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Analyzing food production risk with Monte Carlo simulation

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Abstract

The agricultural sector in the country has a high and growing status and importance, but the growth and development of this sector are not possible without proper and effective risk management. In the current study, using the Monte Carlo simulation method as one of the powerful tools in risk analysis, the production risk due to the effects of climate change on the dominant agricultural products of Plovdiv, Bulgaria in the period 1990-2017, is predicted and measured. The results showed that Lentils has the highest risk (Product risk index was -0.25%) and bean has the lowest risk (Product risk index was 0.17%). Overall, the research results indicate the significant effect of performance risk in this region. Therefore, farmers should pay special attention to the risk of crop performance in determining their cultivation pattern in addition to other factors and criteria such as price, profitability, self-consumption, etc. Meanwhile, it is suggested that products with higher risk should not be grown alone and should be placed next to the other products with less risk as much as possible to increase food security.

Keywords: Monte Carlo simulation; agricultural products; risk management; food production risk.

Practical Application: In this paper, using the Monte Carlo simulation method, the production risk due to the effects of climate change on the dominant agricultural products of Plovdiv, Bulgaria is predicted and measured.

1 Introduction

Human life has coexisted throughout history and around the world, exposed to a variety of natural hazards (Ataseven et al., 2020). Part of these risks and accidents are caused by geological activities and processes (Demir et al., 2003; Ferrari et al., 2021). Another number of them, which are relatively more abundant and extensive, are due to climatic processes. These events include severe storms, droughts, torrential rains, and thunderstorms, among which drought is of considerable importance and extent (Wong et al., 2020). Drought is a long-term phenomenon that causes significant damage to human life and economic losses, and this phenomenon plays an important role in many human affairs. Drought and other risk factors such as pests and changes in agricultural prices, government decisions on imports and exports of agricultural products have made the production of agricultural products always associated with risk (Moreira & Barrufet, 1996; Bemrah et al., 2003; Molajou et al., 2021; Afshar et al., 2022).

Risk management is essential for optimal crisis management (Cruz et al., 2019). Because through it and by evaluating and preparing risk maps, dangerous areas are identified. Before the crisis occurs, the risk caused by these phenomena is minimized (Cronin et al., 2003; Rajkumar et al., 2003; Kovalenko et al., 2021). Assessing the efficiency of agricultural production is an important issue in the implementation of the agricultural development process in developing countries. Because in this way, useful information in the field of appropriate decision-makers for accurate management in the allocation of resources and regulation of agricultural policies is provided to planners (Cunha et al., 2020; Boubguira et al., 2021). The uncertainty in estimating the data of the data envelopment analysis model for the agricultural sector has been inevitable due to sampling errors or the use of centrifugal indices. The need to use patterns that are able to control changes due to erratic data is strongly felt (Jacintho et al., 2020; Galhardo et al., 2021).

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The Monte Carlo method is a computational algorithm that uses random sampling to calculate the results (den Aantrekker et al., 2003). The Monte Carlo method is commonly used to simulate physical, mathematical, and economic systems. Because of their reliance on iterative calculations and random or pseudo-random numbers, the Monte Carlo method is often set to be performed by a computer (Baudry et al., 2018). The tendency to use this method is especially useful in the study of systems where there are a large number of variables related to the degree of freedom in pairs (Djekic et al., 2021; Hu et al., 2020). This method is also useful for simulating phenomena where there is a lot of certainty in their inputs. The Monte Carlo method is one of the universal accurate numerical techniques used, especially where random effects are important (Sanaei et al., 2021). Questions have arisen about the uncertainty of a model in all fields of engineering and science. In recent years, significant advances have been made in the field of uncertainty analysis (Ewertowska et al., 2017). Scientists are trying to model and propagate uncertainty. In general, uncertainty analysis requires random modeling environments. Analysts often develop models based on each input variable's unique value or estimation point, ignoring uncertainty. In general, this is a definite solution for modeling or analysis (Han et al., 2021).

2 Material and methods

One of the main factors in creating production risk is climate change, and these changes are not the same in the whole study area (Nourani et al., 2019; Nourani et al., 2020; Afshar et al., 2021). Therefore, in addition to using the Monte Carlo simulation method, used the normal percentage index to classify different climate groups so that based on this index, the relationship between crop yield and the type of comparing the weather in each year in Plovdiv, Bulgaria between 1990 to 2017.

2.1 Drought index percentage of normal

To study the phenomenon of drought, the existence of appropriate and long-term data on climatic and hydrological parameters is essential. One of the indicators that are based on the use of rainfall parameter and only the factor needed to calculate that rainfall is the normal percentage index (PN) (Nicolaï & Baerdemaeker, 1999; Nourani & Molajou, 2017; Syed & Lawryshyn, 2020). Index (PN) is obtained by dividing the actual amount of precipitation by normal precipitation and multiplying it by 100. According to this index, the severity of drought is divided into very humid (Rainfall more than 160 mm), almost humid (Rainfall between 145 to 165 mm), wet (Rainfall between 130 to 145 mm), semi-humid (Rainfall between 120 to 130 mm), normal (Rainfall between 80 to 120 mm), mild drought (Rainfall between 70 to 80 mm), moderate drought (Rainfall between 55 to 70 mm), severe drought (Rainfall between 40 to 55 mm), and very severe drought (Rainfall less than 40 mm).

2.2 Monte Carlo simulation method

Simulation implies the creation of a virtual model of a real system for studying and understanding the system. Monte Carlo is a method of analysis based on recreating and virtualization using a random process that has been performed many times, and the results are directly visible. In this method, it is not necessary to assume that the efficiency distribution is normal but to predict future changes using random processes and the use of many computer-generated simulated samples. In this research, to assess the risk of products, first, the possible processes and process parameters for the variable are determined (Oscar, 2021). Hypothetical simulation for the variables used (based on the process of creating random numbers) values is performed for that variable. The value of the expected variable is calculated and determined from the simulated variable (Varga et al., 2000). Finally, the last two steps are repeated for scenario building, and the values obtained from the previous steps are compared with the actual values, and the risk of the products is examined (Öksüz & Buzrul, 2020).

3 Results and discussion

First, the climatic conditions were classified based on the obtained indicators. According to the performance changes of the products based on their climatic conditions, the normal average performance of each product was obtained, and using random numbers and simulations were performed to compare the expected performance with the actual. In addition, by making scenarios the weather conditions, the expected performance was compared with the real conditions, and the performance risk of the products in each of the different scenarios was investigated.

3.1 Climatic conditions

Using rainfall statistics, the total annual rainfall for the years 1990 to 2017 was obtained. Then, the annual long-term average and the normal percentage index for the desired years were calculated. Based on the value obtained from this index, the severity of drought in these years was classified (Table 1).

3.2 Normal average performance and change in product performance

The average normal yield of products was calculated according to the performance data in each year and according to the type of weather phenomenon in that year. Thus, according to the number of normal climates available for the product, the performance of the product in this type of climate was averaged. Product performance change was calculated using Equation 1. Table 2 shows the calculation of the average performance in different weather conditions.

$$\text{Change in product performance} = \frac{\textit{Annual performance}}{\textit{Annual normalized average performance}} - 1 \quad (1)$$

3.3 Grading of weather conditions according to the frequency percentage

The relative frequency criterion has been used to grade the weather conditions. According to Table 3, the frequencies for each type of weather phenomenon are specified. Based on this table, a specific range was determined for each type of weather phenomenon based on their intensity from the worst case to the best case.

Table 1. Calculation of normal rainfall percentage index and its classification based on the type of climate.

Descriptive index	Year
Normal	1990
Moderate drought	1991
Normal	1992
Moderate drought	1993
Normal	1994
Mild drought	1995
Mild drought	1996
Normal	1997
Normal	1998
Mild drought	1999
Normal	2000
Normal	2001
Mild drought	2002
Normal	2003
Mild drought	2004
Normal	2005
Mild drought	2006
Mild drought	2007
Normal	2008
Normal	2009
Very wet	2010
Normal	2011
Normal	2012
Moderate drought	2013
Very wet	2014
Normal	2015
Moderate drought	2016
Very wet	2017

3.4 Product performance simulation results

In this study, 10000 random numbers have been created using real product performance data, which is related to the product statistics available in different years. According to the percentage of changes in climate fluctuations that cause a decrease or increase in crop yield (percentage of probability of damage to yield in the long run), the change in yield for each crop was simulated separately and compared with its normal value. Table 4 shows the expected performance results of products after climate change simulation.

According to the results in the table, the percentage change in the mean yield of the simulated wheat for -0.14% is obtained. This number shows that due to the weather phenomena in this region and performance fluctuations for this product, the expected value for the performance of this product is 0.14% less than the average normal performance of this product. This decrease in yield is due to the impact of production risk on the yield of this product in this region. Figure 1 indicates the severity of product risk. In other words, it shows the degree of risk of products, which is an indicator in risk management. Among the available products, Lentils has the highest risk. However, the bean has the lowest risk.

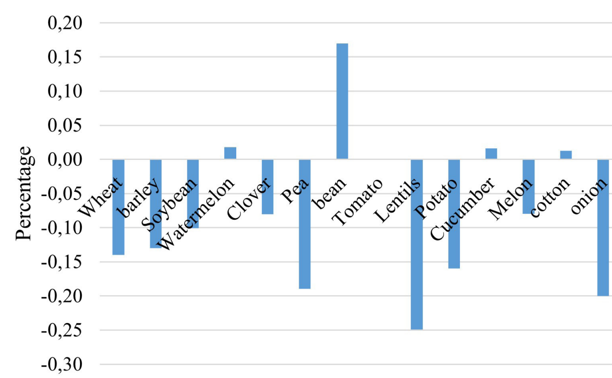

Figure 1. Product risk index.

Table 2. Average performance in different weather conditions.

Product	Average normal performance (kg/h)	Average drought performance (kg/h)	Mean mild drought performance (kg/h)	Average wet performance (kg/h)
Wheat	2178	1940	1710	1153
Barley	1752	1402	1003	1057
Soybean	1502	1200	910	1000
Watermelon	11806	10311	7931	6146
Clover	15887	23010	15574	23000
Pea	956	700	1168	717
Bean	1035	674	900	734
Tomato	15928	14562	12256	15717
Lentils	750	533	420	955
Potato	11883	4843	8097	1058
Cucumber	11172	19400	15166	14840
Melon	9057	7851	7016	9379
Cotton	1239	1129	1262	1382
Onion	10934	11577	9033	8027

Table 3. Grading of weather conditions.

Weather condition	Absolute frequency	Relative frequency
Mild drought	7	25%
Moderate drought	4	14%
Normal	14	50%
Very wet	3	11%

Table 4. Grading of weather conditions.

Product	Average normal performance (kg/h)	Expected performance value (kg/h)	Percentage change of simulated average performance
Wheat	2178	1873	-0.14
Barley	1752	1524	-0.13
Soybean	1502	1351	-0.10
Watermelon	11806	12019	0.02
Clover	15887	14616	-0.08
Pea	956	775	-0.19
Bean	1035	1211	0.17
Tomato	15928	15928	0.00
Lentils	750	563	-0.25
Potato	11883	9982	-0.16
Cucumber	11172	11355	0.02
Melon	9057	8333	-0.08
Cotton	1239	1255	0.01
Onion	10934	8747	-0.20

4 Conclusion

In the present study, the effect of increasing or decreasing rainfall on crop yield in Plovdiv, Bulgaria, has been evaluated. According to the results, climate and rainfall fluctuations can cause significant fluctuations in performance and thus create performance risk in the region's products. Therefore, more attention can be paid to the rainfall variable as one of the important parameters in predicting crop performance.

The results showed that Lentils has the highest risk (Product risk index -0.25%) and bean has the lowest risk (Product risk index 0.17%). Therefore, farmers should pay special attention to the risk of crop performance in determining their cultivation pattern in addition to other factors and criteria such as price, profitability, self-consumption, etc. Based on the results of the high risk of crops, it is suggested that higher risk crops should not be grown alone as much as possible.

Using the Monte Carlo simulation method to measure risk showed that this method can be used to determine and prioritize the risk of different products. Therefore, it is suggested to use this method on a larger scale and different products in the country.

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