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## Correlating respiratory disease incidences with corresponding trends in ambient particulate matter and relative humidity

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### ABSTRACT

Investigation over 14 months was undertaken at a representative rural location in the state of Himachal Pradesh to understand the putative correlation between the reported high Respiratory Disease Incidences (RDI) with air/particulate pollution exposure in a time series based investigations. Time series data on RDI cases from public health centers of Jawali, the sampling location, was obtained along with the corresponding time series data of ambient particulate matter (PM) concentrations in two size fractions (PM<sub>10</sub> and PM<sub>2.5</sub>). The time series of PM associated carbon forms — elemental carbon (EC), black carbon (BC), organic carbon (OC), and UV absorbing organic compounds (UVOC)— and meteorological factors were taken into consideration as explanatory variables. De-composition of respective time series data-sets using Empirical Ensemble Mode De-composition of separating trends from the multiple cyclic influences of variable periods enabled to establish a correlation in the RDI trends with trends in ambient PM<sub>2.5</sub> concentrations and Relative Humidity (RH). Multiple linear regression analysis adequately explained 99% of the variation in the RDI trends as a function of the trends in ambient PM<sub>2.5</sub> and relative humidity (RH); 77% of the variation was explained by the trends in PM<sub>2.5</sub> and 22% by RH.

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### 1. Introduction

Globally, an estimated 7 million premature deaths from air pollution exposure were reported in year 2012, 88% of these were from developing countries (Lim et al., 2013; WHO, 2014). In India, air pollution associated death rates have registered an increase of 12% between 2005 and 2010 (UNEP, 2014). Investigations from different geographical locations associate ambient air pollution exposure with Respiratory Disease Infections (RDI): Acute respiratory Infection, acute lower respiratory infection, lung cancer, chronic obstructive pulmonary diseases, cardio vesicular diseases and ischemic heart disease etc (Balakrishnan et al., 2013; Brauer et al., 2012; Ezzati and Kammen, 2001; Mehta et al., 2013; Pope et al., 2011; Pope et al., 2009; Pope and Dockery, 2006; Smith et al., 2014). Ambient particulate matter (PM) concentrations,

particularly PM size fraction having aerodynamic diameter <2.5 μ (PM<sub>2.5</sub>), stand as a metric for air pollution exposure (Brauer et al., 2012). Statistical modeling of health outcome time series data with corresponding air pollution exposure data, also takes into consideration other factors (e.g., meteorological factors) which may also play a role in causing the health outcome (Arundel et al., 1986; Lowen et al., 2007). The association between health outcome and explanatory variables is not always straightforward; temporal profiles of data-sets in question display not only non-linearity but also oscillations in the data on account of the presence of multi-cyclic influences of varying periodicity. Consequently, in an exploratory investigation the detection of association between the health outcome and explanatory variables requires appropriate considerations of multi-cyclic variable periodic influences: short-term, seasonal, and trend (Peng and Dominici, 2008; Merrill, 2010). It is common to evaluate association between the two by using overdispersed generalized additive model (GAM) (Merrill, 2010; Peng and Dominici, 2008). De-composition of respective time series data over different time scale enables the separation of trend from cyclic variations to examine their association separately (Cleveland et al., 1990). In the present context, the estimation of the

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trend in RDI cases and its correlation with the corresponding trends in PM, and meteorological variables was accomplished by using Ensemble Empirical Mode Decomposition (EEMD) method; the estimation of the trends using this approach follows the stepwise de-composition of the respective time series data-sets (RDI, PM and meteorology variables) to separate the embedded cyclic influences with minimum assumptions from the trend (Franzke, 2012; Huang et al., 1998). This approach was used in the present context to analyze the correlation between the RDI trends with the trends in PM exposure and meteorological factors from an investigation undertaken in the state of Himachal Pradesh, part of the Western Himalayan region, which has reported high incidences of RDI cases (NHP, 2005–2013).

An exploratory investigation spanned over fourteen month was undertaken at Jawali, a rural site in Kangra district (31°2′–32°5′N and 75°0′–77°45′E) of Himachal Pradesh (Fig. S1, supplementary material) to understand a putative association between environmental factors and reported RDI cases. The state has recorded  $1,514,082 \pm 78,576 \text{ year}^{-1}$  acute respiratory infection cases between 2005 and 2013 (NHP, 2005–2013). The region surrounding the site spreads over  $36 \text{ km}^2$  and has a population of 25,000; the surrounding region is devoid of any industrial activity and has low vehicular traffic. Geophysical attributes of the sampling site are representative of the state's rural regions. The Jawali region has three state government funded primary health centers (HC) catering to the population; the health centers maintains daily outpatient data records in conformity with ICD10 code (Narayana et al., 2010; CBHI report, 2005). The prevalence of state-wide practice of biomass combustion as a primary energy source exists in the Himalayan region, which to a large extent contributes to the poor ambient air quality and high concentration of PM in the environment (Kumar and Attri, 2016). The predominant emissions from biomass combustion, fine PM ( $\text{PM}_{2.5}$ ), Elemental Carbon (EC), Black Carbon (BC), Organic Carbon (OC) and UV absorbing Organic Compounds (UVOC) affects the ambient environment quality and may in turn have a role in the reported RDI from this region; at the same time the role of other environmental factors (e.g. meteorological variables) cannot be ruled out (Goswami and Baruah, 2014).

The manuscript presents the collection and analysis of time series data-sets of Respiratory Disease Infections (RDI) counts, ambient PM (proxy for air pollution) and meteorological variables over fourteen months. The counts included cases of respiratory distress syndrome, cough and cold, bronchial asthma, bronchiolitis, pneumonitis, pharyngitis, laryngitis and tonsillitis as classified by Central Council of Indian Medicine conforming to ICD10 code. In addition to the consideration of mass concentration of collected PM ( $\text{PM}_{2.5}$  and  $\text{PM}_{10}$ ) their composition in terms of associated carbon forms (TC, EC, BC, OC and UVOC contents) were also taken into account as explanatory variables. Average meteorological variables conforming to the PM sample collection time span were considered as a part of the analysis. The analysis of the time series data-sets (RDI with PM, PM-composition and meteorological factors) were subjected to descriptive exploratory statistical analysis (Merrill, 2010). The appraisal of the time scale of multi-cyclic influences in the respective time series data-sets was detected by measuring AutoCorrelation Function (ACF). The respective time series data was analyzed using Ensemble Empirical Mode De-composition (EEMD) algorithm to extract and evaluate the present multi-cycles in the respective time series data-sets as internal mode functions (IMF) and determines non-linear trends. Multiple linear regression analysis (MLR) was done to evaluate the association of trend in RDI with the trends in the respective explanatory variables (PM, PM-composition and meteorological variables).

## 2. Material and methods

### 2.1. Ambient $\text{PM}_{10}$ and $\text{PM}_{2.5}$ load and meteorological variables

The sampling of PM in two size fractions were initiated from Jan 2012 to Feb 2013 over fourteen months in a time series, the collection of each sample was done over 24–30 h at a height of 20 feet above the ground. The collection of  $\text{PM}_{2.5}$  was done at a fixed time interval of 5 days on 46.2 mm PTFE filters (EPA certified, Whatman 7592–104), using a low volume sampler operated at a constant air flow of  $16.7 \text{ l min}^{-1}$  (Envirotech–APM 550 MFC); whereas  $\text{PM}_{10}$  samples were collected in a time interval of 10 days on Quartz microfibre filters (Whatman QMA 1851–865) using a high volume sampler (Envirotech, Model-APM 460 BL) at a constant air flow rate of 1.0 and  $1.1 \text{ m}^3 \text{ min}^{-1}$ . The quartz filters used were prebaked at  $550^\circ\text{C}$  for 6 h prior to their use in the collection. The mass of the collected PM ( $\text{PM}_{10}$  and  $\text{PM}_{2.5}$ ) samples was estimated gravimetrically ( $\mu\text{g}/\text{m}^3$ ) using a Sartorius electronic micro-balance (precision  $\pm 10 \mu\text{g}$ ) and stored at  $-18^\circ\text{C}$  until their analysis. The corresponding time series data of meteorological variables for the sampling location— Dew point (DP), Planetary Boundary Layer (PBL), Relative Humidity (RH), ambient temperature (T), Precipitation (PPT), Wind Direction (WD) and Wind speed (WS)— was accessed from Air resource laboratory (<http://ready.arl.noaa.gov/EADYcmet.php>).

### 2.2. The analysis of $\text{PM}_{10}$ and $\text{PM}_{2.5}$ associated carbon forms: TC, OC, EC, BC and UVOC

The mass of the collected PM ( $\text{PM}_{10}$  and  $\text{PM}_{2.5}$ ) samples were estimated gravimetrically ( $\mu\text{g}/\text{m}^3$ ). Carbon species (TC, OC and EC) present in the samples were estimated by using Thermal/optical carbon analyzer (DRI Model 2001A, Atmos-lytic, Inc., Calabasas, CA, USA) following IMPROVE\_A protocol (Chow et al., 2007). The estimation of BC and UVOC (UV absorbing organic carbon) present in the  $\text{PM}_{2.5}$  samples was done using a dual wavelength measurements (880 and 370 nm) Transmissometer (Magee scientific, USA). The measured values were appropriately corrected with reference to the field blanks.

### 2.3. Statistical analysis of time series data-sets: RDI, $\text{PM}_{10}$ , $\text{PM}_{2.5}$ , PM associated carbon forms and meteorological variables

Time series data-sets of RDI cases,  $\text{PM}_{10}$ ,  $\text{PM}_{2.5}$ , PM associated carbon forms (TC, OC, EC, BC, UVOC) and of meteorological variables (DP, PBL, RH, T, PPT, WD and WS) were subjected to descriptive and analytical statistical analysis (skewness, kurtosis, mean, median and mode). The average values of the collected  $\text{PM}_{10}$  and  $\text{PM}_{2.5}$  samples and the associated carbon forms, obtained over the duration of investigation, are given in Table 1. Calculated estimates of non-parametric Spearman's  $\rho$ -correlation (Table S1) and Autocorrelation Function (ACF) was used to detect the presence of persistence (multi-cycles) in the respective time series data-sets. Presence of multi-collinearity between the time series data-sets of all variables was calculated by estimating their Variation Inflation Factor (VIF). Selection of explanatory variables having  $\text{VIF} < 3.0$  were considered as an independent variables for MLR modeling to explain the association of RDI trends.

### 2.4. Determination of time dependent cyclic variability and trend in time series data-sets

The temporal profiles of all data-sets, RDI cases and predictor variables manifested a large time dependent variation; attributes common to almost all environmental geophysical proxy temporal

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