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AN ASSESSMENT OF SEVERITY OF ENVIRONMENTAL AEROSOL PARTICLES DURING PRECIPITATION

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Abstract

Africa is one of the sources of biomass burning emissions. It is estimated that about 6 million tons of fuel per day is consumed in the southern hemisphere. Biomass burning has an important contribution on aerosol particle concentrations in the atmosphere. Efforts have been made to conduct research in Gaborone to monitor the concentration of atmospheric aerosols in atmosphere. These studies were mainly confined to measurement of concentration of aerosols and establishing a relation with determinants such as carbon dioxide concentration, biomass burning, and precipitation among others. However, very little seems to have been done in relating the empirical data to a mathematical model or to study quantitatively the impact of precipitation on the concentration for classifying measurements on concentration of atmospheric aerosol particles and build a mathematical model that helps us to understand variations in weekly aerosol concentrations in terms of their severity. We also construct an index of severity which when applied to different seasons under the study period indicates that precipitation significantly scavenges atmospheric aerosols.

Keywords: Atmospheric aerosols, Biomass, Classification rule, Multinomial model, Precipitation, Severity index

Introduction

Precipitation is the process of transporting water from the atmosphere back to earth's surface. It links climate, weather and the global hydrological cycle. Atmospheric aerosol particles can contribute in climate change by absorbing and scattering solar and infrared radiation. It can indirectly influence climate by altering the properties of clouds (Lohmann and Feichter, 2005). It can also collect other cloud droplets and leads to in cloud scavenging (Andronache et al., 2005). Removal of atmospheric particles during precipitation is the major way of sink of aerosols. The atmospheric particle concentration measurements were made over different parts of the world by various researchers (Wallace and Hobbs, 1977; Verma and Javaratne, 2001; Hitchins et al., 2000). Many studies have been conducted to monitor the aerosol particles due to biomass burning. For example, Xuejiao et al, 2008 showed that the biomass burning in south East Asia has an important contribution on aerosol concentrations. A study in Southeast Asia (Ma et al., 2003) showed that the biomass burning plume contributes approximately 35-40% of the fine organic aerosol mass in the Pacific Ocean. The concentration of aerosol particle were observed to decrease during rain (Sisterson et al., 1985) The studies conducted in Gaborone, Botswana (Jayaratna and Verma, 2001; Verma and Thomas, 2007) also showed that there is an increase in atmospheric particle concentration during winter season due to biomass burning.

The study reported here was an ongoing research in the department of Physics, University of Botswana. The various studies on aerosol particles were mainly confined to measurements of concentration and establishing a possible relation with determinants such as carbon dioxide concentration, biomass burning and precipitation among others. However, very little seems to have been done in relating the empirical data to a mathematical model or to assess quantitatively the impact of precipitation on the concentration of aerosols larger than 0.3 µm in the atmosphere. In this paper, we provide an objective criterion for classifying measurements on concentration of atmospheric aerosols depending on their severity and construct a mathematical model that helps us to understand variations in weekly aerosol concentrations in terms of their severity. The analysis from the stated mathematical model indicates that precipitation scavenges atmospheric aerosols.

The research to establish the relationship between particle concentration and rainfall was carried out around Gaborone, Botswana. Botswana, as shown in the map in Figure 1, is a land-locked country in southern Africa surrounded by Namibia to the west, South Africa to the east and south and Zambia and Zimbabwe to the north. The Country lies between longitudes 20 and 30 degrees east of Greenwich and between the latitudes 18 and 27 degrees approximately south of the equator. It is approximately 500 km from the nearest coast line; to the south west (Geographical info, 1996).



Figure 1. Map of Botswana showing the experimental site

Botswana is hot and dry for much of the year. The rainy season is in summer, which brings high temperature and is between November and March with the peak in January and February. Rain is unpredictable and regional, sometimes followed by sunshine. The mean annual rainfall is about 650 mm in the north and 250 mm in extreme south (Botswana geographical info, 1996). Winter is in between May and August. Winter days are sunny and warm; but night temperature can drop below freezing point in some places. Since study was done in Gaborone, it would help to state annual rainfall in Gaborone as well as common range of temperatures for Gaborone in winter.

Materials and methods

The atmospheric particle concentration was monitored in the Physics department at the University of Botswana in Gaborone. The measurements were made using automatic laser scattering particle counters from Rion KC-18, which detects particles as a function of size and separates them into five categories (0.1 μ m, 0.15 μ m, 0.20 μ m, 0.30 μ m and 0.50 μ m) larger than or equal to 0.1 μ m and the model KC-01, which detects particles larger than or equal to 0.3 μ m and separates them into 6 categories (0.3 μ m, 0.5 μ m, 0.7 μ m, 1.0 μ m, 2.0 μ m and 5.0 μ m). The air sample was drawn through plastic tubes of diameter 5 mm and of length 1.8 m from outside and about 10 m above the ground. The humidity and temperature at all times of observations were also recorded. Readings

were taken at 12 noon every day, assuming that, at that time of the day atmosphere was relatively calm. Rain fall data was collected from the Botswana meteorological department in Gaborone.

The study period consisted of 91 weeks from September 2006 to August 2008. In each week measurements were taken on successive days. The frequency of sampling in each week varied from two to seven days depending on the availability of experimental, human and capital resources.

For the purpose of the study, the recorded measurements were grouped into three distinct non overlapping seasons namely dry season (April, September and October), rainy season (November, December, January, February and March) and winter season (May, June, July and August). This classification of seasons is consistent with the practice followed by Botswana meteorological department. For the dry season, observations were obtained for 27 weeks, for winter season for 34 weeks and for rainy season for 30 weeks. The average aerosol concentration for each week was computed and the following table displays the summary findings.

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Season	No.of Weeks	Minimum	Maximum	Weekly Mean	Weekly Variance							
Dry	27	15.92 138.28		80.024	908.10							
Rainy	30	32.53	118.25	61.544	466.77							
Winter	34	13.86	164.15	76.136	1609.34							

 Table 1. Summary statistics

From Table 1, it is evident that weekly mean aerosol particle concentration measurements vary in between 61.544 particles /cc and 80.024 particles /cc during the three seasons, but they are subject to large magnitude of variations due to one or more factors. As the atmospheric aerosol particles are known to influence climate adversely, it may be of interest to study the weekly variations in an objective way. As a naïve approach, one may categorize weekly variations into certain classes based on percentage increase or decrease in the corresponding weekly mean with respect to a reference time. However, this categorization may appear subjective as percentage cutoff points may be arbitrarily defined and more over such categorization is not data driven. An objective way of categorizing weekly variations is to adopt a rule that is defined by the underlying parameters of the sampling distribution of the weekly averages; for example, the mean and standard deviation. The parameters mean and standard deviations are chosen for simplicity, as it is well known that mean measures the central tendency while the standard deviation, the spread of the underlying distribution of the data. Moreover, the interval (mean \pm 3 standard deviation) covers almost all the data. For example, when the underlying sampling distribution is Gaussian, as may be the case in several atmospheric data, the intervals (mean ± 3 standard deviation), (mean ± 2 standard deviation), (mean \pm standard deviation), are respectively known to cover approximately 97%, 95% and 68% of the observations in a given data. The concept of severity of concentration is linked to these intervals. These intervals inter alia may be used to define the severity or criticality of concentration characterizing how far individual observations are spread from the centre of the data. We essentially use this principle in our study to define classes that categorize weekly atmospheric aerosol concentration measurements.

Severity states for aerosol particle concentrations

Let the variable 't'refer to the day and 'w' denote the week. Suppose that we have a time series data of daily aerosol particle concentration measurements, P_t , t = 1, ..., N, where 'N' is the length of the study period in days. Assume that 'n' corresponds to the total number of weeks during the study period. Let ' n_w ' be the number of days in a week 'w'. (Usually n_w varies between 2 to 7, the number of days in a typical week during which particle concentration was monitored). Let the mean of aerosol particle concentration for week we given by

$$\overline{P}_{w} = \frac{1}{n_{w}} \sum_{t=1}^{n_{w}} P_{t}, w = 1, ..., n$$
 (1)

and the variance of aerosol concentration for week w be given by

$$s_{w}^{2} = \frac{1}{(n_{w} - 1)} \sum_{t=1}^{n_{w}} \left(P_{t} - \bar{P_{w}} \right)^{2}$$
(2)

Assuming that the weekly mean aerosol particle concentration measurements can be classified into seven states depending on their severity, we may define the following seven states: S₁: Extremely Negligible State, S₂: Moderately Negligible State, S₃: Negligible State, S₄: Normal State, S₅: Critical State, S₆: Moderately Critical State, S₇: Extremely Critical State. Further, if we assume that \overline{P}_w 's come from a population with finite mean μ_w and finite variance σ_w^2 , then we know that $E(\overline{P}_w) = \mu_w$ and $Var(\overline{P}_w) = \frac{\sigma^2}{n_w}$. Then one may use the statistic $Z = \sqrt{n_w} \left(\frac{\overline{P}_w - \mu_w}{\sigma}\right)$ to construct

appropriate classification rules for the severity of states. In Z, we replace the population mean μ_w by its unbiased estimator \overline{P}_w and the population variance σ_w^2 by its unbiased estimator s_w^2 , respectively given by (1) and (2) above. Thus, we may classify the severity of atmospheric aerosol particle concentrations in weekly data into seven states S_j , j = 1, ..., 7 as follows. For a week (w+1), w = 1, ..., n-1 the aerosol particle concentration measurement is said to belong to

(i) State S₁, if $\overline{P}_{w+1} < \overline{P}_w - 3\frac{s_w}{\sqrt{n_w}}$ (ii) State S₂, if $\overline{P}_w - 3\frac{s_w}{\sqrt{n_w}} \le \overline{P}_{w+1} < \overline{P}_w - 2\frac{s_w}{\sqrt{n_w}}$ (iii) State S₃, if $\overline{P}_w - 2\frac{s_w}{\sqrt{n_w}} \le \overline{P}_{w+1} < \overline{P}_w - \frac{s_w}{\sqrt{n_w}}$ (iv) State S₄, if $\overline{P}_w - \frac{s_w}{\sqrt{n_w}} \le \overline{P}_{w+1} < \overline{P}_w + \frac{s_w}{\sqrt{n_w}}$ (3) (v) State S₅, if $\overline{P}_w + \frac{s_w}{\sqrt{n_w}} \le \overline{P}_{w+1} < \overline{P}_w + 2\frac{s_w}{\sqrt{n_w}}$

(vi) State S₆, if
(vii) State S₇, if
$$\overline{P}_{w+1} \ge \overline{P}_w + 3 \frac{s_w}{\sqrt{n_w}}$$

 $\overline{P}_{w+1} \ge \overline{P}_w + 3 \frac{s_w}{\sqrt{n_w}}$

In the above stated classification rule, we compare the current week's mean particle concentration with previous week's mean particle concentration plus or minus a multiplier of the standard error of that week's mean to decide the state of severity that the current week's mean belongs to. The

multipliers ± 3 and ± 2 of $\frac{s_w}{\sqrt{n_w}}$ suggested here is quite appropriate in the sense that the intervals

formed with these multipliers can be shown to capture almost all variations that exist in the weekly means. For example, when the underlying distribution of weekly mean is Gaussian, the interval

$$\left(\overline{P}_{w} - \frac{3}{\sqrt{n_{w}}}s_{w}, \overline{P}_{w} + \frac{3}{\sqrt{n_{w}}}s_{w}\right)$$
 is known to cover approximately 99.73% of the variations in the

weekly means (See for example, Stuart and Ord (1994)).

A multinomial probability model for severity of states

The volatility or wide swings that are prevalent in weekly mean aerosol particle concentration measurements can be approached from the classical probability point of view in that one may model different states of severity based on a certain probability distribution. Here the volatility in means refers to the swings from one state to another over certain period of weeks. In general, suppose that there are k mutually exclusive and exhaustive states, say $S_1, ..., S_k$ to which the weekly mean P_w can be assigned based on a certain classification rule, say for example, rule (3) and let $P_r(S_j) = \theta_j$ denote the probability that a typical weekly mean $\overline{P_w}$ belongs to the state j for j = 1, ..., k. We let n_j , j = 1, ..., k to denote the number of occurrences of the state S_j in an independent sequence of the phenomena observed say, for $n = \sum_{i=1}^{k} n_i$ weeks. Then the vector $\mathbf{n} = (n_1, ..., n_k)$ follows a multinomial distribution (See for example, Stuart and Ord (1994)) with the joint probability mass function (p.m.f.) given by

$$p(n_1, n_2, ..., n_k) = \prod_{j=1}^k \frac{n!}{n_j!} \theta_j^{n_j}$$
(4)

where, $0 < \theta_j < 1$, $\sum_{j=1}^k \theta_j = 1$, $n = \sum_{j=1}^k n_j$. In general, the parameters θ_j 's in the model given by (4)

are unknown and can be estimated by their empirical estimates

$$\theta_j = \frac{n_j}{n}, \ j = 1, \dots, k.$$
(5)

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It may be pointed out that θ_j 's are in fact the unrestricted maximum likelihood estimators of θ_j 's, j = 1, ..., k. For the aerosol particle concentration data, the multinomial model that best describes different severity states given by

$$p(n_{1},...,n_{7}) = \frac{n!}{n_{1}!n_{2}!n_{3}!n_{4}!n_{5}!n_{6}!n_{7}!} \theta_{1}^{n_{1}} \theta_{2}^{n_{2}} \theta_{3}^{n_{3}} \theta_{4}^{n_{4}} \theta_{5}^{n_{5}} \theta_{6}^{n_{6}} \theta_{7}^{n_{7}}, \qquad (6)$$

for $0 < \theta_{j} < 1, j = 1,...,7, \theta_{7} = 1 - (\theta_{1} + ... + \theta_{6}), n = \sum_{j=1}^{7} n_{j}.$

Given the data on mean weekly aerosol particle concentration, using the classification rule (3) we can obtain n_j 's, j = 1,...,7 and then estimate the probabilities using (5). These probabilities may be used to interpret the likelihood of different states of severity in the long run. Finally, given the severity states of each week, one can propose a measure or an index of severity which may be used to compare severity of aerosol particle concentration across different seasons. Thus let 'j', j = 1,...,7 denote the severity states, then an index of severity is given by

$$I_{s} = \frac{1}{n} \sum_{j=1}^{n} (t_{j} - 4)^{2}, \qquad (7)$$

where, t_j is the value of the severity state corresponding to the week 'j'.For example, $t_j = 1$, if in the jth week ,the severity is state is S_1 and so on. It is seen that when weekly aerosol particle concentration measurements show normal variations purely as a consequence of randomness, then S_4 will be the severity state, in which case $t_j = 4$ and $I_s = 0$. On the other hand if weekly means show swings on either side of the normal state, I_s will be significantly different from 0. In the extreme case, it can be easily shown that the severity index $I_s = 9$. Thus, greater the value of severity index, more pronounced is the variations in the states of aerosol particle concentration. These considerations precisely constitute the rationale behind the measure I_s proposed here and in particular given different series of aerosol particle concentration measurements one can compare them in terms of the index I_s .

Results and discussion

The graphs (Figure 2- Figure 4) show the weekly mean of particle concentration for $\geq 0.3 \ \mu m$ size particles during the experimental period. It is observed from Figures that the highest concentration of particles of size $\geq 0.3 \ \mu m$ was in the winter season and the lowest concentration of particles was mainly in the rainy reason. During the winter and dry seasons, when the rain fall is low the particle counts of size $\geq 0.3 \ \mu m$ are comparatively higher than those during the rainy season for most of the weeks. The increase in particles count during the absence of rainfall could be due to the increase in biomass burning for heating purposes during that time as June – July months are the coldest months of the year in Botswana. Biomass usage for heating and cooking is very common in this country. The biomass contain large concentrations of small particles that can be activated as

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cloud condensation nuclei, which increase cloud droplet concentrations, decrease cloud droplet sizes and hence tend to inhibit precipitation due to the lack of sufficient numbers of large drops.

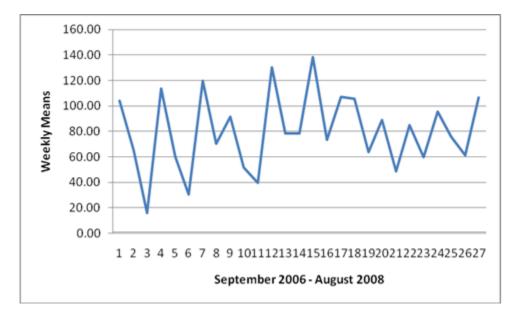


Figure 2. Weekly means of aerosol particle concentrations during dry season

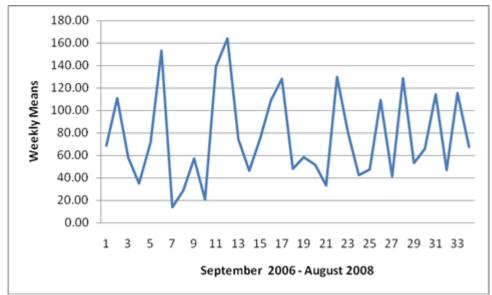


Figure 3. Weekly means of aerosol particle concentrations during winter season

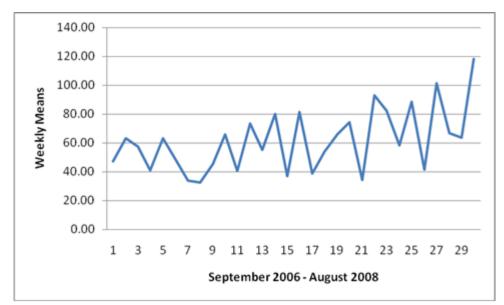
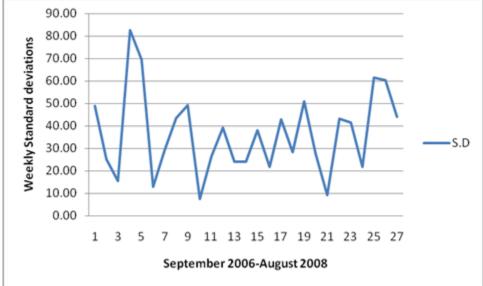
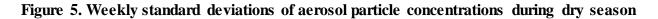


Figure 4. Weekly means of aerosol particle concentrations during rainy season The graphs(Figure 5-7) indicate the standard deviations of weekly means of aerosol particle concentration during the three seasons. It is evident that the weekly standard deviations display significant variations from one week to another in all the three seasons and therefore the magnitude of variations is another critical factor to be studied while assessing the impact of aerosol concentration in three seasons.





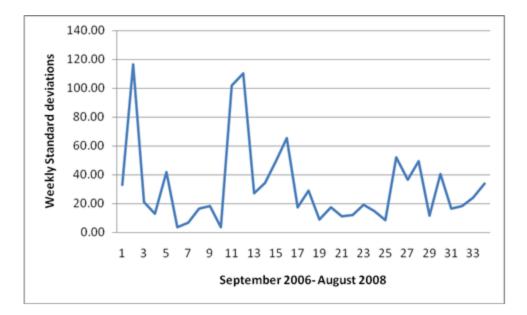


Figure 6. Weekly standard deviations aerosol particle concentrations during winter season

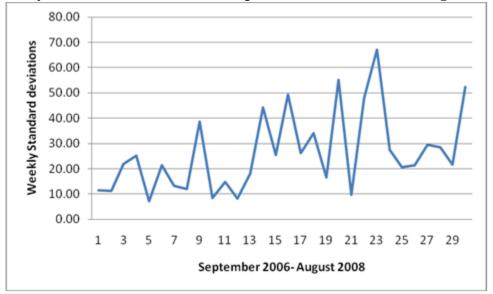


Figure 7. Weekly standard deviations of aerosol particle concentrations during rainy season

Next, we may proceed to classify the severity of weekly means of aerosol particle concentrations into seven states S_j , j = 1,...,7 following the classification rule outlined in (3). The different states of severity during the three seasons are exhibited in the following table.

Weeks /	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Seasons																	
Dry	4	3	1	7	3	4	7	2	4	3	1	7	2	4	5	1	7
Winter	4	6	4	3	7	7	1	7	7	1	7	4	3	2	6	5	4
Rainy	3	5	3	3	5	1	3	4	5	5	1	7	1	7	2	7	3
Weeks	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
Seasons																	
Dry	4	1	5	1	7	3	4	2	4	5	-	-	-	-	-	-	-
Winter	2	4	3	2	7	1	1	4	7	1	7	1	6	6	1	7	1
Rainy	5	4	5	3	7	4	4	6	1	7	2	4	7	-	-	-	-

Table 2. States of severity of weekly means of aerosol particle concentrations in 3 seasons

The graphs (Figure 8- Figure 9) depict the severity states on the weekly basis during the three seasons under study. It is very evident from the graphs that aerosol particle concentrations attain weekly peaks more often during the winter seasons followed by dry and rainy seasons. These visual findings are summarized in the following table 3.

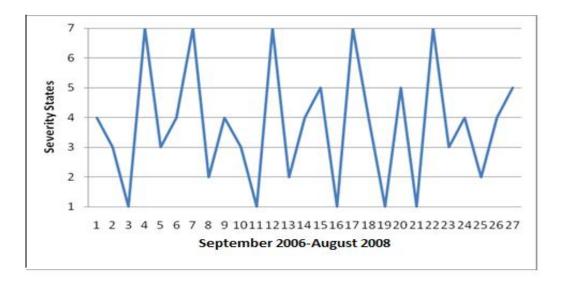


Figure 8. Weekly severity of states of aerosol particle concentrations during dry season

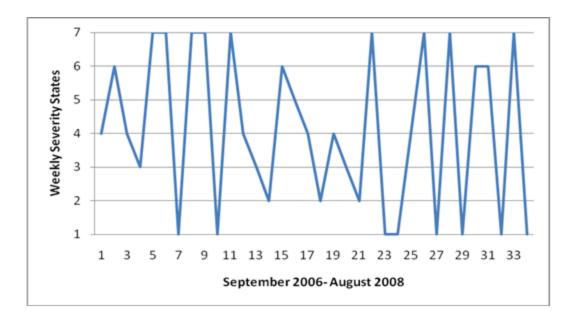


Figure 9. Weekly severity states of aerosol particle concentrations during winter season

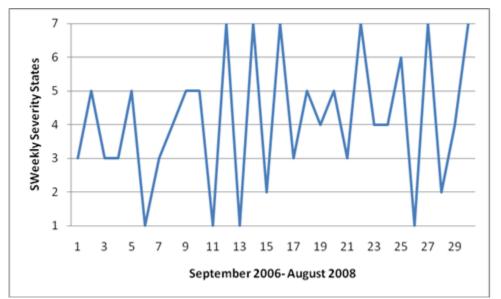


Figure 10. Weekly severity states of aerosol particle concentrations during rainy season Table 3. Summary of severity states frequencies in three seasons

States	1	2	3	4	5	6	7	Total		
Seasons										
Dry	5	3	4	7	3	0	5	27		
Winter	8	3	3	6	1	4	9	34		
Rainy	4	2	6	5	6	1	6	30		

The multinomial probability model for severity of states for three different seasons can be constructed using the frequency of severity states displayed in the above table. Table 4 below provides the empirical estimates of probabilities of severity states for the three seasons. From Table 3 and Table 4, it is seen that

- (i) The highest number of weeks (9) that stay in severity state (7) belongs to the winter season.
- (ii) If the experiment is repeated sufficiently long, out of every 100 weeks in the winter season, one would find the aerosol particle concentrations in excess of mean + 3.S.D in about 26 weeks while these would be respectively 19 and 20 for the dry and rainy seasons.

For the study period September 2006 – August 2008, it is seen that out of 91 weeks, the aerosol particle concentrations were in excess of mean + 2 S.D (severity states S_5, S_6, S_7) in about 35 weeks (38%). This finding suggests that aerosol particle concentrations are likely to be one of the agents climate change in Botswana.

States	1	2	3	4	5	6	7	Total
Seasons								
Dry	0.19	0.11	0.15	0.25	0.11	0	0.19	1.00
Winter	0.24	0.09	0.09	0.18	0.03	0.11	0.26	1.00
Rainy	0.13	0.07	0.20	0.17	0.20	0.03	0.20	1.00

Table 4. Empirical estimates of probabilities of severity of states

Finally, we compute severity indices I_s for the three seasons using the formula (7) and Table 3. It turns out that severity indices respectively for the three seasons, dry, winter and rain are given by $I_s(dry) = 4.037037$, $I_s(winter) = 5.441176$, $I_s(rainy) = 3.8$. It can be observed that the severity index for the aerosol particle concentrations is the smallest for the rainy season and the largest for the winter seasons. Recalling that severity index is a measure of departure from the normal level of aerosol particle concentrations, our analysis confirms the hypothesis that atmospheric aerosol concentration is highest during the winter months and lowest during the months of rain, the precipitation being the scavenging factor

Conclusion

The focus of this paper is to analyze variations in weekly mean aerosol concentration measurements and establish a possible relationship with the three climatic seasons in Gaborone, Botswana. The analysis is based on a new approach wherein natural variations in weekly means are perceived to belong to different categories depending on their severity of variations. These categories are defined in terms of magnitude of the spread of the daily measurements from weekly mean, a concept used in statistical theory. From our analysis, it is revealed that

- (i) severity of aerosol particle concentrations differ appreciably among the three seasons
- (ii) there is a greater likelihood of weeks being classified as extremely critical during the winter season than the dry and rainy seasons
- (iii) the amount of aerosol particles ($\geq 0.3 \mu m$) were higher when the rain fall was minimum and the amount of aerosol particles ($\geq 0.3 \mu m$) were minimum when the rain fall was

maximum. The increase in particles count during the absence of rainfall could be due to the increase in biomass burning during winter days and reduction of particle count could be due to the wash out during the rain fall.

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