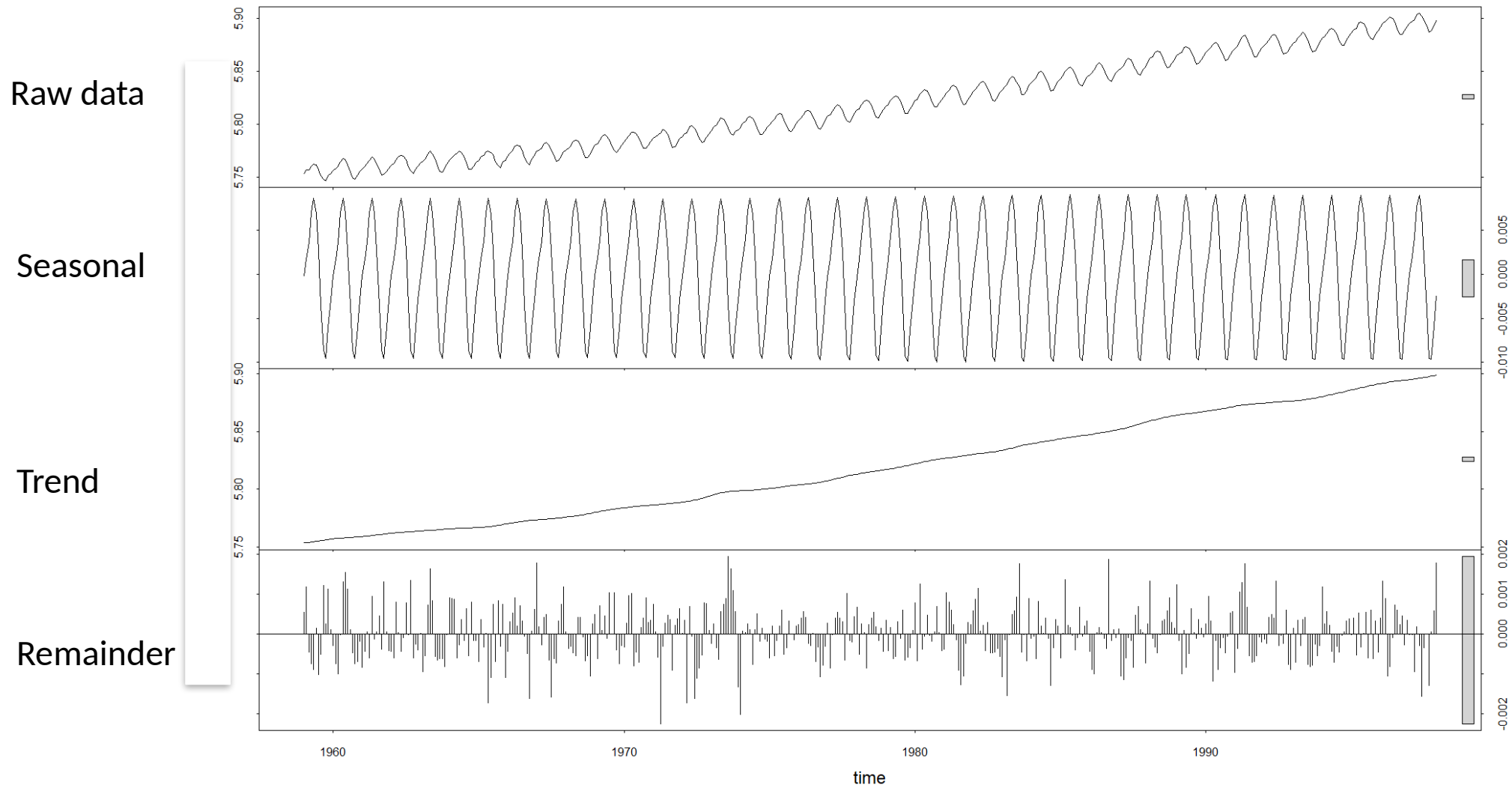
2) PM_{2.5} modelling



Model	Step 1 (base model)	Step 4 (final model)
# variables	259	37
RMSE (oob)	4.82	4.42
R-squared (oob)	66.7%	72.0%
RMSE (test)	4.40	4.07
R-squared (test)	64.3%	69.7%
RMSE (train)	2.42	2.07
R-squared (train)	93.8%	95.2%

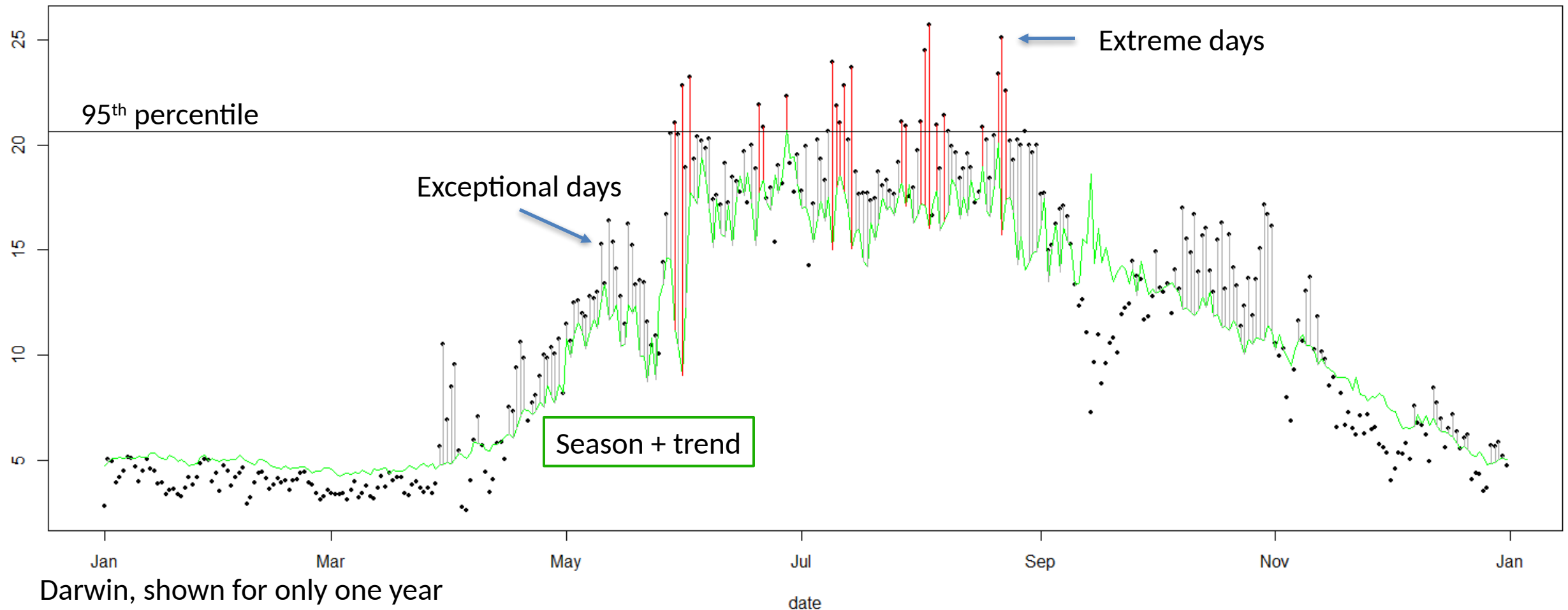
Seasonal Trend Lowess (STL) Decomposition

Robust time-series modelling technique: extract season, trend and remainder



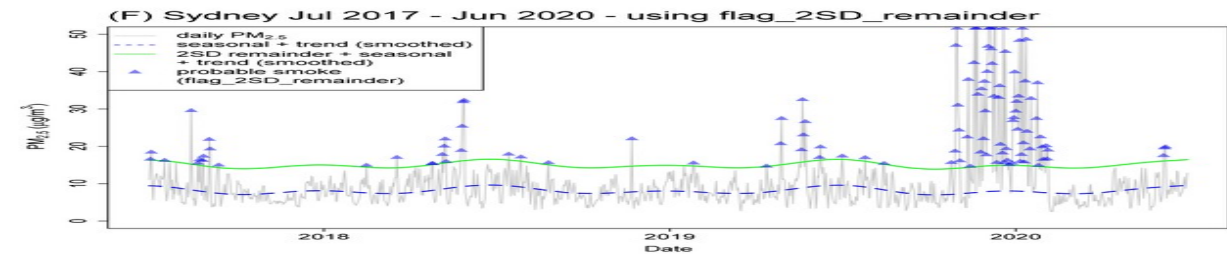
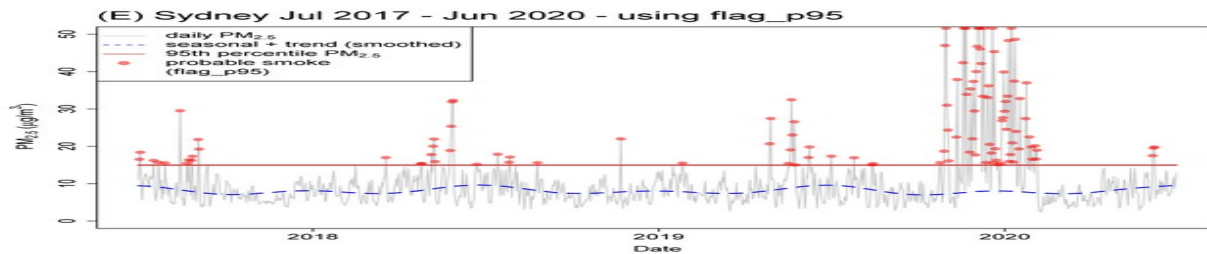
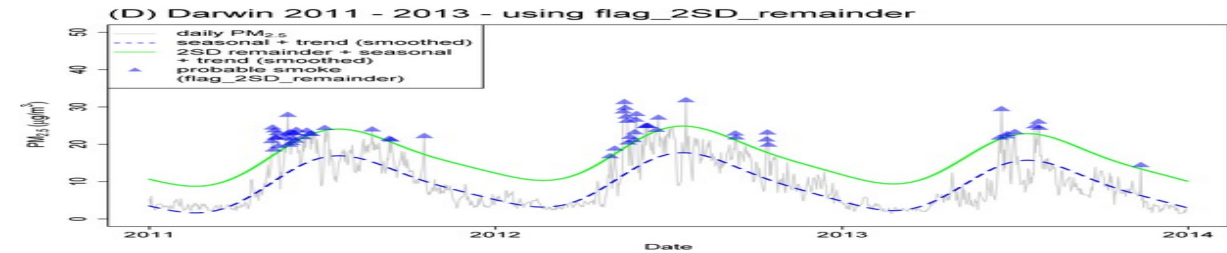
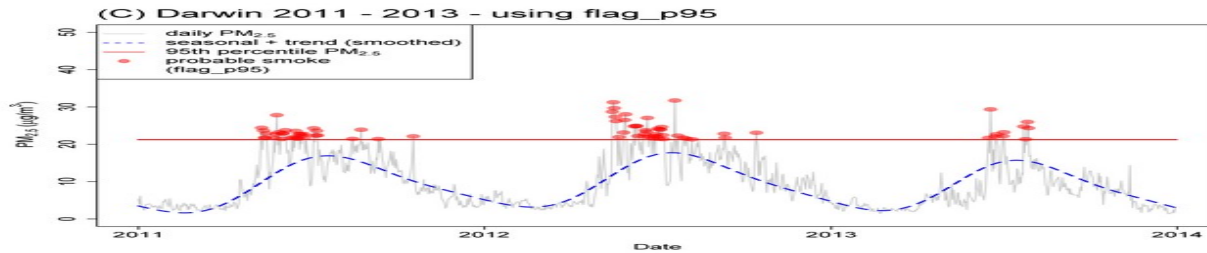
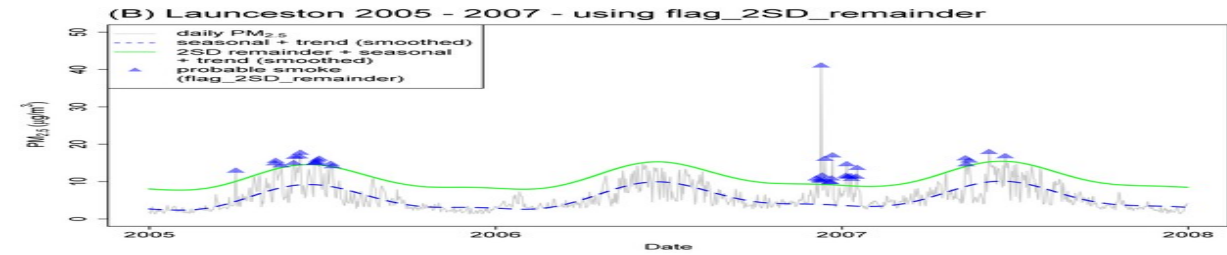
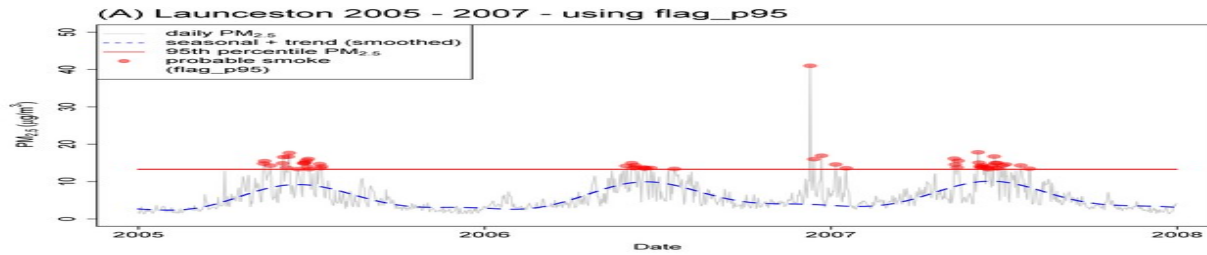
STL analysis on dailydata

Results look “noisy”. The 95th percentile can be used to identify extreme and exceptional events



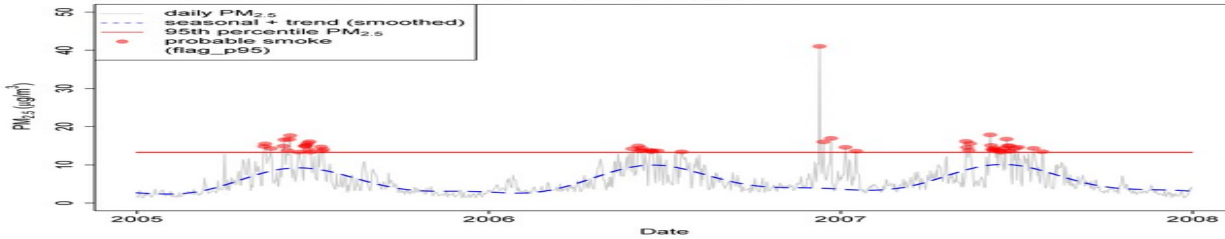
Flags in high winter woodsmoke city

Frequently used criterion is 95th percentile, or 2 standard deviations of the error term

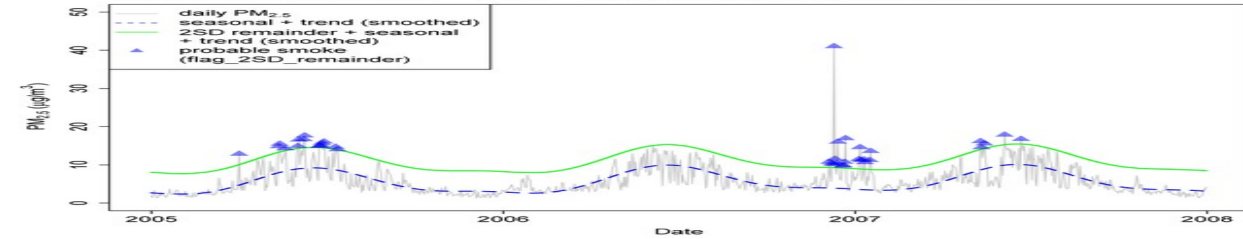


Flags in low seasonality location

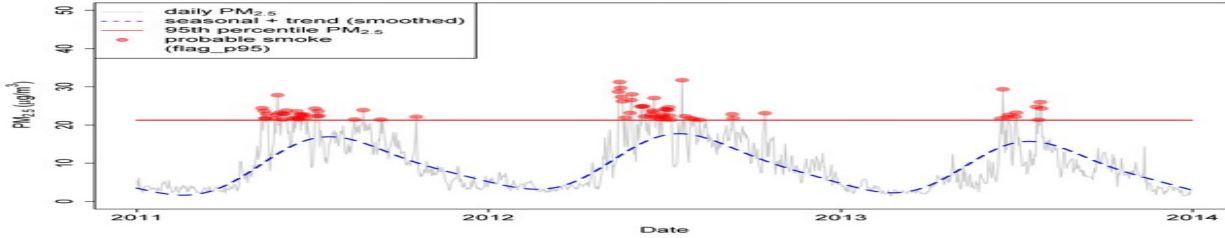
(A) Launceston 2005 - 2007 - using flag_p95



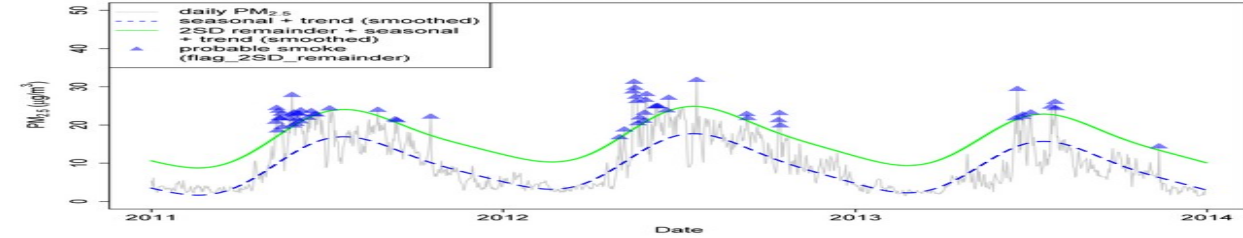
(B) Launceston 2005 - 2007 - using flag_2SD_remainder



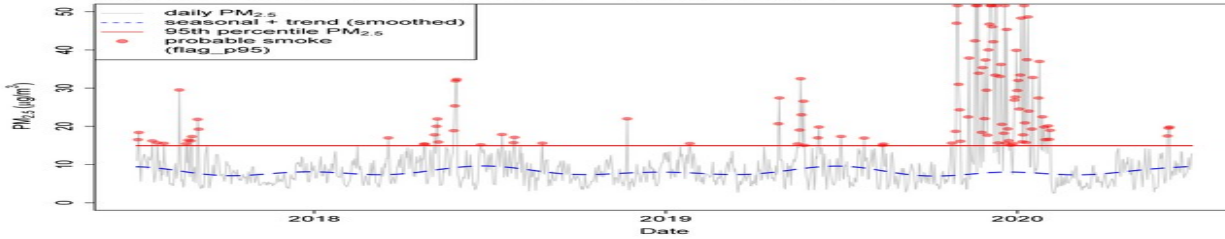
(C) Darwin 2011 - 2013 - using flag_p95



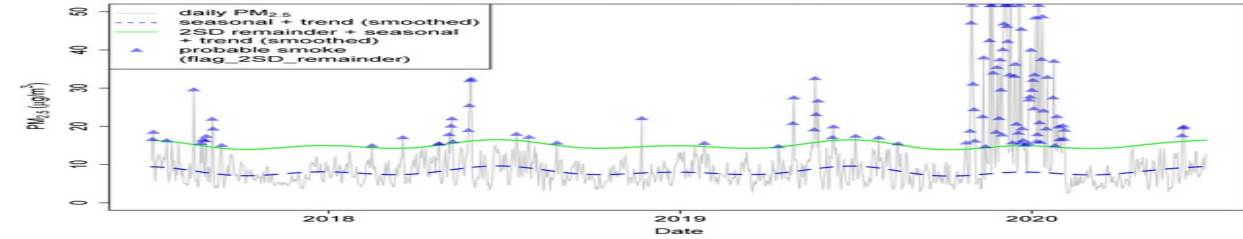
(D) Darwin 2011 - 2013 - using flag_2SD_remainder



(E) Sydney Jul 2017 - Jun 2020 - using flag_p95



(F) Sydney Jul 2017 - Jun 2020 - using flag_2SD_remainder



Validated events database

- 16 sites, manual review
- Additional flags
 - i) active fire hotspots
 - ii) CTM dust (CAMS)
 - iii) heating deg days
- Classification and Regression Tree CART model to predict validated events DB
- USYD team TODO



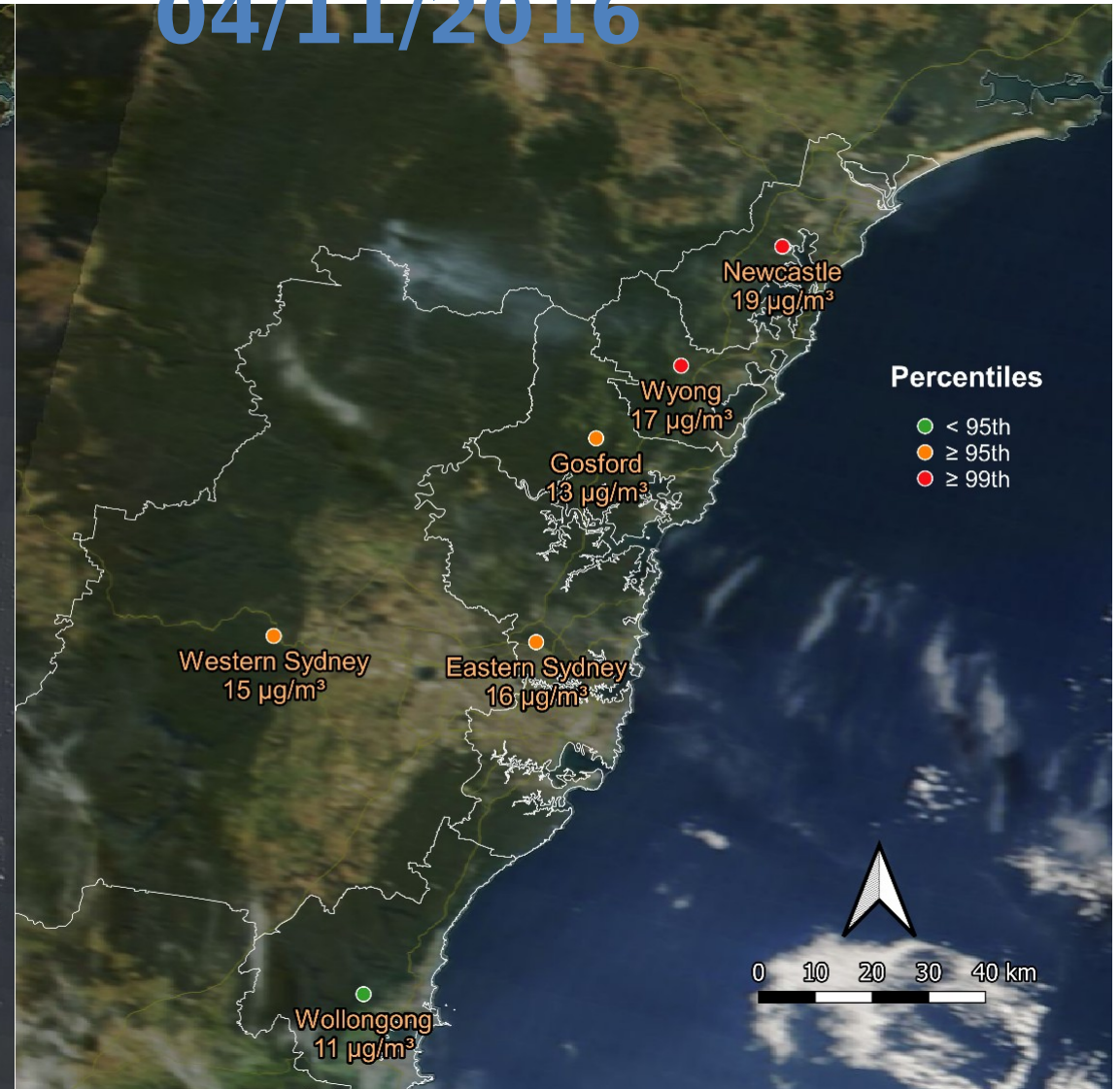
Hanigan, Morgan, Williamson et al (2018). Extensible Database of Validated Biomass Smoke Events for Health Research. MDPI Fire, 1, 50; <http://doi.org/10.3390/fire1030050>

Validated events database: current gold standard, validated by manual process

Obvious 20/10/2013



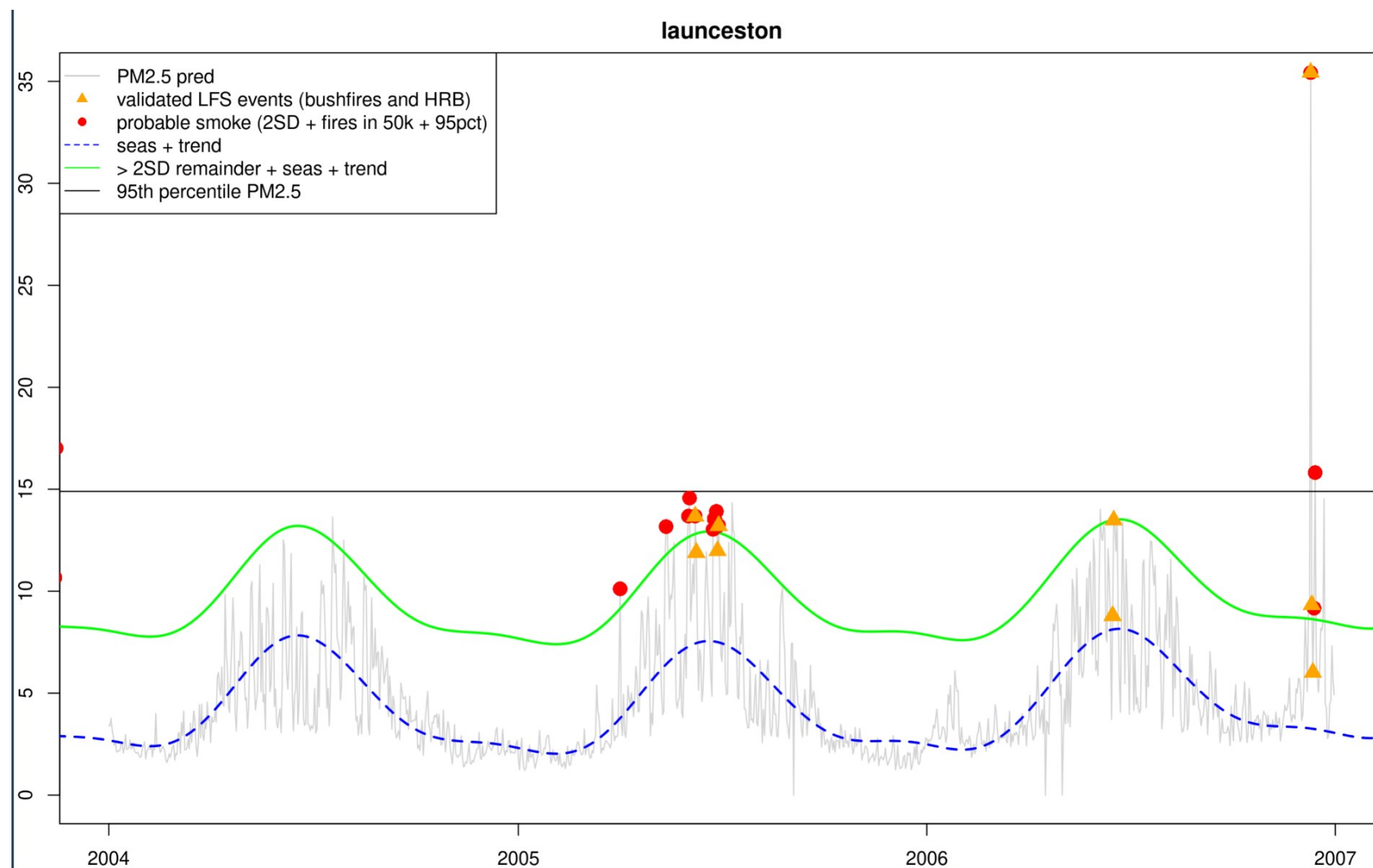
**Ambiguous
04/11/2016**



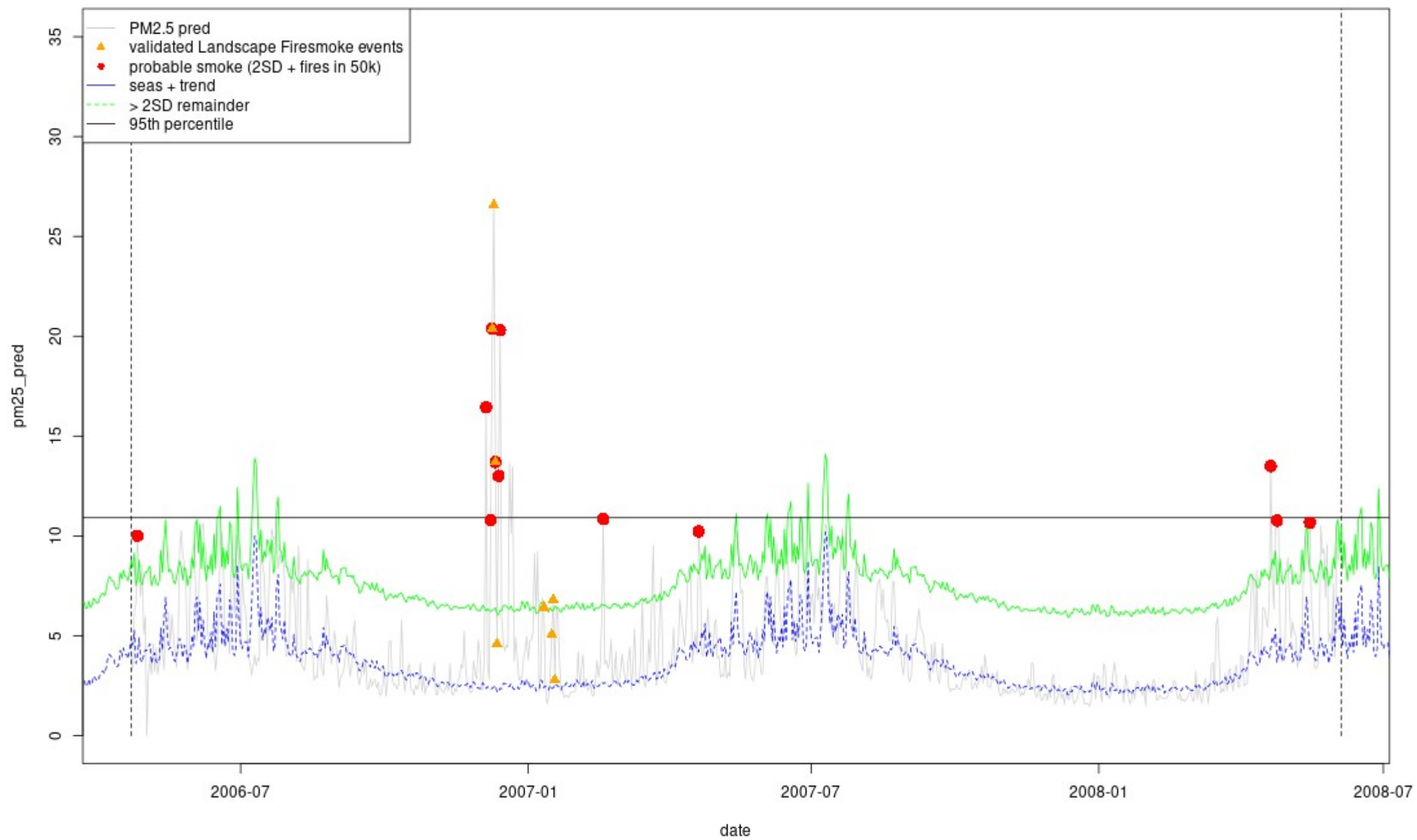
Using validated events and the flags we can find coinciding events or false positives, false negatives

Launceston, TAS

PM2.5

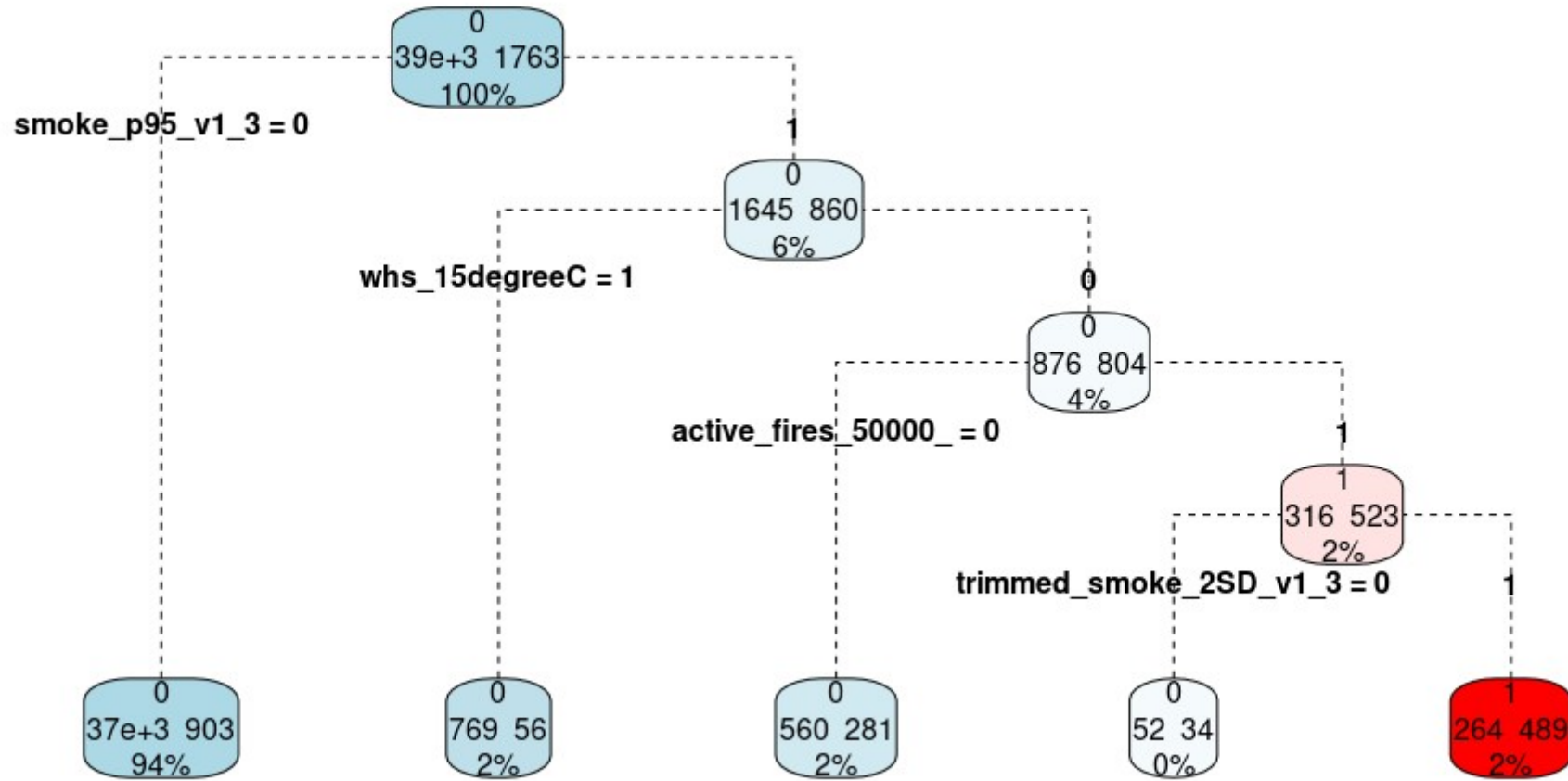


hobart



Classification tree machine learning model

Preliminary
results



IF > 95th pctl AND heating-degree-days-less-than-15deg AND active fires within 50K AND remainder > 2SD from season-trend THEN **probably a true positive.**

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- 1. Menzies Institute for Medical Research, University of Tasmania, Tasmania, Australia
- 2. Sohn Hearts and Minds Research Fellow
- 3. Centre for Safe Air, NHMRC Centre for Research Excellence, 17 Liverpool Street, Hobart, Tasmania, Australia (<https://ror.org/04ccf0j10r>).
- 4. Sydney School of Public Health, Faculty of Medicine and Health, University of Sydney, Australia
- 5. Health Environments and Lives (HEAL) National Research Network, Australia (Grant No. 2008937)
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