Chapter 5

The Impact of Temperature on Mortality: A Time Series Analysis using GAM

“Success in life comes not from holding a good hand, but from playing a poor hand well.”

-Denis Waitley

5.1 Introduction

There is strong evidence that episodes of extremely hot or cold temperatures are associated with increased mortality in many parts of the world. Time series designs are extremely useful to examine association between daily apparent temperature and mortality counts. Hence, the effect of temperature on mortality has been studied in Ludhiana city of Punjab in Northern India. As a part of the Health Effects Institute (HEI), Boston USA, project, Meteorological and mortality data were obtained for the years 2002-2004. Sahnewal Airport in Ludhiana City records temperature, dew point, wind speed and relative humidity at 8.30AM, 11.30AM, and 5.30PM every day. The daily death records were obtained from the civil registration system in Ludhiana. The association between temperature and mortality was established using the generalized additive model (GAM) with penalized as well as natural spline smoothers at 8,4,4 and 6,3,3 degrees of freedom (df) in R software with mortality count (excluding accidents) as a dependent variable. Smoothers for day of the week, the relative humidity and wind speed were included in the model.

Most of the contents of this Chapter have been published in International Journal of Environmental Sciences (Ref. Sharma et al. (2013))
Time Series analysis using Generalized Additive Model (GAM) (Ref. Hastie and Tibshirani (1990)) show an association between temperature and mortality across a range of less extreme temperatures after smoothing the effects of day of the week, relative humidity and wind speed.

In this Chapter, we describe the temperature-mortality association for years 2002-2004 in Ludhiana City of northern India by estimating the relative risks of mortality using GAM with quasi-Poisson function for mortality due to natural causes (excluding accidents) as the dependent variable and temperature as the independent variable with penalized and natural spline smoothers for day of the week, relative humidity and wind speed. Current and recent day’s temperatures are the weather components that most strongly predict mortality and mortality risk is generally found to decrease as temperature increased from the coldest days to a certain threshold temperature, above which mortality risk increases as temperature increases to highest level or decreases to the lowest level. The model developed in this analysis is potentially useful for projecting the consequences of climate change scenarios and offering insights into susceptibility to the adverse effects of temperature.

5.1.1 Background of the Study

The present study is a part of Public Health and Pollution Control in Asia (PAPA) project, sponsored by Health Effect Institute (HEI), Boston USA. It is carried out in Ludhiana city, which is the largest city of Punjab in northern India with a population of 1.6 million and an area of 135 square Km. The city is located at a longitude of 76°54'E and latitude of 30°42'N. The Indian meteorological Department, New Delhi, records meteorological data at the Sahnewal airport of Ludhiana city. Temperature, relative humidity, dew point, wind speed and wind direction is recorded daily at 8.30AM, 11.30AM and 5.30PM and the data is available for all the 365 days in a year.

Municipal Corporation of Ludhiana records mortality data at two centres which register deaths for zones A and B & C and D of the city respectively. Government and Private Hospitals report deaths that occur in their premises to their respective zones. The heads of families reports deaths which occur at home or places other than hospital to the municipal corporation office in their respective zone. The data available in the registers by registration number, name of the deceased, father’s name, age, sex, date of death, cause of death, place of death and address of the deceased were entered in computer for
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analysis. Standard operating procedures are developed for maintaining the quality of data. During data entry, 2% of the entries are randomly compared with the records, each week in each of the two zones. At the end of data entry, a 100% recheck is again carried out. It has been found out that sex and age are not mentioned in 207(0.7%) and 21(0.1%) of the deaths during 2002 - 2004. The entire data were examined for quality and consistency.

5.1.2 Meteorology Monitoring Methods

Temperature

Temperature is measured by means of a thermometer which consists of a glass bulb containing mercury/spirit connected with a glass tube of very small bore that is closed at the top. The rise or fall in mercury/spirit is measured by calibrating the tube with standard temperatures. Thermometers are graduated in different scales. The accepted scale for use by the India Meteorological Department is the Celsius scale. Thermometers are of four types:

(i) **Dry-Bulb Thermometer**: Used for measuring temperature of the surrounding air.

(ii) **Wet-Bulb Thermometer**: This helps to find out the relative humidity of the surrounding air.

(iii) **Maximum Thermometer**: Used to indicate the highest temperature reached, since the time of its last setting.

(iv) **Minimum Thermometer**: Used to indicate the lowest temperature reached, since the time of its last setting.

Relative Humidity

The most convenient method of determining the humidity of air for meteorological purpose is by the use of wet and dry thermometers. August’s modification of Regnault’s formula for deriving the vapour pressure, which has been in use in India Meteorological Department since 1876 (with temperature in Celsius (C) instead of Fahrenheit (F)) is as follows:

For temperature of the Wet Bulb below 0°C

\[ X = f' - \frac{0.48(T - T')}{671 - T'} * P \]

For temperature of Wet Bulb above 0°C

\[ X = f' - \frac{0.48(T - T')}{610 - T'} * P \]
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where

\[ X = \text{pressure of vapour present in the air} \]
\[ T = \text{temperature of the Dry Bulb in } ^\circ\text{C} \]
\[ T' = \text{temperature of the Wet Bulb in } ^\circ\text{C} \]
\[ f' = \text{saturation vapour pressure at temperature } T' \text{ (in } ^\circ\text{C}) \text{ of the Wet Bulb} \]
\[ P = \text{pressure of air} \]

The relative humidity is given by this equation

\[ U = \frac{X}{f'} \times 100 \]

where \( U = \text{relative humidity} \) and \( f' = \text{saturation vapour pressure at temperature of the Dry Bulb} \).

**Dew Point**

The Dew Point temperature is the temperature to which the air should be cooled in order to cause condensation or the temperature at which the saturation vapour pressure is equal to the pressure of the vapour in the air.

**Wind Speed (Cup Anemometer)**

It is a mechanical device which measures the spontaneous wind speed. Generally, simple cup anemometer is used to measure the average wind speed during the 24 hours. The cups are put into motion by a thrust caused by the movement of the air mass. The movement is recorded by the meter and from the meter reading, the flow of the air mass can be ascertained which can be termed as calm or windy.

**Wind Direction**

Wind direction is monitored by wind vane instrument. It is used to record the wind direction in terms of 8 points. Wind is an important weather element whose direction and velocity influence the vegetation of any area. Every direction indicates the sky conditions. If the wind direction is from N or NW, then generally dry air prevails over the region. If the wind direction is from E or SE, then humid conditions prevail over the region. For example, during monsoon period, E and SE winds prevail over Punjab. A platform is fixed on the top of a pillar and an arrow is fixed at the top of the platform. The arrow indicates the direction of the wind from which the wind approaches the station. Four letters N,E,S and W are fixed on a rod above the platform to indicate north, east, south and west respectively.
In this Chapter, we work on fitting a GAM to see the impact of temperature on mortality using R software. Section 5.2 gives the statistical analysis of the data considered in the study. Section 5.3 provides the results of fitting of GAM for penalized and natural splines using different degrees of freedom. Section 5.4 shows the sensitivity analysis carried out separately for deaths in the 65+ years age group.

5.2 Statistical Analysis

The data were examined for quality and consistency. Summary statistics, mean, standard deviation, minimum, maximum and range were computed as per Table 5.2.1 for temperature, relative humidity and wind speed. Overall in the 3 years period from 2002-2004, 28007 deaths were registered with an average of 25.4 deaths per day. The age-sex distribution of the deaths is shown in Table 5.2.2. There were more deaths among males (65%) and in the above 45 years age group (67%). Only 787 (2.8%) of the deaths were due to accidents and these were excluded from analysis. Most of the deaths (71.2%) fall under the category of “symptoms, signs and abnormalities classified elsewhere” due to improper certification of the cause of death.

Table 5.2.1 Summary Statistics of Meteorological Parameters

<table>
<thead>
<tr>
<th>Statistics (°C)</th>
<th>Temperature</th>
<th>Relative Humidity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
<td>2002</td>
</tr>
<tr>
<td>Mean</td>
<td>25.9</td>
<td>25.9</td>
</tr>
<tr>
<td>S.D.</td>
<td>7.72</td>
<td>8.37</td>
</tr>
<tr>
<td>Minimum</td>
<td>8.13</td>
<td>6.2</td>
</tr>
<tr>
<td>Maximum</td>
<td>41.5</td>
<td>41.5</td>
</tr>
</tbody>
</table>

Table 5.2.1 Summary Statistics of Meteorological Parameters

Table 5.2.1 Summary Statistics of Meteorological Parameters

<table>
<thead>
<tr>
<th>Statistics (°C)</th>
<th>Temperature (km/hour)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Overall</td>
</tr>
<tr>
<td>Mean</td>
<td>7.5</td>
</tr>
<tr>
<td>S.D.</td>
<td>5.22</td>
</tr>
<tr>
<td>Minimum</td>
<td>0</td>
</tr>
<tr>
<td>Maximum</td>
<td>42.7</td>
</tr>
</tbody>
</table>
Table 5.2.2 Age and Sex distribution of Registered Deaths

<table>
<thead>
<tr>
<th>Age Group</th>
<th>2002 Male</th>
<th>2002 Female</th>
<th>2003 Male</th>
<th>2003 Female</th>
<th>2004 Male</th>
<th>2004 Female</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;1 year</td>
<td>380</td>
<td>149</td>
<td>375</td>
<td>120</td>
<td>318</td>
<td>143</td>
<td>1485</td>
</tr>
<tr>
<td>1-4 yrs</td>
<td>73</td>
<td>39</td>
<td>63</td>
<td>34</td>
<td>52</td>
<td>37</td>
<td>298</td>
</tr>
<tr>
<td>5-64 yrs</td>
<td>1680</td>
<td>739</td>
<td>1620</td>
<td>742</td>
<td>1668</td>
<td>715</td>
<td>7164</td>
</tr>
<tr>
<td>45-64 yrs</td>
<td>1313</td>
<td>815</td>
<td>1897</td>
<td>963</td>
<td>1990</td>
<td>931</td>
<td>8409</td>
</tr>
<tr>
<td>65+ yrs</td>
<td>1889</td>
<td>1408</td>
<td>2102</td>
<td>1486</td>
<td>2065</td>
<td>1473</td>
<td>10423</td>
</tr>
<tr>
<td>Total</td>
<td>5835</td>
<td>3150</td>
<td>6057</td>
<td>3345</td>
<td>6093</td>
<td>3299</td>
<td>27779</td>
</tr>
</tbody>
</table>

*Age and sex missing in 207 and 21 records respectively (27779+207+21 = 28007)
In Northern India, Ludhiana city is the largest City of Punjab state with population of 1.6 million (projected from census 2001) and having area of 135 square km (Fig. 5.2.1). This city is located at a distance of about 100 km from Chandigarh and about 360 km from New Delhi (Fig. 5.2.1). The industrial city of Ludhiana has high temperature variations from 0°C to 49 °C with a mean temperature of around 26 °C (Fig. 5.2.2).

To describe the daily variation in weather data, smoother plots for relative humidity and wind speed were drawn for years 2002-2004 with 20 df (Fig. 5.2.3 and Fig. 5.2.4). It is observed that smooth plot of relative humidity follows similar trends for almost three years. However, wind speed variations are observed quite frequently during three years. Extreme values of wind speed varies from 15 km/h to 38 km/h in all the three years. These variations could not be controlled even when df were increased up to 30. In this part of the region, some dust storms are always expected, particular, during summer (June-July) and winter (December-January) season.
5.3 Development of GAM Model

GAM function fits a generalized additive model to data. The degree of smoothness of model terms is estimated as part of fitting. Smooth terms are represented using penalized regression splines or natural splines with smoothing parameters selected by GCV criterion with fixed degrees of freedom. Multi-dimensional smoothers are available using penalized regression splines (isotropic) or Natural splines.

First of all, base core model was developed in R package (Ref. Peng et al. (2008), Wood (2006)).

Generalized Additive Model for effect of Temperature on Mortality can be written as:

\[
\log(E(\text{mortality})) = \text{Temperature} + s(\text{day effect}) + s(\text{relative humidity}) + s(\text{wind speed})
\]

The above model is a Generalized Additive Model (GAM) with penalized/natural spline smoothers in R which has Quasi-Poisson link function with mortality from all natural causes as the dependent variables. Also, this model has

- smoothers for day effect (from Monday through Sunday), relative humidity and wind speed
- exposure at single day lags of 0 to 3 days.
The GAM model fits three types of plots

(i) **Residual Plot**: A residual plot is a graph that shows the residuals on the vertical axis and the independent variable on the horizontal axis. If the points in a residual plot are randomly dispersed around the horizontal axis, a linear regression model is appropriate for the data otherwise, a non-linear model is more appropriate. The difference between the observed value of the dependent variable (y) and the predicted value (ŷ) is called the residual (e). Each data point has one residual. Thus, Residual = Observed value - Predicted value. A plot of residuals versus predicted response is essentially used to spot possible heteroscedasticity (non-constant variance across the range of the predicted values) as well as influential observations (possible outliers). Usually, we expect such a plot to exhibit no particular pattern (a funnel-like plot indicates that variance increase with mean). Plotting residuals against one predictor can be used to check the linearity assumption.

(ii) **Partial Autocorrelation Function Plots (PACF)**: A characteristic feature of time series is that the observations are ordered through time. A consequence of this is autocorrelation, that is, an underlying pattern between observations from one time period to the next within a time series (Ref. Barron (1992), Peng and Dominici (2008), Ha et al (2011)). We can define autocorrelation at lag k as the correlation between observations that are k time periods apart. This can be estimated for lags \( k = 0, 1, 2 \ldots \) as

\[
r_k = \frac{\sum_{t=k+1}^{n}(x_t - \bar{x})(x_{t-k} - \bar{x})}{\sum_{t=1}^{n}(x_t - \bar{x})^2}
\]

where \( x_t \) denotes the observation at time \( t \) and \( \bar{x} \) denotes the sample mean of the series \( \{x_t\} \). The partial autocorrelation at lag \( k \) is defined as the partial correlation between observations that are \( k \) time periods apart. That is, it is the correlation between \( x_t \) and \( x_{t-k} \) after taking out the effect of the intervening observations \( x_{t-1}, \ldots, x_{t-k+1} \). It can be estimated using a fast computational algorithm. The collection of autocorrelations at lags \( k = 1, 2, \ldots \) is known as the autocorrelation function (ACF) and the collection of partial autocorrelations is known as the partial autocorrelation function (PACF).
(iii) **Predicted Plot:** The GAM produces predicted plot based on penalized spline or natural spline, with appropriate degrees of freedom, for number of episodes (mortality) against the data points.

Since a GAM is just a penalized GLM, residual plots are checked, exactly as for a GLM. The distribution of scaled residuals was examined marginally and plotted against covariates and fitted values. In R software, residuals (model) extracts residuals and `gam.check(model)` produces simple residual plots and summary of convergence information. `Plot(model,residuals=TRUE)` plots smooth terms with partial residuals overlaid.

### 5.3.1 Results

Fitting of the BASE model is carried out with penalized splines (PS) and natural splines (NS) at 8,4,4 df and at 6,3,3 df respectively, by considering day effect, relative humidity and wind speed as covariates. After that, the main risk variable, temperature is added in the model. In the sequel, we work out the relative risk, PACF and Residual plots for Lag0, Lag1, Lag2 and Lag3 (Ref. Schwartz (2000)) along with predicted plot of mortality in R for all the models.

The results given below are based on the data from 2002 - 2004 for Ludhiana city in India. The results for four models include

(i) the parameter estimates for all the four models
(ii) significance of the smoothing terms
(iii) residual plots
(iv) PACF plots
(v) observed and predicted plot

**Model: PS(8,4,4)**

\[
mortality \sim \text{temp} + s(\text{day}, k = 24 + 1, \text{fx} = \text{F, bs = \"cr\")} + s(\text{rh}, k = 4 + 1, \text{fx} = \text{F, bs = \"cr\")} + s(\text{ws}, k = 4 + 1, \text{fx} = \text{F, bs = \"cr\")}
\]

[temp: temperature, rh: relative humidity, ws: wind speed]

For each lag, \(\beta\)-coefficients and relative risk along with 95% confidence intervals are presented in Table 5.3.1 for model PS(8,4,4).
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Table 5.3.1: Effect of Temperature on Mortality in Ludhiana 2002-2004, PS(8,4,4)

<table>
<thead>
<tr>
<th>Lag Effects</th>
<th>N</th>
<th>β-coeff.</th>
<th>Temperature</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 0</td>
<td>1095</td>
<td>0.0154</td>
<td>1.1669</td>
<td>0.0000118**</td>
</tr>
<tr>
<td>Lag 1</td>
<td>1094</td>
<td>0.0118</td>
<td>1.1256</td>
<td>0.0000421**</td>
</tr>
<tr>
<td>Lag 2</td>
<td>1093</td>
<td>0.0078</td>
<td>1.0811</td>
<td>0.0048 **</td>
</tr>
<tr>
<td>Lag 3</td>
<td>1092</td>
<td>0.0055</td>
<td>1.0573</td>
<td>0.0406 *</td>
</tr>
</tbody>
</table>

** (p<.01), * (p<.05)

The lag effects of temperature on mortality are shown in Table 5.3.1. The relative risk has been computed for every 10 °C increase in temperature. The highest relative risk was for Lag0 and it goes on decreasing from Lag1 to Lag3. High value of relative risk for Lag0 indicates that mortality is more on the same day. All the lag effects are found to be significant. The relative risk for Lag0 indicates that for every 10° increase in temperature, the expected number of deaths amounts to 1.17 (approximately). The 95% confidence intervals are also close for Lag0 to Lag3.

Residual and PACF plots for PS(8,4,4) model along with predicted plot of mortality (Lag0)

Figure 5.3.1

It is evident from PACF and Residual plots that there is significant effect of temperature on mortality after smoothing the effects of day, relative humidity and wind speed. The predicted plot of mortality for Lag0 can be used to determine episodes of mortality during a particular day (Fig. 5.3.1). Except few outliers, particularly, during the months of January and July (2002-2004), predictions for episodes of mortality seem to be reasonably well and it can be depicted from the predicted plot. PACF plot shows that mortality is high during first three days at Lag0 and after that, it starts declining. Residual
plot shows that difference between actual and predicted values. They are evenly distributed around zero.

Table 5.3.2: Significance of Smooth terms for PS(8,4,4), Lag0

<table>
<thead>
<tr>
<th>Significance of Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>s(day)</td>
<td>21.524</td>
<td>5.850</td>
<td>&lt;2e-16 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>1.088</td>
<td>0.366</td>
<td>0.578</td>
</tr>
<tr>
<td>s(ws)</td>
<td>1.001</td>
<td>0.036</td>
<td>0.851</td>
</tr>
</tbody>
</table>

R-sq.(adj) = 0.121  Deviance explained = 13.9%
GCV score = 1.1983  Scale est. = 1.1703  n = 1095

For Lag0, effect of the day of week terms (Monday through Sunday) are highly significant (p < 0.00001). However, the relative humidity and wind speed are non-significant (p > 0.05). The deviance explained by the model is 13.9% with GCV score of 1.1983.

Residual and PACF plots for PS(8,4,4) model along with predicted plot of mortality (Lag1)

Figure 5.3.2

We observe almost similar pattern for Lag1 with significant effects of temperature on mortality for first three days (PACF plot). The predicted model fits well to the observed data (Fig. 5.3.2).
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Table 5.3.3: Significance of Smooth terms for PS(8,4,4), Lag1

<table>
<thead>
<tr>
<th>Significance of Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>s(day)</td>
<td>21.580</td>
<td>5.683</td>
<td>3.2e-16 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>1.001</td>
<td>7.433</td>
<td>0.00648 **</td>
</tr>
<tr>
<td>s(ws)</td>
<td>1.000</td>
<td>0.297</td>
<td>0.58627</td>
</tr>
</tbody>
</table>

R-sq.(adj) = 0.118  Deviance explained = 13.7%
GCV score = 1.202  Scale est. = 1.11739  n = 1093

The smoothers of day effect (p < 0.00001) and relative humidity (p < 0.05) are significant for Lag1, but for wind speed, the smoother is non-significant (p > 0.05), with GCV score of 1.202 and the deviance explained by the model for Lag1 is 13.7%. As compared to Lag0, Lag1 results are computed for n = 1094 observations because of one day lag.

Residual and PACF plots for PS(8,4,4) model along with predicted plot of Mortality(Lag2)

As expected, very little difference was observed between Lag2 and Lag1 in terms of PACF, residual and predicted plots (Fig. 5.3.3). However, analysis is based on n = 1093 observations because of two days lag.

Table 5.3.4: Significance of Smooth terms for PS(8,4,4), Lag2

<table>
<thead>
<tr>
<th>Significance of Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>s(day)</td>
<td>21.340</td>
<td>4.956</td>
<td>2.22e-13 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>1.330</td>
<td>9.094</td>
<td>0.000637 ***</td>
</tr>
<tr>
<td>s(ws)</td>
<td>1.001</td>
<td>0.350</td>
<td>0.554567</td>
</tr>
</tbody>
</table>

R-sq.(adj) = 0.111  Deviance explained = 12.9%
GCV score = 1.2134  Scale est. = 1.1849  n = 1093
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It is concluded on the basis of values in Table 5.3.4 that the smoothers for day effect (p < 0.00001), relative humidity (p < 0.0001) are significant and non-significant for wind speed (p > 0.05).

**Residual and PACF plots for PS(8,4,4) model along with predicted plot of mortality(Lag3)**

The above figure shows that concentrated band is observed between 20-32 (number of episodes of mortality) for Lag3.

**Table 5.3.5: Significance of Smooth terms for PS(8,4,4), Lag3**

<table>
<thead>
<tr>
<th>Significance of Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>s(day)</td>
<td>21.210</td>
<td>4,565</td>
<td>6.95e-12 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>1.514</td>
<td>9.551</td>
<td>0.000165 ***</td>
</tr>
<tr>
<td>s(ws)</td>
<td>1.002</td>
<td>0.346</td>
<td>0.557022</td>
</tr>
<tr>
<td>R-sq.(adj)</td>
<td>0.107</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Deviance explained</td>
<td></td>
<td>12.6%</td>
<td></td>
</tr>
<tr>
<td>GCV score</td>
<td>1.2191</td>
<td>1.1903</td>
<td></td>
</tr>
<tr>
<td>n</td>
<td>1092</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

On the basis of values in Table 5.3.5 smoothers for day effect (p < 0.00001), relative humidity (p < 0.0001) are significant but non-significant for wind speed (p > 0.05). For this model, n = 1092 because of three days lag.

**Model: PS(6,3,3)**

\[
\text{mortality} - \text{temp} + s(\text{day}, k = 18 + 1, f = F, \text{bs} = "cr") + s(\text{rh}, k = 3 + 1, f = F, \text{bs} = "cr") + s(\text{ws}, k = 3 + 1, f = F, \text{bs} = "cr")
\]

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Table 5.3.6: Effect of Temperature on Mortality for years 2002-2004

<table>
<thead>
<tr>
<th>Lag Effects</th>
<th>N</th>
<th>β-coeff.</th>
<th>Relative Risk</th>
<th>p-value</th>
<th>95% CI Lower</th>
<th>95% CI Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 0</td>
<td>1095</td>
<td>0.0136</td>
<td>1.1461</td>
<td>0.000122 **</td>
<td>1.0694</td>
<td>1.2284</td>
</tr>
<tr>
<td>Lag 1</td>
<td>1094</td>
<td>0.0106</td>
<td>1.1119</td>
<td>0.000279 **</td>
<td>1.0503</td>
<td>1.1773</td>
</tr>
<tr>
<td>Lag 2</td>
<td>1093</td>
<td>0.0068</td>
<td>1.0712</td>
<td>0.0135 *</td>
<td>1.0144</td>
<td>1.1312</td>
</tr>
<tr>
<td>Lag 3</td>
<td>1092</td>
<td>0.0047</td>
<td>1.0487</td>
<td>0.0815 .</td>
<td>0.9941</td>
<td>1.1064</td>
</tr>
</tbody>
</table>

The relative risk for this model is highest for Lag 0 and goes on decreasing for other lags which indicates that the maximum effect on mortality is on the same day.

Residual and PACF plots for PS(6,3,3) model along with predicted plot of mortality (Lag 0)

![Residual and PACF plots](image)

Figure 5.3.5

There is a significant effect of temperature on mortality after smoothing the effects of day, relative humidity and wind speed. The points in the residual plots are symmetrically distributed over and above the baseline zero. The predicted plot of mortality (Fig. 5.3.5) for Lag 0 can be used to determine episodes of mortality during a particular day.

Table 5.3.7: Significance of Smooth terms for PS(6,3,3), Lag 0

<table>
<thead>
<tr>
<th>Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>s(day)</td>
<td>17.032</td>
<td>5.752</td>
<td>3.17e-13 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>2.139</td>
<td>1.190</td>
<td>0.303</td>
</tr>
<tr>
<td>s(ws)</td>
<td>1.001</td>
<td>0.182</td>
<td>0.670</td>
</tr>
</tbody>
</table>

R-sq.(adj) = 0.0973  Deviance explained = 11.4%  GCV score = 1.2249  Scale est. = 1.2001  n = 1095
Only the day effect is found to be significant for this model, with GCV score of 1.2249 and Deviance explained by model as 11.4%.

Residual and PACF plots for PS(6,3,3) model along with predicted plot of mortality (Lag1)

![Residual plot](image1)

![PACF plot](image2)

![Predicted plot](image3)

**Figure 5.3.6**

Fig. 5.3.6 shows similar pattern for Lag1 with significant effect of temperature on mortality. The predicted model also shows that fit is good.

<table>
<thead>
<tr>
<th>Significance of Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>s(day)</td>
<td>17.168</td>
<td>5.603</td>
<td>8.4e-13 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>2.179</td>
<td>4.131</td>
<td>0.0101 *</td>
</tr>
<tr>
<td>s(ws)</td>
<td>1.000</td>
<td>0.039</td>
<td>0.8430</td>
</tr>
</tbody>
</table>

For Lag1, day effect and relative humidity are found to be significant.
Residual and PACF plots for PS(6,3,3) model along with predicted plot of mortality (Lag 2)

Figure 5.3.7

The interpretation for Lag 2 is very much similar to that of Lag 1 in terms of PACF, residual and predicted plots (Fig. 5.3.7).

Table 5.3.9: Significance of Smooth terms for PS(6,3,3), Lag 2

<table>
<thead>
<tr>
<th>Significance of Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>s(day)</td>
<td>17.105</td>
<td>4.921</td>
<td>9.62e-11 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>2.389</td>
<td>6.618</td>
<td>0.000385 ***</td>
</tr>
<tr>
<td>s(ws)</td>
<td>1.000</td>
<td>0.059</td>
<td>0.808481</td>
</tr>
</tbody>
</table>

R-sq.(adj) = 0.0904  Deviance explained = 10.8%
GCV score = 1.236  Scale est. = 1.2106  n = 1093

For this model, day and relative humidity are found to be significant (p < 0.001) while they are non-significant for wind speed (p = 0.81).

Residual and PACF plots for PS (6,3,3) model along with predicted plot of mortality (Lag 3)

Figure 5.3.8
The effect of temperature on mortality is non-significant for Lag3 (p = 0.08) (Table 5.3.6), which means that there is no effect of temperature on mortality on third day.

<table>
<thead>
<tr>
<th>Significance of Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>s(day)</td>
<td>17.06</td>
<td>4.443</td>
<td>2.51e-09 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>2.430</td>
<td>7.779</td>
<td>8.27e-05 ***</td>
</tr>
<tr>
<td>s(ws)</td>
<td>1.001</td>
<td>0.062</td>
<td>0.803</td>
</tr>
</tbody>
</table>

R-sq.(adj) = 0.0877 Deviance explained = 10.5%
GCV score = 1.2408 Scale est. = 1.2152 n = 1092

For Lag3, day effect and relative humidity are significant.

In the sequel, we consider models for natural spline.

Model: NS(8,4,4)
mortality $\sim$ temp + s(day, k = 24 + 1, fx = T, bs = "cr") + s(rh, k = 4 + 1, fx = T, bs = "cr") + s(ws, k = 4 + 1, fx = T, bs = "cr")

<table>
<thead>
<tr>
<th>Mean temp</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 0</td>
<td>0.016747</td>
</tr>
<tr>
<td>Lag 1</td>
<td>0.012613</td>
</tr>
<tr>
<td>Lag 2</td>
<td>0.008813</td>
</tr>
<tr>
<td>Lag 3</td>
<td>0.006834</td>
</tr>
</tbody>
</table>

The lag effects of temperature on mortality are shown in Table 5.3.11. The highest relative risk is for Lag0 and it goes on decreasing from Lag1 to Lag3. All the lag effects are found to be significant. The relative risk for Lag0 indicates that for every 10°C increase in temperature, the expected number of deaths amounts to 1.18 (approximately) for this model. The 95% confidence intervals for relative risk are close for all the lags.
Residual and PACF plots for NS(8,4,4) model along with predicted plot of mortality (Lag0)

![Figure 5.3.9](image)

Table 5.3.12: Significance of Smooth terms for NS(8,4,4), Lag0

<table>
<thead>
<tr>
<th>Smooth Term</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>S(day)</td>
<td>24</td>
<td>5.975</td>
<td>&lt;2e-16 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>4</td>
<td>0.394</td>
<td>0.813</td>
</tr>
<tr>
<td>s(ws)</td>
<td>4</td>
<td>0.833</td>
<td>0.504</td>
</tr>
</tbody>
</table>

R-sq.(adj) = 0.119  Deviance explained = 14.4%
GCV score = 1.2099  Scale est. = 1.1724  n = 1095

For NS(8,4,4) model, only the effect of the day is significant (p < 0.001) while the effects of other covariates are non significant (p > 0.05). The deviance explained is 14.4% with GCV score of 1.2099.

Residual and PACF plots for NS(8,4,4) model along with predicted plot of mortality (Lag1)

![Figure 5.3.10](image)
For NS(8,4,4) model, the effect of the day and relative humidity is significant \((p < 0.001)\) for Lag1 while the effect of wind speed is non significant \((p > 0.05)\).

Residual and PACF plots for NS(8,4,4) model along with predicted plot of mortality (Lag2)

<table>
<thead>
<tr>
<th>Significance of Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>S(day)</td>
<td>24</td>
<td>5.779</td>
<td>&lt;2e-16 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>4</td>
<td>2.593</td>
<td>0.0352 *</td>
</tr>
<tr>
<td>s(ws)</td>
<td>4</td>
<td>0.782</td>
<td>0.5371</td>
</tr>
</tbody>
</table>

R-sq(adj) = 0.117  Deviance explained = 14.2%  
GCV score = 1.2141  Scale est. = 1.1763  \(n = 1094\)

For NS(8,4,4) model, the effect of the day and relative humidity is significant \((p < 0.001)\) for Lag2 while the effect of wind speed was non significant \((p > 0.05)\).
Residual and PACF plots for NS(8,4,4) model along with predicted plot of mortality (Lag3)

For NS(8,4,4) model, the effect of the day and relative humidity is significant (p < 0.001) for Lag3 while the effect of wind speed is non significant (p > 0.05).

Model: NS(6,3,3)

mortality ~ temp + s(day, k = 24 + 1, fx = T, bs = "cr") + s(rh, k = 4 + 1, fx = T, bs = "cr") + s(ws, k = 4 + 1, fx = T, bs = "cr")

Table 5.3.16: Effect of Temperature on Mortality for years 2002-2004

<table>
<thead>
<tr>
<th>Lag Effects</th>
<th>N</th>
<th>( \beta )-coeff.</th>
<th>Relative Risk</th>
<th>p-value</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 0</td>
<td>1095</td>
<td>0.0145</td>
<td>1.1568</td>
<td>0.000736**</td>
<td>1.0767</td>
<td>1.2429</td>
</tr>
<tr>
<td>Lag 1</td>
<td>1094</td>
<td>0.0114</td>
<td>1.1210</td>
<td>0.000143**</td>
<td>1.0571</td>
<td>1.1887</td>
</tr>
<tr>
<td>Lag 2</td>
<td>1093</td>
<td>0.0079</td>
<td>1.0831</td>
<td>0.00536**</td>
<td>1.0240</td>
<td>1.1456</td>
</tr>
<tr>
<td>Lag 3</td>
<td>1092</td>
<td>0.0060</td>
<td>1.0621</td>
<td>0.0327*</td>
<td>1.0050</td>
<td>1.1225</td>
</tr>
</tbody>
</table>
For this model, all the lag effects are found to be significant. The relative risk is highest for Lag0 which is the case for other models also.

**Residual and PACF plots for NS(6,3,3) model along with predicted plot of mortality (Lag0)**

<table>
<thead>
<tr>
<th>Significance of Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>S(day)</td>
<td>18</td>
<td>5.945</td>
<td>6.93e-14 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>3</td>
<td>2.196</td>
<td>0.0869  .</td>
</tr>
<tr>
<td>s(ws)</td>
<td>3</td>
<td>0.312</td>
<td>0.8166</td>
</tr>
</tbody>
</table>

In this model, only the effect of day was significant (p < 0.01).

**Residual and PACF plots for NS(6,3,3) model along with predicted plot of mortality (Lag1)**
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Table 5.3.18: Significance of Smooth terms for NS(6,3,3), Lag1

<table>
<thead>
<tr>
<th>Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>S(day)</td>
<td>18</td>
<td>5.778</td>
<td>2.23e-13 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>3</td>
<td>5.216</td>
<td>0.00141 **</td>
</tr>
<tr>
<td>s(ws)</td>
<td>3</td>
<td>0.134</td>
<td>0.93956</td>
</tr>
</tbody>
</table>

R-sq.(adj) = 0.0947 Deviance explained = 11.5%
GCV score = 1.2335 Scale est. = 1.2041 n = 1094

In this model, the effect of day and relative humidity is significant (p < 0.01).

Residual and PACF plots for NS(6,3,3) model along with predicted plot of mortality (Lag2)

Table 5.3.19: Significance of Smooth terms for NS(6,3,3), Lag2

<table>
<thead>
<tr>
<th>Smooth Terms</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>S(day)</td>
<td>18</td>
<td>5.164</td>
<td>1.58e-11 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>3</td>
<td>8.021</td>
<td>2.74e-05 ***</td>
</tr>
<tr>
<td>s(ws)</td>
<td>3</td>
<td>0.171</td>
<td>0.916</td>
</tr>
</tbody>
</table>

R-sq.(adj) = 0.0892 Deviance explained = 10.9%
GCV score = 1.2419 Scale est. = 1.2124 n = 1093

Lag2 results are similar as that of Lag1.
The Impact of Temperature on Mortality: A Time Series Analysis using GAM

Residual and PACF plots for NS (6,3,3) model along with predicted plot of mortality (Lag3)

![Residual and PACF plots](image)

Figure 5.3.16

Table 5.3.20: Significance of Smooth terms for NS(6,3,3), Lag3

<table>
<thead>
<tr>
<th>Smooth term</th>
<th>DF</th>
<th>F</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>S(day)</td>
<td>18</td>
<td>4.826</td>
<td>1.61e-10 ***</td>
</tr>
<tr>
<td>s(rh)</td>
<td>3</td>
<td>9.353</td>
<td>4.18e-06 ***</td>
</tr>
<tr>
<td>s(ws)</td>
<td>3</td>
<td>0.226</td>
<td>0.878</td>
</tr>
</tbody>
</table>

R-sq.(adj) = 0.0866 Deviance explained = 10.7%
GCV score = 1.2465 Scale est. = 1.2168 n = 1092

For this model, the effects of day and relative humidity are significant.
Smooth plots of mortality versus temperature and days are shown below.

![Smooth plots](image)

Figure 5.3.17
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Temperature and mortality plot (Fig. 5.3.17) show that there are more deaths (all-cause mortality) during summer (>40 °C) season as compared to the winter (<15 °C) season. It is also evident that from Fig. 5.3.18 that there are more male deaths as compared to female deaths.

5.4 Sensitivity Analysis

Separate analysis is carried out for elderly people with greater than or equal to 65 years. However, smaller number of deaths in 0-4 year’s age group does not allow us to do age specific analysis for this group. There are more deaths for elderly people during winter season, particularly, when the temperature is below 15 °C (Fig. 5.4.1) as compared to summer season. All the lag effects except Lag3 are found to be significant (Table 5.4.1). For Lag0, Lag1, Lag2 smoothers are found to be significant for day effect (p < 0.00001), humidity and wind speed (p < 0.05). However, for Lag3, significant smoothers are observed for day effect (p < 0.00001) as well as for relative humidity (p < 0.01) but non-significant for wind speed (p > 0.05).
The entire analysis in this Chapter is based on four models viz. PS(8,4,4), PS(6,3,3), NS(8,4,4) and NS(6,3,3). However, we have presented the sensitivity analysis results only for PS(8,4,4) model because it has the minimum GCV score.

Table 5.4.1: Sensitivity Analysis for Elderly People (age > 65 Years)

<table>
<thead>
<tr>
<th>Lag Effects</th>
<th>N</th>
<th>β-Coeff.</th>
<th>Relative Risk</th>
<th>p-value</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag 0</td>
<td>1095</td>
<td>0.0130</td>
<td>1.1389</td>
<td>0.0195 **</td>
<td>1.0213</td>
<td>1.2702</td>
</tr>
<tr>
<td>Lag 1</td>
<td>1094</td>
<td>0.0156</td>
<td>1.1694</td>
<td>0.000661 *</td>
<td>1.0690</td>
<td>1.2794</td>
</tr>
<tr>
<td>Lag 2</td>
<td>1093</td>
<td>0.0102</td>
<td>1.1075</td>
<td>0.0205 *</td>
<td>1.0160</td>
<td>1.2073</td>
</tr>
<tr>
<td>Lag 3</td>
<td>1092</td>
<td>0.0079</td>
<td>1.0822</td>
<td>0.0687</td>
<td>0.9940</td>
<td>1.1783</td>
</tr>
</tbody>
</table>

Sensitivity results show that for elderly people (age >= 65 years), relative risk for Lag1 is higher as compared to other lags. However for all lags, relative risk is found to be significant. Table 5.4.2 and 5.4.3 display the results of sensitivity analysis for females and males separately.
The values in the above tables show that Lag0, Lag1, Lag2, and Lag3 effects are significant for females but for males it is significant only for Lag0. For every 10°C increase in temperature, mortality for elderly people increased by 1.14%, for females by 1.21% and for males by 1.13%. Also for every 10°C decrease, mortality increases by 0.88% for elderly, 0.83% for females and 0.89% for males.

5.5 Results and Conclusions

The estimated number of deaths in Ludhiana city varies from 9000 to 10000 deaths mid-year population. The total recorded deaths in Ludhiana city from 2002 – 2004 are 28,007 with an average of 25.4 deaths per day. If the deaths of non-residents are excluded, the total deaths are 19335 (69.3%). The age and sex distribution of deaths are shown in Table 5.2.2. There are more deaths among males (65%) and in the above 45 years age group (67%). Only 787 (2.8%) of the deaths are due to accidents and they have been excluded from the analysis. Most of the deaths (71.2%) fall under the category of “symptoms, signs and abnormalities classified elsewhere” due to improper certification of the cause of death. The mean (s.d.) of temperature is 25.6 (7.9)°C, relative humidity 58.1 (19.3)% , and wind speed 6.87 (4.88) km/hour. The annual mean temperature ranges

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from 8.1°C to 41.5°C for 2002, 6.2°C to 41.5°C for 2003 and from 8.4°C to 40.6°C for 2004; relative humidity from 11.0% to 93.7% for 2002, 10.3% to 99.7% for 2003 and from 13.7% to 99.7% for 2004 and wind speed varies from 0.00 to 42.67 for 2002, 0.00 to 35.67 for 2003 from 0.00 to 27.33 for 2004. Overall 28,007 deaths are registered, with an average of 25.4 deaths (s.d = 5.8) per day. The association between temperature and mortality by smoothing the effects of day of the week, relative humidity and wind speed is found to be statistically significant. For every 10°C increase in temperature, mortality due to natural causes increases by 1.17% and for every 10°C decrease in temperature, mortality increased by 0.86% for PS(8,4,4) model.

We have worked out the PACF and Residual plots for Lag0, Lag1, Lag2 and Lag3 along with predicted plot of mortality in R. It is evident from PACF and Residual plots that there is significant effect of temperature on mortality after smoothing the effects of day, relative humidity and wind speed. All the lag effects except Lag3 for model PS(6,3,3) (Table 5.3.6) are found to be significant.

Sensitivity analysis is carried out separately for deaths in the 65+ years’ age group. Smaller number of deaths in 0-4 years’ age group does not allow us to do age specific analysis. Sensitivity analysis shows that elderly (>65 years) population is much affected by temperature variations.

As a part of the Health Effects Institute, Boston USA (PAPA project) this analysis gives the impact of temperature on mortality in Ludhiana City of India. The mortality rates of Urban Punjab for the years 2002, 2003 and 2004 are 6.2, 6.0 and 7.2 deaths per 1,000 mid-year population (Source: SRS Bulletin). Apart from the analysis of the relation between temperature and mortality in the city, the smoothing effects of day, relative humidity and wind speed have also been worked out. The PACF i.e. partial autocorrelation function and residual plots are plotted for Lag0, Lag1, Lag2 and Lag3 along with the predicted plots (all-cause mortality). It is evident from PACF and Residual plots that there is significant effect of temperature on mortality after smoothing the effects of day, relative humidity and wind speed.

Studies based on retrospective data face several difficulties and this study is no exception. On the basis of the age-specific mortality rates and age distribution of the population of urban India, it seems that about 15-23% may not have been registered under various age groups. However, there is no suggestion that this proportion would vary day by day. In conclusion, there is need to improve the overall registration system of deaths. Cause specific analysis is not possible as cause of death is not clearly mentioned.
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in most of the cases. It seems there is under reporting of deaths, particularly, among children below the age of 5 years. We suggest that the ICD-10 system should be introduced properly so that each case has proper code and cause-specific analysis may be performed to get better results in future.
5.6 Programs in R

PS(8,4,4) model - Lag0

lag0<-read.table("C:/ldh24lag0.txt",header=TRUE,sep="t")
day<-lag0$day
ws<-lag0$ws
temp<-lag0$temp
dp<-lag0$dp
rh<-lag0$rh
mortality<-lag0$deaths
data1<-data.frame(cbind(mortality,day,ws,dp,rh,temp))
model<-gam(mortality~temp+s(day,k=24+1,fx=F,bs="cr")+
s(rh,k=4+1,fx=F,bs="cr")+
s(ws,k=4+1,fx=F,bs="cr"),family=quasipoisson,na.action=na.omit, data=data1)
summary(model)
source("C:/dia_plt_fim.R")
dia.plt(model)
source("C:/pred_plt_fim.R")
pred.plt(model)

Remark 5.6.1: The same program works for Lag1, Lag2 and Lag3 if we replace the Lag0 by Lag1, Lag2 and Lag3 in following command

lag0<-read.table("C:/ldh24lag0.txt",header=TRUE,sep="t")

and their respective files.

PS(6,3,3) model - Lag0

lag0<-read.table("C:/ldh24lag0.txt",header=TRUE,sep="t")
day<-lag0$day
ws<-lag0$ws
temp<-lag0$temp
dp<-lag0$dp
rh<-lag0$rh
mortality<-lag0$deaths
data1<-data.frame(cbind(mortality,day,ws,dp,rh,temp))
model<-gam(mortality~temp+s(day,k=18+1,fx=F,bs="cr")+
s(rh,k=3+1,fx=F,bs="cr")+
s(ws,k=3+1,fx=F,bs="cr"),family=quasipoisson,na.action=na.omit, data=data1)
summary(model)
source("C:/dia_plt_fim.R")
dia.plt(model)
source("C:/pred_plt_fim.R")
pred.plt(model)

Remark 5.6.2: The same program works for for Lag1, Lag2 and Lag3 if we replace the Lag0 by Lag1, Lag2 and Lag3 in following command

lag0<-read.table("C:/ldh24lag0.txt",header=TRUE,sep="t")
with Lag1, Lag2 and Lag3 and their respective files.

**NS(8,4,4) model – Lag0**

```r
lag0 <- read.table("C:/ldh241lag0.txt", header=TRUE, sep="\t")
day <- lag0$day
ws <- lag0$ws
temp <- lag0$temp
dp <- lag0$dp
rh <- lag0$rh
mortality <- lag0$deaths
data1 <- data.frame(cbind(mortality, day, ws, dp, rh, temp))
model <- glm(mortality ~ temp + s(day, k=24+1, bs="cr") + s(rh, k=4+1, bs="cr") +
+ s(ws, k=4+1, bs="cr"), family=quasipoisson, na.action=na.omit, data=data1)
summary(model)
```

**Remark 5.6.3:** The same program works for Lag1, Lag2 and Lag3 if we replace the Lag0 in following command

```r
lag0 <- read.table("C:/ldh241lag0.txt", header=TRUE, sep="\t")
```
by Lag1, Lag2 and Lag3 and their respective files.

**NS(6,3,3) model – Lag0**

```r
lag0 <- read.table("C:/ldh241lag0.txt", header=TRUE, sep="\t")
day <- lag0$day
ws <- lag0$ws
temp <- lag0$temp
dp <- lag0$dp
rh <- lag0$rh
mortality <- lag0$deaths
data1 <- data.frame(cbind(mortality, day, ws, dp, rh, temp))
model <- glm(mortality ~ temp + s(day, k=18+1, bs="cr") + s(rh, k=3+1, bs="cr") +
+ s(ws, k=3+1, bs="cr"), family=quasipoisson, na.action=na.omit, data=data1)
summary(model)
```

**Remark 5.6.4:** The same program works for Lag1, Lag2 and Lag3 if we replace the Lag0 in following command

```r
lag0 <- read.table("C:/ldh241lag0.txt", header=TRUE, sep="\t")
```
with Lag1, Lag2 and Lag3 and their respective files.

**Remark 5.6.5:** For Sensitivity Analysis, we just need to filter the data for Age >= 65 years and run the above programs for that data.