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Verification of TAPM meteorological predictions in the Melbourne region for a winter and summer month

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The Air Pollution Model (TAPM), newly developed in CSIRO, solves the fundamental fluid dynamics and scalar transport equations to predict meteorology and pollutant concentration for a range of pollutants important for air pollution applications. The meteorological component of TAPM predicts the mesoscale flows important to local-scale air pollution, such as sea breezes and terrain-induced flows, and in this work has been evaluated in the Melbourne region for two months (July and December 1998) characterised by high air-pollution concentrations. A major advantage of TAPM over other prognostic modelling systems is that it is much faster to run, and it is therefore a more practicable model for long-period simulations.

TAPM predictions have been compared with available meteorological data from air quality stations run by the Environment Protection Authority, Victoria (EPAV); statistics of observed versus model predictions were used to assess the performance of the model. The results showed that winds were predicted well, with an average root mean square error of about 2 m s^{-1}, an average index of agreement of 0.82, and the model predictions showed good variational skill. Temperatures were also predicted well, with an average root mean square error of about 3.6°C, an average index of agreement of 0.78 for July 1998 and 0.90 for December 1998, and good variational skill was shown, although predictions performed better for December. These index of agreement values are very good compared with values of 0.5-0.6 obtained in other studies.

Generally, the results showed that TAPM has demonstrated good performance in predicting the near-surface meteorology in the Melbourne region for both a winter and a summer month, and can be used with confidence to describe the local-scale meteorology needed for air pollution applications.

Introduction

Air pollution models that can be used to predict pollution concentrations for periods of up to a year are generally semi-empirical/analytic approaches based on Gaussian plumes or puffs. These models typically use either a simple surface-based meteorological file or a diagnostic wind-field model based on available observations. The Air Pollution Model (TAPM) (Hurley 1999), newly developed in CSIRO, is different to these approaches in that it solves the funda-

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mental fluid dynamics and scalar transport equations to predict mesoscale meteorology and pollutant concentrations for a range of pollutants important for air pollution applications, and so eliminates the need to have site-specific meteorological observations to drive the model. Instead the model relies on large-scale synoptic fields of meteorological variables to provide the baseline climatology, and it predicts the local-scale flows important to local-scale air pollution, such as sea-breezes and terrain-induced flows. A major advantage of TAPM over other prognostic meteorological/airshed modelling systems is that it is much faster to run, and it is therefore a more practicable model for long simulation periods rather than being limited to the more usual case study approach. For example, benchmarking tests for the meteorological component of TAPM have shown that, when using similar parametrisation options in the models, TAPM is approximately four times faster than the Lagrangian Atmospheric Dispersion Model (LADM) (see Physick et al. (1994) for a description of LADM), and approximately twenty times faster than the Mesoscale Model (MM5) (see Grell et al. (1994) for a description of MM5). This speed increase is due, in part, to the use of efficient numerical techniques and time-splitting methods in TAPM, and in part to TAPM being able to use a relatively large timestep because the model is non-hydrostatic/incompressible (solutions contain no sound waves), whereas LADM is hydrostatic/compressible (solutions contain horizontal sound waves), and MM5 is non-hydrostatic/compressible (solutions contain vertical and horizontal sound waves). TAPM aims to achieve a balance between model complexity and efficient run time.

The meteorological model component of TAPM is an incompressible, non-hydrostatic, primitive equation model with a terrain-following vertical coordinate for three-dimensional simulations. It solves the momentum equations for horizontal wind components, the incompressible continuity equation for vertical velocity, and scalar equations for potential virtual temperature and specific humidity of water vapour, cloud water and rain water, and turbulence kinetic energy and eddy dissipation rate. Pressure is split into hydrostatic and non-hydrostatic components and a Poisson equation is solved for the non-hydrostatic component. Parametrisations include explicit cloud microphysics, a vegetative canopy and soil scheme at the surface, and of radiation both at the surface and at upper levels. The air pollution model component uses the predicted meteorology and turbulence at each timestep, and represents pollutant dispersion through a combined Eulerian and Lagrangian approach. It also includes plume rise, gas and aqueous-phase chemical reactions, and wet and dry deposition.

In this paper, only the meteorological component of TAPM is considered – future work will examine model performance for predictions of air pollution concentration. TAPM is used to predict local-scale meteorology in the Melbourne region for two months characterised by high pollution concentrations. The simulations are for a winter month characterised by high concentrations of particles, and a summer month that contained days with high ozone levels. The meteorological predictions are compared with available meteorological data at air quality stations run by Environment Protection Authority, Victoria (EPAV), to examine model performance. The next section presents an overview of the meteorological model component of TAPM, while subsequent sections describe results of meteorological simulations for a winter and a summer month, and the conclusions.

Overview of meteorological component of TAPM

The following two subsections provide an overview of the meteorological component of TAPM. More details on both the meteorological and the air pollution components of TAPM can be found in the report by Hurley (1999), and work with earlier versions of the model can be found in Hurley (1997, 1998), and Hurley and Luhar (2000).

Meteorological equations and parametrisations

The mean wind is determined for the horizontal components u and v from the momentum equations and the terrain following vertical velocity $\dot{\sigma}$ from the continuity equation. Potential virtual temperature θ_v is determined from an equation combining the conservation of heat and water vapour. The Exner pressure function (defined as $\pi = c_p(p/p_0)^{R_d/c_p}$, where p is pressure, $p_0 = 10^5$ Pa, $R_d = 287$ J kg^{-1} K^{-1} and $c_p = 1006$ J kg^{-1} K^{-1}) is determined from the sum of the hydrostatic component π_H and non-hydrostatic component π_N ($\pi = \pi_H + \pi_N$), with a Poisson equation solved for π_N. Conservation equations are solved for specific humidities $q = q_V + q_C$ and q_R, representing the sum of water vapour and cloud water, and rain water respectively. Microphysics is based on Katzfey and Ryan (1997) for warm rain, and includes bulk parametrisations for condensation of water vapour, evaporation of cloud water and rain water, auto-conversion and collection of cloud water to form rain water, and an expression for the rainfall terminal velocity.

Turbulence closure in the mean equations uses a gradient diffusion approach with diffusivity K, and includes a counter-gradient correction for temperature based on Deardorff (1966). An E-ε turbulence scheme is used to calculate K using prognostic equations for the turbulence kinetic energy (E) and the eddy dissipation rate (ε). Eddy dissipation rate equation constants are derived from the analysis of Duynkerke (1988); see Hurley (1997) for more details on the performance of the turbulence scheme used relative to other commonly used schemes.

Radiation at the surface is used for the computation of surface boundary conditions and scaling variables, with the clear-sky incoming shortwave component from Mahrer and Pielke (1977), and the clear-sky incoming long wave component from Dilley and O'Brien (1998). These clear-sky contributions are then modified for liquid water effects using an approach based on Stephens (1978).

Boundary conditions for mean variables at the surface are zero velocity, pressure calculated from the hydrostatic equation, and surface temperature and moisture calculated from a weighted average of soil and vegetation values. The soil and vegetation parametrisations are based on those from Kowalczyk et al. (1991), which use a force-restore approach for soil temperature and moisture, and a surface energy approach for the vegetation temperature. Boundary conditions for the turbulent fluxes are determined by Monin-Obukhov surface-layer scaling variables with stability functions from Dyer and Hicks (1970), and parametrisations for stomatal resistance. Turbulence boundary conditions are specified at the first model level for E and ε using surface and mixed-layer scaling. At the model top boundary all variables are set at their synoptic values, while zero gradient boundary conditions are used for all variables at the lateral boundaries. The terrain is smoothed near the lateral boundaries to reduce noise. Optionally, one-way nested boundary conditions can be used for the main prognostic equations using an approach based on Davies (1976), with the model nested within itself.

The model is initialised with the synoptic values of variables with isolines of these variables oriented to be parallel to mean sea level (i.e., cutting into the terrain). Turbulence levels are set to their minimum values. The Exner pressure function is integrated from mean sea level to the model top to determine the top boundary condition. The Exner pressure and terrain- following vertical velocity are then diagnosed in the usual way.

Synoptic conditions are obtained from digital large-scale analyses, which are routinely available from meteorological centres such as the Australian Bureau of Meteorology (BOM). The model can use three possible modes of synoptic variability:

- Synoptic winds, temperature, and humidity varying with height;
- Synoptic winds, temperature, and humidity varying with height and time;
- Synoptic winds, temperature, and humidity varying with height and time, and synoptic winds also varying with horizontal position.

The model is nudged towards the synoptic situation with an e-folding time of twice the time interval between synoptic information.

Numerical methods

The model uses a large timestep of 300 s on which radiation and surface processes are calculated, while meteorological and turbulence equations are solved with a timestep of $\Delta t_M = 1/U_M \min(\Delta x, \Delta y)$, where $U_M = 30$ m s^{-1}, and Δx and Δy are the horizontal grid spacings in metres. Model equations are solved using second-order finite difference methods with no grid stagger, a constant grid spacing in the horizontal directions, and a variable grid spacing in the vertical direction.

Horizontal advection for all prognostic variables is calculated using the semi-Lagrangian technique of McGregor (1993) with the quasi-monotone conversion of Bermejo and Staniforth (1992), with timestep Δt_M , and Lagrange cubic polynomial interpolation. Vertical advection for all prognostic variables except θ_v is calculated using the same approach as for horizontal advection. The approach used is second-order accurate in time, and fourth-order in space.

Meteorological variables u, v, $\dot{\sigma}$, θ_v and π_H are solved using a time-split approach whereby gravity wave terms (including vertical advection of θ_v) are separated from the other terms and solved on a small timestep $\Delta t_G = 1/U_G \min(\Delta x, \Delta y)$, where $U_G = 120$ m s^{-1}. These prognostic equations are solved using the second-order Adams-Bashforth scheme, while diagnostic vertical integration using the trapezoidal rule is performed from the ground to the model top to obtain $\dot{\sigma}$, and from the model top to the ground to obtain π_H. On the timestep Δt_G, an implicit tri-diagonal horizontal filter described by Pielke (1984) is used instead of horizontal diffusion. The filter is applied separately in each horizontal direction with a filter coefficient of $\delta = 0.10$ (increased values are used near the top of the model). On the timestep Δt_M, vertical diffusion is solved using a first-order implicit approach with special treatment of fluxes at the surface boundary.

All other prognostic equations including those for specific humidities and turbulence are solved using a semi-implicit approach with second-order three-level time-differencing, explicit horizontal diffusion, implicit vertical diffusion and optionally implicit loss or destruction terms (used for ε). A time-split approach is used in the turbulence equations for the energy production/dissipation terms with a small timestep of 100 s. The non-hydrostatic pressure perturbation equation is solved using the Successive Over Relaxation iteration method.

Meteorology in the Melbourne region

TAPM was used to model the hour-by-hour meteorology of July and December 1998 in the Melbourne region, using six-hourly analysis data at 0.75° grid resolution from the Bureau of Meteorology Limited Area Prediction System (LAPS) to provide the synoptic conditions (see Puri et al. (1998), for a description of LAPS), Rand's global sea-surface temperatures from the US National Center for Atmospheric Research (NCAR), terrain height data from the Australian Land Information Group (AUSLIG) at 9 second grid resolution, and soil and vegetation classification data from CSIRO Wildlife and Ecology as model input. The model was run with a doubly nested grid of 40 x 40 x 20 points at 10,000 m and 3,000 m horizontal grid spacing, centred on (longitude, latitude) = (144°58′, -37°49′), with vertical levels: 10, 50, 100, 150, 200, 300, 400, 500, 750, 1000, 1250, 1500, 2000, 2500, 3000, 4000, 5000, 6000, 7000 and 8000 m. Model options used included time and space-varying synoptic conditions, vegetation, E - ε turbulence, and a deep soil moisture content of 0.2 (wet) for July and 0.1 (dry) for December 1998. The model predictions on the 3,000 m spaced grid were compared with measurements from available EPAV near-surface monitoring stations (see Fig. 1 for site locations). Note that most of these sites are urban, and although the model and land-use database do have an urban category, it is a highly simplified formulation that does not properly distinguish between the many different urban variations, and so the model will not be able to properly predict effects such as the urban heat island effect. Model performance will not only be dependent on the model formulation, but also on the quality of the input data to the model, particularly the LAPS analyses.

The winter month of July 1998 was characterised by long periods of locally light winds and high particle concentrations, while December 1998 was representative of a summer month, which included days with high temperatures and the potential to recirculate pollutants and cause high ozone concentrations (EPAV 1999, personal communication). These months are therefore of interest from an air pollution perspective and will be used to assess the performance of TAPM for predictions of meteorology with a view to air pollution applications.

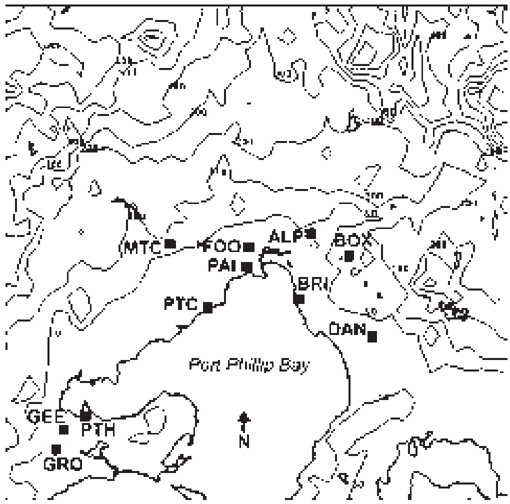


Fig. 1 Melbourne inner grid domain at 3,000 m resolution with a west-east and south-north extent of 117 km. A detailed coastline and marked terrain height (m) contours are shown. The EPAV monitoring sites are marked, and correspond to: Alphington (ALP), Box Hill (BOX), Brighton (BRI), Dandenong (DAN), Footscray (FOO), Geelong South (GEE), Grovedale (GRO), Mt Cottrell (MTC), Paisley (PAI), Pt Cook (PTC) and Pt Henry (PTH).

Model predictions of hourly average horizontal wind components (u, v) at 10 m above the ground (first model level) and temperature (T) at 1.5 m above the ground (extrapolated from 10 m using surface-layer scaling) were extracted at the nearest grid-point to each of the EPAV monitoring sites for the 3,000 m spaced inner grid. These predictions were used along with the hourly average measurements to produce statistics based on the recommendations of Willmott (1981) (see the Appendix for a summary of the formulae). As well as the usual mean and standard deviations, the statistics include a breakdown of root mean square errors (RMSE) into systematic (RMSE_S) and unsystematic (RMSE_U) components, the Index Of Agreement (IOA), which provides a more consistent measure of performance than the correlation coefficient (also shown for comparison), and measures of variational skill as recommended by Pielke (1984). Low rmse values in a model indicate that the model is explaining most of the variation in the observations, while in a model lacking bias, RMSE_S should approach zero, and consequently RMSE_U should be close to rmse. According to Pielke (1984), a model is predicting with skill if two conditions are satisfied: (a) the standard deviations of the predictions and observations are approximately the same; and (b) rmse is less than the standard deviation of the observations. The index of agreement is a measure of how well the predictions' departures from the observed mean match the observations' departures from the observed mean, and in particular how well is the match in the sign of the departures (Physick 1999, personal communication).

Examples of previous quantitative model evaluations include the case studies of Steyn and McKendry (1988) (SM88) using the Colorado State University (CSU) model for the Vancouver area, Ulrickson and Mass (1990) (UM90) using the CSU model for the Los Angeles basin, Seaman et al. (1995, 1996) (S95, S96) using the MM5 model for Southern California, and Lyons et al. (1995) (L95) using the Regional Atmospheric Modelling System (RAMS) for the Lake Michigan region. These studies presented statistics for near-surface monitoring stations, which included wind speed (all studies) and temperature (SM88 only) using selections of the statistical measures described above. A summary of IOA values from these studies for wind speed are: 0.52 (SM88), 0.54 (UM90), 0.52 (S95), 0.58 (S96), and 0.59 (L95); and for temperature: 0.33 (SM88). The quality of the simulations from these studies was considered to be good, except that the SM88 simulation had a systematic bias in the temperature that affected the IOA value. This implies that an IOA of 0.5 or greater represents a good result.

Results for July 1998

Generally, model predictions of winds have reproduced the light and variable conditions that characterised the observations during the middle part of this month. Tables 1(a) and (b) show statistics for observed (OBS) versus model predicted (MOD) near-surface horizontal wind components (*u, v*) for each of the monitoring sites, and for an average (AVG) over all of the sites. The results show that the mean (MEAN) and standard deviation (STD) of the velocity distributions were predicted well, although the *v* component of the wind was predicted slightly better than the u component. The average root-mean-square errors (RMSE) for (*u, v*) were 1.63 m s^{-1} and 1.78 m s^{-1} respectively, with the systematic error (RMSE_S) less than the unsystematic error (RMSE_U) as it should be for an unbiased simulation. The average indices of agreement (IOA) for (*u, v*) were 0.82 and 0.85 respectively (see Fig. 2), with generally similar values for all sites except Box Hill (BOX), which had values of 0.74. This site also had the fewest measurements available, and the data were dominated by the low wind speed days as indicated by the low mean values and standard deviations at this site. This feature alone can explain the lower than average IOAs, as the index of agreement measures the degree to which variations in observations can be predicted. Nevertheless, a value of 0.74 is still a good result. The measures of skill show that, on average, the standard deviations of winds were predicted well with their ratio (SKILL_V) being 0.87 and 1.08 for (*u,v*) respectively, compared to the ideal value of 1.0. The other two skill variables (SKILL_E and SKILL_R) show that unsystematic and total RMSE values are less than the standard deviation of the observations (SKILL values less than one), which indicates skill. The results show that the winds for July 1998 were predicted well.

Table 1(c) shows statistics for predicted versus observed near-surface temperature (T) for each of the monitoring sites, and for an average (AVG) over all of the sites. The results show that the mean (MEAN) and

Table 1(a). West-east (*u*) component of the wind (m s^{-1}) statistics for TAPM simulation of July 1998 at EPAV near-surface meteorological monitoring sites (see Fig. 1 for site information). Note that AVG represents the average for all sites.

Site name	*Number*	*MEAN_OBS*	*MEAN_MOD*	*STD_OBS*	*STD_MOD*	*CORR*	*RMSE*	*RMSE_S*	*RMSE_U*	*IOA*	*SKILL_E*	*SKILL_V*	*SKILL_R*
ALP	744	0.4	0.6	1.6	1.4	0.68	1.23	0.69	1.01	0.81	0.63	0.86	0.77
DAN	743	0.5	0.8	1.7	1.5	0.67	1.35	0.77	1.11	0.80	0.65	0.87	0.78
FOO	729	1.0	1.1	1.6	1.2	0.69	1.16	0.76	0.88	0.81	0.55	0.76	0.73
MTC	744	1.9	2.2	2.8	1.9	0.75	1.86	1.40	1.23	0.82	0.44	0.67	0.67
PTC	739	1.5	1.9	2.5	2.3	0.71	1.84	0.92	1.59	0.83	0.65	0.92	0.75
PAI	744	1.0	1.2	2.2	1.5	0.70	1.58	1.16	1.07	0.80	0.49	0.68	0.72
BRI	714	0.7	0.6	1.8	1.9	0.74	1.35	0.43	1.28	0.85	0.71	1.06	0.75
BOX	499	0.3	0.0	1.2	1.7	0.62	1.32	0.28	1.29	0.74	1.12	1.44	1.15
PTH	744	2.9	2.0	4.0	2.5	0.79	2.70	2.22	1.54	0.82	0.38	0.63	0.67
GEE	731	2.0	2.0	2.6	2.3	0.75	1.75	0.86	1.52	0.86	0.59	0.89	0.68
GRO	744	2.4	2.3	2.9	2.2	0.78	1.84	1.20	1.39	0.86	0.48	0.76	0.63
AVG	716	1.3	1.3	2.3	1.8	0.72	1.63	0.97	1.27	0.82	0.61	0.87	0.75

KEY: OBS = Observations, MOD = Model Predictions, MEAN = Arithmetic mean, STD = Standard Deviation, CORR = Pearson Correlation Coefficient (0=no correlation,1=exact correlation), RMSE = Root Mean Square Error, RMSE_S = Systematic Root Mean Square Error, RMSE_U = Unsystematic Root Mean Square Error, IOA = Index of Agreement (0=no agreement, 1=perfect agreement), SKILL_E = (RMSE_U)/(STD_OBS) (<1 shows skill), SKILL_V = (STD_MOD)/(STD_OBS) (near to 1 shows skill), SKILL_R = (RMSE)/(STD_OBS) (<1 shows skill).

Table 1(b). South-north (*v*) component of the wind (m s^{-1}) statistics for TAPM simulation of July 1998 at EPAV near-surface meteorological monitoring sites (see Fig. 1 for site information). Note that AVG represents the average for all sites.

Site name	*Number*	*MEAN_OBS*	*MEAN_MOD*	*STD_OBS*	*STD_MOD*	*CORR*	*RMSE*	*RMSE_S*	*RMSE_U*	*IOA*	*SKILL_E*	*SKILL_V*	*SKILL_R*
ALP	744	-1.0	-1.4	2.0	2.0	0.71	1.58	0.74	1.39	0.83	0.71	1.01	0.80
DAN	743	-1.8	-1.9	2.4	2.3	0.69	1.86	0.87	1.64	0.83	0.67	0.93	0.76
FOO	729	-1.1	-1.5	2.2	2.1	0.79	1.47	0.72	1.28	0.88	0.57	0.94	0.66
MTC	744	-1.5	-2.2	2.9	2.9	0.81	1.93	0.93	1.69	0.88	0.58	0.98	0.66
PTC	739	-1.6	-1.6	3.1	3.4	0.80	2.03	0.36	2.00	0.89	0.65	1.10	0.66
PAI	744	-1.4	-1.5	2.4	2.4	0.76	1.66	0.51	1.58	0.87	0.67	1.03	0.70
BRI	714	-1.0	-1.5	1.9	2.6	0.78	1.72	0.56	1.63	0.84	0.87	1.39	0.92
BOX	499	-0.7	-0.7	1.5	1.5	0.56	1.42	0.68	1.25	0.74	0.81	0.99	0.93
PTH	744	-1.6	-1.2	2.9	3.0	0.77	2.06	0.73	1.93	0.87	0.67	1.04	0.71
GEE	731	-1.6	-1.1	2.0	2.8	0.72	1.99	0.49	1.92	0.80	0.98	1.41	1.02
GRO	744	-1.5	-1.1	2.6	2.8	0.76	1.89	0.55	1.81	0.86	0.71	1.10	0.74
AVG	716	-1.3	-1.4	2.3	2.5	0.74	1.78	0.65	1.65	0.85	0.72	1.08	0.78

KEY: OBS = observations, MOD = model predictions, MEAN = arithmetic mean, STD = standard deviation, CORR = Pearson Correlation Coefficient (0=no correlation,1=exact correlation), RMSE = root mean square error, RMSE_S = systematic root mean square error, RMSE_U = unsystematic root mean square error, IOA = Index of Agreement (0=no agreement, 1=perfect agreement), SKILL_E = (RMSE_U)/(STD_OBS) (<1 shows skill), SKILL_V = (STD_MOD)/(STD_OBS) (near to 1 shows skill), SKILL_R = (RMSE)/(STD_OBS) (<1 shows skill).

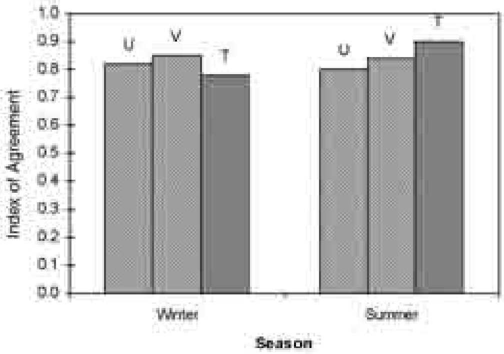
Table 1(c). Temperature (°C) statistics for TAPM simulation of July 1998 at EPAV near-surface meteorological monitoring sites (see Fig. 1 for site information). Note that AVG represents the average for all sites.

Site name	*Number*	*MEAN_OBS*	*MEAN_MOD*	*STD_OBS*	*STD_MOD*	*CORR*	*RMSE*	*RMSE_S*	*RMSE_U*	*IOA*	*SKILL_E*	*SKILL_V*	*SKILL_R*
ALP	744	8.6	6.8	3.6	5.2	0.74	3.94	1.76	3.52	0.79	0.99	1.46	1.10
DAN	744	9.2	7.9	3.0	4.6	0.75	3.35	1.46	3.01	0.80	1.00	1.52	1.11
FOO	729	9.1	7.1	3.2	5.4	0.72	4.28	2.08	3.74	0.74	1.15	1.66	1.32
MTC	744	8.6	7.5	3.1	4.1	0.76	2.85	1.10	2.63	0.83	0.84	1.29	0.91
PTC	744	8.2	9.8	3.3	2.8	0.77	2.68	2.01	1.77	0.82	0.53	0.84	0.80
PAI	744	9.1	7.6	3.0	4.9	0.70	3.81	1.62	3.45	0.75	1.16	1.63	1.28
BRI	714	10.3	8.1	3.0	4.8	0.74	3.92	2.26	3.21	0.74	1.06	1.57	1.30
BOX	743	8.3	6.9	3.2	4.8	0.76	3.44	1.52	3.09	0.80	0.96	1.48	1.07
PTH	744	9.0	8.5	2.4	3.6	0.57	3.03	0.60	2.97	0.71	1.25	1.52	1.28
GEE	744	8.8	8.1	3.3	4.0	0.70	2.97	0.83	2.85	0.82	0.88	1.23	0.91
GRO	744	8.3	8.1	2.9	3.9	0.68	2.89	0.24	2.88	0.80	1.00	1.37	1.01
AVG	740	8.9	7.9	3.1	4.4	0.72	3.38	1.41	3.01	0.78	0.98	1.42	1.10

KEY: OBS = observations, MOD = model predictions, MEAN = arithmetic mean, STD = standard deviation, CORR = Pearson Correlation Coefficient (0=no correlation,1=exact correlation), RMSE = root mean square error, RMSE_S = systematic root mean square error, RMSE_U = unsystematic root mean square error, IOA = Index of Agreement (0=no agreement, 1=perfect agreement), SKILL_E = (RMSE_U)/(STD_OBS) (<1 shows skill), SKILL_V = (STD_MOD)/(STD_OBS) (near to 1 shows skill), SKILL_R = (RMSE)/(STD_OBS) (<1 shows skill).

standard deviation (STD) of the temperature distributions were predicted well, although on average the mean value was under-predicted by 1°C and the standard deviation was over-predicted by 1.3°C. This difference can be explained, in part, by an underprediction of temperature overnight on some nights. Possible reasons for this could be that the model underpredicted cloud amounts on partially cloudy occasions, or that the urban heat island effect (which is not accounted for in the model) is having an effect as most of the sites are urban, or that the interpolation of temperature from the lowest model level to screen level is not performing well (similarity theory is not valid under very stable conditions), or a combination of these reasons. In general, the daytime variation and maximum temperature, and days that had persistent

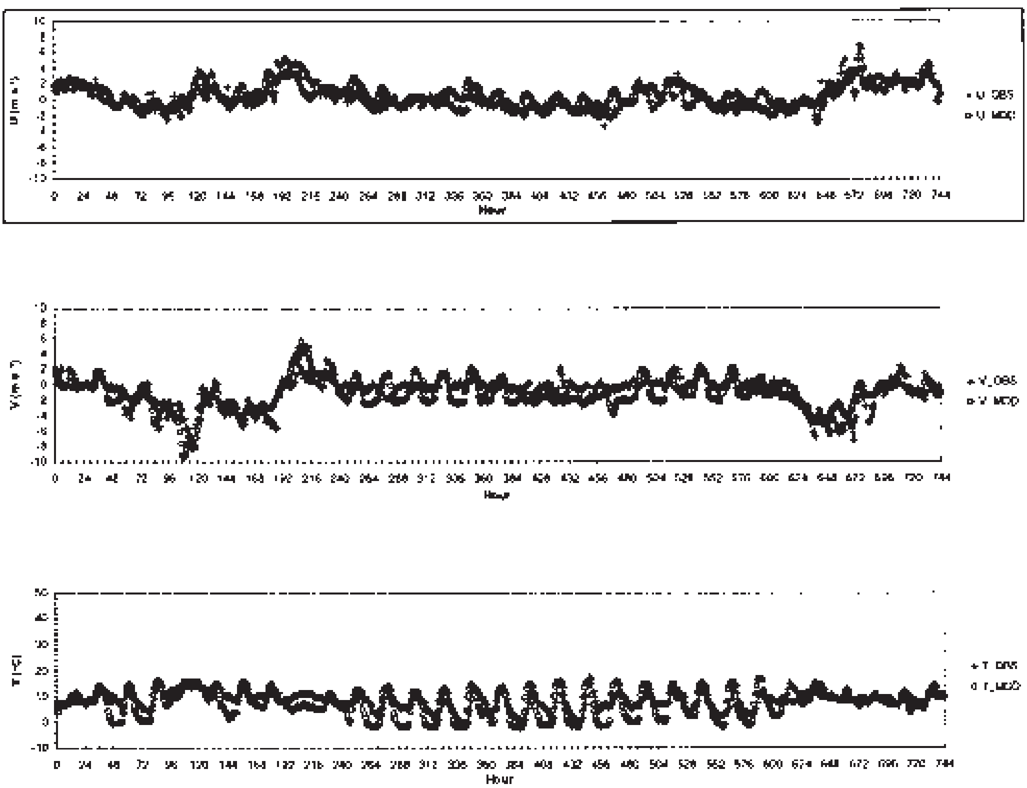
Fig. 2 **Index of Agreement (IOA) values (0 = no agreement, 1 = perfect agreement) for each of the winter (July 1998) and summer (December 1998) months for the west-east (*u*) and south-north (*v*) components of the wind (m s^{-1}) and temperature (°C) averaged over all of the EPAV near-surface monitoring sites.**



regional cloud coverage, were predicted well. The average root mean square error (RMSE) was 3.38°C, with the systematic error (RMSE_S) less than the unsystematic error (RMSE_U) as it should be for an unbiased simulation. The average index of agreement (IOA) was 0.78 (see Fig. 2). The measures of skill show that, on average, the standard deviations of temperature were over-predicted by 42 per cent as explained above, compared to the ideal value of 1.0 for SKILL_V. The other two skill variables (SKILL_E and SKILL_R) show that unsystematic and total RMSE values were of the same order as the standard deviation of the observations. The results show that the temperatures for July 1998 were predicted well, except that minimum night-time temperatures were under-predicted during some nights.

The good statistical performance described above is reinforced by the time-series plots for winds and temperature at the Alphington monitoring site shown in Fig. 3.

Fig. 3 **Observed (OBS) and TAPM modelled (MOD) time series of the west-east (*u*) and south-north (*v*) components of the wind (m s^{-1}) and temperature (°C) for July 1998 at the EPAV near-surface monitoring site at Alphington (ALP) (see Fig. 1 for site location).**



Results for December 1998

Tables 2(a) and (b) show statistics for observed (OBS) versus model predicted (MOD) near-surface horizontal wind components (*u, v*) for each of the monitoring sites, and for an average (AVG) over all of the sites. The results show that the mean (MEAN) and standard deviation (STD) of the velocity distributions were predicted well, although the mean *v* component and the standard deviation of the *u* component were slightly underpredicted. The average root mean square errors (RMSE) for (*u, v*) were 2.21 m s^{-1} and 2.31 m s^{-1} respectively, with the systematic error (RMSE_S) less than the unsystematic error (RMSE_U) as it should be for an unbiased simulation. The average indices of agreement (IOA) for (*u, v*) were 0.80 and 0.84 respectively (see Fig. 2). The measures of skill show that on average the standard deviations of winds were predicted well with their ratio (SKILL_V) being 0.74 and 1.02 for (*u, v*) respectively, compared to the ideal value of 1.0. The other two skill variables (SKILL_E and SKILL_R) show that unsystematic and total RMSE values were less than the standard deviation of the observations (SKILL values less than one), which indicates skill. The results show that the winds for December 1998 were predicted well.

Table 2(c) shows statistics for predicted versus observed near-surface temperature (T) for each of the monitoring sites, and for an average (AVG) over all of

Table 2(a) West-east (*u*) component of the wind (m s^{-1}) statistics for TAPM simulation of December 1998 at EPAV near-surface meteorological monitoring sites (see Fig. 1 for site information). Note that AVG represents the average for all sites.

Site name	*Number*	*MEAN_OBS*	*MEAN_MOD*	*STD_OBS*	*STD_MOD*	*CORR*	*RMSE*	*RMSE_S*	*RMSE_U*	*IOA*	*SKILL_E*	*SKILL_V*	*SKILL_R*
ALP	741	0.9	0.6	1.8	1.4	0.64	1.40	0.94	1.04	0.77	0.58	0.76	0.78
DAN	742	0.3	0.4	3.0	1.8	0.70	2.18	1.75	1.30	0.77	0.43	0.60	0.72
FOO	624	0.5	0.7	1.9	1.4	0.63	1.54	1.07	1.12	0.77	0.57	0.74	0.79
MTC	740	1.1	1.4	3.6	2.5	0.71	2.59	1.87	1.78	0.81	0.49	0.69	0.71
PTC	743	0.4	0.6	4.1	2.8	0.69	3.02	2.25	2.01	0.79	0.48	0.67	0.73
PAI	616	0.4	0.6	2.7	1.8	0.61	2.15	1.62	1.41	0.74	0.53	0.66	0.80
BRI	741	0.6	0.4	2.7	1.8	0.61	2.18	1.68	1.38	0.73	0.50	0.64	0.79
BOX	743	0.2	0.3	1.7	1.6	0.66	1.38	0.72	1.17	0.80	0.67	0.89	0.79
PTH	743	1.3	0.5	4.7	3.4	0.75	3.19	2.31	2.20	0.83	0.47	0.72	0.68
GEE	476	0.6	0.6	3.9	3.2	0.76	2.53	1.47	2.06	0.86	0.53	0.82	0.65
GRO	738	1.2	0.9	3.4	3.2	0.79	2.16	0.95	1.93	0.88	0.57	0.93	0.64
AVG	695	0.7	0.6	3.1	2.3	0.69	2.21	1.51	1.58	0.80	0.53	0.74	0.73

KEY: OBS = observations, MOD = model predictions, MEAN = arithmetic mean, STD = standard deviation, CORR = Pearson Correlation Coefficient (0=no correlation,1=exact correlation), RMSE = root mean square error, RMSE_S = systematic root mean square error, RMSE_U = unsystematic root mean square error, IOA = Index of Agreement (0=no agreement, 1=perfect agreement), SKILL_E = (RMSE_U)/(STD_OBS) (<1 shows skill), SKILL_V = (STD_MOD)/(STD_OBS) (near to 1 shows skill), SKILL_R = (RMSE)/(STD_OBS) (<1 shows skill).

Table 2(b) South-north (*v*) component of the wind (m s^{-1}) statistics for TAPM simulation of December 1998 at EPAV near-surface meteorological monitoring sites (see Fig. 1 for site information). Note that AVG represents the average for all sites.

Site name	*Number*	*MEAN_OBS*	*MEAN_MOD*	*STD_OBS*	*STD_MOD*	*CORR*	*RMSE*	*RMSE_S*	*RMSE_U*	*IOA*	*SKILL_E*	*SKILL_V*	*SKILL_R*
ALP	741	0.9	0.1	2.1	2.4	0.80	1.68	0.82	1.46	0.86	0.69	1.15	0.80
DAN	742	0.9	0.0	2.8	2.6	0.75	2.13	1.24	1.73	0.84	0.63	0.95	0.77
FOO	624	1.5	0.5	2.7	2.6	0.83	1.85	1.14	1.46	0.88	0.53	0.96	0.68
MTC	740	1.6	0.2	3.6	3.7	0.80	2.69	1.54	2.20	0.86	0.61	1.02	0.74
PTC	743	2.4	1.1	4.1	3.6	0.77	2.96	1.85	2.31	0.85	0.56	0.88	0.72
PAI	616	1.9	0.7	3.3	2.8	0.81	2.30	1.59	1.66	0.86	0.50	0.85	0.70
BRI	741	1.2	0.4	2.3	2.8	0.77	1.99	0.85	1.80	0.84	0.79	1.23	0.87
BOX	743	1.1	0.3	2.5	2.4	0.79	1.78	0.99	1.48	0.86	0.60	0.97	0.72
PTH	743	2.6	1.2	3.7	3.2	0.62	3.31	2.20	2.47	0.76	0.67	0.86	0.90
GEE	476	1.6	1.0	2.7	3.1	0.64	2.51	0.91	2.34	0.80	0.88	1.15	0.94
GRO	738	1.4	1.2	2.7	3.1	0.71	2.24	0.53	2.18	0.84	0.80	1.15	0.83
AVG	695	1.5	0.6	2.9	2.9	0.75	2.31	1.24	1.92	0.84	0.66	1.02	0.79

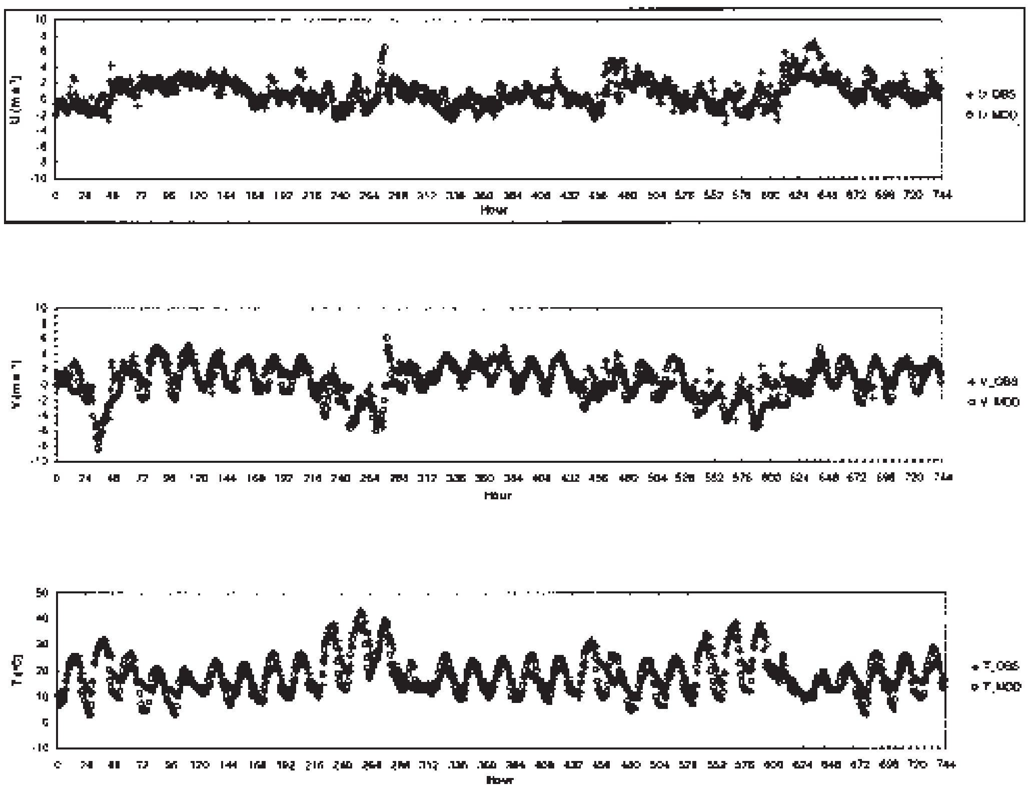
KEY: OBS = observations, MOD = model predictions, MEAN = arithmetic mean, STD = standard deviation, CORR = Pearson Correlation Coefficient (0=no correlation,1=exact correlation), RMSE = root mean square error, RMSE_S = systematic root mean square error, RMSE_U = unsystematic root mean square error, IOA = Index of Agreement (0=no agreement, 1=perfect agreement), SKILL_E = (RMSE_U)/(STD_OBS) (<1 shows skill), SKILL_V = (STD_MOD)/(STD_OBS) (near to 1 shows skill), SKILL_R = (RMSE)/(STD_OBS) (<1 shows skill).

Table 2(c). Temperature (°C) statistics for TAPM simulation of December 1998 at EPAV near-surface meteorological monitoring sites (see Fig. 1 for site information). Note that AVG represents the average for all sites.

Site name	*Number*	*MEAN_OBS*	*MEAN_MOD*	*STD_OBS*	*STD_MOD*	*CORR*	*RMSE*	*RMSE_S*	*RMSE_U*	*IOA*	*SKILL_E*	*SKILL_V*	*SKILL_R*
ALP	741	19.0	17.7	6.8	7.8	0.83	4.54	1.30	4.35	0.90	0.64	1.14	0.67
DAN	742	18.6	18.3	6.2	7.6	0.87	3.80	0.49	3.77	0.92	0.61	1.22	0.61
FOO	624	19.4	18.4	6.3	8.0	0.83	4.53	1.06	4.40	0.89	0.70	1.27	0.72
MTC	741	18.4	18.6	6.5	7.4	0.87	3.63	0.14	3.63	0.93	0.56	1.14	0.56
PTC	743	18.0	17.5	5.6	4.2	0.90	2.65	1.88	1.87	0.92	0.33	0.75	0.47
PAI	616	19.3	18.0	5.8	7.1	0.82	4.24	1.27	4.05	0.88	0.70	1.23	0.74
BRI	741	19.9	18.3	6.0	7.1	0.85	4.04	1.59	3.71	0.90	0.62	1.18	0.67
BOX	743	18.2	17.6	6.3	7.4	0.85	3.91	0.61	3.86	0.91	0.61	1.16	0.62
PTH	743	17.4	18.4	4.9	6.7	0.79	4.26	1.12	4.11	0.86	0.85	1.38	0.88
GEE													
GRO	738	17.8	18.5	5.6	6.9	0.85	3.77	0.76	3.70	0.90	0.66	1.24	0.67
AVG	717	18.6	18.1	6.0	7.0	0.85	3.94	1.02	3.74	0.90	0.63	1.17	0.66

KEY: OBS = observations, MOD = model predictions, MEAN = arithmetic mean, STD = standard deviation, CORR = Pearson Correlation Coefficient (0=no correlation,1=exact correlation), RMSE = root mean square error, RMSE_S = systematic root mean square error, RMSE_U = unsystematic root mean square error, IOA = Index of Agreement (0=no agreement, 1=perfect agreement), SKILL_E = (RMSE_U)/(STD_OBS) (<1 shows skill), SKILL_V = (STD_MOD)/(STD_OBS) (near to 1 shows skill), SKILL_R = (RMSE)/(STD_OBS) (<1 shows skill).

Fig. 4 Observed (OBS) and TAPM modelled (MOD) time series of the west-east (*u*) and south-north (*v*) components of the wind (m s^{-1}) and temperature (°C) for December 1998 at the EPAV near-surface monitoring site at Alphington (ALP) (see Fig. 1 for site location).



the sites. The results show that the mean (MEAN) and standard deviation (STD) of the temperature distributions were predicted well, although on average the standard deviation was over-predicted by 1°C. This difference can be explained, in part, by an underprediction of temperature on some nights, possibly due to the same reasons outlined in the previous section, although the number of nights in December 1998 with this characteristic was fewer than in July 1998. The average root mean square error (RMSE) was 3.94°C, with the systematic error (RMSE_S) less than the unsystematic error (RMSE_U) as it should be for an unbiased simulation. The average index of agreement (IOA) was 0.90 (see Fig. 2), which is an excellent value. The measures of skill show that, on average, the standard deviations of temperature were over-predicted by 17 per cent as explained above, compared to the ideal value of 1.0 for SKILL_V. The other two skill variables (SKILL_E and SKILL_R) show that unsystematic and total RMSE values were less than the standard deviation of the observations. The results show that the temperatures for December 1998 were predicted very well.

The good statistical performance described above is reinforced by the time-series plots for winds and temperature at the Alphington monitoring site shown in Figs 3 and 4.

Conclusions

The Air Pollution Model (TAPM) was used to model the meteorology of July and December 1998 in the Melbourne region, and model predictions of near-surface horizontal wind components and temperature for a 3,000 m grid resolution were compared with observations at available EPAV monitoring sites. The winter month of July 1998 was characterised by long periods of locally light winds and high particle concentrations, while December was representative of a summer month that included days with high ozone concentrations. Statistics based on the recommendations of Willmott (1981) and Pielke (1984) were used to assess the performance of the model, and included mean (MEAN) and standard deviations (STD), root-mean-square errors (RMSE), the index of agreement (IOA), and measures of variational skill (SKILL).

The results showed that winds were predicted well, with average RMSE of about 1.7 m s^{-1} for July 1998 and 2.2 m s^{-1} for December 1998. The results showed that the RMSE was dominated by the unsystematic error as it should be for an unbiased simulation. The average IOAs were 0.82 for July 1998 and 0.83 for December 1998. The model predicted good variational skill, with similar STDs between observed and predicted, and RMSE values much less than the standard deviation of the observations. Temperatures were also predicted well, although on average the MEAN value was underpredicted by 1°C for July 1998 and 0.5°C for December 1998, and the STDs were overpredicted by around 1°C. This difference can be explained, in part, by an underprediction of temperature overnight on some nights, and a number of possible reasons for this have been given. The average RMSE was 3.4°C for July 1998 and 3.9°C for December 1998. The average IOA was 0.78 for July 1998 and 0.90 for December 1998. The model predicted good variational skill, although the predictions for December 1998 were better than for July 1998, as explained above. These IOA values were shown to be very good compared to values of 0.5-0.6 reported in other studies.

Generally, the results showed that TAPM has demonstrated good performance in predicting the near-surface meteorology in the Melbourne region for both a winter and a summer month, and can be used with confidence to describe the local-scale meteorology needed for air pollution applications. These good results also illustrate the good performance of the inputs to the model, in particular the LAPS analysis data.

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Appendix

The statistics used to measure model performance in this paper are based on those used by Willmott (1981) and Pielke (1984), as described below:

Predicted mean

$$P_{mean} = \frac{1}{N}\sum_{i=1}^{N} P_i$$

Observed mean

$$O_{mean} = \frac{1}{N}\sum_{i=1}^{N} O_i$$

Predicted standard deviation

$$P_{std} = \sqrt{\frac{1}{N\text{-}1}\sum_{i=1}^{N}(P_i - P_{mean})^2}$$

Observed standard deviation

$$O_{std} = \sqrt{\frac{1}{N\text{-}1}\sum_{i=1}^{N}(O_i - O_{mean})^2}$$

Pearson Correlation Coefficient

$$r = \frac{N\left(\sum_{i=1}^{N} O_i P_i\right) - \left(\sum_{i=1}^{N} O_i\right)\left(\sum_{i=1}^{N} P_i\right)}{\sqrt{\left[N\left(\sum_{i=1}^{N} O_i^2\right) - \left(\sum_{i=1}^{N} O_i\right)^2\right]\left[N\left(\sum_{i=1}^{N} P_i^2\right) - \left(\sum_{i=1}^{N} P_i\right)^2\right]}}$$

Root Mean Square Error

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2}$$

Systematic Root Mean Square Error

$$RMSE\_S = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{P}_i - O_i)^2}$$

Unsystematic Root Mean Square Error

$$RMSE\_U = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{P}_i - P_i)^2}$$

Index of Agreement

$$IOA = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(|P_i - O_{mean}| + |O_i - O_{mean}|)^2}$$

Measures of skill

$$SKILL\_E = \frac{RMSE_U}{O_{std}}, \quad SKILL\_V = \frac{P_{std}}{O_{std}} \quad \text{and} \quad SKILL\_R = \frac{RSME}{O_{std}}$$

Note that N is the number of observations/predictions and $\hat{P}_i = a + bO_i$ is the linear regression fitted formula with intercept (a) and slope (b).