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The influence of climate change and country-based conflict on crop production: Evidence based on global panel data in the last decade

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ABSTRACT

In the past decade, the food crisis has become a special concern for the international community. This is in the spotlight as the earth ages, increasingly changing climatic conditions lead to erratic crop yields and worsening crop quality. On the other hand, this condition is exacerbated by the increasingly tense dynamics of international politics which leads to conflict between countries. For this reason, we investigated the relationship between these conditions using the linear mixed model method. In this article, the model obtained is able to describe the real conditions currently occurring regarding the relationship between climate change, conflict between countries and crop production. Among other things, it is known that the majority of continents are carrying out agricultural extensions and intensifying efforts to reduce CO2 emissions, to increase crop production. On the other hand, as time goes by, the model shows that environmental temperature fluctuations are getting bigger. Apart from that, conflict factors apparently exacerbate the effects of climate change which directly affects crop production. This article also provides suggestions for countries on a continent to increase crop production while maintaining climate balance.

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INTRODUCTION

Food is one of the basic human needs. Therefore, to meet world food needs, the United Nations (UN) launched the Sustainable Development Goals (SDGs) program with 17 goals, of which SDG2 is Zero Hunger or the absence of hunger (Taghvaee et al., 2022). Due to the food crisis phenomenon currently occurring in the world, it is estimated that population growth will increase the level of malnutrition(Hall et al., 2017)because intense exploitation of natural resources will lead to land degradation and also reduced land productivity, the majority of which occurs in urban areas(Fitzgerald et al., 2020; Tóth et al., 2018). Coupled with the increase in extreme events such as conflict and increasing pests and diseases followed by the climate crisis which is the cause of crop failures and other disasters(Richardson et al., 2018; Spence et al., 2020).

To overcome the reduction in world harvest yields, to increase world food yields, a distance approach to the potential world harvest yields is very crucial(Prishchepov et al., 2019)since there is a large gap in developing countries and transition countries(RONG et al., 2021). Therefore, it is important to have adequate agriculture to meet the food needs of a country and the world. The diversity of crop yields can qualitatively explain differences in natural conditions and human factors in crop production(RONG et al., 2021). Natural conditions such as climate and soil quality, which are important elements for crop growth, directly influence crop yields(van Loon et al., 2019; Zhi et al., 2022). One of the famous harvest products is rice (Oryza sativa) which is a staple food for almost half of the world's population, especially in Asia.(Min et al., 2022). Therefore, rice can be a reference in monitoring world harvest yields in order to bring the world harvest closer to the potential harvest yields it should be.

The climate crisis affects crop yields directly, consistently leading to changes in soil quality(Culbertson et al., 2016; Kalcic et al., 2019). The most influencing factors are temperature and CO2, although for some types of plants this does not have much of an influence, such as in Ontario where the average annual rainfall for 50 years only reaches 843 mm.(He et al., 2018).High temperatures are very detrimental to crop yields and can reduce agricultural productivity(Schauberger et al., 2017; Wang et al., 2021). Extreme events such as drought can result in large crop losses on a global scale(Powell & Reinhard, 2015). For example, the drought that occurred in 2003 and 2018 resulted in massive crop failures in several crops in various countries.(Schmitt et al., 2022; Webber et al., 2020).

Chronic food insecurity can trigger conflict and violence due to the struggle for natural resources(Martin-Shields & Stojetz, 2019). Previous research has also proven that there is a reciprocal relationship between food insecurity and certain incidents of violence(Brück et al., 2016). This phenomenon is what attracted the author's interest in researching the influence of conflict and the climate crisis on world harvests.

METHOD

Nowadays, linear mixed models and general mixed models are more widespread, partly due to their computational power and ease of use of packages (Bates et al., 2015). The advantages of mixed models are well documented but there is still debate in the choice of certain parameters, especially for random slopes (Barr et al., 2013; Bates et al., 2015; Matuschek et al., 2017). For an overview of the theoretical background and applications, see several studies by (Barr et al., 2013; Jost & Jansen, 2022) or a more beginner-friendly tutorial by (Winter, 2013.)

The method used in this research is linear mixed models. Linear mixed models are a development of linear models in which there are fixed effects and random effects that influence the response variable. Fixed effects themselves are explanatory variables, while random effects are other additional influences.

In this study, two types of models were used, namely no random effect or without random effects and with random effect or accompanying random effects.

For a model without random effects, the general form is

$$Y_{ij} = \beta_0 + \beta_1 t_j + \epsilon_{ij}$$

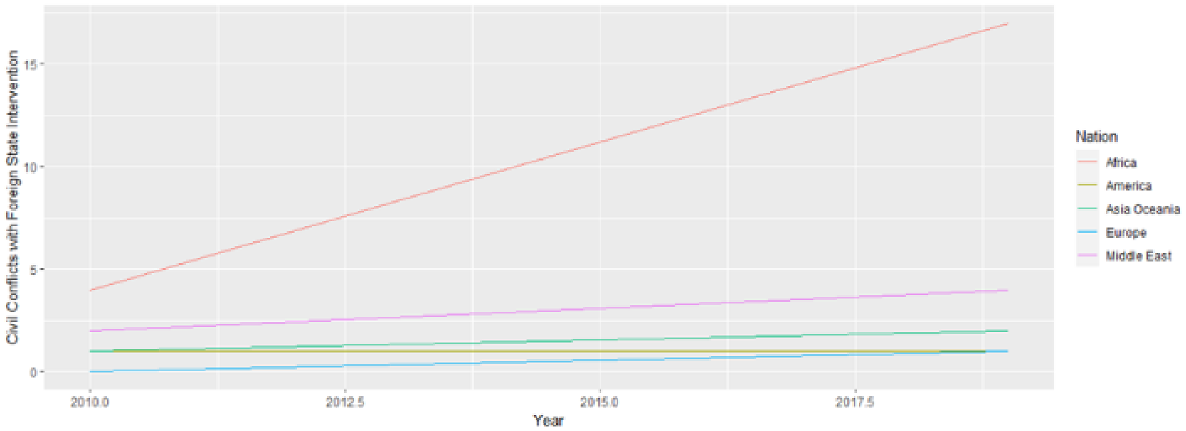
Meanwhile, for models with random effects, the general form is

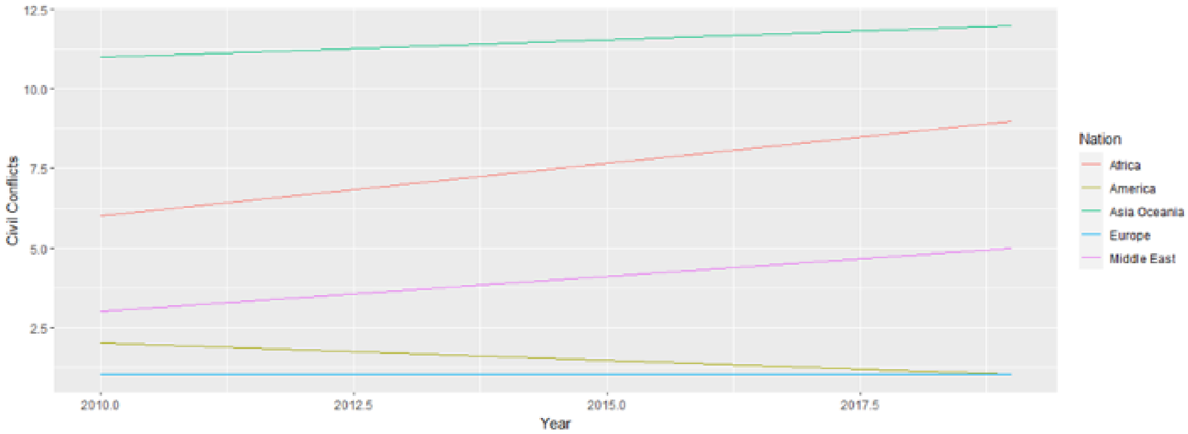
$$Y_{ij} = \beta_0 + \beta_1 t_j + \cdots + \beta_n X_n + \alpha_i + \epsilon_{ij}$$

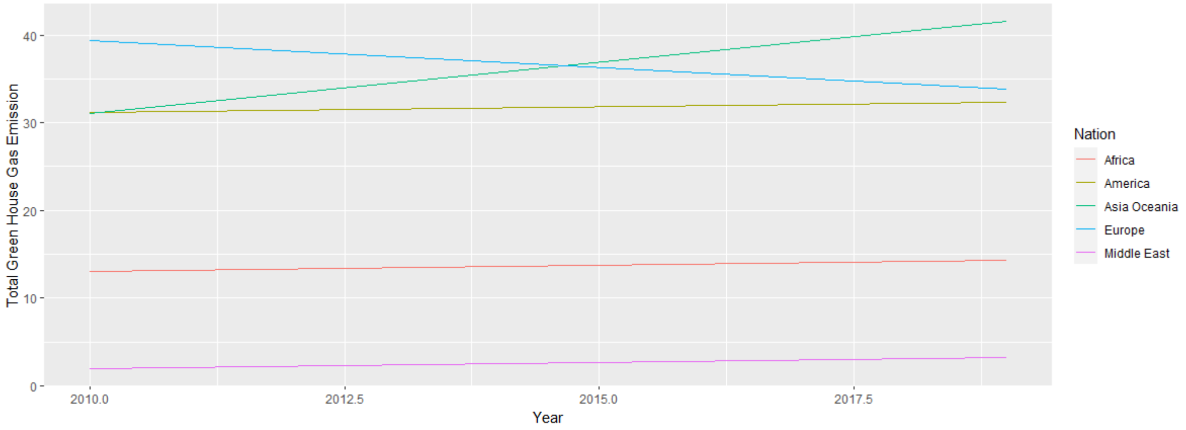
Where is the time before and after passing 10 years, j is the region which in this study is the continent. $i \in [0,1]$

1. **Datasets**

The scope of this research covers conditions of climate change and nation-based conflict experienced by all countries in the world taken in the period 2010-2019. The representation of climate change variables in this research is taken from independent variables including forest area (FA), CO2 emissions (CO2E), total green house gas emissions (TGHGE), environment temperature change (ETC). Meanwhile, for the nation-based conflict variable, we divide it into two categories of independent variables, namely Number of CC with foreign state intervention (CCFSI), and Number of civil conflicts (CC). And the dependent variable is Crop Production (tonnes per hectare) which is interpreted as a measure of the agricultural harvest produced (tons) per one hectare. For the purpose of simplification, we took data from a country with the lowest change in climate change and Crop Production factors during that time period as a representation of the condition of a continent (Africa, America, Asia&Oceania, Europe, Middle East). So the model we built will be significant in countries where changes are small, even more so in countries where changes are large.



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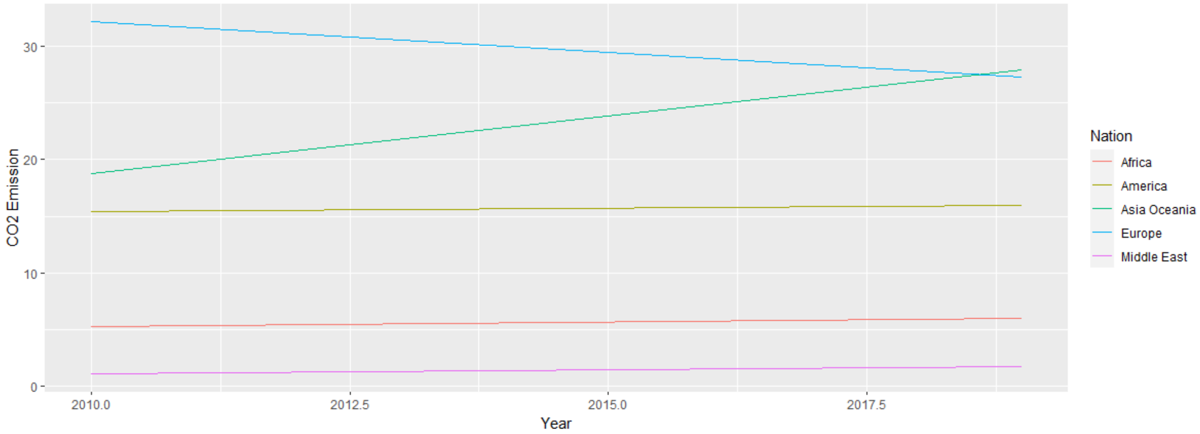
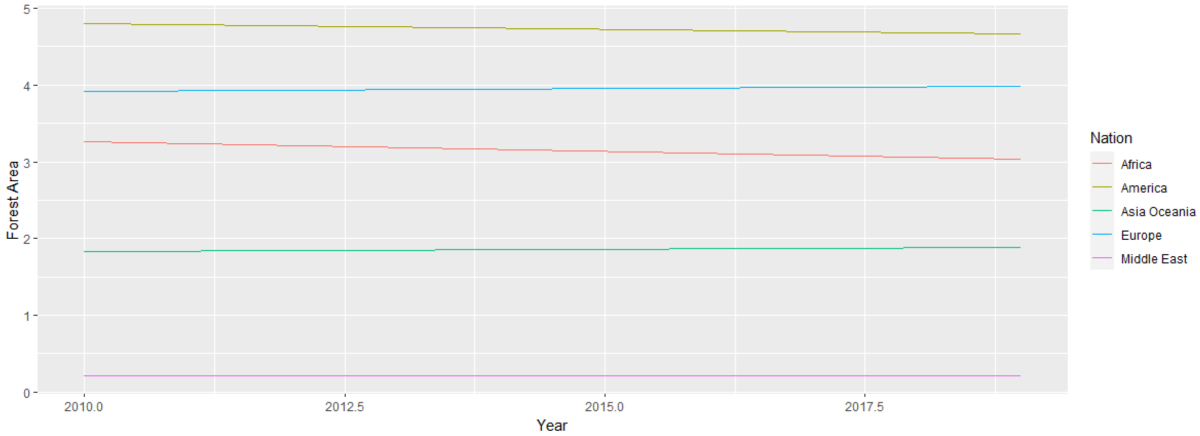
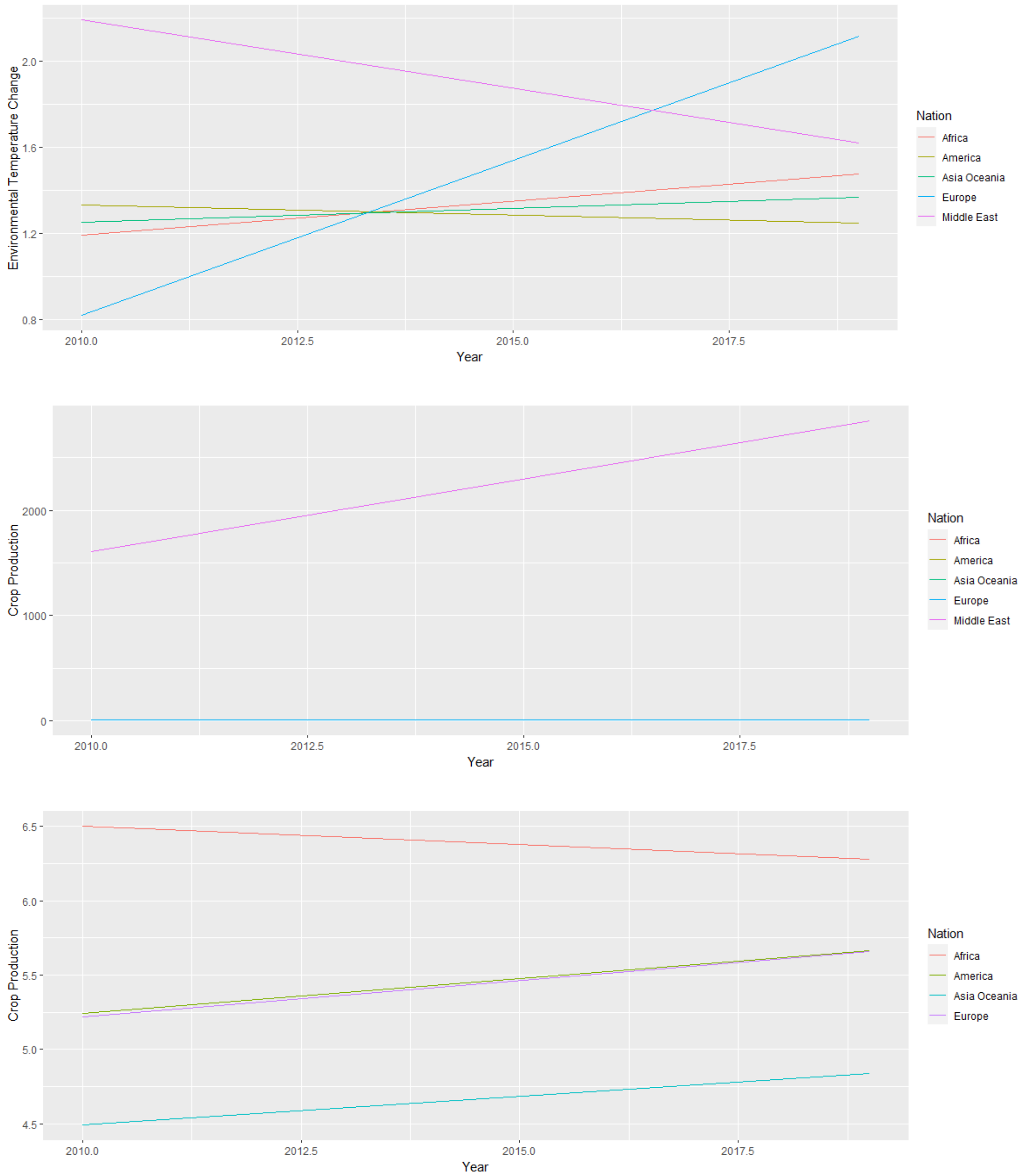
Year
Nation
Africa
America
Asia Oceania
Europe
Middle East


CO2 Emission
Year
Nation
Africa
America
Asia Oceania
Europe
Middle East


Forest Area
Year
Nation
Africa
America
Asia Oceania
Europe
Middle East



Picture 1. Visual Dataset

2. Model Analysis

Several models for describing longitudinal evolution will be illustrated and compared.

Table 1. Model Summary

Model	CCFSI	CC	F.A (%land area)	CO2E (kilotons)	TGHGE (kilotons)	ETC (celsius degrees)	Year	Interaction	Random State Effects
0							✓		
1			✓				✓		✓
2			✓				✓	**Year : FA**	✓
3					✓		✓		✓
4						✓	✓	**Year : ETC**	✓
5	✓		✓				✓		✓
6	✓			✓			✓		✓
7	✓				✓		✓		✓
8	✓	✓	✓				✓		✓

In the first stage, we initially explore each independent variable that has a significant influence on Crop Production on a continent without involving random effects. This means that we assume that the continents have the same average internal conditions in terms of the ability to produce agricultural products. Furthermore, from the exploration results involving each independent variable, it was found that there was no model that had a significant influence on the independent variable, namely the null model. As a representative we introduce a null model that relates the time variable (year) to Crop Production.

$$Y_{ij} = \beta_0 + \beta_1 t_j + \varepsilon_{ij} \qquad (0)$$

$$\varepsilon_{ij} \sim N(0, \sigma_{res}^2)$$

The null model illustrates that there is no significant influence of changes in time (years) on the size of a continent's Crop Production. This means that under normal conditions (without considering other variables) as time goes by, Crop Production will not be affected. This is proven by the p-value year of 0.92943850. So next we continued our investigation by adding Random Effects in the form of Random State Effects and we also carried out various combinations of involving independent variables in the model, which then obtained a model that contained variables that had a significant effect, namely model one.

$$Y_{ij} = \beta_0 + \beta_1 t_j + \beta_2 X_4 + \alpha_i + \varepsilon_{ij} \qquad (1)$$

$$\alpha_i \sim N(0, \sigma_{state}^2)\ , \varepsilon_{ij} \sim N(0, \sigma_{res}^2)$$

Model one presents the influence of time (year) and FA area on the Crop Production size of a continent by including random state effects. The FA p-value results show significance and a strong inverse relationship, amounting to 0.011992610 and a value of -1.9441387. This can be interpreted as that the FA area has a direct influence on the size of Crop Production on a continent by considering the influence of the time variable (year). In addition, this illustrates that the extent of a continent's FA has implications236quite strong statistics for Crop Production. This is what is currently happening, in various countries, a lot of land has been used as urban areas so that increasing agricultural production is often attempted through extensification, namely reducing the area of FA for clearing agricultural land. On the other hand, the addition of random state effects produces a significant random state effect intercept p-value of 0.001021835, which indicates that there is no continent whose internal conditions in terms of ability to produce agricultural products are different from the average of other continents. Which adds to the information that on average the continent must reduce its Fauna area to increase its Crop Production. Furthermore, this also confirms the uniformity of the downward graphic pattern in the FA sector in Table 1.

Then, to find a more significant model, we developed model one by adding an interaction between the independent variable time (year) and FA, which was later named model two.

$$Y_{ij} = \beta_0 + \beta_1 t_j + \beta_2 X_4 + \beta_3 t_j * X_4 + \alpha_i + \varepsilon_{ij} \quad (2)$$

$$\alpha_i \sim N(0, \sigma^2_{state}), \varepsilon_{ij} \sim N(0, \sigma^2_{res})$$

It was found that the independent variable FA still had a significant effect and still had implications237statistics on Crop Production. However, the interaction between the independent variable FA and time (year) does not have a significant influence on Crop Production. But on the other hand, the addition of this interaction component reduces the residual variance value of the model quite significantly. This means that the model is getting better at estimating data values even though in the model structure, the interaction component does not have a significant influence. So from the first three models it can be concluded that on average continents are currently clearing forests to increase their crop production through land clearing, even though this is 237 statistics have proven to be significant in increasing Crop Production, but it needs to be considered regarding the balance of forest ecosystem sustainability, because statistically, changes in time have almost a significant impact on the decreasing area of FA.

Table 2. Summary of Model Significance Values

Model		Value	Std Error	p-value
1	(Intercept)	2.8127	1.1970	0.0466**
	Year	0.1547	1.6927	0.9294
		Value	Std Error	p-value
	(Intercept)	4.0296	0.4706	0.0010***
	Year	0.1347	0.1249	0.3598
	Log(FA)	-1.9441	0.3552	0.0120*
			Variance	
	(Intercept)		0.8214	
	Residual		0.0390	
2		Value	Std Error	p-value
	(Intercept)	3.9432	0.4673	0.0011**
	Year	0.2556	0.0727*	0.0722
	Log(FA)	-1.8061	0.3514	0.0358**
	Year:Log(FA)	-0.1940	0.0558	0.0737*
			Variance	
	(Intercept)		0.8398	
	Residual		0.0102	

with a significance level(= 0.05 , * ** ***)α

Even though model two is quite good at explaining the interference between climate change factors and Crop Production with a fairly small residual variance, indicating that the data distribution from the model is not far from the average, the climate change factor involved in this case is only the FA area factor. . For this reason, we continue our exploration by involving other factors and hope to obtain a significant model involving many climate change factors in one model. And as a result of this exploration, we obtained models three and four.

$$Y_{ij} = \beta_0 + \beta_1 t_j + \beta_2 X_6 + \alpha_i + \varepsilon_{ij} \quad (3)$$

$$\alpha_i \sim N(0, \sigma^2_{state}) , \varepsilon_{ij} \sim N(0, \sigma^2_{res})$$

$$Y_{ij} = \beta_0 + \beta_1 t_j + \beta_2 X_7 + \beta_3 t_j * X_7 + \alpha_i + \varepsilon_{ij} \quad (4)$$

$$\alpha_i \sim N(0, \sigma^2_{state}) , \varepsilon_{ij} \sim N(0, \sigma^2_{res})$$

Table 3. Summary of Model Significance Values

Model		Value	Std Error	p-value
3	(Intercept)	8.0517	1.2806	0.0033***
	Year	0.4591	0.3229	0.2502
	Log(TGHGE)	-1.9050	0.4297	0.0213**
			Variance	
	(Intercept)		0.9674	
	Residual		0.2488	
4		Value	Std Error	p-value
	(Intercept)	2.9920	1.2402	0.0734*
	Year	-0.3268	0.1233	0.1178
	Log(ETC)	-0.7071	0.1327	0.0332**
	Year:Log(ETC)	1.4084	0.3097	0.0451**
			Variance	
	(Intercept)		7.6818	
	Residual		0.0036	

with significance level (= 0.05 , * ** ***)α

As seen in Table 3, model three presents other factors that can influence the size of a continent's Crop Production, namely TGHGEs. This is new information that the size of TGHGEs can have a significant effect with negative implications on the size of Crop Production. In contrast to model one which is not surprising when the size of FA affects the size of Crop Production, model three provides very interesting information. And also the small p-value of the intercept indicates that on average the continents have the same initial conditions in terms of the ability to produce Crop Production, which then across all continents the TGHGEs effect phenomenon has a significant influence on their Crop Production results. Apart from that, the small variance values in each model indicate that the distribution of data from each model is not far from the average, indicating that the selected model is quite good at representing the phenomena that occur. So it can be concluded that on average, if the continent wants to increase its Crop Production, it must intensify efforts that can reduce its TGHGE.

Furthermore, something more interesting was found in model four. observed in table 3, that there is a new climate change factor which also influences Crop Production significantly, namely Environmental Temperature Change with negative implications. It does not stop there. It is also known that the interaction between the independent variable time (year) and environmental temperature change is significant and has positive implications. This indicates that as time goes by (years) on all continents, environmental temperature change fluctuations become greater, which then leads to a reduction in Crop Production for a continent, this is proven by the Log (ETC) value of -0.7071598. So this urgency needs to be taken into account by each continent if they want to increase their Crop Production, So it is necessary to intensify efforts in the long term to reduce fluctuations in ETC. This is because statistical evidence shows that without the intervention of other factors, over time, fluctuations in environmental temperature change increase by themselves. In addition, the advice above is reinforced by the small residual variance value which indicates that the model represents the original data (actual conditions) very well.

After five models have been introduced and their interpretations, none of them involve nation-based conflict factors in the model components that influence Crop Production. For this reason, the exploration continues by involving nation-based conflict factors in it. And as a result of this exploration, we obtained models five, six, and seven.

$$Y_{ij} = \beta_0 + \beta_1 t_j + \beta_2 X_1 + \beta_3 X_4 + \alpha_i + \varepsilon_{ij} \quad (5)$$

$$\alpha_i \sim N(0, \sigma^2_{state}) , \varepsilon_{ij} \sim N(0, \sigma^2_{res})$$

$$Y_{ij} = \beta_0 + \beta_1 t_j + \beta_2 X_1 + \beta_3 X_5 + \alpha_i + \varepsilon_{ij} \quad (6)$$

$$\alpha_i \sim N(0, \sigma^2_{state}) , \varepsilon_{ij} \sim N(0, \sigma^2_{res})$$

$$Y_{ij} = \beta_0 + \beta_1 t_j + \beta_2 X_1 + \beta_3 X_6 + \alpha_i + \varepsilon_{ij} \quad (7)$$

$$\alpha_i \sim N(0, \sigma^2_{state}) , \varepsilon_{ij} \sim N(0, \sigma^2_{res})$$

Table 4. Summary of Model Significance Values

Model		Value	Std Error	p-value
5	(Intercept)	4.1970	0.5571	0.0017***
	Year	0.2369	0.2111	0.3785
	Log(CCFSI+1)	-0.1773	0.2862	0.5987
	Log(FA)	-1.9796	0.3723	0.0336**
			Variance	
	(Intercept)		0.8818	
	Residual		0.0434	
6		Value	Std Error	p-value
	(Intercept)	9.0307	1.2236	0.0018***
	Year	1.3785	0.5773	0.1396
	Log(CCFSI+1)	-1.4166	0.5782	0.1339
	Log(CO2E)	-2.3233	0.3750	0.0250**
			Variance	
	(Intercept)		0.3850	
	Residual		0.4820	
7		Value	Std Error	p-value
	(Intercept)	10.7293	0.7865	0.0002***
	Year	1.2282	0.4308	0.1041
	Log(CCFSI+1)	-1.1565	0.3159	0.0672*
	Log(TGHGE)	-2.5342	0.21005	0.0007***
			Variance	
	(Intercept)		0.0000	
	Residual		0.3628	

with significance level (= 0.05 , * ** ***)α

It can be seen from Table 4 that the independent variable CCFSI appears in the model components that influence Crop Production. Even though it does not have a significant effect on Crop Production, it indirectly has an effect on the independent variable which is a climate change factor in the model. For example, in model six, in our initial exploration the independent variable CO2E had no significant effect on Crop Production so we did not show it. However, once involved, the independent variable CCFSI, CO2E becomes significantly influencing Crop Production results and of course with negative implications. This can be interpreted as meaning that the existence of CCFSI increases the influence of CO2E through increasing CO2E levels. Besides that, with a small variance value in each model, indicating that the data distribution is quite good for each model, indicating that the model is quite good at representing the phenomenon. This can be understood in the current era, that when there is conflict between continents, with their armed forces there will be exhaust gas as a destructive bad effect from the use of weapons, such as missiles or rockets. So that initially it had no impact on Crop Production, as CO2E increases it brings a decrease in Crop Production results. So after this, each continent must think again if it wants to conflict with foreign interference and consider the effects of decreasing Crop Production and increasing CO2E. that when there is conflict between continents, with their armed forces there will be exhaust gas as a destructive bad effect from the use of weapons, such as missiles or missiles. So that initially it had no impact on Crop Production, as CO2E increases it brings a decrease in Crop Production results. So after this, each continent must think again if it wants to conflict with foreign interference and consider the effects of decreasing Crop Production and increasing CO2E. that when there is conflict between continents, with their armed forces there will be exhaust gas as a destructive bad effect from the use of weapons, such as missiles or missiles. So that initially it had no impact on Crop Production, as CO2E increases it brings a decrease in Crop Production results. So after this, each continent must think again if it wants to conflict with foreign interference and consider the effects of decreasing Crop Production and increasing CO2E.

It doesn't stop there, in model seven it is known that the involvement of the CCFSI variable causes TGHGEs to also have a more significant influence on Crop Production. It can be seen from the p-value which is much smaller than model three. In addition, model seven is able to represent the original data (real conditions) much better than model three, which is confirmed by the variance values of the residual and intercept of the model. So it can be concluded that CCFSI has an indirect influence which causes TGHGEs to increasingly influence Crop Production results. And with increasing TGHGEs, a large amount of Crop Production on a continent will decrease.

However, different statistical information is presented through model five. Compared to model one, model five can be said to have a p-value and coefficient that is close to model one. This indicates that in the FA sector, the effect of CCFSI can be said to be almost non-existent. So the effect of FA on Crop Production will not change with or without the effect of CCFSI. This may happen when the conflicts that occur today tend to be through technological wars, trade wars, cyber wars, etc., and even the areas being bombarded are no longer forest areas but urban areas.

Although the last three models have succeeded in presenting the relationship between climate change factors and nation-based conflict, our goal has not been achieved. For this reason, we carried out further exploration by involving more combinations of independent variables involved in the model. So finally at the end of this exploration a significant model was obtained, namely model eight.

$$Y_{ij} = \beta_0 + \beta_1 t_j + \beta_2 X_1 + \beta_3 X_2 + \beta_4 X_4 + \alpha_i + \varepsilon_{ij} \quad (8)$$

$$\alpha_i \sim N(0, \sigma^2_{state}), \varepsilon_{ij} \sim N(0, \sigma^2_{res})$$

Table 5. Summary of Model Significance Values

Model		Value	Std Error	p-value
8	(Intercept)	5.3904	0.3515	0.0001***
	Year	-0.1300	0.2696	0.7139
	Log(CCFSI+1)	0.6333	0.2312	0.2229
	Log(CC+1)	-1.1770	0.2256	0.1205
	Log(FA)	-2.0852	0.1147	0.0350**
			Variance	
	(Intercept)		0.0086	
	Residual		0.1439	

with significance level (= 0.05 , * ** ***)α

It can be seen from Table 5 that there is a special relationship between models one, five and eight. This can be seen from the climate change factors involved, namely FA. Of the three models, either after adding the independent variable CCFSI, or after adding CCFSI and civil conflict. It was found that the p-value of the independent variable FA did not change drastically. Even the coefficients of the independent variable FA from the three models are not much different. This model does not have a large variance value so this model has a good ability to describe the phenomena that occur. This indicates that based on current data, the existence of CCFSI and civil conflict does not reduce or increase FA significantly. Which means this strengthens the argument in the interpretation in model five.

CONCLUSIONS AND SUGGESTIONS

Based on the simulation results of all models that contain variables that have a significant influence on crop yields or Crop Production, it can be concluded that climate change variables have a significant influence on Crop Production with quite large negative coefficient values. These results are in accordance with previous research conducted byChandio et al (2020). These results also explain that climate change has a negative impact on a continent's crop yields which can result in hunger, increased food prices, reduced food availability, and increased poor health conditions.(Mason-D'Croz et al., 2019). On the other hand, the simulation results show that nation-based conflict variables do not have a significant direct influence on the harvest results of a continent(Turner et al., 2020), however, these variables can increase the significance of the influence of climate change variables when added to the model. This indicates that conflicts that occur on a continent can exacerbate climate change that is currently occurring on that continent, resulting in reduced crop yields.

This research provides an overview and explanation of the variables of climate change and nation-based conflict which significantly influence Crop Production. Apart from that, this research also provides an explanation that the interaction of these jm variables can also have a significant influence on Crop Production. In addition, this research can help the government in drafting regulations and implementation related to follow-up on variables that can influence crop yields to prevent food crises, inflation, hunger and various other problems. However, this research is only aimed at seeing and describing the influence of climate change and nation-based conflict on a continent's crop yields or Crop Production. In future research, it is hoped that further exploration can be carried out regarding the variables that have a significant influence in modeling the harvest yields of a continent and a more efficient method can be created in variable selection that can make it easier to select variables that have a significant influence on the model. Apart from that, it is hoped that there will be further research that can produce products from the analysis of the influence of climate change and nation-based conflict variables on Crop Production and can better improve the country's food security.

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