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QUALITATIVE CHARACTERISTICS OF THE IMPACT OF PERCENTAGE VARIATION OF THE INTRA-COMPETITION COEFFICIENT PARAMETER VALUE OF PM_1 IN THE INTERACTION BETWEEN PM_1 AND RELATIVE HUMIDITY ON THE ENVIRONMENT

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Abstract

Numerical method was carried out computationally for qualitative characteristics of the impact of percentage variation of the intra-competition coefficient parameter value of PM_1 in the interaction between PM_1 and Relative Humidity on the environment by decreasing and increasing the intra-competition coefficient parameter value of PM_1 in terms of percentage variation in it interaction with relative humidity. In this study, we have adopted the mathematical modelling approach of numerical simulation using Matlab ODE45 numerical scheme for a time interval of 0(30)360 months. We observed that due to a Due to a 50% variation of the intra-comp coeff of the pollutant level 1 at an interval of 30days for a total time period of 366 days, we observed that the modified value of the PM_1 experienced a gain down the trend from an initial value of 6.30 and increases to a converging saturated value of 30.1011 in amount over an optimal time of 360days with the relative

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humidity having a slight depletion from an initial value of 62.0 which increased to a converging saturated value of 64.8304 in amount over an optimal time of 360days when compared to the fixed coordinates and the quantification which measures this slight depletion and severe gain were also computed as well. In this scenario, we observed that on the base day of the experimental time, there was no impact as the quantification measured were recorded as zero (0) for both coordinates respectively. However, from the 1st 30days up to 366 days, the quantification for the PM_1 ranges from 100.0795 percent gained to a converging value of 100.3659 percent gained, and that of relative humidity ranges from 4.3327 percent depleted to a converging value of 7.2193 percent gain. The full results and discussion of these novel contributions to knowledge are fully presented in this work.

Introduction

The relationship between PM_1 and relative humidity is complex and multifaceted, encompassing various physical and chemical processes. As relative humidity levels fluctuate, PM_1 particles may undergo transformations such as hygroscopic growth, deliquescence, and efflorescence, which can influence their size, composition, and atmospheric behavior. These transformations, in turn, have far-reaching implications for processes like cloud formation, visibility reduction, and pollutant dispersion.

Guo *et al.,* (2021) highlighted the limited nationwide studies in developing countries that examine the effects of climatic modifications on the association between air pollution and health outcomes, particularly focusing on PM_1 pollution and its greater health effect. The study aimed to determine the modification effects of climatic factors on the associations between PM_1 and the incidence rates of lung cancer for males and females in China. Using a nationwide analysis in 345 Chinese counties from 2014 to 2015, the study utilized mean air temperature and relative humidity as proxies for climatic conditions. The findings revealed a stronger association between PM_1 and the incidence rate of male lung cancer in counties with high levels of air temperature or relative humidity. The study demonstrated that male residents in high temperature or humidity counties experienced a larger effect of PM_1 on the incidence rate of lung cancer in China. The authors recommended that future research on air pollution-related health impact assessment should take into account the differential effects of air pollution across different climatic conditions.

Huang *et al.,* (2020) addressed the lack of understanding regarding the sources and processes of secondary particulate matter (PM) species during haze periods in Beijing, particularly under low- and high-relative-humidity (RH) conditions. The study conducted a

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systematic comparison of submicron particles (PM1) species in wintertime Beijing for clean periods and pollution periods under low- and high-RH conditions. Measurements were taken using an aerosol chemical species monitor (ACSM) and an Aethalometer, and the organic aerosol (OA) sources and processes were resolved using positive matrix factorization (PMF) with a multilinear engine 2 (ME-2). The study found that OA was the dominant component of PM_1, with higher mass concentrations and fractions during low-RH pollution periods. Sulfate had higher concentrations and mass fractions during high-RH pollution periods, while nitrate had higher concentrations and mass fractions during low-RH pollution periods. Diurnal variations showed an increase in nitrate and oxygenated organic aerosol (OOA) concentrations during all three types of periods. Nitrate had similar growth rates during both low- and high-RH pollution periods, while OOA had a higher growth rate during low-RH pollution periods. Sulfate showed a decreasing trend during low-RH pollution periods but increased significantly during high-RH pollution periods. The distinctions in mass concentrations, mass fractions, and growth rates were attributed to differences in formation processes influenced by meteorological conditions, with photochemical oxidation and aqueous-phase processes playing a role in the production of sulfate and nitrate. The study also suggested additional OOA formation under high-RH conditions, indicating the importance of aqueous-related formation pathways. Overall, this study provided valuable insights into haze formation in Beijing under different meteorological conditions.

The problem of air pollution in cities has become so severe that there is need for timely information about changes in the pollution level. The primary significance of this research is to expose the reader to the fact that various pollutants are released into the environments as we go about our day to day lives. This poses hazards to human health and deteriorates the quality of air. More significant in this study, is the exposition on the need to protect the environment and maintain as much as possible, the air quality to avoid some of the unhealthy consequences of particulate air pollution.

The behavior of suspended particulate matter (PM_1) in the atmosphere is a topic of increasing interest and concern in the field of environmental science. PM_1, characterized by particles with diameters of 1 micron or less, holds significant implications for air quality and human health due to its ability to penetrate deep into the respiratory system. However, understanding the qualitative behavior of PM_1, particularly its interactions with relative humidity, represents a critical area of research that requires comprehensive investigation.

Air pollutants whose concentrations and impacts are known to be affected by heatwaves include ozone (O_3), particulate matter (PM) and nitrogen dioxide (NO_2). These pollutants, when emitted into the atmosphere from a variety of natural and anthropogenic sources,

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are a major threat to human health (World Health Organization, 2017). The concentration of these pollutants in ambient air depends on the level of emission and the ability of the atmosphere to absorb or disperse these pollutants (World Health Organization, 2017). Since meteorological variables such as relative humidity and concentrations of air pollutants vary on a daily basis, it is important to consider their relationship in the planetary boundary layer, since the atmosphere is the medium in which air pollutants are transported away from the source (Ekaba *et al.*,2022). Gee and Sollans, 1998, Gobo et al., 2012 indicated that during photochemical pollution episodes, air pollutants (O_3, PM_{10}, and NO_2) are the result of a mixture of various meteorological effects and chemical reactions. These pollutants are of the greatest health concern, as their emissions may be exacerbated during heatwaves (Fenger,1999), Gobo *et al*. (2010)). As a result, sensitive individuals may not only be stressed by high temperatures, but may be more subject to mortality due to air pollution during heatwaves. Unusually hot weather during summer led to elevated levels of air pollutants during the heatwaves that occurred in Athens, Greece, between June and July 2007 (Paul *et al*., 2004). He found a significant correlation between heatwaves and average hourly concentrations of O_3, NO_2 and SO_2 in Athens.
Similarly, the combination of elevated air pollution levels and high temperatures was implicated in the increase in urban heat islands (UHIs) and air pollution in London, England (McMichael *et al*., 2003; Rooney *et al*., 1998). Heatwaves are particularly intense in urban areas, where surface characteristics alter the temperature differences between urban and rural areas. The differences are generated by low levels of vegetation in cities, and the production of anthropogenic heat and air flow caused by extreme air temperatures in cities (UHIs) increase heat- and air pollution-related mortality and raise the energy demands for cooling buildings, which in turn leads to a further increase in air pollutants and greenhouse gas emissions. Despite this, several studies have shown that sustainable urban planning, and smart city design including green roofs and cool pavements could significantly reduce both UHIs and air pollution; especially O_3, NO_2, andPM_{10} (Bibri & Krogstie, 2017; McDonald *et al*., 2007; Silva *et al*., 2018; Yang *et al*., 2008).

Mathematical Model Formulation

Considering the interacting model of the interaction between particulate matter PM_1 and relative humidity R_H in the absence of the inter-competition coefficient we have:

$$\frac{dPM_1(t)}{dt} = PM_1(t)[\alpha_1 - \beta_1 PM_1(t)] \quad (1)$$

$$\frac{dR_H(t)}{dt} = R_H(t)[\alpha_2 - \beta_2 R_H(t)]$$

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Following Lotka (1956), our model formulation for the interaction between relative humidity and particulate matter PM_1 is based on a system of two non-linear first-order ordinary differential equations stated as follows:

$$\frac{dPM_1}{dt} = PM_1[\alpha_1 - \beta_1 PM_1 - \gamma_1 R_H], \quad PM_1(0) = \mathrm{PM}_0 > 0 \qquad (2)$$
$$\frac{dR_H}{dt} = R_H[\alpha_2 - \beta_2 R_H - \gamma_2 PM_1], \qquad R_H(0) = R_{H_0} > 0$$

Where

$\frac{dPM_1}{dt}$ represents the rate of change of particulate matter level 1 PM_1.

PM_1 represents the concentration of particulate matter PM_1 over time.

α_1 represents the intrinsic growth rate parameter value for the particulate matter PM_1.

β_1 represents the intra-competition coefficient of particulate matter PM_1.

γ_1 represents the inter competition coefficient of the relative humidity amount to inhibits the growth of the relative humidity.

$\frac{dR_H(t)}{dt}$ represents the rate of change in relative humidity.

R_H represents the amount (%) of relative humidity over time.

α_2 represents the intrinsic growth rate parameter values for the relative humidity amount.

β_2 represents the intra-competition coefficient of relative humidity.

γ_2 represents the inter-competition coefficient of the concentration of the particulate matter PM_1 to inhibits the growth of the relative humidity amount.

$PM_1(0)$ represents the initial condition of the particulate matter PM_1.

$R_H(0)$ represents the initial condition of the relative humidity amount.

Determination of Steady-State Solutions of the First-Order Model of the Interacting Environmental Variables

To study the qualitative behavior of the steady-state solution of the relative humidity and particulate pollutant level PM_1 interaction model, we had to derive from the dynamical system of four (4) steady-state solutions of the variables. From equation (2) we have:

$$\frac{dPM_1}{dt} = PM_1[\alpha_1 - \beta_1 PM_1 - \gamma_1 R_h], \quad PM_1(0) = PM_{1_0} > 0$$
$$\frac{dR_h}{dt} = R_h[\alpha_2 - \beta_2 R_h - \gamma_2 PM_1], \quad R_h(0) = R_0 > 0$$

To study the steady-state solutions of the system and its qualitative behavior;
At a steady-state solution:

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$$\frac{dPM_1}{dt} = 0 \quad \text{and} \quad \frac{dR_h}{dt} = 0$$

Thus,

$$PM_1[\alpha_1 - \beta_1 PM_1 - \gamma_1 R_h] = 0$$
$$R_h[\alpha_{21} - \beta_2 R_h - \gamma_2 \text{Voc}] = 0$$

Suppose (PM_{1_e}, R_e) is an arbitrary steady-state solution, then

$$PM_{1_e}[\alpha_1 - \beta_1 PM_{1_e} - \gamma_1 R_e] = 0$$
$$R_e[\alpha_{21} - \beta_2 R_e - \gamma_2 PM_{1_e}] = 0$$

Suppose the assumption holds true that

$$\alpha_1 - \beta_1 PM_{1_e} - \gamma_1 R_e \neq 0$$
$$\alpha_{21} - \beta_2 R_e - \gamma_2 PM_{1_e} \neq 0$$

Then $PM_{1_e} = 0$ and $R_e = 0$ is a possible steady state solution.
Therefore, we have the trivial steady-state solution $(0, 0)$.
Suppose we assume that $PM_{1_e} = 0$ and $R_e \neq 0$, then

$$PM_{1_e}(\alpha_1 - \beta_1 PM_{1_e} - \gamma_1 R_e) = 0$$

and

$$R_e \neq 0,\ \alpha_2 - \beta_2 R_e - \gamma_2(0) = 0$$
$$\alpha_2 - \beta_2 R_e = 0$$
$$\beta_2 R_e = \alpha_2$$
$$R_e = \frac{\alpha_2}{\beta_2}$$

$\left(0, \frac{\alpha_2}{\beta_2}\right)$ is a possible steady-state solution

Also, suppose the assumption holds true that $PM_{1_e} \neq 0$ and $R_e = 0$, then

$$R_e(\alpha_2 - \beta_2 R_e - \gamma_2 PM_{1_e}) = 0$$

and

$$PM_{1_e} \neq 0,\ \alpha_1 - \beta_1 PM_{1_e} - \gamma_1(0) = 0$$
$$\alpha_1 - \beta_1 PM_{1_e} = 0$$
$$\beta_1 PM_{1_e} = \alpha_1$$
$$PM_{1_e} = \frac{\alpha_1}{\beta_1}$$

$\left(\frac{\alpha_1}{\beta_1}, 0\right)$ is a possible steady-state solution

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Finally, assuming that $PM_{1_e} \neq 0$ and $R_e \neq 0$, using Crammer's rule, we obtain

$$PM_{1_e}(\alpha_1 - \beta_1 PM_{1_e} - \gamma_1 R_e) = 0$$
$$R_e(\alpha_2 - \beta_2 R_e - \gamma_2 PM_{1_e}) = 0$$

(o, o) is a possible steady-state solution

$\mathrm{PM}_e \neq 0$ and $R_e \neq 0$

$$\alpha_1 - \beta_1 PM_{1_e} - \gamma_1 R_e = 0 \text{ and}$$
$$\alpha_2 - \beta_2 R_e - \gamma_2 PM_{1_e} = 0$$

In matrix form

$$\beta_1 PM_{1_e} + \gamma_1 R_e = \alpha_1$$
$$\gamma_2 PM_{1_e} + \beta_2 R_e = \alpha_2$$
$$\begin{pmatrix} \beta_1 & \gamma_1 \\ \gamma_2 & \beta_2 \end{pmatrix} \begin{pmatrix} PM_{1_e} \\ R_e \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix}$$

Where $Ax = b$

Let $H = \begin{pmatrix} \beta_1 & \gamma_1 \\ \gamma_2 & \beta_2 \end{pmatrix}$, $\det H = |H| = \begin{vmatrix} \beta_1 & \gamma_1 \\ \gamma_2 & \beta_2 \end{vmatrix}$

$$|H| = \beta_1\beta_2 - \gamma_1\gamma_2$$

Let $\Delta PM_{1_e} = \begin{pmatrix} \alpha_1 & \gamma_1 \\ \alpha_2 & \beta_2 \end{pmatrix}$, $\det \Delta PM_{1_e} = |\Delta PM_{1_e}| = \begin{vmatrix} \alpha_1 & \gamma_1 \\ \alpha_2 & \beta_2 \end{vmatrix}$

$$|\Delta PM_{1_e}| = \alpha_1\beta_2 - \gamma_1\alpha_2$$

Let $\Delta R_e = \begin{pmatrix} \beta_1 & \alpha_1 \\ \gamma_2 & \alpha_2 \end{pmatrix}$, $\det \Delta R_e = |\Delta R_e| = \begin{vmatrix} \beta_1 & \alpha_1 \\ \gamma_2 & \alpha_2 \end{vmatrix}$

$$|\Delta R_e| = \beta_1\alpha_2 - \gamma_2\alpha_1$$
$$PM_{1_e} = \frac{|\Delta PM_{1_e}|}{|H|} = \frac{\alpha_1\beta_2 - \gamma_1\alpha_2}{\beta_1\beta_2 - \gamma_1\gamma_2}$$
$$R_e = \frac{|\Delta A_e|}{|H|} = \frac{\beta_1\alpha_2 - \gamma_2\alpha_1}{\beta_1\beta_2 - \gamma_1\gamma_2}$$

Hence, the positive co-existence steady-state solution is provided.

$$[PM_{1_e}, R_e] = \left[\frac{\alpha_1\beta_2 - \gamma_1\alpha_2}{\beta_1\beta_2 - \gamma_1\gamma_2}, \frac{\beta_1\alpha_2 - \gamma_2\alpha_1}{\beta_1\beta_2 - \gamma_1\gamma_2}\right]$$

$$\alpha_1\beta_2 - \gamma_1\alpha_2 > 0, \quad \beta_1\alpha_2 - \gamma_2\alpha_1 > 0, \quad \beta_1\beta_2 - \gamma_1\gamma_2 > 0$$

This assumption is purely based on the fact that the amount of pollutant level PM_1 and meteorological variables in an ecosystem are purely non-negative dependent variables. For the purpose of this study, we have used the method of p-vector norms with respect to the 1-norm, 2-norm and infinity-norm to obtain best fit model parameter values which

has small error used for the prediction of the interaction between particulate matter PM_1 and relative humidity environmental variables.

Existence of solutions for initial value problems

This subsection deals with qualitative analysis related to the solution of the initial-value problems for ordinary differential equations. Referring to the above class of mathematical formulations, the following definitions can be given:

Well-Posedness:

A problem is well formulated if the evolution equation is associated with the correct number of initial (or boundary) conditions for its solution, while a problem is well posed if the solution exists, it is unique and depends continuously on the initial data. The main purpose of a model related to a certain physical system is to predict, for a certain time interval, the behavior of the system starting from the knowledge of the state at the initial time t_0. The predictions of the model are then obtained by solving the initial-value problem. To do that, there are some basic requirements that a problem should satisfy:

i) The solution should exist at least for the period of time desired.

ii) The solution should be unique.

iii) The solution should depend continuously on the initial data and on the parameters of the model so that if a small error is made in describing the present state, one should expect the effect of this error to be small in the future. As already stated, if these requirements are satisfied, then the initial-value problem is said to be well posed.

Numerical Iterations Mathematical Preliminaries

Following Akpodee (2019), when numerical solutions to initial value problems (IVPs) are required that cannot be obtained by analytical means, it is necessary to use numerical methods. From the numerical methods that exist in solving initial value problems, we have only considered the popular fourth-order Runge-Kutta method in this study as part of the mathematical preliminaries. The mathematical structure and the theoretical definitions of this method are presented as follows:

The fourth-order Runge-Kutta (R-K) method is an accurate and flexible method based on a Taylor series approximation to the function $f(x, y)$ in the initial value problem

$$\frac{dy}{dx} = f(x, y)$$

Subject to the initial condition $y\ (x_o) = y_o$

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The increment *h* in *x* may be changed at each step, but is usually kept constant so that after *n* steps, we have

$$x_n = x_o + nh$$

The Runge-Kutta algorithm for the determination of the approximation y_{n+1} to $y(x_{n+1})$ is

$y_{n+1} = y_n + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4)$

Where,

$$k_1 = hf(x_n, y_n,)$$
$$k_2 = hf(x_n + \frac{1}{2}h,\ y_n + \frac{1}{2}k_1)$$
$$k_3 = hf(x_n + \frac{1}{2}h,\ y_n + \frac{1}{2}k_2)$$
$$k_4 = hf(x_{n+1}, y_n + k_3)$$

The local error involved in the determination of y_{n+1} from y_n is $0(h^5)$

The above method can be extended to find solution to a system of differential equations such as

$$\frac{dy}{dx} = f(x, y, z)$$

$$\frac{dz}{dx} = g(x, y, z)$$

Subject to the initial condition $y\ (x_o) = y_o$ and $z\ (x_o) = z_o$

These are the types of equations considered by this study which consists of a system of two first order nonlinear differential equations.

At the *nth* integration step, using a step of length *h*, the Runge-Kutta Algorithm for the system takes the form

$$y_{n+1} = y_n + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4)$$

$$z_{n+1} = z_n + \frac{1}{6}(K_1 + 2K_2 + 2K_3 + K_4)$$

Where,

$$k_1 = hf(x_n, y_n, z_n)$$
$$k_2 = hf(x_n + \frac{1}{2}h\ ,\ y_n + \frac{1}{2}k_1,\ z_n + \frac{1}{2}K_1)$$

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$$k_3 = hf(x_n + \frac{1}{2}h\,,\ y_n + \frac{1}{2}k_{2,}z_n + \frac{1}{2}K_2)$$
$$k_4 = hf(x_n + h\,,\ y_n + k_3,\ \ z_n + K_3)$$

and

$$K_1 = hg(x_{n,}y_{n,}z_n)$$
$$K_2 = hg(x_n + \frac{1}{2}h\,,\ y_n + \frac{1}{2}k_{1,}z_n + \frac{1}{2}K_1)$$
$$K_3 = hg(x_n + \frac{1}{2}h\ ,\ y_n + \frac{1}{2}k_2,\ z_n + \frac{1}{2}K_2)$$
$$K_4 = hg(x_n + h\,,\ y_n + k_3z_n + K_3)$$

As with the Runge-Kutta method, the local error involved in the determination of y_{n+1} from y_n and z_{n+1} from z_n is $0(h^5)$

It is a good numerical analysis practice that in the event of a complex dynamical system that can not admit an analytic solution for impact and sensitivity analysis of pollutant level PM_1 interactions with meteorological variables, we have to adopt an alternative method to study the qualitative characteristics of such interactions. This is a challenging environmental problem that will be tackled computationally using MATLAB ODE45 numerical scheme.

In this study, the submission and rationale that underpin the choice of numerical simulation approach (Iterations) for the pollutant level PM_1 interactions with meteorological variables mathematical model formulation are stated as follows:

i. The closed-form solution (Exact solution by direct integration) maybe very complicated and difficult to evaluate analytically because of its complex environmental complication.
ii. There is no other choice which is to say that in such situation or scenario, no closed-form solution can be found.
iii. Computational approach required a large number of steps (Iterations) with chosen small step size so that a great deal of round off error can be accumulated.
iv. This approach will enhance multiple precision computations on our predictions and projections.
v. The meteorological variables relative abundance/ pollutant level PM_1 stock can be estimated accurately because of its role in climate change and also its role in environmental decision and policy making by environmental protection agencies.

The parameters are stated as follows for PM_1-RH Interaction:
alpha1=0.299516529; beta1=0.019423899416; r1=0.00011004102; alpha2=0.04725; beta2=0.00063084; r2=0.000211;

Results and Discussions:

Table 1: **Impact of 50% variation of the intra-comp coefficient of PM_1 in the interaction between PM1 and Relative Humidity RH.**

Here, quantification of the impact of a 50% variation of the intra-competition coefficient of PM_1 interacting with relative humidity for a time interval 0(30)360 in months was studied. The decreased in the intra-competition coefficient parameter of PM_1 captured grey areas where there are depletions and gains in the coordinates of the interacting variables and its impact on the environment in terms of percentage quantification.

Figure 1: Solution trajectory of the impact of 50% variation of the intra-comp coeff. of PM1 in PM1 and RH interaction against time for an interval of 0(30)360 days

Table 2: **Impact of 150% variation of the intra-competition coefficient. of PM1 in the interaction between PM1 and Relative Humidity RH.**

Here, quantification of the impact of a 150% variation of the intra-competition coefficient of PM_1 interacting with relative humidity for a time interval 0(30)360 in months was studied. The increased in the intra-competition coefficient parameter of PM_1 captured grey areas where there are depletions and gains in the coordinates of the interacting variables and its impact on the environment in terms of percentage quantification.

Figure 2: Solution trajectory of the impact of 150% variation of the intra-comp coeff. of PM1 in PM1 and RH interaction against time for an interval of 0(30)360 days

Table 1: Impact of 50% variation of the intra-comp coeff. of PM_1 in the interaction between PM_1 and Relative Humidity RH

Time (Months)	N3(PM_1)	N31(PM_1)m	EPD	N4(Rh1)	N41(Rh2)m	EPG
0	6.3000	6.3000	0	62.0000	62.0000	0
29.0000	15.0348	30.0816	100.0795	67.7135	64.7796	4.3327
58.0000	15.0229	30.1068	100.4062	69.2572	64.8154	6.4134
87.0000	15.0294	30.1103	100.3425	69.7016	64.8262	6.9947
116.0000	15.0150	30.1116	100.5437	69.8258	64.8295	7.1554
145.0000	15.0246	30.1117	100.4159	69.8614	64.8305	7.2012
174.0000	15.0161	30.0965	100.4279	69.8707	64.8300	7.2143
203.0000	15.0220	30.1088	100.4318	69.8737	64.8308	7.2173
232.0000	15.0237	30.0819	100.2298	69.8746	64.8293	7.2205
261.0000	15.0219	30.1052	100.4092	69.8747	64.8306	7.2188

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290.0000	15.0354	30.0934	100.1506	69.8756	64.8300	7.2208
319.0000	15.0230	30.1019	100.3724	69.8749	64.8304	7.2192
348.0000	15.0231	30.1011	100.3659	69.8749	64.8304	7.2193

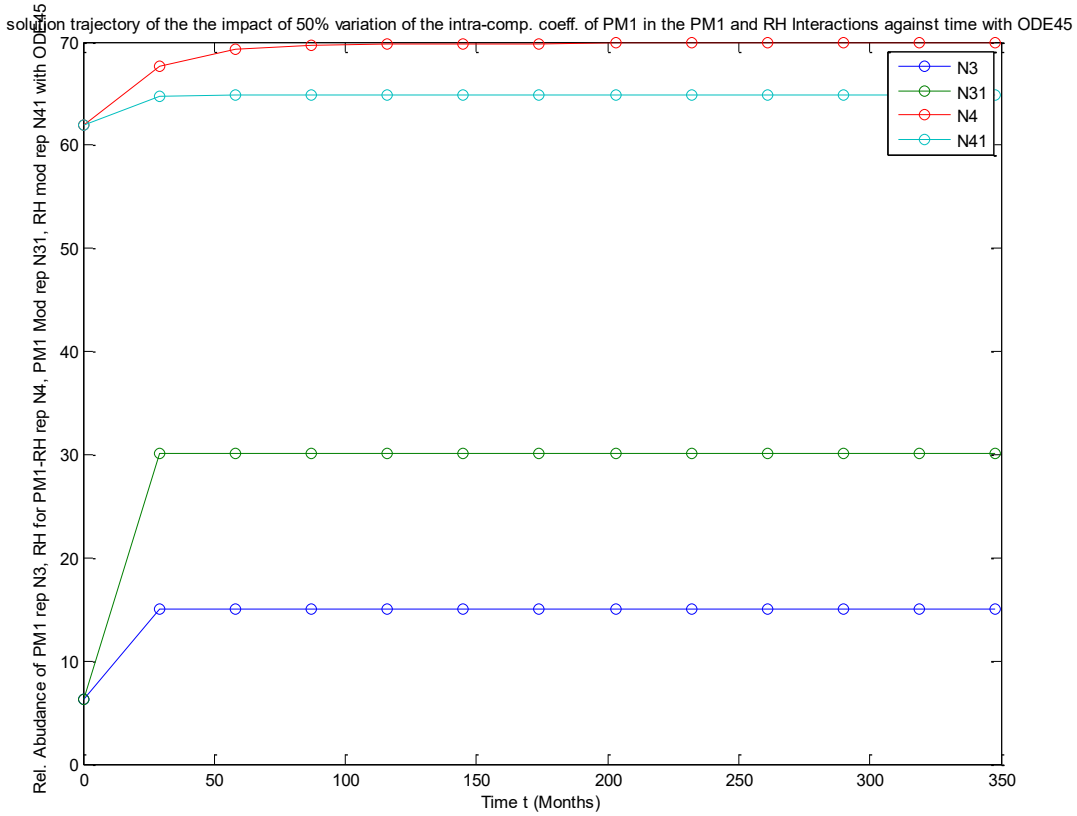


Figure 1: Solution trajectory of the impact of 50% variation of the intra-comp coeff. of PM_1 in PM_1 and RH interaction against time for an interval of 0(30)360 days

Table 2: Impact of 150% variation of the intra-comp coeff. of PM_1 in the interaction between PM_1 and Relative Humidity RH

Time(Months)	N3(PM_1)	N31(PM_1)m	EPD	N4(Rh1)	N41(Rh2)m	EPG
0	6.3000	6.3000	0	62.0000	62.0000	0
29.0000	15.0348	10.0211	33.3476	67.7135	68.7703	1.5608
58.0000	15.0229	10.0117	33.3568	69.2572	70.7773	2.1948
87.0000	15.0294	10.0102	33.3963	69.7016	71.3408	2.3516
116.0000	15.0150	10.0074	33.3507	69.8258	71.4946	2.3900
145.0000	15.0246	10.0078	33.3910	69.8614	71.5365	2.3977
174.0000	15.0161	10.0103	33.3361	69.8707	71.5480	2.4006
203.0000	15.0220	10.0089	33.3719	69.8737	71.5509	2.4003
232.0000	15.0237	10.0163	33.3296	69.8746	71.5522	2.4009

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261.0000	15.0219	10.0102	33.3625	69.8747	71.5521	2.4005
290.0000	15.0354	10.0205	33.3538	69.8756	71.5527	2.4002
319.0000	15.0230	10.0104	33.3661	69.8749	71.5521	2.4004
348.0000	15.0231	10.0090	33.3757	69.8749	71.5521	2.4003

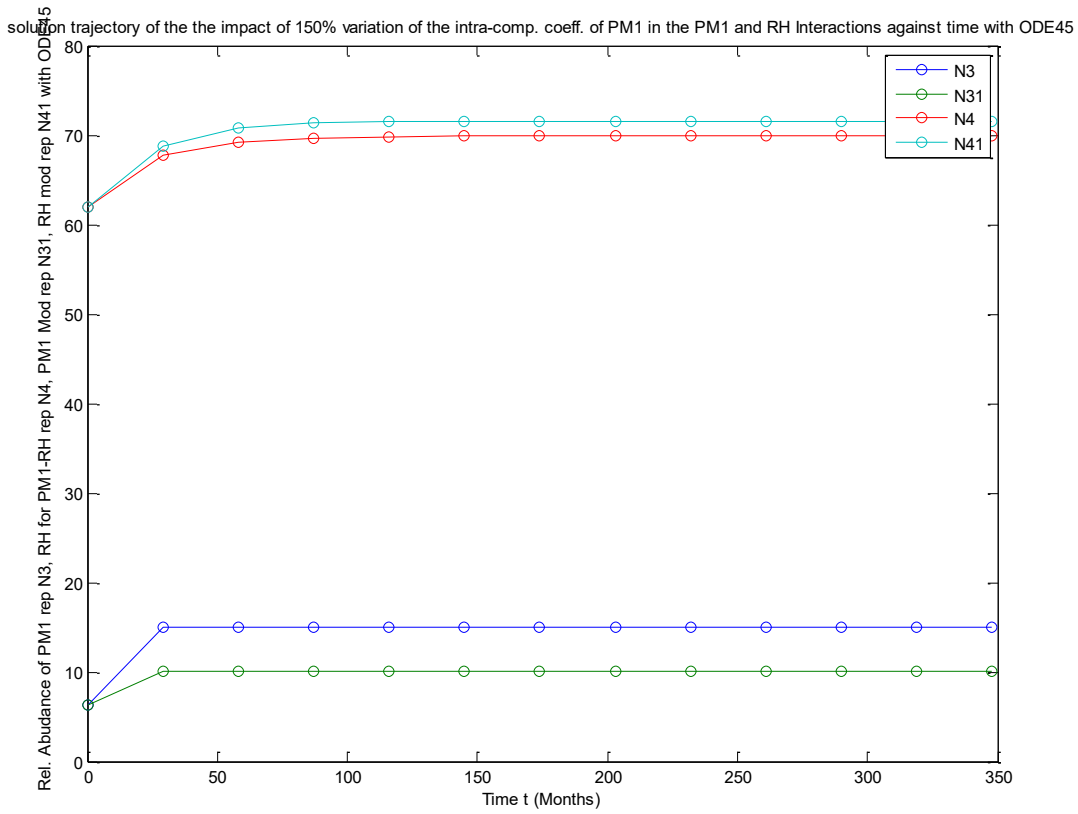


Figure 2: Solution trajectory of the impact of 150% variation of the intra-comp coeff. of PM_1 in PM_1 and RH interaction against time for an interval of 0(30)360 days

Impact of 50% variation of the intra-comp coefficient of PM_1 in the interaction between PM_1 and Relative Humidity RH

In quantifying the impact of a 50% variation of the intra-comp coefficientparameter value of PM_1 interacting with relative humidity, in the same scenario, we observed that on the base day of our experimental time, the initial value here called initial condition (IC) when all model parameter values are fixed for both the pollutant level 1 and the relative humidity are recorded as 6.30 and 62.0 respectively in amount and further fluctuates to a converging saturated value of 30.1011 and 64.8304 respectively in amount at an optimal time of over 360 days.

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Due to a 50% variation of the intra-comp coeff of the pollutant level 1 at an interval of 30days for a total time period of 366 days, we observed that the modified value of the PM_1 experienced a negligible gain down the trend from an initial value of 6.30 and increases to a converging saturated value of 22.7463 in amount over an optimal time of 360days with the relative humidity having a severe gain from an initial value of 62.0 which increased to a converging saturated value of 64.8304 in amount over an optimal time of 360days when compared to the fixed coordinates and the quantification which measures this slight depletion and severe gain were also computed as well.

In this scenario, we observed that on the base day of the experimental time, there was no impact as the quantification measured were recorded as zero (0) for both coordinates respectively. However, from the 1st 30days up to 366 days, the quantification for the PM_1 ranges from 100.0795 percent gained to a converging value of 100.3659 percent gained, and that of relative humidity ranges from 4.3327 percent depleted to a converging value of 7.2193 percent gain.

In terms of environmental studies and modeling, these quantification shows that a severe gained in the pollutant level 1 will serve as a good information since the environment will be vulnerable of the pollutant concentration as well as high risk of health exposure and hostility with the slight depletion in the relative humidity indicates an inhospitable environment and unconducive for ecosystem functioning. The trend of the solution trajectory of this qualitative behaviour showed clearly their various optimal characteristics due to 50% percentage increase of the PM_1 as well as their converging saturated values of the modified coordinates with expected percentage effects in quantifications. This information is vital for various pollution and meteorological agencies and will serves as a guide for environmental and ecosystem functioning.

Impact of 150% variation of the intra-comp coefficient of PM_1 in the interaction between PM_1 and Relative Humidity RH

In quantifying the impact of a 150% variation of the intra-comp coefficientparameter value of PM_1 interacting with relative humidity, in the same scenario, we observed that on the base day of our experimental time, the initial value here called initial condition (IC) when all model parameter values are fixed for both the pollutant level 1 and the relative humidity are recorded as 6.30 and 62.0 respectively in amount and further fluctuates to a converging saturated value of 15.0231 and 69.8749 respectively in amount at an optimal time of over 360 days.

Due to a 150% variation of the intra-comp coeff of the pollutant level 1 at an interval of 30days for a total time period of 366 days, we observed that the modified value of the PM_1 experienced a negligible gain down the trend from an initial value of 6.30 and

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increases to a converging saturated value of 10.0090 in amount over an optimal time of 360days with the relative humidity having a severe gain from an initial value of 62.0 which increased to a converging saturated value of 71.5521 in amount over an optimal time of 360days when compared to the fixed coordinates and the quantification which measures this slight depletion and severe gain were also computed as well.

In this scenario, we observed that on the base day of the experimental time, there was no impact as the quantification measured were recorded as zero (0) for both coordinates respectively. However, from the 1st 30days up to 366 days, the quantification for the PM_1 ranges from 33.3476 percent gained to a converging value of 33.3757percent gained, and that of relative humidity ranges from 1.5608 percent depleted to a converging value of 2.4003 percent gain.

In terms of environmental studies and modeling, these quantification shows that a severe gained in the pollutant level 1 will serve as a good information since the environment will be vulnerable of the pollutant concentration as well as high risk of health exposure and hostility with the slight depletion in the relative humidity indicates an inhospitable environment and unconducive for ecosystem functioning. The trend of the solution trajectory of this qualitative behaviour showed clearly their various optimal characteristics due to 150% percentage increase of the PM_1 as well as their converging saturated values of the modified coordinates with expected percentage effects in quantifications. This information is vital for various pollution and meteorological agencies and will serves as a guide for environmental and ecosystem functioning.

Summary of Environmental Implications of Results Discussions

Low relative humidity can be influenced by several factors related to suspended particulate matter, particularly PM_1 (particulate matter with a diameter of 1 micrometer or less) and $PM_{2.5}$ (particulate matter with a diameter of 2.5 micrometers or less). Here are some key factors:

1. **Aerosol Properties**: PM_1 and $PM_{2.5}$ can affect humidity levels due to their ability to absorb and scatter water vapor. Smaller particles can have a higher surface area-to-volume ratio, which can influence their hygroscopic properties, potentially leading to lower humidity levels in the surrounding air.
2. **Source of Particulates**: The origin of PM1 and PM2.5, such as industrial emissions, vehicle exhaust, or natural sources like wildfires, can impact their chemical composition. Some particles may be less hygroscopic, meaning they do not attract water vapor effectively, contributing to lower relative humidity.
3. **Atmospheric Conditions**: Weather conditions, including temperature and pressure, play a significant role in relative humidity. High temperatures can increase the

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capacity of air to hold moisture, while the presence of particulate matter can alter local microclimates, potentially leading to lower humidity levels.

4. **Urbanization and Land Use**: Urban areas often have higher concentrations of PM1 and PM2.5 due to human activities. The heat island effect in cities can lead to increased temperatures, which may lower relative humidity levels.
5. **Chemical Reactions**: Particulate matter can participate in chemical reactions in the atmosphere that may consume water vapor or produce compounds that do not retain moisture, further contributing to lower humidity.
6. **Transport and Dispersion**: The movement of air masses can influence humidity levels. If PM_1 and $PM_{2.5}$ are transported from areas with low humidity, they can bring those conditions to new locations, affecting local humidity levels.

Understanding these factors is crucial for addressing air quality and its impacts on health and the environment.

High relative humidity can be influenced by several factors related to suspended particulate matter, particularly PM1 (particulate matter with a diameter of 1 micrometer or less) and $PM_{2.5}$ (particulate matter with a diameter of 2.5 micrometers or less). Here are some key factors:

1. **Aerosol Properties**: PM1 and $PM_{2.5}$ can act as cloud condensation nuclei (CCN), which are essential for the formation of clouds and precipitation. The presence of these particles can enhance the ability of water vapor to condense, leading to increased humidity levels.
2. **Chemical Composition**: The chemical makeup of particulate matter can affect its hygroscopicity, or its ability to attract and hold water. Particles that contain salts, sulfates, or organic compounds can absorb moisture from the air, contributing to higher relative humidity.
3. **Temperature and Pressure**: Higher temperatures can increase the capacity of air to hold moisture. When PM1 and PM2.5 are present in warmer conditions, they can facilitate the retention of moisture, leading to elevated humidity levels.
4. **Urbanization and Pollution**: Areas with high levels of PM_1 and $PM_{2.5}$, often due to urbanization and industrial activities, can experience localized increases in humidity. The combination of heat from urban surfaces and the presence of particulate matter can create microclimates with higher humidity.
5. **Meteorological Conditions**: Weather patterns, such as low-pressure systems and stagnant air, can lead to the accumulation of particulate matter and moisture in the atmosphere, resulting in higher relative humidity.

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6. **Vegetation and Land Use**: Areas with significant vegetation can influence humidity levels through transpiration, which can interact with particulate matter in the air, potentially increasing humidity.

Understanding these factors is crucial for addressing air quality and its impacts on health and the environment.

Impact of relative humidity on suspended particulate matter PM_1 and $PM_{2.5}$

Relative humidity (RH) has a significant impact on suspended particulate matter, particularly PM1 (particulate matter with a diameter of 1 micrometer or less) and $PM_{2.5}$ (particulate matter with a diameter of 2.5 micrometers or less). Here are some key effects:

1. **Hygroscopic Growth**: Many particulate matter components, especially those containing salts and other hygroscopic materials, can absorb moisture from the air when relative humidity is high. This leads to an increase in the size of the particles, which can affect their behavior in the atmosphere, including their ability to scatter light and their deposition rates.
2. **Cloud Condensation Nuclei (CCN)**: At higher relative humidity levels, PM_1 and $PM_{2.5}$ can act as cloud condensation nuclei, facilitating cloud formation and influencing precipitation processes. This can lead to changes in local weather patterns and affect air quality.
3. **Chemical Reactions**: High humidity can enhance chemical reactions involving particulate matter. For example, moisture can facilitate the formation of secondary organic aerosols (SOAs) and other compounds, which can alter the composition and toxicity of PM_1 and $PM_{2.5.}$
4. **Transport and Dispersion**: Relative humidity can influence the transport and dispersion of particulate matter. High humidity can lead to the aggregation of particles, making them heavier and potentially causing them to settle more quickly. Conversely, low humidity can keep particles suspended in the air for longer periods.
5. **Health Implications**: The size and composition of PM_1 and $PM_{2.5}$ can change with varying humidity levels, which may affect their inhalation and deposition in the respiratory system. Changes in particle size and composition can influence their toxicity and health impacts.
6. **Visibility and Aesthetics**: High humidity can lead to increased visibility issues due to the scattering of light by larger, hygroscopic particles. This can affect air quality perceptions and have implications for tourism and outdoor activities.
7. **Seasonal Variations**: Relative humidity often varies seasonally, which can lead to fluctuations in PM1 and $PM_{2.5}$ concentrations. For instance, during the summer

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months, higher humidity levels may lead to increased aerosol formation, while winter months may see lower humidity and different particulate matter dynamics.

Understanding the relationship between relative humidity and suspended particulate matter is crucial for air quality management, climate modeling, and public health assessments.

Conclusion

The key results that this work have achieved are stated as follows:

1) The Impact of 50% variation of the intra-competition coefficient of PM_1 in the interaction between PM_1 and Relative Humidity RH.
2) The Impact of 150% variation of the intra-competition coefficient of PM_1 in the interaction between PM_1 and Relative Humidity RH.
3) Solution trajectory of the Impact of 50% variation of the intra-competition coefficient of PM_1 in the interaction between PM_1 and Relative Humidity RH against time for an interval of 0(30)360 days.
4) Solution trajectory of the Impact of 150% variation of the intra-competition coefficient of PM_1 in the interaction between PM_1 and Relative Humidity RH against time for an interval of 0(30)360 days.

Recommendations

This study work will recommend the following open research problem namely:

1.) The impact of the variation of the intra-competition coefficient of the pollutant level 1 and relative humidity together.
2.) The impact of the variation of the inter-competition coefficient of the pollutant level 1 and relative humidity together.
3.) The impact of changing initial condition of the pollutant level 1 and relative humidity together.
4.) The parameter estimation of other pollutants and meteorological variables over time.
5.) The impact of a mild and severe random perturbation on the pollutant level 1 and relative humidity together for two scenarios.

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