A Satellite-based Model for Estimating $PM_{2.5}$ Concentration in a Sparsely Populated Environment Using Soft Computing Techniques

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Highlights

- We used comprehensive satellite-based, meteorological and geographical data to develop a satellite-based model for estimating the $PM_{2.5}$ concentration.
- Representative animations are created to visualize the spatiotemporal variation of the predictors.
- We applied the adaptive neuro-fuzzy inference system (ANFIS) for the first time as a core model to estimate the spatiotemporal variation of $PM_{2.5}$ concentration.
- We compared ANFIS with support vectors machine and back-propagation artificial neural network.
- Adaptive model identification technique has been used to identify the optimal predictive model.

Abstract

We applied three soft computing methods including adaptive neuro-fuzzy inference system (ANFIS), support vectors machine (SVM) and back-propagation artificial neural network (BPANN) algorithms for estimating the ground-level $PM_{2.5}$ concentration. These models were trained by comprehensive satellite-based, meteorological, and geographical data. A 10-fold cross-validation (CV) technique was used to identify the optimal predictive model. Results showed that ANFIS was the best-performing model for predicting the variations in $PM_{2.5}$ concentration. Our findings demonstrated that the CV-R^2 of the ANFIS (0.81) is greater than that of the SVM (0.67) and BPANN (0.54) model. The results suggested that soft computing methods like ANFIS, in combination with spatiotemporal data from satellites, meteorological data and geographical information improve the estimate of $PM_{2.5}$ concentration in sparsely populated areas.

Keywords: $PM_{2.5}$; Aerosol optical depth; ANFIS; SVM; BPANN; Australia.

Data availability

The type and source of the data set considered in this study.

Name of the data set	Data source (Developer) (All websites accessed on Jan 2016)	Data format	Software required	Data availability
OMI Near-UV AOD	Aura OMI AOD product via NASA Giovanni interface http://giovanni.sci.gsfc.nasa.gov/giovanni/?instance_id=omil2g	HDF / NetCDF files	ArcGIS	Freely available
Major road	PSMA Australia Transport and Topography product https://www.psma.com.au/products/transport-topography	ESRI shape files	" "	Price depends on the area of interest
Minor road	" "	" "	" "	" "
Industrial point source $PM_{2.5}$ emissions	Australia National Pollutant Inventory http://www.npi.gov.au/reporting/industry-reporting-materials	xml files	Microsoft Excel / R	Freely available
Australia population density	Australian Bureau of Statistics http://www.abs.gov.au/ausstats/abs@.nsf/mf/1270.0.55.007	PNG ESRI Grid GeoTIFF	ArcGIS	" "
Australia land use classification	Australian Bureau of Statistics http://www.abs.gov.au/websitedbs/censushome.nsf/home/meshblockcounts	Excel spreadsheets / CSV files	Microsoft Excel / R / ArcGIS	" "
Elevation	U.S. Geological Survey https://www.usgs.gov/products/maps/topo-maps	PNG GeoTIFF	ArcGIS	" "
Normalized difference vegetation index	Terrestrial Ecosystem Research Network http://www.auscover.org.au/node/9	NetCDF files	" "	" "
Temperature **Rainfall** **Humidity** **Solar exposure**	Australian Bureau of Meteorology http://www.bom.gov.au/climate/maps/#tabs=Maps	ESRI Grid GIF	" "	" "

Software availability

The following software has been used in this study for statistical analysis, spatial data processing and map creation:

- R v.3.2.3 (R Foundation for Statistical Computing, Vienna, Austria)
- MATLAB R2014b (MathWorks Inc., Natick, USA)
- ArcGIS version 10.2 (ESRI Inc., Redlands, USA)

Note: No specific software component has been developed for this study.

1. Introduction

Exposure to fine particulate matter ($PM_{2.5}$, particles with aerodynamic diameter less than 2.5 μm) is a leading environmental risk factor associated with respiratory and cardiovascular morbidity and mortality (Franklin et al., 2007) and it is the twelfth-ranked contributor to the global burden of diseases (Forouzanfar et al., 2015).

Urbanisation increases the risk of being exposed to $PM_{2.5}$ (Han et al., 2015), and Australia, as one of the most urbanised countries in the world , is faced with adverse health effects of $PM_{2.5}$. To date, very little attention has been paid to the health effect of exposure to $PM_{2.5}$ in Australia. Some studies consistently suggest that $PM_{2.5}$ is associated with respiratory diseases and has significant effects on mortality (Barnett et al., 2005; Simpson et al., 2005), while conflicting results have been reported on cardiovascular health effects (Hinwood et al., 2006). These inconsistent results could be due to difficulties in assessing the Australian population exposure to $PM_{2.5}$.

Ground level aerosol measurement has been historically provided by ground monitoring networks, but there are high establishing and maintaining expenses associated with these measurements (Wu et al., 2012). The sparse ground $PM_{2.5}$ measurement network in Australia makes it difficult to evaluate the spatiotemporal variability of $PM_{2.5}$ and has significantly restrained the epidemiological studies on $PM_{2.5}$ health effects. Australia is the sixth largest country in the world by area while its population is quite small compared to the land size (Australian Government, 2015). Australia is one of the 10 least dense populated countries in the world (United Nations, 2015). The majority of the Australian population is living in the east and west coasts (Lunn et al., 2002). The population within these areas is concentrated in urban centres, particularly the capital cities (Australian Bureau of Statistics, 2012; Lunn et al., 2002).

Therefore, limited monitoring stations were established only in populated areas due to population distribution in Australia. Had such monitoring networks existed, there would have been no guarantee of an effective measurement of the spatiotemporal variation of $PM_{2.5}$, since it is changing on scales much smaller than monitoring networks density.

Estimates of air pollution exposure have been traditionally provided by assigning measurements derived from one (Chen et al., 2006) or several air pollution monitors (Barnett et al., 2005; Brook et al., 2010; Chan et al., 2006), allocating exposure using the nearest monitoring station (Lee et al., 2014) or using different proxies to estimate a local population's exposure (Hoffmann et al., 2007; Salam et al., 2008; Samet, 2007). There is potential for over-smoothing the exposure estimation and the results are likely to be biased with all these approaches (Jerrett et al., 2005a).

Satellite imagery is another important tool rapidly gaining interest in air pollution monitoring as it provides sequential observations over a broad area. Satellite sensors can be coupled with ground-based sensors at different spatiotemporal scales to reduce the limitations of surface monitoring station (Reis et al., 2015). Aerosol Optical Depth (AOD) is the most common parameter derived from satellite observations and applied to estimate $PM_{2.5}$. AOD describes the level of which aerosols attenuate the electromagnetic radiation at a given wavelength by absorption or scattering in an atmospheric column (Chudnovsky et al., 2012; Kaufman et al., 2002; NASA, 2013). The availability of satellite-derived AOD has helped to overcome the problems associated with sparse monitoring networks by providing observations where previously there were none (Hoff and Christopher, 2009; Reis et al., 2015).

A variety of methods have been used to investigate the quantitative relationship between satellite-derived AOD and ground-level $PM_{2.5}$ measurements. These studies mainly fall into two major classes: numerical-based methods and empirical observation-based methods (Lin et al., 2014).

Numerical-based models, including dispersion and chemical transport models, are still under development due to the uncertainties regarding the definition of source inventories, and chemical and dynamical processes of aerosols in atmosphere (Gupta and Christopher, 2009b; Kondragunta et al., 2008). Empirical observation-based methods rely on the relationship between air quality measurements and different observations (Maciejewska et al., 2015). Several techniques have been used to describe this relationship including simple regression (Chu et al., 2003), multiple regression (Dirgawati et al., 2015; Gupta and Christopher, 2009b; Li et al., 2011), geostatistical methods (Jerrett et al., 2005b; Kunzli et al., 2005), generalized additive models (GAM) (Strawa et al., 2013), land use regression (Henderson et al., 2007; Kloog et al., 2011; Knibbs et al., 2014; Liu et al., 2009), and hybrid approaches (Beckerman et al., 2013b; Lindstrom et al., 2011). Soft computing refers to computational techniques which are able to achieve optimal solutions for analysing complicated phenomena at reasonable costs (Carnevale et al., 2016; Kruse et al., 2013; Ovaska, 2004). In recent years, soft computing techniques such as support vector machine (SVM) (Moazami et al., 2016; Reid et al., 2015; Yeganeh et al., 2012), Bayesian models (Corani and Scanagatta, 2016; McBride et al., 2007), *k*-nearest neighbours (kNN) (Reid et al., 2015), and artificial neural network (ANN) (Al-Alawi et al., 2008; Gupta and Christopher, 2009a; Ordieres et al., 2005; Wu et al., 2012) have been gaining popularity in air quality modelling because of their high flexibility and well documented prediction abilities. However, other soft comuting methodes like adaptive neuro-fuzzy inference system (ANFIS), which is accepted as an efficient and robust method for multivariate analysis, have not been used for modelling the spatiotemporal variations of $PM_{2.5}$ concentrations.

Although most of the aforementioned methods can be applied to determine the relationship among AOD and $PM_{2.5}$, imposing a specific method could make it difficult to select the best predictive model. Hence, adaptive model identification approach is used to choose the most efficient model by using cross-validation technique rather than fitting a specific model to the dataset (Reid et al., 2015; Syed, 2011).

Few studies have investigated the relationship between $PM_{2.5}$ and satellite-based AOD in Australia (Gupta et al., 2007; Gupta et al., 2006; Meyer et al., 2008). While other studies have recommended the meteorological and geographical factors incorporation to the AOD–$PM_{2.5}$ relationship to improve models' performance (Chudnovsky et al., 2014; Liu et al., 2009), there is a clear need to conduct an Australian study to develop a satellite-based model investigating significant geographical and meteorological factors including humidity, planetary boundary layer, and wind speed and direction.

In this study, we aimed to improve the estimate of $PM_{2.5}$ concentration by using remotely-sensed AOD in conjunction with comprehensive meteorological and geographical data. Three different soft computing algorithms were applied to estimate the monthly average exposure to $PM_{2.5}$ in the South-east Queensland (SEQ) region of Australia, from 2006 to 2011. In turn, an adaptive model identification approach was used to choose the optimal model from ANFIS and other soft computing methods: SVM and BPANN, by using 10-fold cross-validation (Pandey et al., 2013; Syed, 2011). We ultimately used the model with the best predictive ability to estimate spatiotemporal variation of $PM_{2.5}$ in this sparsely populated area with dense vegetation cover.

2. Materials and Methods

2.1. Study location and ground-level $PM_{2.5}$ measurements

SEQ is a region in the state of Queensland, Australia, which covers 22,420 km^2 and is home to 3.05 million people out of the state's population of 4.58 million based on the 2011 Australian census (Australian Bureau of Statistics., 2012). The study area consists of Brisbane, the state's capital city, as well as other urban and rural centres including Ipswich, Logan City, Gold Coast, Sunshine Coast, and the Lockyer Valley. Motor vehicle emissions and industrial boilers are identified as major sources of $PM_{2.5}$ in SEQ (Queensland Government., 2014). The Queensland government and other agencies are responsible for regulatory aerosol monitoring in SEQ. We obtained quality-assured 24 h ground-level $PM_{2.5}$ measurements from January 2006 to December 2011. During the study period, $PM_{2.5}$ was measured at 8 monitoring sites across SEQ (supplement, page S3). We used monthly averages of the daily measured $PM_{2.5}$, and the inclusion criteria for a given month was that less than 5% of the daily measurements were missing.

2.2. Land use data

We obtained data on anthropogenic and natural land use variables as spatial predictors that were possible predictors of measured $PM_{2.5}$ concentrations. The selected land use variables, summarised in Table 1, were examined to discover which ones improved the prediction of $PM_{2.5}$ (Knibbs et al., 2014). They included proxies for emissions from traffic, point sources and changing land cover conditions.

The impacts of vegetation cover and its phenological state on the relationship between the $PM_{2.5}$ and satellite AOD were also examined in the present study. Normalized difference vegetation index (NDVI) is used to provide a measure of greenness and vegetation cover. NDVI was found to be an effective predictor for pollutant concentrations in previous studies (Chudnovsky et al., 2014; Dirgawati et al., 2015; Su et al., 2009). The monthly mean NDVI data were derived from an Advanced Very High Resolution Radiometer (AVHRR) sensor carried on the National Oceanic and Atmospheric Administration (NOAA) satellite and processed by the Australian Bureau of Meteorology (BoM) at a spatial resolution of 1 km (Bureau of Meteorology, 2015).

2.3. Satellite data

Daily global gridded observations of AOD at a resolution of 0.25 degrees latitude and longitude are derived from the Ozone Monitoring Instrument (OMI) aboard the Aura satellite (Levelt et al., 2006). Aura crosses the equator in a sun-synchronous polar orbit for the daylight ascending orbit (Torres et al., 2007), and it passes over SEQ at approximately 14:00 local time. We download the monthly average OMI AOD level 2 Near-UV AOD and single Scattering Albedo product (OMAERUVG.003 at 342.5 nm) from NASA Giovanni interface for each month from 2006–2011.

Table 1. Independent variables included as potential predictors of $PM_{2.5}$

Variables (units)	Spatial resolution	Point or buffer	Data source
OMI Near-UV AOD	0.25 degrees Lat/Lon	Point	Aura OMI AOD product via NASA Giovanni interface
Distance to coast (m)	-	Point	ArcGIS geoprocessing tools
Distance to port (m)	-	Point	" "
Distance to airport (m)	-	Point	" "
Distance to nearest major road	-	Point	" "
Distance to nearest minor road	-	Point	" "
Airport (present/not present)	-	Buffer	" "
Major road (m)	-	Buffer	PSMA Australia Transport and Topography product
Minor road (m)	-	Buffer	" "
Industrial point source $PM_{2.5}$ emissions (kg/yr)	-	Buffer	Australia National Pollutant Inventory
Time (Julian month)	-	Point	ArcGIS geoprocessing tools
Population density (person/km^2)	1 × 1 km^2	Point	Australian Bureau of Statistics
Land use by type (% area)[b]	Mesh block[c]	Buffer	Australian Bureau of Statistics
Elevation (m)	30 m	Point	U.S. Geological Survey
Normalized difference vegetation index	1 × 1 km^2	Point	Terrestrial Ecosystem Research Network, Australian Bureau of Meteorology, AusCover project and NASA NOAA satellite
Mean daily maximum temperature (°C)	5 × 5 km^2	Point	Australian Bureau of Meteorology
Mean daily minimum temperature (°C)	5 × 5 km^2	Point	" "
Rainfall (mm)	5 × 5 km^2	Point	" "
Humidity (hPa)	5 × 5 km^2	Point	" "
Solar exposure (MJ/m^2)	6 × 6 km^2	Point	" "
Planetary boundary layer height (m)	3 × 3 km^2	Point	Derived from Weather Research and Forecasting model
U-component of wind speed (m/s)	3 × 3 km^2	Point	" "
V-component of wind speed (m/s)	3 × 3 km^2	Point	" "
Wind speed (m/s)	3 × 3 km^2	Point	" "
Wind direction (Degrees)	3 × 3 km^2	Point	" "

[a] 22 Circular buffers were generated with radii of 50 m, 100 m, 200 m, 300 m, 400 m, 500 m, 600 m, 700 m, 800 m, 900 m, 1000 m, 1200 m, 1500 m, 1800 m, 2000 m, 2500 m, 3000 m, 3500 m, 4000 m, 5000 m, 7500 m, and 10,000 m (Novotny et al., 2011).

[b] Four different land use classes were investigated including industrial, commercial, residential, and open space (which contains the agricultural land, parks, and water bodies (Rose et al., 2010)).

[c] Mesh Block is the smallest geographic unit defined by the Australian Statistical Geography Standard for which the Census data is available (Australian Bureau of Statistics, 2011), and can be variable in size.

2.4. Meteorological Data

We obtained surface meteorological parameters including mean maximum and minimum temperature, rainfall, and humidity from high-quality spatial climate data-sets developed by BoM which provides gridded climatological maps for each month of the year (Jones et al., 2009). In addition, monthly solar exposure maps are also obtained from BoM during the study period.

Planetary boundary layer height (PBLH), wind direction (WD) and wind speed (WS) can play a critical role in the transport and dilution of $PM_{2.5}$ (Harrison et al., 1997); hence, special attention was paid to these parameters in this study. The Weather Research and Forecasting model (WRF) was used to calculate these parameters as at 2:00 pm local time at a spatial resolution of 3 km to match the over-pass time of the Aura satellite. Details on the WRF configuration are provided in the supplement (page S3-S7).

2.5. Modelling approach

Following similar studies (Knibbs et al., 2014; Novotny et al., 2011), 22 circular buffers were created around each monitoring site to obtain local and more remote sources of $PM_{2.5}$ (Table 1). Certain variables were calculated within a buffer (e.g., land use type, road length) while others were extracted at each monitoring site (e.g., wind speed, humidity, temperature). In total, 194 independent variables were obtained including 18 point variables and 176 buffer variables (8 variables calculated at 22 buffers each).

2.6. Statistical analysis

In this study, there were 194 predictor variables to choose from, hence choosing the optimum subset was a complicated process and needed to be carefully conducted. In many soft computing and data mining tasks, there can be some irrelevant variables which may affect the derived statistical relationship between the dependent variable and the other relevant predictors. A common solution to overcome this problem is to use a variable selection process which can help to select a subset of the most relevant and representative predictors from input predictors. The Least Absolute Shrinkage and Selection Operator (Lasso) is a well-known method which is widely used to suppress or shrink variables to select the most relevant predictor variable set. Lasso-type variable selection method was used in this study since it was successfully adopted in many applications (Hu et al., 2015; Li and Shao, 2015; Tibshirani, 2011).

Following Beelen et al. (2013), we only included potential predictor variables with less than 10% null values and centred and standardised some independent variables to improve model convergence and make the parameter estimates more interpretable. Subsequently, all remaining predictor variables were evaluated, and variables with p-value greater than 0.10 or variance inflation factor (VIF) greater than 6 were removed in order to avoid multicollinearity (see Table S2). As suggested by other studies (Beelen et al., 2013; Henderson et al., 2007; Novotny et al., 2011; Vienneau et al., 2013), if two buffer sizes of a particular variable were found to be collinear, donut ring buffers (so called concentric adjacent rings) were replaced with original circular buffers and the analysis was redone. Ring buffers (i.e., annulus) were calculated by differencing the circular buffers.

In this study, we employed the soft computing techniques ANFIS, BPANN and SVM. The soft computing techniques employed here are explained in the supplement, page S8-S17. The input variables were composed of different types of data, including land use, meteorological, and satellite data. We matched the selected variables with the $PM_{2.5}$ measurements at 8 monitoring sites during the study period (72 months) which resulted in more than 550 observation sets in total. These observations were divided into training, validation, and test subsets. The majority of the observations (70%) were used for training the models. In order to avoid over-training, 15% of the observations were used for validation and checking the model's generalisation (Wu et al., 2012). Finally, the remaining 15% of the observations were employed as the test subset to estimate the $PM_{2.5}$ concentration by the models.

In this study, 10-fold cross validation (CV) method was applied to evaluate the performance of the BPANN, ANFIS, and SVM models and identify the optimal model for estimating the $PM_{2.5}$ concentration. This method has the ability to examine the model's predictive ability (Beckerman et al., 2013a). This examination was accomplished by randomly splitting the data into 10 equal-sized folds. Subsequently, one of the folds was used to test the model and the remaining 9 folds were used to train the model (Kim, 2009; Refaeilzadeh et al., 2009). This process was repeated 10 times for each candidate model while all folds were used as the test subset and the 10 results were averaged to obtain the overall CV-R^2 and CV-RMSE. The best predictive model was selected from those with the smallest CV-RMSE and highest CV-R^2 (Dirgawati et al., 2015).

Bland-Altman plot was also used to examine the agreement between the observations and predictions. In this plot, X axis shows the average of the model predictions and observations, and Y axis represents the difference between these values. Bland-Altman plot also provides statistical limits by calculating the average and mean and the standard deviation (*sd*) of the differences between observations and predictions (Giavarina, 2015). These limits were used to evaluate the agreement between observations and model predictions. For more explicit information on Bland-

Altman plot see Giavarina (2015). Figure 1 illustrates the overall research process used in this study.

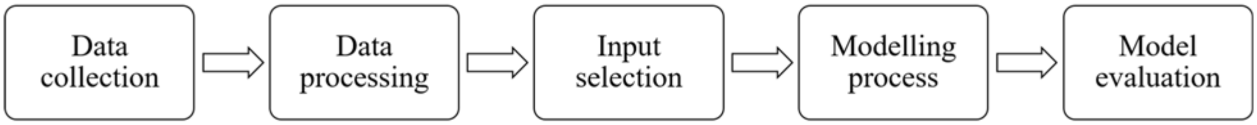


Figure 1. General research process for estimating $PM_{2.5}$ concentration.

We used R v.3.2.3 (R Foundation for Statistical Computing, Vienna, Austria) and MATLAB R2014b (MathWorks Inc., Natick, USA) for all statistical and soft computing analyses and ArcGIS version 10.2 (ESRI Inc., Redlands, USA) for spatial data processing and map creation.

3. Results

3.1. Modeling results and evaluation

In this study, a wide range of ground-based $PM_{2.5}$ measurements, land use, meteorological, and remotely-sensed AOD data were employed to estimate the $PM_{2.5}$ concentration using soft computing techniques. In following section, the agreement between predicted and observed $PM_{2.5}$ concentration is evaluated. 10-fold cross validation is also used to compare the potential of different algorithms for estimating $PM_{2.5}$ concentration.

The variable selection results showed that 16 variables were the most effective predictors of $PM_{2.5}$ concentration. The variables most correlated with the outcome were firstly humidity, followed by maximum temperature, AOD and then the length of the major roads. The results of the variable selection process are provided in the supplement (Table S2).

Using the testing dataset for each of the developed models, $PM_{2.5}$ concentrations were then predicted. A summary of the observed and predicted $PM_{2.5}$ concentrations is presented in Fig. 2.

The mean observed $PM_{2.5}$ concentration for the testing dataset is 6.77 μg/m^3. All three models approached this value within a numerical range of -0.02 to +0.38 μg/m^3. The non-parametric Wilcoxon test was performed to check if there was any significant difference between the predicted and observed mean $PM_{2.5}$ concentrations of each model. The test on all models yielded p-values greater than 0.01, showing an insignificant difference between the predicted and observed $PM_{2.5}$ concentration at 1% significant level. A comparison of the predicted values demonstrated that the ANFIS model predicted values were slightly closer to the full range of the observed monitoring data than the SVM and BPANN models. In general, Fig. 2 shows that all models reliably calculated the average and range of $PM_{2.5}$ concentration; therefore, predicted-observed plots are used to evaluate the predictive abilities of the models (Fig. 3).

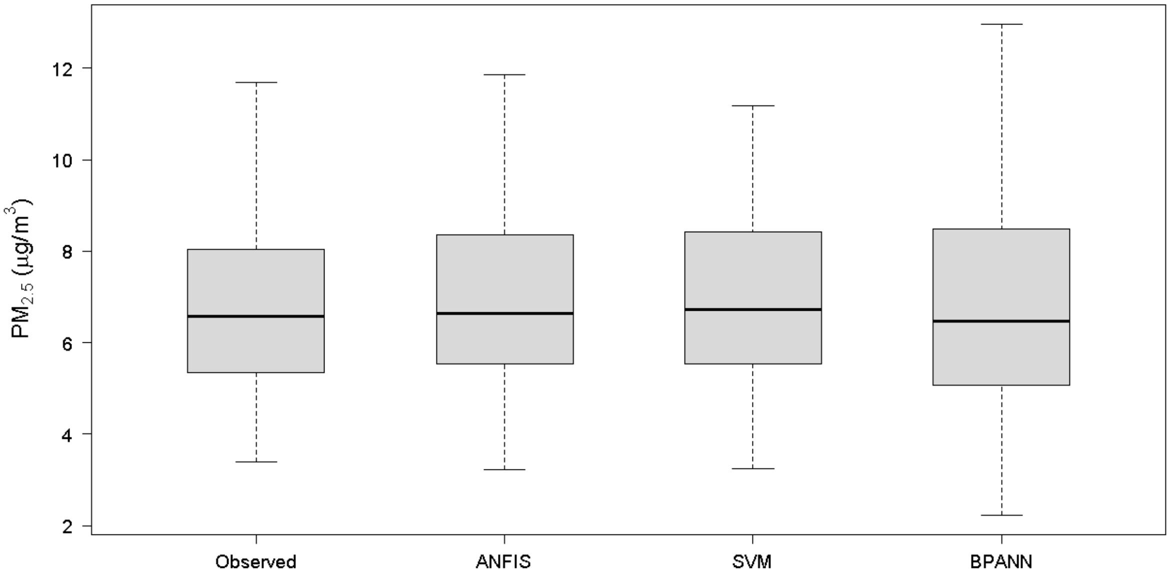


Figure 2. Summary of $PM_{2.5}$ model predictions on the testing dataset.

We compared the observed $PM_{2.5}$ concentrations to the predicted values of the ANFIS, SVM, and BPANN models. The ANFIS's predicted-observed plot indicates that the values are more equally scattered across the line of agreement at the low and high $PM_{2.5}$ concentrations whereas the SVM model under-predicts and over-predicts these values, respectively. In addition, the predicted-observed plot shows relatively weak correlation between the BPANN's predictions and actual observations.

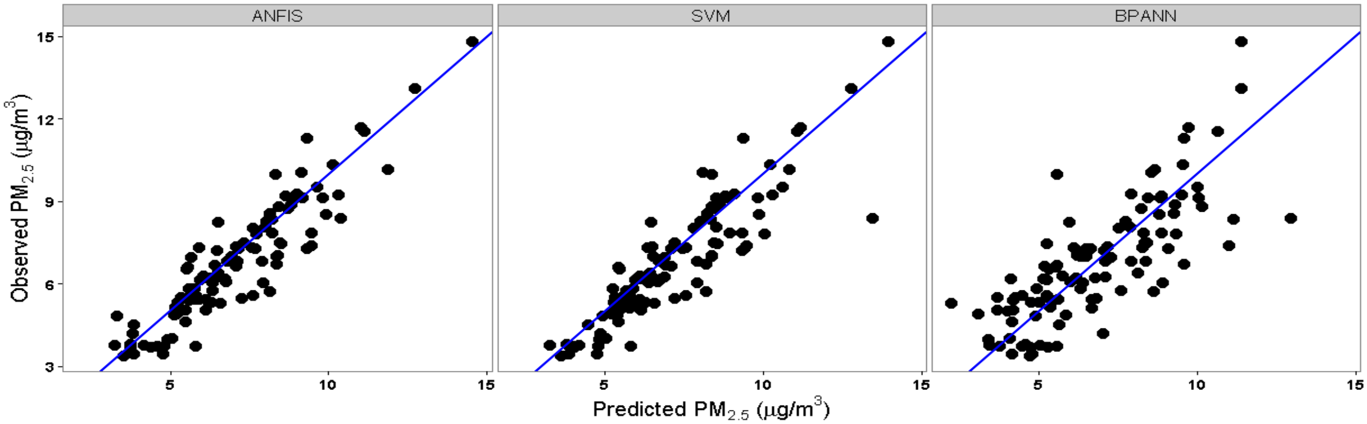


Figure 3. Scatter plots of observed vs. predicted $PM_{2.5}$ for the optimal model fitting on the testing dataset using ANFIS, SVM, and BPANN, respectively. Blue line indicates the line of agreement (y = x).

Table 2 compares the R^2 and RMSE for model fitting and cross validation. For the model fit the R^2 values are 0.61, 0.73, and 0.84 for the BPANN, SVM and ANFIS models, respectively. The RMSE values are 1.57 μg/m^3, 1.36 μg/m^3, and 0.94 μg/m^3 for the BPANN, SVM, and ANFIS models, respectively. Comparing the model fittings and cross validation, CV-R^2 decreases by just 0.03 and CV-RMSE increases by 0.85 μg/m^3 for the ANFIS model indicating negligible model overfit. The CV-R^2 of the SVM and BPANN decreased by 0.06 and 0.07, respectively indicating both models overfit more than ANFIS.

Table 2. R-squared and RMSE for model fittings vs. cross validation

	R^2	**RMSE ($\mu g/m^3$)**	**CV-R^2**	**CV-RMSE ($\mu g/m^3$)**
ANFIS	0.84	0.94	0.81	1.79
SVM	0.73	1.36	0.67	2.02
BPANN	0.61	1.57	0.54	2.11

Our findings demonstrated that the CV-R^2 of the ANFIS (0.81) was higher than that of the SVM (0.67) and BPANN (0.54) model. Also, the CV-RMSE of the ANFIS model (1.79 $\mu g/m^3$) was lower than that of the SVM (2.02 $\mu g/m^3$) and BPANN (2.11 $\mu g/m^3$) model. Compared to SVM and BPANN models, the ANFIS model had higher accuracy without causing more overfit.

Bland-Altman analysis was used to evaluate the agreement between the observation and predictions of ANFIS and SVM since both models showed promising performance in the testing stage (Figure 4). The Bland-Altman plots demonstrated low bias in both models; however, the ANFIS model had slightly tighter agreement than the SVM with fewer large residuals.

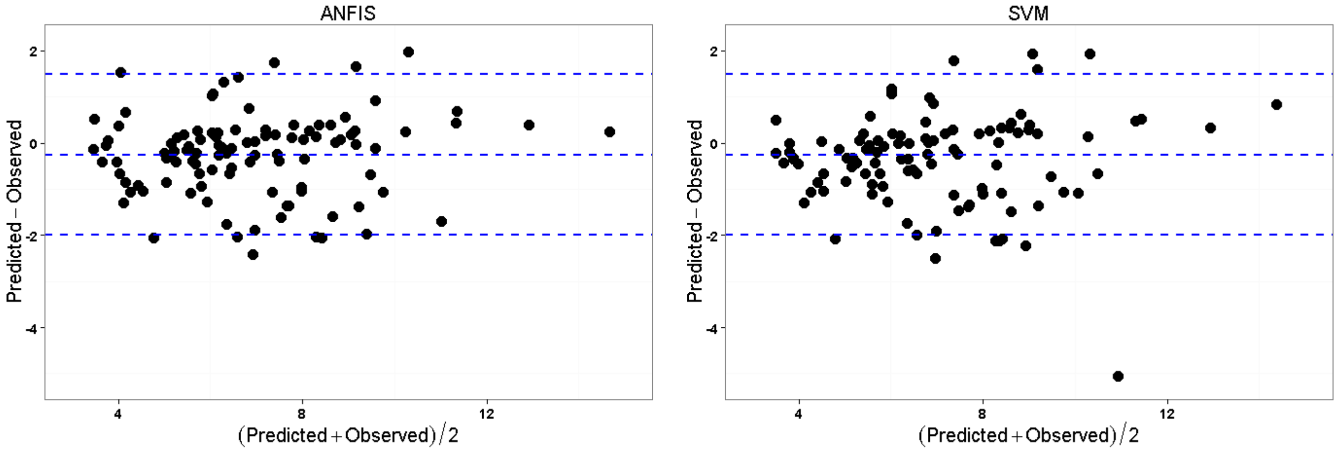
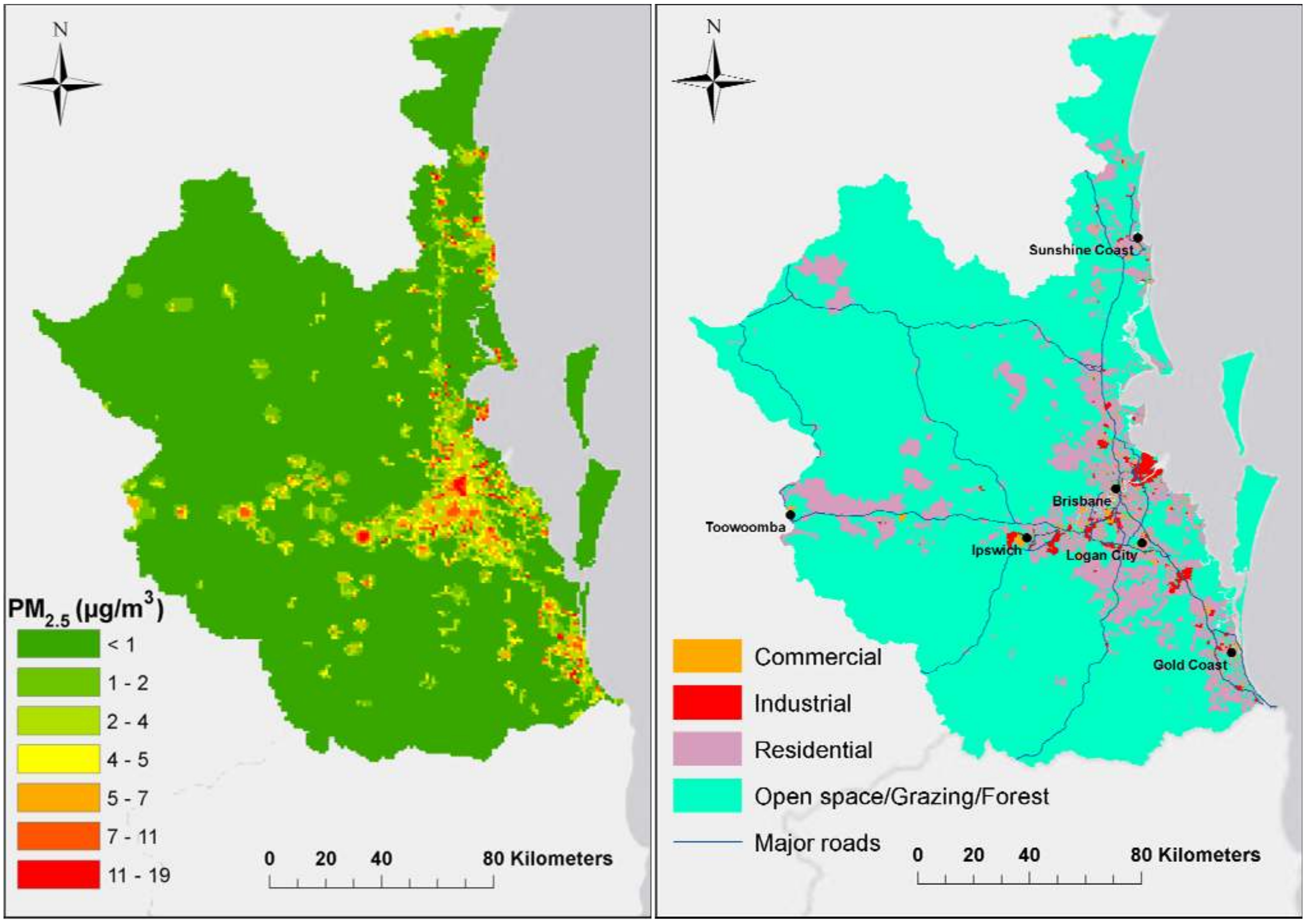


Figure 4. Bland-Altman plots of predicted and observed $PM_{2.5}$ concentrations ($\mu g/m^3$)

3.2. Application of the model

The predicted values of PM2.5 concentration in September 2011, selected from the 6-year study period, using ANFIS model for the study area 1 km grid is presented in Figure 5a.



(a) (b)

Figure 5. a) Monthly average PM2.5 concentration in September 2011 predicted by ANFIS model b) land use map of SEQ

Figure 5b illustrates land use map of SEQ. Concentrations ranged from less than 2 to 19 µg/m^3. Areas with higher concentrations (7 to 19 µg/m^3) corresponded to cities and major towns. Higher concentrations were predicted in locations with extensive adjacent industrial areas and major roads. This pattern was observed in all 6 cities of the study area. The highest levels were predicted for the three largest cities: Brisbane (with 1.977 million people), Gold Coast (494,500) and Logan (287,474).

4. Discussion

We employed soft computing techniques to improve concentration estimates for $PM_{2.5}$ using satellite, meteorological and land use predictor variables in South-east Queensland, Australia. The ANFIS model utilized in this work was the first attempt to apply it for spatiotemporal modelling of $PM_{2.5}$. Using cross validation technique, the ANFIS model was found to have the best performance compared to SVM and BPANN models, and better agreement with the observed data. The results provide estimates of monthly $PM_{2.5}$ concentrations for SEQ from 2006 to 2011.

ANFIS is a hybrid system that combines the strengths of fuzzy logic and artificial neural network (Jang, 1993; Lin and Lee, 1991), which provides a robust and accurate method for predicting $PM_{2.5}$ concentration over the range of observations used in this study.

In this research, WRF used to calculate PBLH, and WS. Both parameters were highly associated with $PM_{2.5}$ concentration across ANFIS runs. In addition, daily maximum temperature had higher importance compared to the daily minimum temperature. This might be because daily maximum temperature is temporally coincident with the Aura satellite overpass time for the study area.

Prior studies mostly considered land use parameters mainly focused on roadways and population-related data. We also evaluated industrial point source emissions, port and airport locations as potential land use predictors. Land use parameters used in our study, may not be important predictors for short term events (e.g. bush fire episode) but our findings revealed that they are of the strong predictors for $PM_{2.5}$ estimation in a long term period.

Data sets with different spatial resolutions have been used in our study. The resolution of NDVI and WRF outputs for example are finer than the OMI sensor data. Individually, OMI AOD data are not spatially fine enough for estimating the $PM_{2.5}$ exposure in epidemiological studies. However, method of combining different buffer sizes of land use parameters with meteorological and satellite-based data enabled the model to integrate fine and more spatially coarse data sets to estimate $PM_{2.5}$ concentration and provide more informative results for epidemiological studies. Our results also corroborated with Reis et al. (2015) who suggested that the incorporation of 'big data' derived from different sources provides new opportunities for data-intensive models to improve the estimates of population exposures to air pollution. Another important finding was that the highest concentrations (10 to 20 $\mu g/m^3$) were estimated in the Brisbane, Gold Coast and Logan City which have the highest population density in SEQ (Fig. 5); hence, the increased risk of population expose to higher concentration of $PM_{2.5}$. Although the average $PM_{2.5}$ concentration was below the WHO guideline (25 $\mu g/m^3$), epidemiological studies have demonstrated that $PM_{2.5}$ exposure to even lower concentrations is associated with high health risks (Burnett et al., 2014). Based on the shape of the $PM_{2.5}$ exposure-response curves derived by Burnett et al. and used in the Global Burden of Disease studies (Burnett et al., 2014), characterizing with a steep slope for concentrations ranging from 10 to 20 $\mu g/m^3$, exposure to $PM_{2.5}$ concentration between 10 to 20 $\mu g/m^3$ highly increases the relative risk of stroke and chronic obstructive pulmonary disease; therefore, even $PM_{2.5}$ concentration below the WHO guideline could not be considered safe.

Different methodologies make it difficult to compare our results to other studies, however we have attempted to compare our results with two studies which have demonstrated the ability of remotely sensed AOD and meteorological data to predict $PM_{2.5}$ concentration (Gupta and Christopher, 2009a; Wu et al., 2012). Both studies used BPANN method to estimate the spatiotemporal variation of $PM_{2.5}$, and reported R^2 lower than 0.61. Our model exhibited better correlations than these models, which could be due to either: (1) the comprehensive input variables used or (2) the more robust modeling algorithms used. We also compared our methodology with a study of the global burden of disease 2013 conducted by Brauer et. al. (2016) which combined ground measurements, chemical transport model outputs, and satellite-based data to provide global estimates of $PM_{2.5}$ concentration. Although, chemical transport model simulations were unavailable for our study area, our model was still able to capture 81% of $PM_{2.5}$ variations.

Previous research demonstrated that PBLH and WS significantly affect the $PM_{2.5}$-AOD relationship. Our results support these findings, but also demonstrate that incorporating other spatial and spatiotemporal data as well as road density, land use types, NDVI, and industrial point sources improves the model's performance.

5. Conclusions

Three different soft computing methods were applied to develop a satellite-based model for estimating the spatiotemporal variation of $PM_{2.5}$. ANFIS performed very well compared to SVM and BPANN. It exhibited satisfactory performance with CV-R^2, and CV-RMSE equals to 0.81, and 1.79 μg/m^3, respectively. It provides estimates of monthly $PM_{2.5}$ concentrations during 2006-2011. The modelling approach used in this study is highly applicable to similar settings anywhere in the world assuming that researchers have access to data sets equivalent to these used in our study. WRF, and its underlying boundary condition data, is a community model available to the world research fraternity. The NASA Giovanni data is available to anyone in the research community who can be registered with NASA as a data user. It is expected that researchers will have access to all other similar data sets or proxies in their own national research and information collection institutions, hence this method could be applied in other regions that experience $PM_{2.5}$ exposure. We hope that our approach will be beneficial for epidemiological studies and other researches seeking spatially accurate estimates of $PM_{2.5}$ with few monitoring stations. It is certainly feasible to develop a model with higher spatial resolution which is a direction of our future research. Further analysis such as global sensitivity and uncertainty analyses (GSUA) can also be done to assess input factor importance and interaction (Lüdtke et al., 2008; Saltelli et al., 2008). Recently developed Unified-Weather Research and Forecasting model (NU-WRF) can be employed to obtain more accurate estimates of meteorological parameters compared to WRF model (Peters-Lidard et al., 2015). Data management remains a major challenge for empirical modelling as it requires to store, process and analyse large data sets containing different types of data from multiple sources. Recently, new information models have been developed to facilitate the data management and validation in observation-based studies (Horsburgh et al., 2016; Shu et al., 2016).

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