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A wavelet analysis of multiday extreme ozone and its precursors in Mexico city during 2015–2016

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ABSTRACT

During the past decades, many authors have studied extreme ozone (O_3) events on successive days in several cities around the world, where extreme pollution concentrations are considered as values exceeding air quality standards. These multiday episodes are caused by different variables: weather conditions, pollution precursors life times and air pollution transport. However, a complete characterization of the temporal behavior of multiday extreme O_3 episodes is still lacking. In the present paper, we used the Haar wavelet transform to study the period (T in days) of multiday extreme O_3 episodes in Mexico city during 2015–2016, when 10 ozone contingencies occurred and changes in driving restrictions were implemented. In addition, we studied the temporal correlations between extreme O_3 and extreme: nitrogen dioxide (NO_2), carbon monoxide (CO) and ultraviolet B radiation (UVB) for a broad range of time scales by means of the Haar Wavelet cross-correlation method. The results show that multiday O_3 episodes mainly exhibit periods of $T > 4$ days, while NO_2 and CO show multiday episodes comprising principally periods of $T > 2$ days. The cross correlation analysis reveals that CO and NO_2 are temporal anti-correlated with O_3 for daily variations $T < 1$. However, NO_2 and CO are strongly and moderately correlated with O_3 for $T > 4$, respectively, indicating that NO_2, CO and O_3 are correlated in a multi-temporal clustered form.

1. Introduction

Recently, there has been an increasing concern about ground-level ozone (O_3) pollutant in urban areas; the large vehicular fleet, meteorological and geographical conditions have led to high ozone concentrations that generate adverse health impacts (Shields et al., 2013; Arceo et al., 2016). O_3 is not a compound that is emitted directly into the atmosphere; its production is a complex phenomenon which conforms a variable system that depends on the non-linear interaction between its precursors operating at different time scales. O_3 is formed from chemical reactions between oxides of nitrogen (NO_x) and volatile organic compounds (VOC's) (Logan, 1985; Monks, 2005; Monks et al., 2015). The production of ozone occurs from the photolysis of NO_2 in nitric oxide (NO) and reactive oxygen (O); the latter reacts with the molecular oxygen of the air (O_2) to form O_3. Ozone also requires sunlight (ultraviolet radiation) for its formation; therefore, peak values always occur during the day. Variations in concentrations of O_3 and its precursors have been widely studied for diurnal and seasonal periods. For example, for diurnal variations, air pollutants have temporal correlation, except for ozone, that in general is temporal anti-correlated with other pollutants (Wang et al., 2014; Bhardwaj, 2012). Besides, the VOC-limited and NO_2-limited regimens determine the daily ozone production. Using fractal and multifractal analysis. Several authors have reported that pollution time series displays long-range time autocorrelations (Meraz et al., 2015; He, 2017; Jiménez-Hornero et al., 2010; Plocoste et al., 2017), indicating that the temporal patterns in pollution concentrations tend to repeat for a broad range of time scales. This fractal behavior has also been found for extreme pollution events (Chelani, 2012, 2016).

Furthermore, O_3 concentrations are frequently reported as a multiday phenomenon, when several factors play important roles: ozone precursors (CO and NO_2) life times (Konovalov et al., 2011), weather conditions (Ryan, 1995) and air transport (Wang and Kwok, 2003; Ding et al., 2004). The spatial extension of multiday O_3 episodes have been studied and forecast (Schnell et al., 2014), and a quantitative analysis of multiday O_3 air visibility was provided in (Fu et al., 2013). Moreover, a complete characterization of the temporal behavior of multiday O_3 episodes is still lacking, particularly, the characteristic frequency of multiday extreme O_3 episodes has been poorly studied by statistic tools. On the other hand, wavelet analysis is not only recognized as a reliable

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method for the detection of fractal behavior (Lowen et al., 2001; Davis, 2017; Domingues et al., 2005; Thurner et al., 1998), but also suitable for the analysis of characteristic frequencies on atmospheric variables (Lau and Weng, 1995).

Mexico city is one of the most populated cities in the world, and has been recently affected by extreme O_3. The extreme concentrations are caused by industrial areas and vehicles that emit O_3 precursors: CO and NO_2 (Molina et al., 2010; Garzón et al., 2015; Baklanov et al., 2016). In addition, the geographic location of Mexico city with mountain ridges affects the air pollutant dispersion and transport (Cassiani et al., 2013). In order to reduce air pollutants, the Mexican government has made some efforts in implementing driving restrictions; the programs "Hoy no circula" (weekday driving restriction) and "Hoy no circula sabatino" (Saturday driving restriction), bans drivers from using their vehicles one weekday per week and some Saturdays depending on the last digit of the vehicle's license plate. However, there is evidence that these programs have not reduced the pollution significantly (Davis, 2017), besides, on March 14, 2016 the ozone values surpassed the threshold alarm contingency reaching 210 ppb, considered as extremely unhealthy. From this date, another 9 ozone contingencies (O_3 > 150pbb) occurred during year 2016 (Velasco and Retama, 2017).

Here, we use wavelet analysis to study the duration and frequency of multiday extreme O_3 episodes in Mexico city. We obtain the Haar wavelet variance of extreme pollutant concentrations. In addition, we study the temporal correlation between multiday O_3 episodes and multiday episodes of O_3 precursors: CO, NO_2 and UVB radiation. The analysis of temporal patterns in O_3 dynamics, including temporal cross-correlation, is a powerful tool for understanding the mechanisms underlying the formation of O_3. We use the wavelet cross-correlation method to identify temporal correlation between extreme values of ozone and its precursors for a broad range of time scales, giving fine time detail about pollutants interaction.

This work is organized as follows. In the Materials and Methods section, we give a brief description of the data preprocessing and the methods: the Haar wavelet variance and the Haar wavelet cross-correlation. The results section presents our findings about the Haar wavelet variance of O_3 and its precursors, and the cross-correlation between O_3 and its precursors. Finally we provide some concluding remarks.

2. Materials and methods

2.1. Data and preprocessing

Data was extracted from the Automated Environment Monitoring Network (Red Automática de Monitoreo Atmosférico, RAMA), which includes 29 stations monitoring air pollution contaminants distributed around Mexico City. From late October 2015 to July 2016, there was an increase of 1 million vehicles caused by the relaxation political decisions about traffic restrictions. The changes in restrictions promoted 10 ozone contingencies from March 14 to August 11, 2016. In order to study the coupling between ozone and its precursors during contingencies, we processed one year data from December 1st, 2015 to November 30th, 2016. The seasons that we considered are winter (December–February), spring (March–May), summer (June–August) and fall (September–November). During spring season, there were 8 ozone contingencies; so we compare the results observed during spring season with the results observed in the rest of the seasons.

We preprocessed each pollutant data in order to analyze only extreme concentrations. First, we obtained the maximum value among all stations for each pollutant per hour, and we call it the *hourly sequence*. This is the same strategy that the Mexican government uses to report hourly concentrations of air pollutants to the public. Next, we stated that an extreme event occurs when the *hourly sequence* exceeds a standard threshold. Finally, from the *hourly sequence*, we created another sequence called point process that consists of 0's and 1's (1 when there is an extreme event) for each pollutant. Extreme ozone concentrations as point process were first studied by Smith (Smith, 1989; Smith and Shively, 1995). In the case of O_3, we used the Mexican legislation threshold value of 95 ppb for one hour concentration; equal or greater values of the standard threshold are considered unhealthy. For CO and NO_2 cases, the pollution data did not reach the Mexican threshold standards for one hour concentration (210 ppb for NO_2 and 11 ppm for CO), and there are no Mexican standards for 8 and 24 h concentrations. Because of the lack of Mexican standards, we used Delhi standards, which have been used in previous studies of extreme values of pollutants (Chelani, 2012, 2013). The standards are: 42 ppb for NO_2 and 1.8 ppm for CO.

In addition, RAMA includes 10 stations that register UVA (315–400 nm) and UVB (280–315 nm) radiation. We also compared temporal correlations between ozone and UVB radiation which is involved in the photo-chemical production of ozone. For UVB radiation, we used the international standard ultraviolet (UV) index (Organization et al., 1998). We analyzed the threshold value UV index 8, that is considered very high.

2.2. Haar Wavelet variance

The Haar wavelet variance or Allan variance was proposed to measure the temporal behavior of events or point process (Torrence and Compo, 1998; Lowen and Teich, 2005). The Haar wavelet variance measures the fractal temporal distribution of successive events and its inter-event time distribution. This temporal pattern (also known as burstiness) has been observed in diverse systems such as earthquakes (Goh and Barabási, 2008), emails (Barabasi, 2005), neural discharges (Lowen et al., 2001), heart beat intervals (Thurner et al., 1998), word-length sequences (Quezada-González et al., 2017) and self-organized critical systems (Aguilar-Velázquez and Guzmán-Vargas, 2017). If we consider $x(t)$ as a point process of the pollution time series, the Haar wavelet coefficients of $x(t)$ are given as a function of time t (in hours) and period T (in days):

$$W(t, T) = \sum_{t-T}^{t+T} x(t)\psi(t-\tau) \tag{1}$$

where

$$\psi(\tau) = \begin{cases} 1 & \text{if } -T < \tau < 0 \\ -1 & \text{if } \ 0 \leq \tau < T \\ 0 & \text{otherwise .} \end{cases} \tag{2}$$

Next, we define the Haar wavelet variance $V(T)$ at period T:

$$V(T) = \frac{\sum_{t=1}^{N} W(t, T)}{2\mu_T} \tag{3}$$

where N is the number of time steps of $x(t)$, $\sum_{t=1}^{N} W(t, T)$ represents the sum of the wavelet coefficients at period T and μ_T is the mean value. We worked with diverse time periods T, from 1 h to 8 days. The Haar wavelet has been used for the detection of high frequency episodes, and can be interpreted as the difference in the number of events in $x(t)$ between two consecutive time windows of period T. For example, if we want to know the frequency of daily ozone between day hours and night hours, we need to set $T = 0.5$ (12 h).

2.3. Haar Wavelet cross-correlation

In order to analyzed the correlation between extreme values of O_3 and its precursors for different time t and period T, we obtained the wavelet cross-correlation coefficients (Torrence and Compo, 1998):

$$C(t, T) = \frac{W_{O_3}(t, T)W_{pre}(t, T)}{\sigma_{O_3}\sigma_{pre}} \tag{4}$$

where $W_{O_3}(t, T)$ is the wavelet coefficient of O_3 at time t and period T,