Atmospheric Environment 98 (2014) 385–393

Contents lists available at ScienceDirect

Atmospheric Environment

journal homepage: www.elsevier.com/locate/atmosenv

Application of a statistical post-processing technique to a gridded, operational, air quality forecast

L.S. Neal*, P. Agnew, S. Moseley, C. Ordóñez, N.H. Savage, M. Tilbee

Met Office, Fitzroy Road, Exeter, EX1 3PB, UK

HIGHLIGHTS

- An automated bias correction scheme for air quality forecasting is described.
- Site specific biases are converted to a gridded field using Kriging.
- Bias reduced from 7.02 to 0.53 μg m^{-3} for O_3, from −4.00 to −0.13 μg m^{-3} for $PM_{2.5}$.
- Post-processing scheme provides improved model performance out to five days ahead.

ARTICLE INFO

Article history:
Received 21 May 2014
Received in revised form
29 August 2014
Accepted 3 September 2014
Available online 4 September 2014

Keywords:
Bias correction
Air quality forecast
Ozone
Particulate matter

ABSTRACT

An automated air quality forecast bias correction scheme based on the short-term persistence of model bias with respect to recent observations is described. The scheme has been implemented in the operational Met Office five day regional air quality forecast for the UK. It has been evaluated against routine hourly pollution observations for a year-long hindcast. The results demonstrate the value of the scheme in improving performance. For the first day of the forecast the post-processing reduces the bias from 7.02 to 0.53 μg m^{-3} for O_3, from −4.70 to −0.63 μg m^{-3} for NO_2, from −4.00 to −0.13 μg m^{-3} for $PM_{2.5}$ and from −7.70 to −0.25 μg m^{-3} for PM_{10}. Other metrics also improve for all species. An analysis of the variation of forecast skill with lead-time is presented and demonstrates that the post-processing increases forecast skill out to five days ahead.

1. Introduction

Regional air quality forecasts have improved significantly over the last decade or so, due to factors such as (i) the availability of near-real-time boundary fluxes provided by improved global composition models; (ii) increased computing power, allowing improved resolution and greater sophistication in the representation of chemical processes; (iii) improved pollutant emission inventories. For a review of air quality forecast modelling in Europe see Kukkonen et al. (2012).

However despite these advances, the spatially and temporally detailed prediction of atmospheric composition at a given site remains a challenging problem and it is not uncommon for forecasts to contain large errors (see Solazzo et al., 2012). These may arise due to errors in inputs of key model parameters such as actual emissions (as opposed to annual mean values: see Pouliot et al., 2012), initial and boundary conditions for chemical species (Schere et al., 2012) as well as meteorology (Vautard et al., 2012). In such circumstances human forecaster intervention may be required to modify the model predictions, based on recent observations and judgement about how conditions are evolving. Alternatively, automated methods may be employed which offer the possibility of improving forecasts and may minimise or completely remove the need for human intervention (e.g. Rouil et al., 2009). A simple daily persistence forecast (i.e. that today's observed values should be the same as yesterday's) is often used as a reference forecast in meteorological verification (e.g. Jolliffe and Stephenson, 2012). This basic idea can be further developed with varying degrees of sophistication. The most advanced methods of using observations to improve air quality forecasts are those of data assimilation (DA, see

* Corresponding author.
E-mail address: lucy.neal@metoffice.gov.uk (L.S. Neal).

http://dx.doi.org/10.1016/j.atmosenv.2014.09.004

Inness et al., 2013). However the high level of additional complexity and computational expense required for constituent DA plus the limited near-real time availability of suitable satellite observations, make the simpler bias correction techniques described in this paper an attractive option.

In this paper we describe a simple scheme for combining model predictions with observations in a post-processing step to generate an improved air quality forecast. In Section 2 we present a short review of various approaches which have been adopted by others and in Section 3 we describe our own scheme. We have evaluated the performance of the scheme over an extended period and the results are presented in Section 4. In Section 5 the results are discussed and possible future developments are described.

2. Air quality forecast bias correction methodologies

We consider the problem of producing the best gridded field of surface air pollutant concentrations given values from a 3-D numerical model forecast plus a set of recent measurements from a sparse surface observation network. The numerical model may be considered to exhibit both random errors and a systematic bias with respect to the observations. It is frequently observed, for example by Kang et al. (2008) and Savage et al. (2013), that this bias remains approximately constant over the timescales typical of air quality episodes (a few days). In this situation a short-term bias correction is able to correct gross errors in the numerical model prediction and allow a significantly improved forecast. Some of the relevant techniques employed by other researchers to address this bias correction problem are described briefly below.

2.1. Model adjustments at a measurement site

Initially, consider producing a forecast for a site where observation data are available. These observations can be used to correct the forecast. For example, the 'Hybrid Forecast' technique (as used by Kang et al., 2008) simply assumes the forecast at the site for a certain time is given by the model value at that time, plus a residual, derived as the difference between the observation and model at a previous time (usually 24 h earlier when observations were available). A more sophisticated method employs the Kalman Filter, which is described in detail by Delle Monache et al. (2008) and is widely used, for example by Kang et al. (2008), Borrrego et al. (2011) and De Ridder et al. (2012). This method was found by Kang et al. (2008) to generally perform better than the Hybrid Forecast, although their Hybrid Forecast captured exceedances better.

2.2. Conversion to gridded data from randomly located measurement sites

Most bias correction techniques involve adjusting the model value at measurement sites initially. However as model forecasts are usually derived on a grid, these adjustments need to be extended to cover not just a few randomly located sites, but across the whole model domain.

For producing gridded historical data, many groups have considered techniques for transforming observations at irregularly located sites into a regular gridded field. Ordinary Kriging is a widely used method for interpolating between a set of sparse observations and is described in detail by Denby et al. (2005). As an extension, Horálek et al. (2005, 2007, 2008) apply Kriging (as well as other interpolation techniques) separately to urban and rural observations to produce fields of each, which they then combine using population density maps to produce a single field.

These interpolation techniques can also be applied to correct model forecasts on a grid. This appears to usually be done by the Kriging of residual fields, also referred to in the literature as a Hybrid Forecast (Kang et al., 2008) or the Innovation Kriging Method (Blond et al., 2003). This technique involves calculating the 'residual' as described above, at an earlier time and then interpolating these values using Kriging. This field of residuals can then be combined with the raw forecast model field at a future time (or the same time for analysis purposes).

3. Statistical Post-Processing of Observations (SPPO): description and evaluation methods

3.1. Air quality forecast model: AQUM

The Met Office air quality forecast is produced using the on-line air quality model AQUM (Air Quality in the Unified Model). This is a limited area configuration of the Met Office Unified Model (MetUM), which has a 12 km horizontal resolution covering a domain containing the UK and nearby western European countries (Fig. 1). There are 38 vertical levels from the surface to 39 km. Lateral boundary conditions for chemistry and aerosols are derived from operational forecasts of the MACC global model (Flemming et al., 2009) for the first two days, before relaxing to a climatology by day five. AQUM is used to provide five day forecast maps and site specific forecasts for approximately 5000 sites across the UK. For further details on AQUM, see Savage et al. (2013).

3.2. Requirements

Our objective has been to develop a simple method for improving the air quality predictions from our gridded forecast model, AQUM. It is essential that any bias correction technique can be applied in forecast mode, not just for the first day of a forecast, but at all lead-times out to Day five. The method must also be able to correct the model across its entire domain from which interpolated values for 5000 sites can then be extracted, the vast majority of which do not have observations. The AQUM model has a known

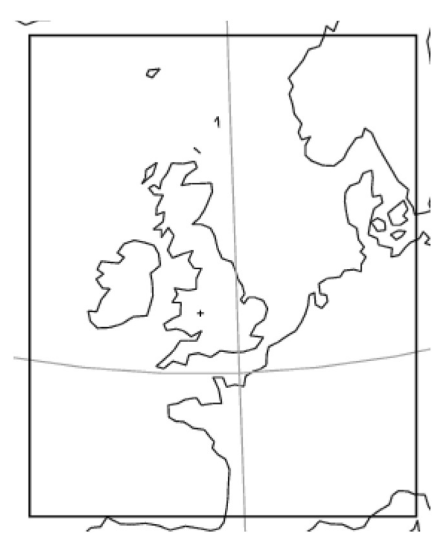

Fig. 1. Model domain for AQUM.