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Desirability Function Approach to Response Surface Optimization Analysis of Atmospheric Carbon Dioxide CO_2 Emissions in Africa

Mohamed Ali Abu Sheha [α], Christ P. Tsokos [σ] & Lohuwa Mamudu [ρ]

Abstract- The continuous growing worlds' impact of climate change (global warming), including frequent natural disasters such as earthquakes, wildfires, etc.; rising food insecurity, infectious diseases, etc.; among others, causing economic, political, and civil unrest cannot be downplayed. Carbon dioxide (CO_2) is the most significant contributor to climate change, mainly generate through human-induced industrial and techno logical advancement activities. Africa is most vulnerable to the impact of climate change in the world. Hence, any effort to combat climate change in Africa will be an outstanding achievement towards mitigating the excessive effect of climate change globally. We proposed a surface response optimization method to optimize (mini mize) the CO_2 emissions in Africa. We utilized the desirability function approach to obtain the optimum value of the risk factors that minimize Africa's CO_2 emissions. The minimum value of the CO_2 was obtained along with a 95% confidence region.

Also, the bivariate interaction effect of the risk factors on the CO_2 was obtained. The optimization process is well-validated to satisfies the necessary conditions, achieving a desirability function of 0.99. The proposed method provides a robust mitigating approach towards combating CO_2 emission, limiting the impact of climate change in Africa and its impact on the world. The subject of essential findings is based on the very high quality of a predictive real data-driven statistical model developed by the authors that identify the significant risk factors and interactions that produce CO_2 emissions in the atmosphere.

I. Introduction

Global warming, also called climate change, is mainly a human-caused rise of the Earth's climate system's average temperature. It is a long-growing global concern politically and economically. It is driven by the greenhouse effect caused by human emissions of harmful gases and wild weather patterns. The physical and natural occurrences causing global warming are inevitable and unequivocal. However, when these occurrences or activities become excessive, our planet earth and the ecosystem's inhabitants pose a danger. Carbon dioxide CO_2 has been identified as the greatest contributor to global climate change, contributing 76% greenhouse gas emissions (GHG) through human activities. Other gases include methane (CH4), contributing 16%, nitrous oxide (N2O) contributing 7%, and fluorinated gases (F-gases) 2%, which include hydrofluorocarbons (HFCs), per-fluorocarbons (PFCs), and sulfur hex afluoride (SF6) [1]. In 2010, the economic activities resulting in global GHG emissions includes electricity and heat production (25%); industry (21%); agriculture, forest, and other land use (24%); transportation (14%); building (6%); and other energy (10%) [20, 21].

Noticeably, the use of fossil fuel is the primary source of CO_2. Other activities resulting in the emission of CO_2 are direct human-induced impacts on the use of land and forest, such as land degradation and deforestation for agricultural purposes [1]. Moreover, the swift increase in climate change is due to the rapidly growing civilization, industrialization, and technological advancement in which Africa is not exempted. In 2014, China, the United States, the European Union, India, the Russian Federation, and Japan were the world's top CO_2 emitters. The primary sources of CO_2 emissions were fossil fuel combustion and cement manufacturing, and gas flaring, representing a large proportion of total global CO_2 emissions [20]. The Inter governmental Panel on Climate Change (IPCC) has notified Africa to be among the most vulnerable continents to climate change [7], mainly due to weak adaptive ca pacity, over-reliance on the ecosystem for livelihood, and less developed agricultural production systems [8], prompting the risk or threat on lives and the sustainable development prospects in Africa [9].

The consequences of climate change can be tremendously dreadful and unprecedented. Most parts of the world are already experiencing and suffering from the impact of climate change, including growing natural disasters such as earthquakes and tsunamis like the 2004 Indian ocean earthquake and tsunami that swept an entire city of Indonesia, killing hundreds of thousands of people and destroying several infrastructures [5]; floodings; hurricanes; volcanic eruptions; a sharp rise in oceans, seas, and earth temperature; wildfires like the Amazon rainforest wildfire in 2019 [3] and 2020 California wildfire [4]; heatwaves; increasing deserts; and many others [6].

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Global Journal of Science Frontier Research (H) Volume XXII Issue VII Version I Year 2022

Many abrupt effects of climate change have been seen in the past and now with the rising current warming level around 1.1°C (2.0 °F) [10]. Climate change impacts have been projected to increase significantly according to a series of reports by the IPCC as warming continues to 1.5°C (2.7 °F) and beyond [11]. A report by NASA shows 2016 was the warmest year since 1880. Figure 1 was published by NASA, which shows a continued rising global temperature trajectory [12].

Although there is a continuous global fight against global warming, the causes and the impact vary from country to country, and so should the mitigation process. For instance, the United Nations fact sheet on climate change reported in 2006 that Africa is the most vulnerable to climate change, and its impact has a direct effect on the lives of the people in Africa. They further reported that Africa has warmed by 0.7°C during the 20th century and project that average surface temperatures in Africa could increase from 2 – 6°C by 2100 [13]. The statistics are alarming and endangering millions of lives if nothing is done. Hence, the need for strong mitigating efforts to fight climate change in Africa. The most vulnerable African countries are the Seychelles Islands, Cape Verde, and Mauritius and large African deltas such as the Niger Delta, Nile Delta in Egypt, the Kalahari, and Okavango Deltas in Botswana. This means that climate change must be taken more seriously and tackled within the African Continent setting rather than the global setting. The bottom-top mitigating strategy will be a more effective and efficient policy in combating global warming. Thus, the fight against climate change should start from country to continent to global and not otherwise, because the cause, effect, and impact varies from country to country and continent to continent.

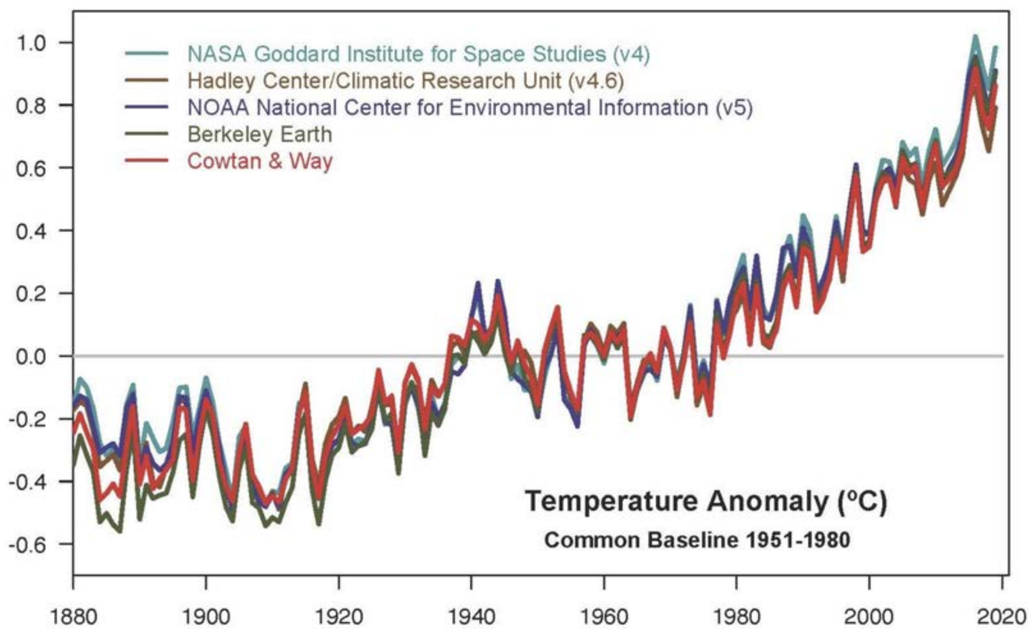

Figure 1: Temperature Data Showing Rapid Warming in the Past Few Decades, the Latest Data Going up to 2019

Admittedly, the mitigation against climate change is a global fight. However, it is only feasible if individual continents and countries play a major independent role in the mitigation process from within. The mitigation course requires great efforts, including research, policies to reduce fossil fuel emissions, developing and adopting low-carbon energy technologies, enhancing reforestation, forest preservation, and energy efficiency. Given that CO_2 is the most significant driver of climate change contributing to 76% of the world's global warming [1], most research to curb global warming has focused on CO2 and remedies to minimize its excessive emission [14] [17]. The increasing use of fossil fuels is the major contributor to CO_2 emissions in the atmosphere.

The current study is about CO_2 minimization in Africa. As mentioned earlier, Africa turns out to be the most at risk in the event of excessive climate change. Most African countries are third-world countries lacking the advanced technologies to combat the impact of climate change. The IPCC predicts a persistent increase in water stress among millions of people in Africa due to climate variability and change [7]. Surface runoff and water availability are directly affected by changes in precipitation patterns [25]. The public health systems are least efficient in African countries globally, the World Health Organization [19]. African countries are highly susceptible to infectious diseases such as malaria, dengue fever, meningitis, schistosomiasis, etc., especially in the Sub-Saharan African region. These diseases continue to exacerbate and are very sensitive to climate variability [25]. Many African countries are already suffering from the impact of climate change, including the rising food insecurity and inadequate or lack of water (especially hygiene water), the increasing mortality rate (especially infant mortality), malnutrition, among others. The combat against climate change in Africa must be taken highly seriously and should not be underestimated. Therefore, it is imperative to research CO_2 emissions in Africa to combat climate change, Africa. As a contribution to mitigating the excessive emissions of CO_2 in Africa, the world at large, Abu Sheha, M. and Tsokos, C. (2019) developed a statistical model of fos sil fuel emission factors contributing to atmospheric carbon dioxide in Africa. They found Liquid fuels (Li), Solid fuels (So), Gas fuels (Ga), Gas flares (Gf), and Cement production (Ce), and seven interaction factors among them to be significant contributions to fossil fuel emissions. Also, they showed the rank of the risk factors' contribution to CO_2 emissions on the Africa map [16]. The present study focused on building upon the model they developed. Thus, in the present study, we employed the desirability function approach to surface response optimization anal ysis of the CO_2 emissions based on the identified risk factors. Our objective is to obtain the optimal or minimum value of the CO_2 by identifying the individual risk factors' optimum value and interactions along with their weights. Lohuwa Mamudu and Chris P Tsokos [23] applied the desirability function approach to optimize corn production returns in the United States (US). However, this study's methods use the *single response surface optimization (SRSO)* and *desirability function approach (DFA)* to optimize Africa's atmospheric carbon dioxide emissions. We also obtained the 95% confidence region of CO_2 for which the hypothesis of the amount of carbon dioxide emissions in Africa can be accessed. The optimization method used has been well-validated and satisfies all necessary conditions utilizing the desirability function, R^2, R^2_{adj} , and R^2_{pred} statistic, and the 95% confidence interval (CI) and prediction interval (PI) of the optimal values.

The data used in this study was obtained from Oak Ridge National Lab (Division of US Department of Energy), consisting of the amount of atmospheric CO_2 emissions in metric tons (MT) along with five risk factors from 1964 to 2014. Figure 2 shows the time series trend of CO_2 emissions in Africa's atmosphere from 1964 to 2014, which is generally increasing.

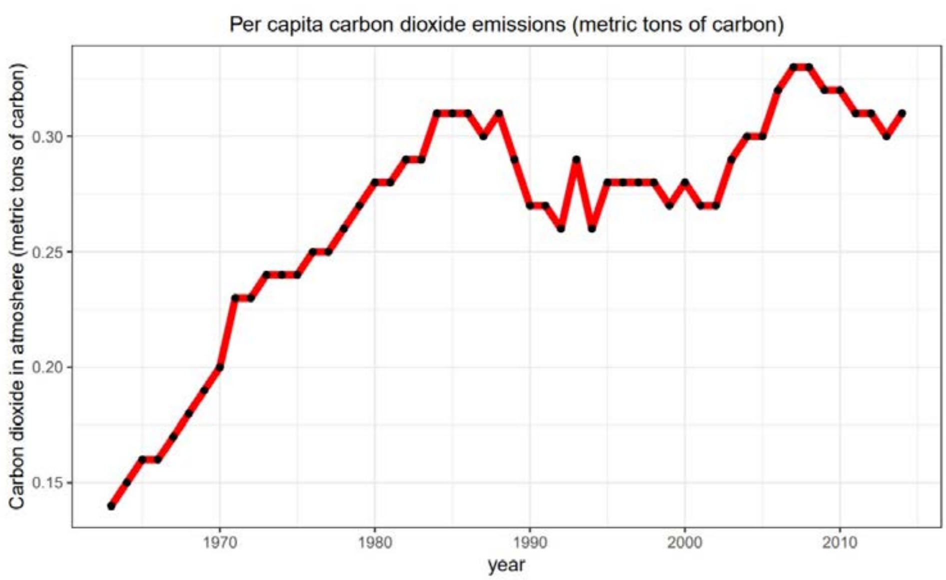

Figure 2: Annual CO_2 Emission in Africa in Metric Tons from 1964 to 2014

II. Method and Results

a) Overview of Desirability Function Approach

In the present study, we utilized the desirability function approach to optimize atmospheric carbon dioxide emissions in Africa. The desirability function approach is a commonly used optimization method that assigns values to a set of responses and chooses the factors that optimize the response's values. [24] proposed the different desirability function classes to optimize the response by obtaining the minimum, max imum, or target values. The method uses the constraints of the factors or predictors, x, and obtain optimum values of x that provide the best-desired value of the response, y. The objective of the optimization process is to maximize, minimize, or obtain a target value of the response, y_i with desirability function $d_i(y_i)$. $d_i(y_i)$ assigns a score between 0 and 1 for each value of y_i, where $d_i(y_i) = 0$ is the most undesired values of y_i and $d_i(y_i) = 1$ is the most desired value of y_i. Thus, as $d_i(y_i)$ approaches 1, the more y_i approaches the optimal point. For example, $d_1(y_1) = 0.75$ gives a more desire optimal

Global Journal of Science Frontier Research (H) Volume XXII Issue VII Version I Year 2022

value of y_1 than $d_1(y_1) = 0.60$. The following are the three-desirability function we can obtain based on the objective of our optimization process.

If the optimization process is to obtain the target value of the response, y_i for a set of values of predictor variables x_i, then the desirability function approach (DFA) $d_i(y_i)$ is given by

$$d_i(\hat{y}_i) = \begin{cases} 0, & \hat{y}_i(x) < l_i \\ \left(\frac{\hat{y}_i(x)-l_i}{t_i-l_i}\right)^{\tau_1}, & l_i \leq \hat{y}_i(x) \leq t_i \\ \left(\frac{u_i-\hat{y}_i(x)}{u_i-t_i}\right)^{\tau_2}, & t_i \leq \hat{y}_i(x) \leq u_i \\ 0, & \hat{y}_i(x) > u_i. \end{cases} \quad (1)$$

Thus; if the optimization process is to maximize the value of the response, y_i for a set of values of predictor variables x_i, then the estimated desirability function $d_i(y_i)$ is given by

$$d_i(\hat{y}_i) = \begin{cases} 0, & \hat{y}_i(x) < l_i \\ \left(\frac{\hat{y}_i(x)-l_i}{t_i-l_i}\right)^{\tau}, & l_i \leq \hat{y}_i(x) \leq t_i \\ 1, & \hat{y}_i(x) > t_i. \end{cases} \quad (2)$$

If the optimization process is to minimize the value of the response, y_i for a set of values of predictor variables x_i, then the estimated desirability function $d_i(y_i)$ is given by

$$d_i(\hat{y}_i) = \begin{cases} 1, & \hat{y}_i(x) < t_i \\ \left(\frac{u_i-\hat{y}_i(x)}{u_i-t_i}\right)^{\tau}, & t_j \leq \hat{y}_i(x) \leq u_i \\ 0, & \hat{y}_i(x) > u_i. \end{cases} \quad (3)$$

where τ_1, τ_2, and τ are the weights that define the shape of the desirability function $d_i(\hat{}y_i)$. In equation (1), if $\tau_1 = \tau_2 = 1$. It means that the shape of $d_i(\hat{}y_i)$ is positively linear; for a concave shape, $\tau_1 > 1$ and $\tau_2 > 1$; and for convex shape, $\tau_1 < 1$ and $\tau_2 < 1$. In equation (2), t_i denotes the large enough value of the response variable and $t_i$in equation (3), represents the small enough value of the response. Furthermore, t_i, l_i, and u_i are the desired target values, lower values, and upper values for the response variable y_i, respectively. To obtain the overall desirability function D, we utilize the geometric mean of a combined function of individual desirability's $d_i(\hat{}y_i)$, given by

$$D = \left[\prod_{i=1}^{c} d_i(\hat{y}_i)\right]^{1/c} = [d_1(\hat{y}_1)d_2(\hat{y}_2)...d_c(\hat{y}_c)]^{1/c}. \quad (4)$$

where c represents the estimated number of responses, $\hat{}y$. Note that the optimization of a single response variable for a set of controllable factors or risk factors is known as a single response optimization. Whereas the optimization of two or more responses is known as multiple response optimization.

b) Statistical Analysis for Optimization of Atmospheric Carbon Dioxide CO_2 Emissions in Africa

We adopt the following algorithmic procedure to optimize a given phenomenon's response based on the desirability function approach.

1. Develop the model that accurately predicts the response y for a set of control lable risk factors or predictors x_i.
2. Obtain the constraints of the response and input factors, for $a < y_i < b$ and $c < x_i < d$.
3. Define the desirability function(s) $d_i(y_i)$ for the response(s) based on the opti mization objective.
4. Obtain the optimal value of the response by maximizing the desirability function concerning the controllable input factors.
5. Validate the optimization process based on the coefficient of variation R^2 and the prediction accuracy R^2_{pred}.

The following are the results obtained in the optimization process of the atmospheric carbon dioxide emission in Africa using the desirability function approach based on the stated algorithm. The objective is to minimize or obtain the minimum CO_2 emissions with respect to the controllable input variable or risk factors Li, So, Ce, Ga, and Gf. In equation 5 below, we obtained a statistical model that predicts CO_2 missions in Africa with R^2 of 97%. We then obtained the constraints of the response and the input factors, as shown in Table 1. Using the defined desirability function as given by in equation 3, we optimize the CO_2 by obtaining the minimum CO_2 with a maximum desirability function, $d(CO\hat{}2) = 0.99$, R^2 along with R^2_{adj} of 98.97% and 98.42%, respectively, and R^2_{pred} of 97.71%, as shown in Table 3. In Table 2, we display the attained minimum values of the CO_2 along with the corresponding optimum values of the input factors. We further obtained a 95% confidence region and predictive interval for the attained minimum value of CO_2 emissions in Africa, as shown in Table 3, below.

$$
\begin{aligned}
\hat{CO_2} = & -0.0656 + 0.18 \times 10^{-3} So + 0.115 \times 10^{-3} Li - 0.882 \times 10^{-5} Ga \\
& -0.195 \times 10^{-3} Ce + 0.126 \times 10^{-3} Gf - 0.13 \times 10^{-8} So.Li \\
& -0.468 \times 10^{-8} So.Ga + 0.184 \times 10^{-7} So.Ce \\
& -0.615 \times 10^{-8} So.Gf + 0.561 \times 10^{-8} Li.Ga \\
& -0.114 \times 10^{-7} Li.Ce + 0.572 \times 10^{-8} Ce.Gf.
\end{aligned} \tag{5}
$$

See [16] for the development of this statistical model.

Table 1: The Constraints of the Response and Risk Factors.

Response (CO_2) in metric tons per capita	**Input Risk Factors**
	$16537 \leq Li \leq 125427$
	$29800 \leq So \leq 124526$
$0.14 \leq CO_2 \leq 0.33$	$1320 \leq Ce \leq 23631$
	$196 \leq Ga \leq 67972$
	$313 \leq Gf \leq 23942$

Table 2: The Minimum Value of the Response and Optimum Value of the Risk Factors

$\hat{CO_2}$	Li	So	Ce	Ga	Gf
-1.13973	16537	29800	23631	67972	313

Also in the Appendix, we display in Figures 3 and 4 a contour plots and their corresponding 3D plots of the combination of two risk factors in maximizing the response holding other risk factors constant.

Table 3: Validation of the Optimization Process and Confidence Regions of the Optimal CO2 Emissions

R-sq	R-sq(adj)	R-sq(pred)	$d(\hat{CO_2})$	95% CI	95% PI
98.79%	98.42%	97.71%	0.99	((-1.386, -0.893)	(-1.387, -0.893)

The validation results attest to the excellent results of obtaining the optimum values of the risk factors that will minimize the output of CO_2 emissions.

III. Discussion

Climate change (global warming) has become the world's greatest problem in recent years. On top of this, no sufficient human or national action has been taken to address climate changes. The United Nations Environment (UN Environment) IPCC outlined climate changes as the defining issue of our time, causing a change in the weather patterns that threatens food production, causing widespread food insecurity, and rising sea level that increases the risk of catastrophic flooding [25], among others. The IPCC further reported that carbon dioxide CO_2, mainly from burning fossil fuel, contributes to two-thirds of greenhouse gas (GHG) emissions. Similarly, the European Environment Agency pointed out climate change as one of the biggest challenges of our time, stating that climate change is already happening with evidence of rising temperatures, drought and wildfires, a shift in rainfall patterns, melting of glacier and snow, and drastic increases in the mean sea level [26]. They further postulated that we could mitigate or reduce climate change by decreasing or preventing the emission of human-linked activities. In 2019, MIT Sloan School Management reported the five biggest challenges of fighting climate change [27]. They mentioned that climate change is a global threat and requires superhuman sacrifice and awareness to address it. They further pointed out that CO_2 is globally polluted and cannot be locally contained.

Given that CO_2 is the biggest threat or risk factor of climate change, most mit igation factors and efforts must reduce CO_2 emissions. The interesting question is, what minimum value of CO_2 emission can be considered less or no threat to climate change or global warming? In the present study, we utilized the desirability function approach of response surface optimization to optimize the atmospheric CO_2 emission in Africa, achieving the minimum value of CO_2 needed as a mitigating factor for climate change -1.13973. The optimal value for CO_2 was attaining after develop ing a high-quality predictive model of CO_2 with an R2 of 97.28%, identifying five individual risk factors and seven interaction terms [16]. We proceeded with the op timization process by obtaining the five individual risk factors' constraints and the response CO_2, as given in Table 1. We then utilized the desirability function method to obtain the minimal value of CO_2, maximizing the value of the desirability func tion. The optimization algorithm resulted in the minimum value of CO_2 emission in Africa of -1.13973 and a maximum desirability value of 0.99. Thus, implying that the controllable risk factors are 99% effective in explaining the attained minimum value of CO_2. The CO_2 of -1.13973 is the minimum value Africa needs to achieve to reduce or control climate change. Our results are consistent with reports by [28], [29], who reported that negative emissions are needed to stabilize global warming to 1.5 degrees Celsius. Almost all studies on pathways to achieving the global warming of 1.5°C in the special report by the Intergovernmental Panel on Climate Change (IPCC) reveal carbon removal to achieve net negative emission is the best approach. Therefore, the minimum negative value of CO_2 emission is ideal for Africa to curb climate change, contributing to stable global warming.

The probability of obtaining the minimum value of CO_2 of exactly -1.13973 seems not feasible. Therefore, we obtained a confidence region of (-1.386, -0.893) along with a predictive interval of (-1.387, -0.893), which gives us 95% confidence in capturing the minimum value of CO_2 emissions. The resulting R^2 at the end of the optimization process was 0.9879, approximately equal to the R^2 of the original model, attesting to the robustness and high quality of the optimization process we performed. Also, the optimization process resulted in a predictive accuracy of 97.71%, as given in Table 3. From Table 2, to attain the minimum value of CO_2 of -1.13973 required the combination of the optimal value of Liquid fuels of 16537, Solid fuels of 16537, Gas fuels (Ga) of 67972, Gas flares (Gf) of 313, and Cement production (Ce) of 23631. Combining the controllable factor needed to attain the optimal value of CO_2 may vary from data to data. However, the Optimal value of CO_2 should be within the limit of the confidence region. The individual risk factors Ga and Ce, including the interactions, $So \cap Li$, $So \cap Ga$, $So \cap Gf$, and $Li \cap Ce$ are negatively associated with the atmospheric CO_2 emissions. Whereas the individual significant risk factor So, Li, and Gf with interactions $So \cap Ce$, $Li \cap Ga$, and $Ce \cap Gf$ are positively related to CO_2. The finding of So and Li as positively associated with CO_2 emissions in Africa is consistent with South Korea's result by D. Kim and C. P. Tsokos [30].

Similarly, Ga's finding as negatively associated with CO_2 emission in Africa is consistent with the results in South Korea and the USA by Yong Xu, Chris P. Tsokos (2013) [17]. In contrast with the USA's findings [17], Ce was found to influence Africa's CO_2 emission negatively. Also, we displayed contour and 3D plots showing the combination of the controllable or attributable factor impact on CO_2 emissions in Africa. The blue-colored region of the contour plots is a region of minimization of CO_2 emission. Thus, the deeper the blue color, the closer the approach to the optimal or minimum region of CO_2 emissions. For example, by reducing Li and So in the first contour plot, we minimize CO_2 emission.

Although mitigation against climate change is a global responsibility, we believe that every country/continent has an independent role to perform if we are to achieve the optimal level of CO_2, which is harmless to our globe. The rate of atmospheric CO_2 emissions and contributing risk factors vary from country to country or continent to continent, with some experiencing higher emissions than others. Therefore, different mitigation policies and efforts will be required. Although a global push for accelerated climate change mitigation is needed, enacting, and implementing policy relevant should be left in the hands of individual countries or continents. Thus, given that an optimal (minimum) CO_2 emissions of -1.13973 within a confidence region of (-1.386, -0.893) needs to be attained to stabilize the impact on global warming in Africa, this may differ from the required minimum emission of CO_2 in other conti nents. As a result, this study is only applicable to global warming policy intervention in Africa. However, the methodology or approach can be applied to find the minimum CO_2 emissions for other countries or continents. The optimization algorithm allows to set the CO_2 to a specific target value and obtain the values of each attributable variable needed to achieve the target value. The present study provides a strategy for controlling CO_2 emissions in Africa, hence a mitigating strategy for controlling climate change or global warming.

IV. Conclusion

In the present study, we achieved five important major uses of the response surface optimization method to minimize the atmospheric CO_2 emissions in Africa. First, the desirability function approach was utilized to determine the attributable variables' values that minimize Africa's CO_2 emissions. Second, we identified the minimum value of -1.13973 CO_2 emission in Africa's atmosphere using a data-driven statistical model with an R2 of 97.28% obtained using real data from 1964 to 2014. Third, we also identified a 95% confidence region for the attained minimum value of CO_2 of (-1.386, -0.893), which can be used to assess the statistical significance of the optimal/minimum value of CO_2 emissions. Fourth, the bivariate interaction effect on atmospheric CO_2 emissions was obtained, including 3D and contour plots to assess the combination of individual risk factors' impact on atmospheric CO_2 emissions in Africa. Lastly, the optimization process is well-validated to satisfy the necessary conditions, achieving an excellent desirability function of 0.99.

Given the IPCC goal of meeting 1.5˚C of global warming, our finding of the minimum value of -1.13973 provides Africa with a real direction, a set goal, and a policy intervention strategy to mitigate climate changes, a contribution effort to fighting global warming. The results obtained from this study are only applicable to the Africa continent and cannot be generalized. However, the optimization approach or algorithm can be applied to CO_2 data from other continents that have been statically modeled to identify the risk factors and interactions to assess the needed minimum value of CO_2 emission.

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Appendix A

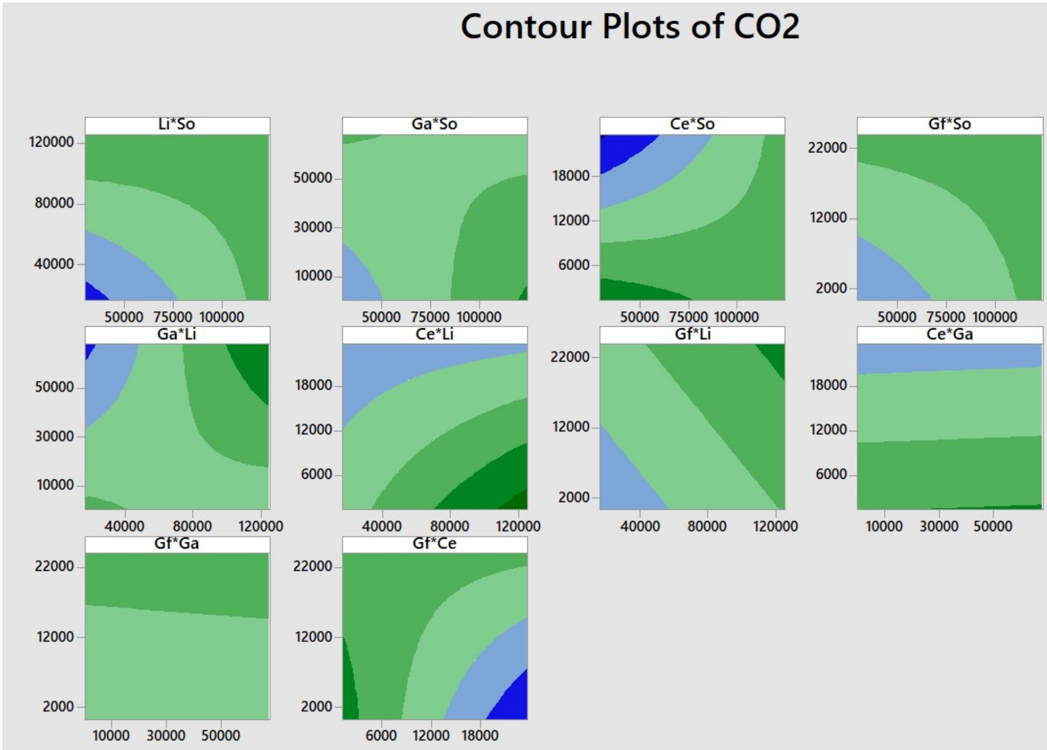

Figure 3: Contour Plots of CO_2 Emission in Africa in Metric Tons

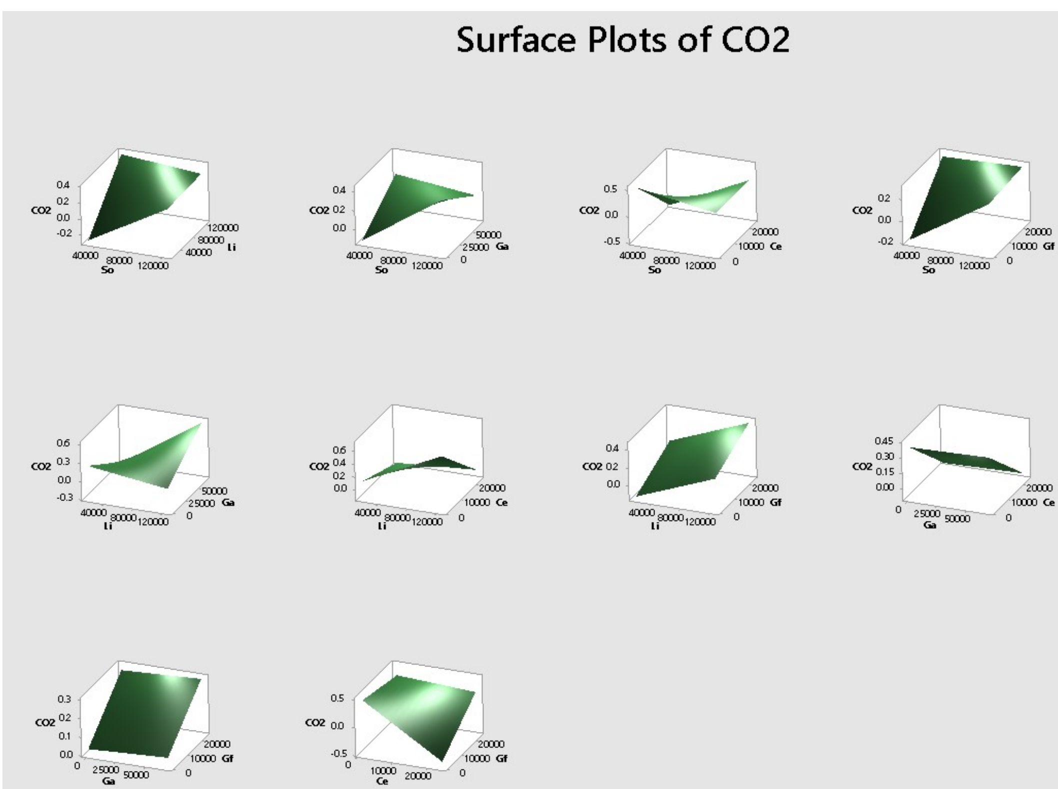

Figure 4: Surface Plots of CO_2 Emission in Africa in Metric Tons