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Analyzing Effects of Forest Fires on Diurnal Patterns of Ozone Concentrations

By

H. K. PREISLER¹⁾, N. E. GRULKE²⁾, A. BYTNEROWICZ²⁾ & A. ESPERANZA³⁾

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Summary

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Monitoring and predicting ozone concentrations are a matter of special concern because ozone is one of the most important plant-damaging air pollutants in the world. High ozone concentrations have been shown to be harmful to plants not only within urban areas but also in remote regions such as national forests and parks in the USA. While meteorological stations collecting hourly data are available in many remote areas, there are only a handful of locations with continuous ozone monitors in the Sierra Nevada. This necessitates the need for a statistical model that predicts ozone concentrations from meteorological data. In this paper we develop an autoregressive model that uses nonparametric smoothing splines to estimate the nonlinear effects of meteorological data and fire history on diurnal ozone levels. The estimated relationships may be useful, among other things, as input to dynamic ozone forecasting models (e.g. MM5) to estimate ozone levels at locations or times with no active monitor data or to study effects of nearby prescribed and wild fires on ambient ozone levels.

Introduction

Monitoring and predicting ozone concentrations are a matter of special concern because ozone is one of the most important plant-damaging air pollutants in the world. High ozone concentrations have been shown to be harmful to plants

¹⁾ USDA Forest Service, Pacific Southwest Research Station, 800 Buchanan St, WAB, Albany, CA 94710, e-mail: hpreisler@fs.fed.us

²⁾ USDA Forest Service, Pacific Southwest Research Station, Riverside, CA 92507.

³⁾ Resource Management Office, Sequoia National Park, 47050 Generals Hwy, Three Rivers, CA 93271.

not only within urban areas but also in remote regions such as the national forests and parks in the USA.

Sequoia National Park is the most polluted National Park in the United States. Averaged over the last 16 years, ozone concentrations exceed the California state standards 30 d per summer (GRULKE & al. 2003). Fossil fuel consumption in the San Francisco Bay area as well as use of nitrogenous fertilizers in the San Joaquin Valley upwind both contribute to poor air quality in Sequoia National Park (UNGER 1978). Because wildland fires produce the precursors of ozone formation, the effect of fires on air quality in Sequoia National Park is an emerging issue.

Previous studies have identified air temperature, relative humidity, solar radiation and wind speed as important meteorological variables for predicting ozone (KRUPA & al. 2003). Proximity to pollution sources (e.g., fires), is another source of variability in ozone levels at a given site. Attributing increases or decreases in ozone to a specific source, such as fire, is a major challenge in using field data because it is not possible to quantify all sources of variations. A statistical model that accounts for some of the sources of variability and predicts concentrations with specified precision is an important tool.

In this paper we describe a statistical model for estimating diurnal ozone patterns using meteorological data. We used multiple regression with cubic splines (GREEN & SILVERMAN 1994) to estimate the simultaneous nonlinear effects of meteorological variables on ozone. The model included an autoregressive error structure to incorporate serial correlations over time. We demonstrate the use of these methods by studying the effects of surrounding fires during a period of 8 year (1996-2003) on ozone levels at a meteorological station site in Sequoia National Park.

Material and Methods

Data

The Lower Kaweah meteorological station was located at 1905 m in elevation, with direct exposure to air masses moving from the San Joaquin Valley. Air flow to the station was not impeded by vegetation. The meteorological data included hourly values of temperature, relative humidity, wind speed, wind direction, and ozone concentrations (ppb). Total global radiation was not used in the model because of autocorrelation with temperature and hour of day. Ozone concentrations were measured with a Thermo Environmental Model 49 UV absorption instrument operated by the National Park Service. The ozone monitor was calibrated at the beginning and end of the season and checked against a calibrator every week. Accompanying air pollutant concentrations are described in BYRNEROWICZ & al. 2002. Air temperature and relative humidity were measured with a Vaisalles sensor mounted at approximately 9 m in a self-ventilated, louvered shelter. Wind speed and direction were monitored with a MetOne anemometer mounted at 10 m. Data was collected on a Campbell 21x data logger, which acted as a data acquisition system for an IBM computer, where data was monitored and stored. We also obtained data on locations, dates, and sizes of all fires within a 100 km radius of the Lower Kaweah meteorological station between 1996-2003 (Fig. 1).

Statistical model

The statistical model we used to describe the simultaneous relationship between hourly ozone concentrations and meteorological and other explanatory variables was

$$Y = \alpha + \beta_1 bs(X_1) + \beta_2 bs(X_2) + \beta_3 bs(X_3) + \beta_4 bs.per(X_4) + \beta_5 bs(X_5) + \beta_7 bs(day) + \beta_8 X_1: bs.per(hour) + \text{error} \quad (1)$$

where Y is the square root of the hourly ozone concentration; X_1, \dots, X_5 are hourly values of the

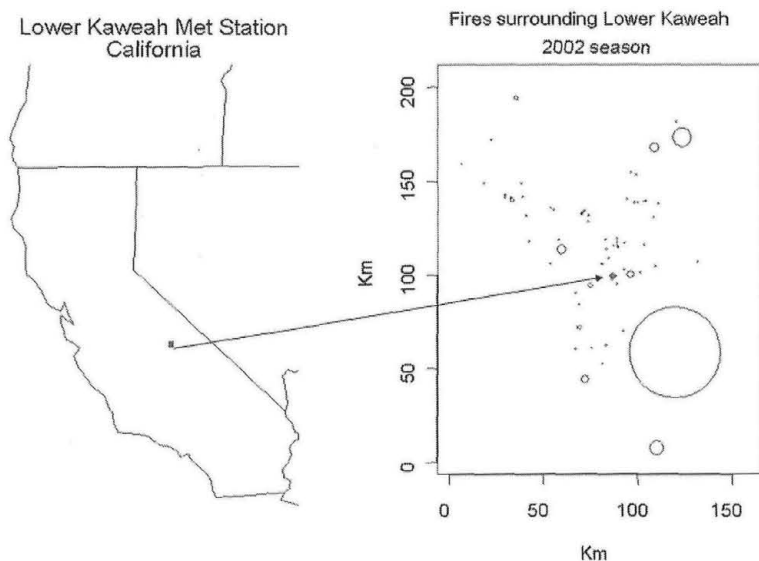


Fig. 1. Location of the Lower Kaweah meteorological station in Sequoia National Park, California, USA (left panel) and fires within 100 km radius of the station for 2002 fire season (right panel). Fire locations are at the center of the circles. Radius of circle is in proportion to the square root of the fire size.

meteorological variables temperature, humidity, wind speed, and wind direction; X_5 is a fire variable described in the next section; *day* is the day in the year; *hour* is the hour in the day. The model above includes interaction between temperature and hour of day. The $bs(X)$ functions represent the piecewise-cubic basis expansions of the original variables (HASTIE & al. 2001). The $bs.per(X)$ function is a periodic spline used for variables that are cyclic such as hour in day and wind direction.

We chose to model the square root of the hourly ozone values because the histogram of the square root data was better approximated by a symmetric distribution (an assumption needed in regression models) than the original untransformed data. Other authors have also indicated the need for fitting distributions other than the Gaussian when analyzing ozone data (KRUPA & al. 2001). Another assumption of ordinary regression is the independence of the error terms. Hourly ozone data exhibit serial correlations between consecutive time points. Our model incorporated serial correlation by fitting an autoregressive model to the error term in equation (1). We used the linear mixed effect model `lme()` in SPlus (S-Plus 6) to produced estimates of the nonlinear relationships in (1) and to extract the effects of fire on ozone levels. In order to incorporate non-linear smooth functions, e.g. splines, in the `lme` model we first had to determine the basis function for each of the explanatory variables. This was done with the function `bs()` in Splus. Once the basis functions are determined they may be included linearly in the linear mixed effect model.

Fire variable

We generated three different variables that describe the level of fire activity within a radius of 100 km from the meteorological station of interest. The variables were weighted sums of all fires within 100 km radius. For each fire, the weights depended on the size of the fire, the location of the fire and the time since the start of the fire. Specifically, the fire variables were defined as follows: Let U_i be the variable describing the fire activity within 100km of the station at time t_i . Let V_{ik} be the contribution of the k^{th} fire at time t_i , then $U_i = \sum_k V_{ik}$. We considered three different quantities for the variable V_{ik} . The simplest variables was given by

$$V_{ik} = \sqrt{\frac{Size_k}{Distance_k}} e^{-0.05\tau_{ik}} \tag{2}$$

where, $Size_k$ is the size of the k^{th} fire when it was finally brought under control; $Distance_k$ is the distance between the point of discovery of the k^{th} fire and the meteorological station; τ_{ik} is the time (hours) since the start of the fire. Note that the variable as defined in (2) does not include effects of wind speed or direction. The second variable we considered included prominent wind directions by multiplying equation (2) by the azimuth angle between the meteorological station and the fire location. Here the assumption is that prominent wind directions in the region are from the north-west. The third fire variable included both wind speed and wind direction in generating V_{ik} . This was done by replacing the $Distance$ variable in (2) by an effective distance (ED) given by

$$ED_{ik} = Distance_k - \sum_{i=1}^{\tau_k} v_{ik} \cos(\theta_{ik}) \tag{3}$$

where θ_{ik} is the wind speed at time t_i and at the location of the k^{th} fire and θ_{ik} is the angle between the direction of the wind and the direction of the fire from the station. In equation (3) the effective distance between the fire and station changes hourly as the wind speed and direction change each hour.

The three different fire variables were generated for each fire season between 1996 and 2003 (Fig. 2). In this study we did not have the wind speed and direction at the fire locations.

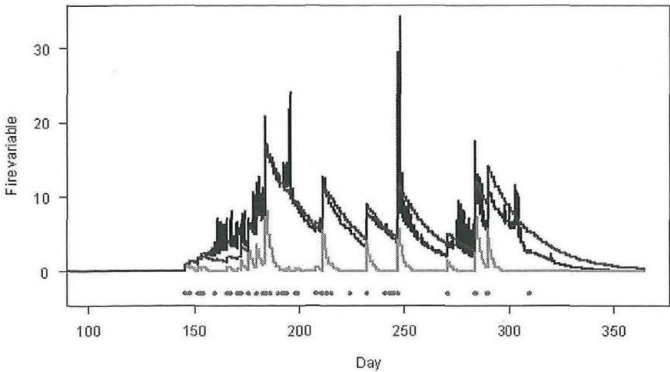


Fig. 2. Three different fire variables describing the activity of 2001 fire season in 100km region surrounding Lower Kaweah meteorological station. Dots below zero indicate the starting time of a fire. Lowest curve is the fire variable with no wind effects. The curve with the highest value is a fire variable with hourly wind effects.

Instead, we used the corresponding values at the meteorological station to generate the effective distances in equation (3). We realize the limitations of this fact, however, we have included the description in (3) as a demonstration of how a fire variable may be generated. We are now in the process of getting more appropriate weather data for calculating the variable in (3).

Results and Discussion

All four meteorological variables included in the model – temperature, relative humidity, wind speed, wind direction- had significant effects on hourly ozone levels (Fig. 3). The hour-in-day and day-in-year variables had the largest effects on ozone. In addition to air temperature, the temporal variables are surrogates for other weather variables (e.g., solar radiation) not included in the model. There was a significant, albeit small, effect of fire activity on hourly ozone concentrations. Of the three fire variables, the one that had the most significant effect was the variable with no wind effects. This may be due to the fact that we did not have wind data at the fire locations and the fire variables was generated using wind data at the meteorological station.

The model fit was reasonable (Fig. 4). The median absolute deviation (MAD) between observed and predicted ozone levels was 6.8 ppb. Using this model one may calculate the effects of fire activity surrounding a given location after taking into account other sources of variation. For example, according to the fitted model, a fire of size 200 hectares and at a distance of 20 km will on average increase ozone levels by 3-5 ppb (95% CI).

We found the statistical methods developed in this work to be a useful tool for predicting and studying effects of weather and other variables on ambient ozone levels. In this particular case study we have demonstrated that a statistical model with a few weather variables, together with a day-in-year and hour-in-day variables, can give reasonable predictions of ozone levels at a given location.

Our future work will concentrate on getting wind data from 'upwind' weather stations; generating better fire activity variables; and including other explanatory variables (e.g. passive sampler data). We are also testing whether this statistical modelling approach of predicting hourly ozone concentrations can be used for other locations.

Based on these preliminary analyses, hourly ozone concentrations can be fairly well predicted from meteorological conditions and time of day and year in the central Sierra Nevada. We can suggest that fire (prescribed and wildfire) affects local ozone concentrations by a small but significant amount (3-5 ppb). We can also make the recommendation that if a decision to prescribe fire were to be based on air quality, the prescription should be delayed until ambient ozone concentrations were 10-12 ppb below the California state standard (90 ppb hourly), when confidence intervals in the data are considered.

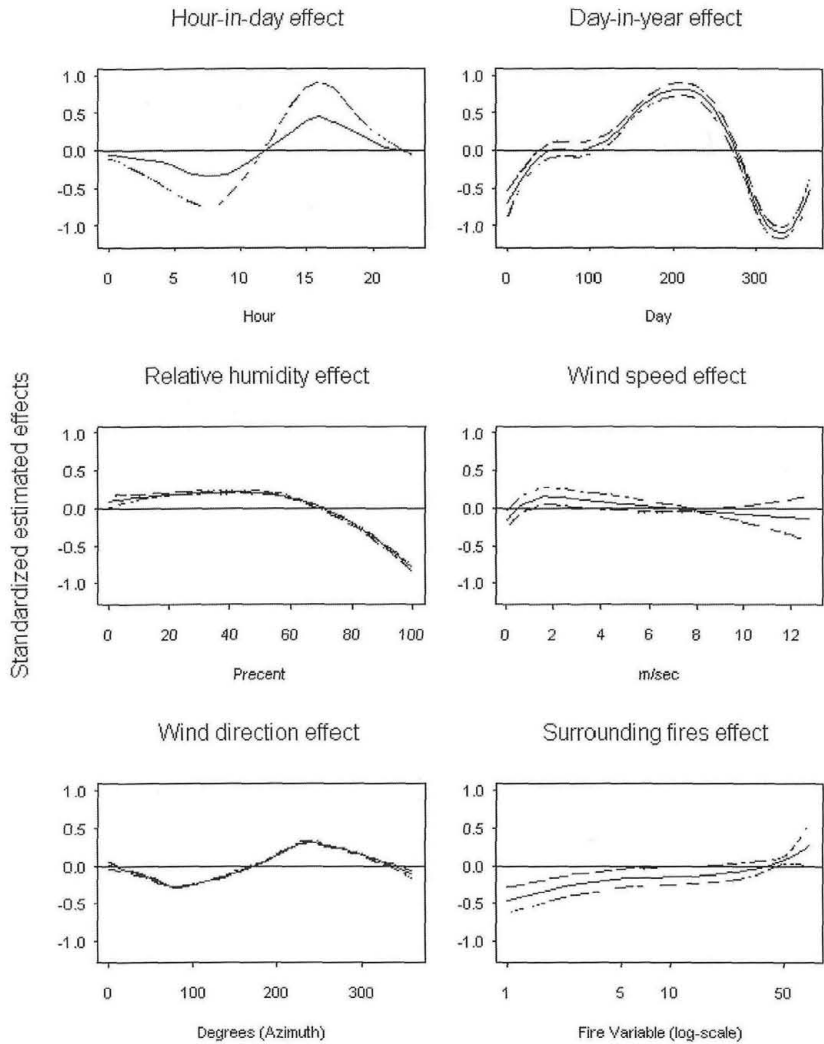


Fig. 3. Standardized estimated partial effects of explanatory variables on hourly ozone concentration. Dashed lines are 95% point-wise confidence bounds. The first panel presents the effect of hour in day that is not explained by changes in wind, relative humidity or fire activity evaluated for a typical spring day with average temperature 8.9 °C (dashed curve) and a typical summer day with average temperature 20.7 °C (solid curve).

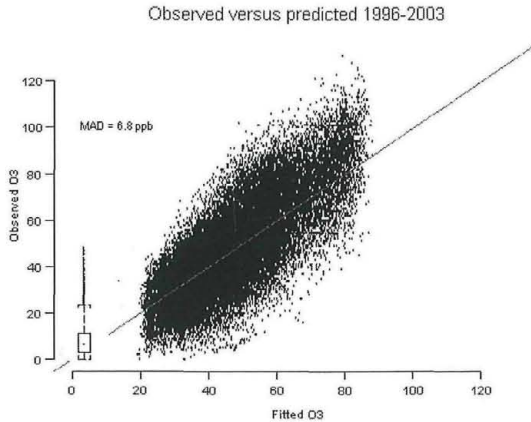


Fig. 4. Observed versus predicted (fitted) values of ozone (ppb) and a boxplot showing the distribution of absolute differences between the observations and their corresponding predicted values from the statistical model.

A c k n o w l e d g e m e n t s

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