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A LONGITUDINAL STUDY OF MORTALITY AND AIR POLLUTION FOR SÃO PAULO, BRAZIL

by

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Palavras-Chave: Air pollution; Kalman estimating equations; Longitudinal count data; State space model.

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A longitudinal study of mortality and air pollution for São Paulo, Brazil

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Abstract

We study the effects of climatic and pollution conditions on the daily death counts in São Paulo, Brazil, from 1991 to 1993. We use a state space model in which the daily counts, given a gamma latent process, follow a Poisson distribution.

Key words: Air pollution; Kalman estimating equations; Longitudinal count data; State space model.

1 Introduction

The association between air pollution and human health in the city of São Paulo, Brazil, has long been of public concern and the subject of several studies. For the present investigation, whose main objective is to examine the relationship between air pollution and mortality, we consider data consisting of daily death counts for people more than 65 years old in São Paulo. This age group, presumably the most likely to be adversely affected by poor ambient air quality, accounts for about 42% of the total death counts, and respiratory diseases is the reported cause of about 11% of these

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deaths.

It is well-known that climatic conditions and air pollution are closely related, mainly due to *thermal inversion*, a phenomenon that occurs at low temperatures and prevents the air pollutants from dispersing. While the emission of air pollutants is roughly constant throughout the year, the ambient air pollution tends to be higher in the winter, a fact that lead the authorities in São Paulo to enforce air pollution control policies, with the aim of lowering the emission of air pollutants during the winter period (July to September). Our data were recorded before these control policies were enforced and we consider both climatic covariates (temperature and humidity) and pollution covariates (Sulphur (SO_2), Particulates, Carbon Monoxide (CO), Ozone (O_3), and Nitrogen Dioxide (NO_2)).

The data have been previously analyzed by Singer e Conceição,[1] who used a normal-theory regression model, and by Koyama,[2] who used Liang and Qaquish[3] approach with a log-linear Poisson model. We use a state space model, first introduced by Jørgensen *et al.*,[4] in which the daily counts, given a Gamma latent process, follow a Poisson distribution. The model allows the covariates to enter either via the observed process or via the latent process and implies serial correlation for the counts, making it a realistic model for the correlation structure of this type of data. Following Jørgensen *et al.*,[5] we use the meteorological variables as *short-term* covariates, entering the model via the observed process and the pollution variables as *long-term* covariates, entering the model via the latent process. This implies that the latent process may be interpreted as a potential morbidity in the population due to pollution. Like us, both Singer e Conceição[1] and Koyama[2] found significant effects of pollution on mortality, but our final model is quite different from those of the above authors. In particular, we include an yearly cycle and lagged effects of covariates. The inclusion of these effects were suggested by the analysis itself. As in Skyøth and Lundbye-Christensen, [6] we use the latent process, together with the diagnostic techniques proposed in Jørgensen *et al.*,[4] in our search for the final model. As it happens, the latent process, being a smoother of the response, tends to absorb effects of missing covariates, making it a useful tool for checking the assumptions of the proposed model.

2 The Data

The data consist of daily death counts for people over the age of 65 in the city of São Paulo from January 1, 1991 to December 31, 1993, and the corresponding daily values of meteorological and air pollution variables. The meteorological variables we consider are temperature (°C) and humidity (%); the air pollution variables are Sulphur -SO_2, ($\mu g/m^3$), Particulates (total suspended particulates), Carbon Monoxide - CO (ppm), Ozone -O_3 ($\mu g/m^3$) and Nitrogen Dioxide - NO_2, ($\mu g/m^3$). All the covariates are daily averages of measurements taken at different locations around the city.

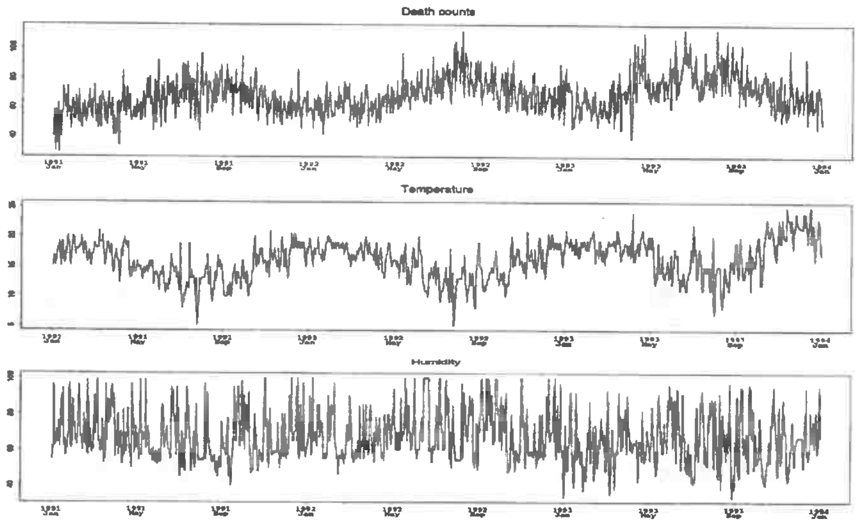

Figure 1: Death counts, temperature and humidity.

Figure 1 shows the time-series plots for the daily death counts and the meteorological variables and Figure 2 shows the air pollution variables series. Also shown in Figure 2, is the *secondary* level of air quality, as established by IBAMA, the Brazilian agency that controls air pollution (not available for NO_2). This is the level below which no negative health or environmental effects of the air pollutants are expected.

Some of the pollution series have a few missing values. These were replaced by means of linear interpolation. However, the NO_2 series has a gap of one hundred missing observations, which were replaced using the predictor based on an ARIMA

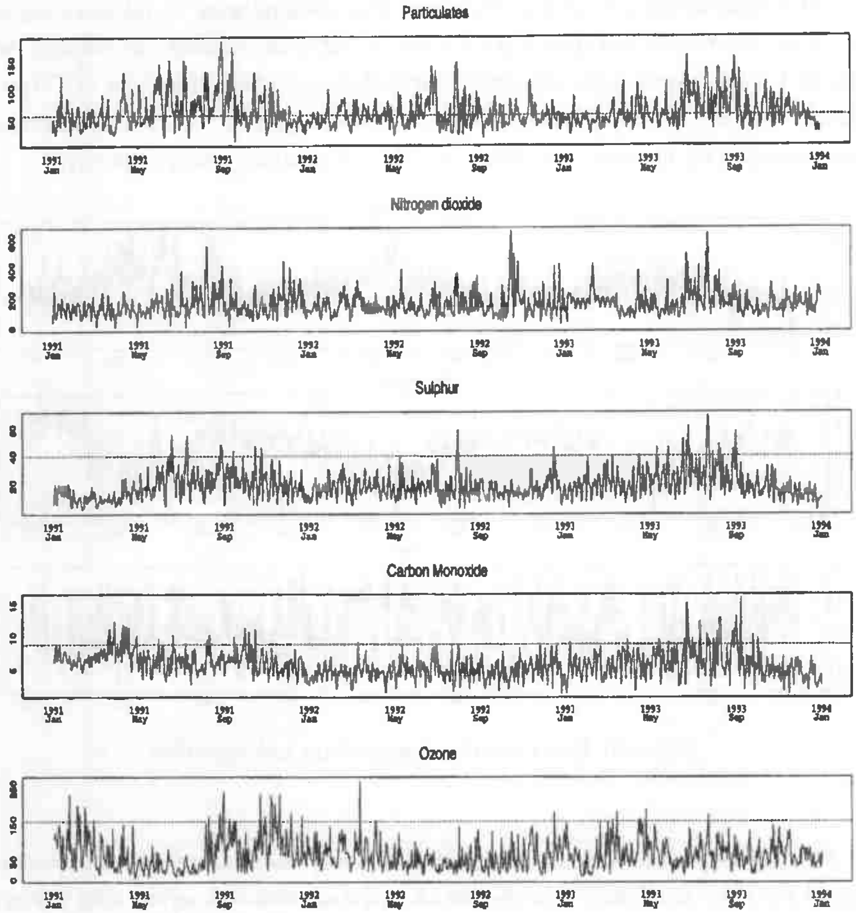

Figure 2: Pollution variables

model fitted to the observations before to the gap. The previous analyses of these data do not mention how the missing data were replaced, thereby making comparisons of the results difficult. In any case, we feel that one hundred missing observations is too wide a gap to be filled in any sensible way, so the results concerning this covariate should be interpreted with care.

3 Methodology

In our analysis, we use the state space model introduced by Jørgensen *et al.*[4] and we present below the main features of this model for the particular case of a univariate response vector.

3.1 The model

Let $\mathbf{Y}$ denote the vector $(Y_1, Y_2, ..., Y_n)$, where Y_t, $t = 1, \ldots, n$ is the count for day t and n is the sample size. The model assumes that the Y_t's are Poisson observations driven by a univariate latent Markov process, θ_t, $t = 0, 1, \ldots, n$, where θ_0 is a initializing constant (assumed to be 1 here). The observations are assumed to be conditionally independent given the latent process, and the conditional distribution depends only on θ_t, as follows:

$$Y_t|\theta_t \sim \mathrm{Po}(a_t\theta_t),$$

where $\mathrm{Po}(\lambda)$ denotes the Poisson distribution with mean λ, $a_t = \exp(\mathbf{x}_t^\top \boldsymbol{\alpha})$, $\mathbf{x}_t$ is a l_1-vector of time varying, short-term covariates and $\boldsymbol{\alpha}$ is a regression parameter.

The latent process θ_t is assumed to follow a gamma Markov process, defined by

$$\theta_t|\theta_{t-1} \sim \mathrm{Ga}\left(b_t\theta_{t-1}, \frac{\sigma^2}{\theta_{t-1}}\right),$$

where $\mathrm{Ga}(\mu, \kappa^2)$ denotes the gamma distribution with mean μ and coefficient of variation κ, $b_t = \exp(\Delta\mathbf{z}_t^\top \boldsymbol{\beta})$, where $\mathbf{z}_t$ is a l_2-vector of time varying, long-term covariates, $\Delta\mathbf{z}_t = \mathbf{z}_t - \mathbf{z}_{t-1}$, $\boldsymbol{\beta}$ is a regression parameter and σ^2 is a dispersion parameter. We centralize the long-term covariates by subtracting $\mathbf{z}_1$ from $\mathbf{z}_t$ and taking $\mathbf{z}_0 = 0$, so $\mathrm{E}(\theta_1) = 1$.

Jørgensen *et. al.*[5] used a similar Poisson gamma model to analyse data on air pollution and respiratory morbidity. Like us, these authors used the pollution covariates as long-term covariates and the meteorological covariates as short-term covariates.

From the definition of the model, the moments for the observed and the latent process are easily obtained. We have, for $t = 1, \ldots, n$:

$$\begin{aligned} \mathrm{E}(\theta_t) &= \tau_t = \exp\left(\mathbf{z}_t^\top \boldsymbol{\beta}\right), \\ \mathrm{E}(Y_t) &= a_t\tau_t = \exp\left(\mathbf{x}_t^\top \boldsymbol{\alpha} + \mathbf{z}_t^\top \boldsymbol{\beta}\right), \qquad (1) \\ \mathrm{Var}(Y_t) &= a_t\tau_t + \sigma^2\phi_t\tau_t a_t^2, \qquad (2) \end{aligned}$$

where $\phi_t = b_t + b_t b_{t-1} + \ldots + b_t b_{t-1} \cdots b_1$.

3.2 Estimation

The regression parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are estimated by means of the Newton scoring method of Jørgensen *et al.*[4] applied to the Kalman estimating functions, which are obtained by replacing the latent process by the Kalman smoother into the Poisson and gamma score functions.

The algorithm updates the regression parameter $\boldsymbol{\eta} = (\boldsymbol{\alpha}^\top, \boldsymbol{\beta}^\top)^\top$ by

$$\boldsymbol{\eta}^{(j+1)} = \boldsymbol{\eta}^{(j)} - \mathbf{S}^{-1}(\boldsymbol{\eta}^{(j)})\boldsymbol{\psi}(\boldsymbol{\eta}^{(j)}),$$

where $\boldsymbol{\psi} = (\boldsymbol{\psi}_1^\top(\boldsymbol{\eta}), \boldsymbol{\psi}_2^\top(\boldsymbol{\eta}))$ is the Kalman estimation function with

$$\begin{aligned} \boldsymbol{\psi}_1(\boldsymbol{\eta}) &= \mathbf{X}^\top(\mathbf{Y} - \mathbf{A}\mathbf{m}^*), \\ \boldsymbol{\psi}_2(\boldsymbol{\eta}) &= \Delta\mathbf{Z}^\top\mathbf{K}_b^{-1}\mathbf{B}\mathbf{m}^*; \end{aligned}$$

and

$$\mathbf{S}(\boldsymbol{\eta}) = \mathrm{E}_{\boldsymbol{\eta}}\left\{\frac{\partial\boldsymbol{\psi}(\boldsymbol{\eta})}{\partial\boldsymbol{\eta}^\top}\right\}$$

is the *sensitivity matrix*. $\mathbf{A}$ and $\mathbf{B}$ are suitable defined matrices such that the elements of $\mathbf{Y} - \mathbf{A}\mathbf{m}^*$ are $Y_t - a_t m_t^*$ and those of $\mathbf{B}\mathbf{m}^*$ are $m_t - b_t m_{t-1}^*$, where m_t^* is the Kalman smoother. $\mathbf{K}_b$ is a matrix given by $\mathrm{diag}\{b_1, \ldots, b_n\}$, and the matrices $\mathbf{X}$ and $\Delta\mathbf{Z}$ are the design matrices corresponding to the short-term covariates and long-term covariates respectively.

To initialize the iterations we use a Poisson log-linear regression, obtaining a starting value for $\boldsymbol{\eta}^{(0)}$ based on model (1). From (2) we get a moment-like estimator for σ^2, based on the fitted values $\hat{Y}_t$ from the above Poisson model. The dispersion parameter σ^2 is updated at each iteration by an adjusted Pearson estimator.

From standard results for unbiased estimating functions, the asymptotic covariance matrix for the regression parameters is given by the inverse of the *Godambe information matrix*, $\mathbf{J}(\boldsymbol{\eta})$. For details, see Jørgensen *et al.*[4] and the references therein. As first noted by Knudsen,[7] these asymptotic standard errors can be calculated as if the dispersion parameters were known. An analogue of Wald's test for testing the significance of a subvector $\boldsymbol{\eta}_1$ of the regression parameter $\boldsymbol{\eta}$, is given by

$$W = \hat{\boldsymbol{\eta}}_1^\top \left\{ \mathbf{J}^{11}(\hat{\boldsymbol{\eta}}) \right\}^{-1} \hat{\boldsymbol{\eta}}_1,$$

where $\mathbf{J}^{11}$ is the corresponding block of $\mathbf{J}(\boldsymbol{\eta})$. Asymptotically, this statistic follows a χ^2 distribution with k_1 degrees of freedom, where k_1 is the dimension of the subvector $\boldsymbol{\eta}_1$.

3.3 Residual Analysis

In order to check the assumptions of the model, we use the *conditional* residuals, or filter residuals, which may be characterized as *observed* minus *predicted* values. They are defined by

$$R_t = Y_t - \mathbf{f}_t,$$

where $\mathbf{f}_t$ is the Kalman filter. The variance of R_t is $b_t d_t a_t^2 + \tau_t a_t$. The filter residuals are useful for checking the correlation structure of the data, because they are uncorrelated over time. For details, see Jørgensen *et al.*.[5]

4 Data Analysis

We begin the analysis with the same set of covariates considered by Singer and Conceição[1] and Koyama.[2] It include factors constructed from the meteorological variables, in order to account for seasonality. We then describe all steps of the analysis, in order to illustrate the use of the diagnostic techniques available for the Poisson-gamma model. A summary of all models are presented in Tables 1 and 2.

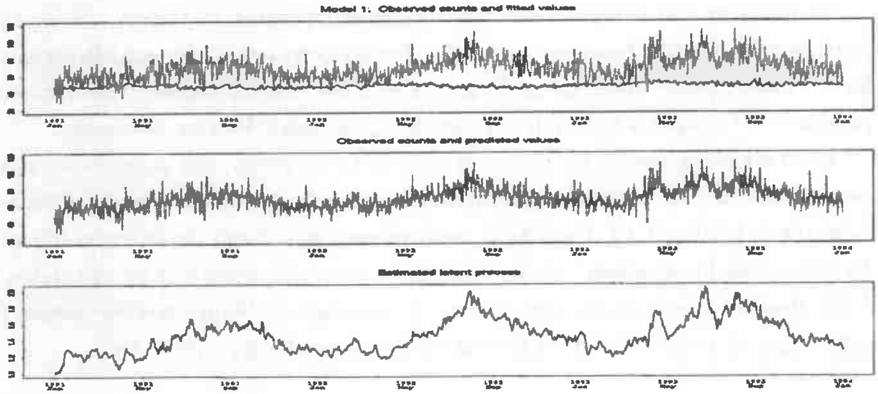

Figure 3: Fitted values, predicted values and estimated latent process for modell.

4.1 Model 1

We consider the following covariates:

Meteorological:
- temperature;
- humidity;

Factors:
- humid days (1, if the humidity is above a certain level, 0 otherwise);
- dry days (1, if the humidity is below a certain level, 0 otherwise);
- hot days (1, if temperature is above certain level, 0 otherwise);
- cold days (1, if temperature is below certain level, 0 otherwise);
- a 4-season factor (summer, spring, fall, winter).

Pollution:
- Particulates;
- Nitrogen Dioxide (NO_2);
- Sulphur (SO_2);
- Ozone (O_3);
- Carbon Monoxide (CO).

We take the pollution variables as long-term and all others as short-term covariates. None of the effects is individually significant. Wald's test for the set of pollution

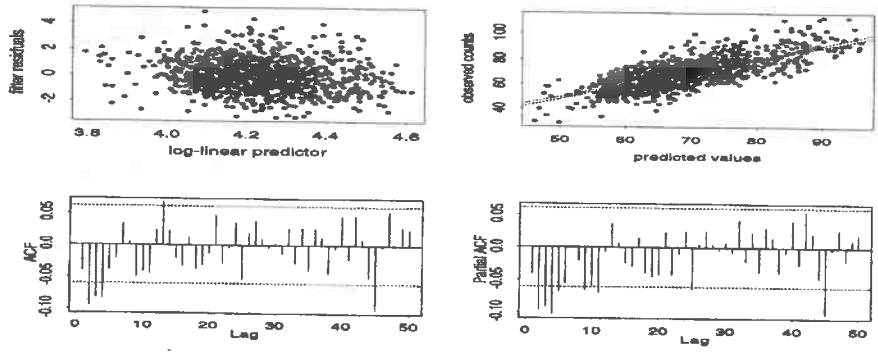

Figure 4: Filter residuals plots for model 1.

variables gives a value of 9.53 on 5 degrees of freedom, corresponding to a p-value of 0.09.

Figure 3 shows the time series plots for the fitted values, for the predicted values and for the estimated latent process. The model underestimates the expected value of the counts although the predicted values give a much better fit. The time-series plot for the estimated latent process suggests a missing cyclic component.

In order to check the distributional assumptions, we plot the filter residuals against the log linear predictor, and the predicted values against observed counts. These plots, shown in Figure 4, present no special features. Also in Figure 4, are the autocorrelation function (ACF) and partial ACF for the filter residuals. Both present unexpected patterns, with some high values for the first few lags.

4.2 Model 2

To the set considered in model 1, we include trend and an yearly cycle, $\cos(2\pi t/365)$ and $\sin(2\pi t/365)$ as short-term covariates. The fitted values in Figure 5 show a better fit than the previous model. Figure 6 shows the residual plots for this model. Both ACF and partial ACF plots for the filter residuals present the first correlation above the asymptotic 95% band at lag 45 and the other residuals plots do not show any unexpected pattern. For this model the Wald's statistics for the pollution variables is 16.62 on 5 degrees of freedom. Hence, the effect of pollution on mortality is significant. None of the meteorological covariates is individually significant, but the combined effect of the covariates *humidity*, *humidays* and *drydays* is. Wald's test for these three

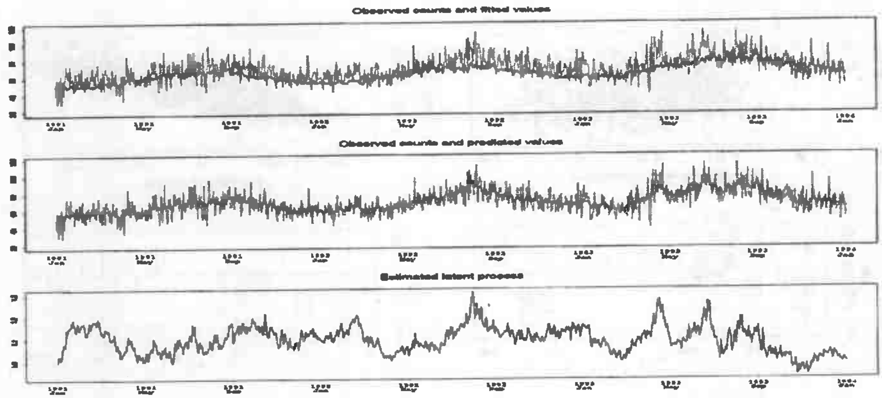

Figure 5: Fitted values, predicted values and estimated latent process for model2.

covariates together gives a value of 8.3 on 3 degrees of freedom, corresponding to a p-value of 0.04. Hence, the effect of humidity is significant. The effect of temperature is also significant, since Wald's test for the combined effect of the covariates *temperature*, *hotdays* and *coldays* gives a value of 12.8 corresponding to a p-value of 0.005. Wald's test for all seven factors together gives a value of 6.6 on 7 degrees of freedom and so, we proceed fitting a model without the factors.

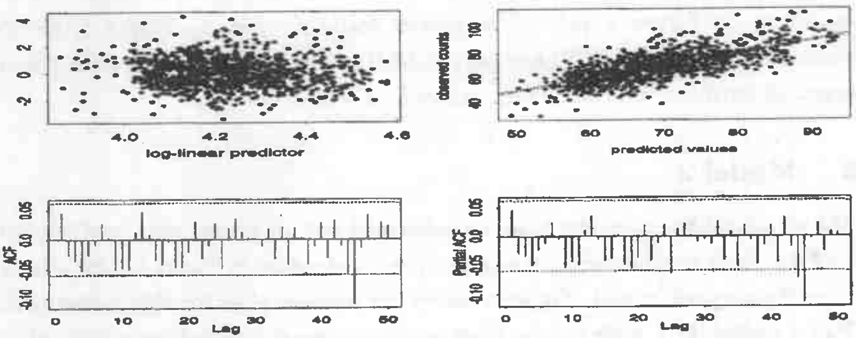

Figure 6: Filter residuals plots for model 2.

4.3 Model 3

As short-term covariates, we consider the yearly cycle, temperature, humidity and trend; as long-term covariates, all the pollution variables. Both temperature and humidity are highly significant and the Wald's test for the pollution variables is also significant (p-value 0.01). The estimated latent process and the residuals plots show no distinct pattern from the previous model. As shown by the previous steps of this analysis, the latent process is likely to absorb effects of missing covariates, so we proceed looking for possible lagged effects of the covariates. As a clue of which lags could be present in the model, we use the cross-correlation function between the residuals and the covariates. The plots (not shown) suggest possible lags for temperature and Sulphur.

4.4 Model 4

To the set of covariates considered in the previous model, we add lag1 to lag3 of temperature as short-term and lag1 to lag3 of Sulphur as long-term covariates. The lag3 of Sulphur is significant and the estimate is negative. Again, the residuals plots show no unexpected pattern (Figure 7). The Wald's statistics for the others pollution variables gives a value of 3.54 on 4 degrees of freedom.

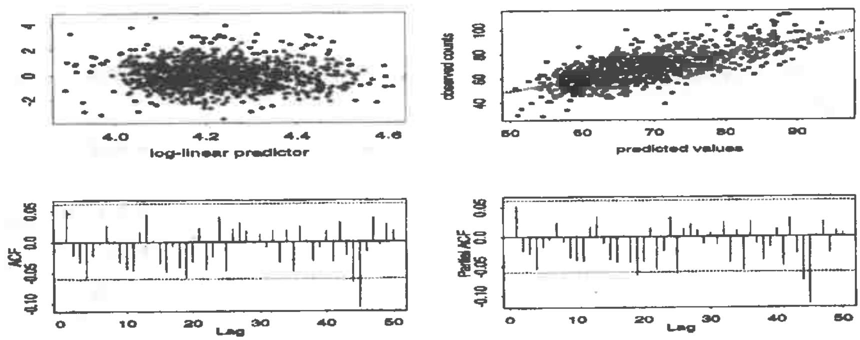

Figure 7: Filter residuals plots for model 4.

Table 1: Summary for models 1 to 3

Effect	Model 1		Model 2		Model 3	
short-term	**estimate**	**(s.e.)**	**estimate**	**(s.e.)**	**estimate**	**(s.e.)**
intercept	3.79	(0.13)	4.00	(0.10)	4.003	(0.079)
temperature	0.0067	(0.0043)	0.0060	(0.0033)	0.0062	(0.0023)
humidity	−0.00081	(0.00085)	−0.00090	(0.00069)	−0.00099	(0.00034)
$\cos(2\pi t/365)$	-	-	−0.123	(0.047)	−0.131	(0.045)
$\sin(2\pi t/365)$	-	-	−0.073	(0.047)	−0.046	(0.045)
drydays	−0.00006	(0.017)	−0.0008	(0.014)	-	-
humidays	−0.003	(0.022)	−0.003	(0.018)	-	-
hotdays	0.014	(0.018)	0.020	(0.014)	-	-
coldays	0.015	(0.021)	0.016	(0.016)	-	-
spring	−0.020	(0.058)	−0.037	(0.036)	-	-
fall	0.057	(0.057)	0.024	(0.036)	-	-
winter	0.013	(0.067)	−0.019	(0.042)	-	-
trend	-	-	0.00019	(0.00052)	0.00020	(0.00054)
long-term						
particulates	0.00021	(0.00036)	0.00028	(0.00028)	0.00030	(0.00028)
NO_2	0.000064	(0.000029)	0.000027	(0.000066)	0.000021	(0.000066)
SO_2	0.0003	(0.0010)	0.00041	(0.00079)	0.00036	(0.00078)
O_3	0.00012	(0.00015)	0.00012	(0.00012)	0.00011	(0.00012)
CO	0.0053	(0.0036)	0.0046	(0.0028)	0.0040	(0.0028)
$\hat{\sigma}^2$	0.00203		0.00029		0.00031	

4.5 Model 5

We consider as short-term covariates the following: $\cos(2\pi t/365)$, $\sin(2\pi t/365)$, lags 0 to 3 of temperature, humidity and time; and as long-term covariates, only SO_2 and its lags.

The residual plots do not show any pattern different from the previous model. The lag 0 and lag 3 of SO_2 are individually significant and their coefficients have opposite sign. Wald's test for lag 0 to lag 3, gives a value of 13.813 with 3 degrees of freedom, corresponding to a p-value of 0.0079. Hence, the covariate SO_2 is highly significant and its effect on today's death counts depends on today's and the previous three days values of SO_2. In order to better understand this effect, we consider the following transformation:

F1 = $\frac{1}{4}$(lag0-SO_2 + lag1-SO_2 +lag2-SO_2 +lag3-SO_2);
F2 = lag0-SO_2 − lag1-SO_2;
F3 = $\frac{1}{2}$ (lag0-SO_2 + lag1-SO_2) − lag2-SO_2;
F4 = $\frac{1}{3}$ (lag0-SO_2 + lag1-SO_2 +lag2-SO_2) − lag3-SO_2.

The effect of F1 can be interpreted as a cumulative effect of today's and the past three day's level of SO_2. Variations in the level of SO_2 in that period are measured by F2 to F4. The individual effects for F1 to F4 are shown in Table 2, under model 5. Only F4 is individually significant. Wald's test for the first three factors gives a value of 1.566 on 3 degrees of freedom, corresponding to a p-value of 0.66.

4.6 Model 6 - Final Model

We consider only F4 as a long-term covariate. Both ACF and partial ACF plots for this model show values above the 95% confidence band for lags 44 and 45, an effect also present in the other models. None of the plots for the final model show any distinct pattern from those of model 4, which included all the pollution covariates together with up to lag 3 of SO_2 and temperature. Also, the cross-correlation function between the filter residuals and the pollution variables show no evidence of residual correlation, so the effect of air pollution effect seems to be well explained by SO_2 alone.

The variable F4 is highly significant and its coefficient is positive. That is, the effect of the covariate SO_2 can be explained by the difference between the mean of

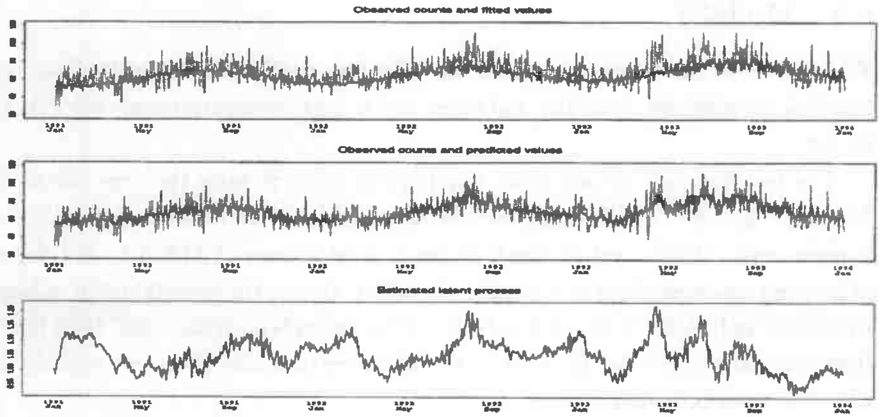

Figure 8: Fitted values, predicted values and estimated latent process for the final model.

the last three days and the recording of four days ago. Hence, the expected death counts are expected not to be affected if the level of SO_2 are constant, but is expected to increase if the SO_2 level is increasing.

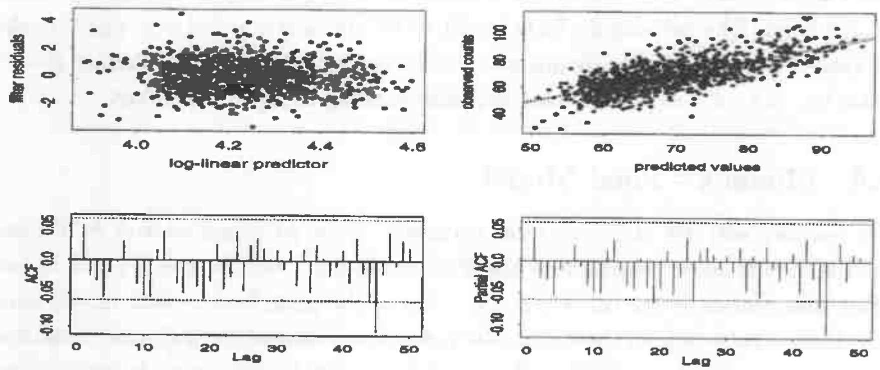

Figure 9: Filter residuals plots for the final model.

Table 2: Summary for models 4 to final model.

Effect	Model 4		Model 5		Model 6	
short-term	**estimate**	**(s.e.)**	**estimate**	**(s.e.)**	**estimate**	**(s.e.)**
intercept	4.139	(0.079)	4.135	(0.078)	4.289	(0.078)
$\cos(2\pi t/365)$	−0.120	(0.040)	−0.122	(0.040)	−0.125	(0.040)
$\sin(2\pi t/365)$	−0.041	(0.040)	−0.044	(0.040)	−0.045	(0.041)
temperature	0.0061	(0.0025)	0.0069	(0.0025)	0.0073	(0.0024)
lag1-temp	−0.0011	(0.0029)	−0.0004	(0.0028)	−0.0005	(0.0028)
lag2-temp	0.0072	(0.0028)	0.0069	(0.0028)	0.0067	(0.0028)
lag3-temp	−0.0118	(0.0024)	−0.0121	(0.0024)	−0.0120	(0.0024)
humidity	−0.00105	(0.00033)	−0.00117	(0.00032)	−0.00122	(0.00031)
trend	0.00020	(0.00048)	0.00018	(0.00048)	0.00018	(0.00048)
long-term						
particulates	0.00027	(0.00028)	-	-	-	-
CO	0.0032	(0.0028)	-	-	-	-
NO_2	7.1×10^{-6}	(6.5×10^{-5})	-	-	-	-
O_3	0.00009	(0.00012)	-	-	-	-
SO_2	0.00017	(0.00079)	0.001071	(0.00056)	-	-
lag1-SO_2	0.00020	(0.00061)	0.00045	(0.00059)	-	-
lag2-SO_2	0.00032	(0.00060)	0.00032	(0.00059)	-	-
lag3-SO_2	−0.00127	(0.00056)	−0.00128	(0.00055)	-	-
F1	-	-	0.00057	(0.00084)	-	-
F2	-	-	−0.00004	(0.00048)	-	-
F3	-	-	0.00053	(0.00048)	-	-
F4	-	-	0.00213	(0.00072)	0.00237	(0.00068)
$\hat{\sigma}^2$	0.00024		0.00024		0.00025	

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