2022-11-07

Mathematical models for aflatoxin contamination in crops, livestock and humans: A review

Mgandu, Filimon

SCIK Publishing Corporation

Available online at http://scik.org
Commun. Math. Biol. Neurosci. 2022, 2022:116
https://doi.org/10.28919/cmbn/7532
ISSN: 2052-2541

MATHEMATICAL MODELS FOR AFLATOXIN CONTAMINATION IN CROPS, LIVESTOCK AND HUMANS: A REVIEW

FILIMON ABEL MGANDU[1,2,*], TRIPHONIA NGAILO[3], ISAAC MUGUME[4,5], ISAMBI MBALAWATA[6], SILAS MIRAU[1]

[1]School of Computational and Communication Sciences and Engineering, The Nelson Mandela African Institution of Science and Technology, Arusha, Tanzania

[2]Department of ICT and Mathematics, College of Business Education, Dodoma, Tanzania

[3]Department of General Studies, Dar es salaam Institute of Technology, Dar es salaam, Tanzania

[4]Department of Geography, Geo-informatics and Climate Sciences, Makerere University, Uganda

[5]Directorate of Forecasting Services, Uganda National Meteorological Authority, Uganda

[6]African Institution of Mathematical Sciences (AIMS)-Rwanda

Abstract: Aflatoxin is among the highest-threatening food contaminants as it affects both the health of consumers and the entire value chain. Researchers are of the view that aflatoxin contamination will increase due to the impacts of climate change. This study aimed to review studies on modelling the impacts of climate change on aflatoxin contamination to gain a deeper understanding of the progress achieved, methodologies used and potential gaps or opportunities for further studies. A critical analysis of the available literature revealed that aflatoxin contamination is a spatial-temporal phenomenon as it depends on both location and time. In many regions, data unavailability has been an obstacle in developing predictive models. We note that it is necessary for each region to have their own models according to the crop, soil characteristics and projected climate of the given area for better and more accurate results. Future studies should focus on the first; surveillance of susceptible crops and gathering of aflatoxin contamination data. Second, developing models to assess the aflatoxin contamination risk due to projected climate change, soil

[*]Corresponding author
E-mail address: mganduf@nm-aist.ac.tz
Received May 30, 2022

properties, and crop characteristics so that proper strategies can be adopted. Third, laboratory experimental results must be validated in fields to increase their usability.

Keywords: aflatoxin contamination; climate change; modelling.

2010 AMS Subject Classification: 92D25.

1. INTRODUCTION

Aflatoxins are poisonous substances produced by *Aspergillus flavus* and *Aspergillus parasiticus* (certain types of fungi) that are found naturally all over the world and they can grow in soil, decaying vegetation and grains if conditions are favourable [1,2]. The optimal conditions for *Aspergillus* to grow and produce aflatoxin are temperature around 30^0C, relative humidity between 80% to 85%, and other factors like water activity and soil PH [2,3]. There are more than 20 different types of aflatoxins, but the most important are B1, B2, G1 and G2 with aflatoxin B1 being the most frequent in food crops and having greater toxin power [2-5]. When contaminated crops are processed, aflatoxins enter the general food supply where they can be found in both human foods and feeds for livestock. Livestock fed on contaminated feed can also pass aflatoxin into eggs, milk products, and meat [6]. Aflatoxins are most commonly ingested, however, the most toxic type of aflatoxin, B1, can also permeate through the skin [7].

The effects of aflatoxins on the health of consumers of contaminated food and business chains have been reported. Consuming contaminated food can cause death (in case of high dosage), lowering body immunity, children's growth stunting and liver cancer [8,9] depending on dose intake and exposure time [2]. Due to these health problems, countries have set standards and restrictions to different food crops and animal feeds to be imported resulting in greater economic losses to farmers, transporters, marketers, and crop processors. The European Union, for example, allows maize and groundnuts with concentrations of aflatoxin below 5μg/kg and 8μg/kg respectively to be imported and consumed for food or feed [10]. In developing countries, it’s difficult to measure levels of aflatoxin in food crops because they are produced for subsistence and most are consumed by locals before entering the business chain. The East African Community has established a limit that the aflatoxin level in maize must not exceed 10μg/kg to facilitate the same standard in importing and export of maize among member countries [11].

Since climate is one of the factors that affect aflatoxin levels, the changing climate is expected to impact the prevalence of aflatoxin in farm produce. The Intergovernmental Panel on Climate Change (IPCC) refers to climate change as any change in average weather conditions over a long period of time as a result of natural factors or human activities [12,13]. On the other hand, the United Nations Framework Convention on Climate Change (UNFCCC) refers to climate change as the change in average weather conditions over a long period of time that is caused directly or indirectly by human activities [12,14]. Climate change has been regarded as one of the causes of various problems in the world today, for example, contamination of crops, flooding, drought, and rise in sea level. Changing climate (for example temperature, rainfall, relative humidity and solar radiation) may threaten food security if they affect staple crops [15]. In general, if the temperature increases in cool or temperate climates, the relevant countries may become more susceptible to aflatoxins and the tropical countries may become too unfriendly to conventional fungal growth and aflatoxin production [15].

A wide body of evidence demonstrates that the ability of fungi to grow, survive and interact with a large variety of crop species and to produce aflatoxins is greatly influenced by environmental factors, mainly temperature and relative humidity [16]. These factors are greatly related to climate change where it's expected a 2^0C to 5^0C increase in temperature by 2100 [17,18]. In this sense, food safety has become a very important issue around the world and the potential effects of climate change on the yields and quality of food crops, especially aflatoxins, have received special attention in recent years, in particular from risk analysis and mitigation perspective [19].

The objectives of this study were (i) to review different publications to gain a deeper understanding of what is already done and what is missing in modelling the dynamics or occurrence (production) of aflatoxin in crops, animals and humans especially due to climate change (ii) to identify the methodologies used in modelling aflatoxin occurrence and (iii) to identify possible gaps or opportunities for further study.

2. MATHEMATICAL MODELS

Mathematical models (eg, Afla-maize, Baranyi model, regression models, and Pitt model) have been used to predict the extent of fungi growth and aflatoxin formation in crops as a function of environmental factors [8, 20-25]. The role of mathematical modelling is to identify the risk factors, levels of aflatoxin contaminations and the associated economical losses, and animal and human health problems. From these models, prevention and mitigation strategies can be developed to prevent losses. There are various types of mathematical models depending on how the input variables have been measured, the number of iterations and the working mechanism [26]. In discrete models, events and variables change over time like hourly, daily, weekly and monthly data, while in continuous models, events and variables are continuous over time and do not change abruptly from one state to another.

Empirical models base on statistical analysis of data observed in field experiments to establish the relationship between aflatoxin contamination and climate variables. On the other hand, mechanistic models are based on cause-and-effect relationships among variables to represent biological, chemical, or physical processes [20,26]. In practice, model development can involve both approaches.

The study conducted a review of literature concerning the predictive modelling of the impacts of climate change on aflatoxin contamination as indicated by selected studies in the following sections. The studies included in this review were categorized into two groups: the first group are studies focusing on aflatoxin dynamics models, and the second group focused on predictive modelling of aflatoxin contamination on crops, livestock, and humans due to environmental and climate factors.

2.1 Aflatoxin dynamics and risk models

The dynamics of systems in mathematics are usually analyzed using the differential equation models where the rates of transfer between compartments are represented by differential equations. The study by [27] used the differential equation model to explain the dynamics of aflatoxin in feeds and foods in plants, animals and humans. The transfer of aflatoxin concentrations from plants to animals and humans is shown in Figure 1. The system of ordinary differential equations was formulated from the model in Figure 1 to represent the dynamics of aflatoxin flow from plants to animals and humans. Stability analysis was performed on equilibrium points using the threshold parameter which is analogous to reproduction number in other epidemiological studies. The results showed that the entire dynamics of aflatoxin flow depends on the threshold value. If the threshold value is greater than the unit, the aflatoxin concentration will reach the toxin limit and vice versa.

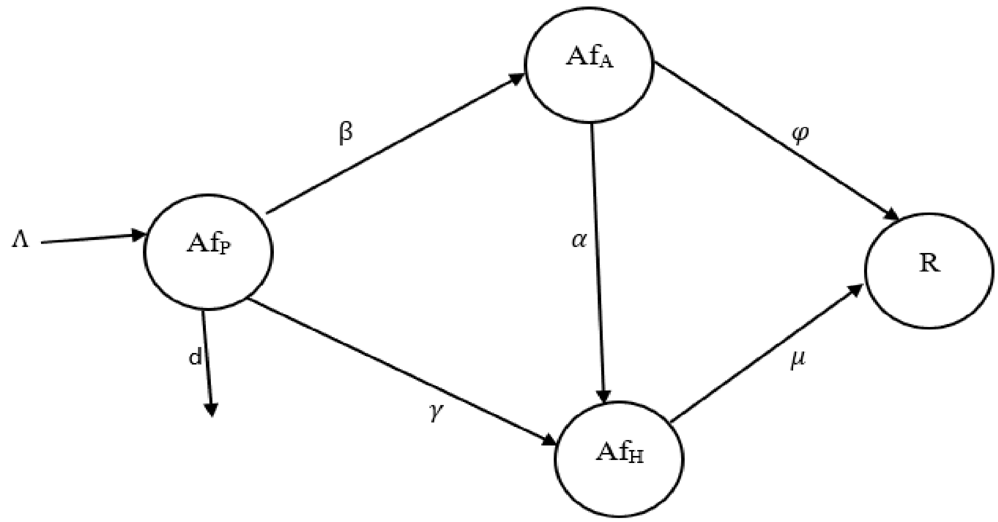

Figure 1: Transfer diagram of Aflatoxin concentration

Where Af_P, Af_A, Af_H are aflatoxin concentration in plants, animals, and humans respectively, R is removed, d is the death rate, Λ is the rate of natural occurrence of aflatoxin, β, α, γ are the transmission rates, μ and φ are removal rates of aflatoxin from humans and animal respectively.

Later on, in 2019 [28] suggested a mathematical model for aflatoxin control using probiotics. The study assumes an ecosystem where aflatoxin fungi and probiotics are placed together like predator-prey systems and the ability of probiotics to detoxify aflatoxin contamination is analyzed. The model used a system of ordinary differential equations to show the effect of probiotics on the aflatoxin concentration. The results of the model indicate that the ability of probiotics to detoxify depends on the rate of the formation of aflatoxin-probiotics complex.

However, all studies [27,28] did not incorporate climate change factor which is considered to be a driving force in the formulation of aflatoxin. Also, the study didn't use the experimental data to test the predictive power of the model developed.

2.2 Aflatoxin prediction models

Different mathematical and statistical approaches have been used on predicting aflatoxin contamination in crops due to climate and environmental factors. Most of these models are site-specific models and they need to be validated before being used in other areas.

One of the famous models is the AFLA-maize [20]. This model was developed in Italy for predicting aflatoxin concentration in maize. AFLA-maize is the mechanistic model developed using logistic regression to determine the probability that the aflatoxin level will exceed 5μg/kg which is the standard level of aflatoxin concentration in the European Union. Weather data were used as independent variables while aflatoxin levels data were used as dependent variables. The dependent variable had two categories: 0 if the aflatoxin level is less than 5μg/kg and 1 if otherwise. The model was able to correctly predict 73% of the samples which were tested, making it a useful tool to support decision-making in aflatoxin risk mitigation. However, the model was developed using weather and aflatoxin data from Northern Italy, so it cannot be used in other geographical areas with different climatic conditions without being calibrated.

Although the AFLA-maize model [20] was developed to predict aflatoxin contamination in maize in Italy, it has been applied in countries and other crops as well. For example, [29] used the AFLA-maize model to develop AFLA-Pistachio, a mechanistic model to predict aflatoxin contamination in pistachio nuts using the binary logistic regression technique. The model included climate variables (rainfall, temperature, and relative humidity) to explain their contribution to aflatoxin contamination in pistachio nuts. Data on aflatoxin contamination were classified based on whether they exceeded the European Union standard of 12μg/kg for pistachio nuts (given value 1) or not (given value 0). The logistic regression provides the probability (chance) of an event to occur and it ranges from 0 to 1. When the probability is greater than or equal to 0.5, it means the aflatoxin concentration will exceed the threshold of 12μg/kg while when it is less than 0.5 it means the concentration will be below. The developed AFLA-pistachio model shows good predicting accuracy of around 80% making it a good tool in decision-making regarding aflatoxin mitigation in pistachio.

Other studies that used the AFLA-maize model include [1] and [8]. The study by [1] developed a model to analyze the impacts of climate change on aflatoxin B1 in maize and aflatoxin M1 in milk by combining models already available and data on aflatoxin in maize and dairy milk for cows in Netherlands. In the forecast stage, the study uses the AFLA-maize model developed by [20] and the aflatoxin simulation model developed by [33]. Then the study used a Carryover simulation model developed by [18] to estimate the concentration of aflatoxin M1 in dairy milk using aflatoxin B1 intake by cows as an input. The model uses Monte Carlo simulation to account for the carryover of aflatoxin B1 in feed to cow body and then to aflatoxin M1 in milk. Results showed that the aflatoxin concentration in milk is expected to increase in future climate (up to 50%) by 2030 in the case study. However, the study insisted that the results mainly depend on the climate and carryover model used, so it can have different results. Further studies are needed on each region with different climate conditions to have appropriate results to support decision-making.

On the other hand, [8] used the AFLA-Maize model to investigate the impacts of climate change on the maize produced in Malawi. The study first used regional climatic models to obtain historical data (1971-2020) and projected data (2021-2039 and 2040-2069) on climate variables. The climate data were used as input on Food and Agriculture Organization's (FAO) AquaCrop model to simulate and assess the impacts of climate change on maize growth cycle [8]. Lastly, the study employed AFLA-Maize model [20] to calculate the aflatoxin index in all regions of Malawi. The results revealed that Climate change will lead to an increase in aflatoxin concentrations in all regions under study. However, the study faced some challenges in data availability for example historical relative humidity data were not found for Malawi causing uncertainty.

Mathematical models can base on laboratory results where crop plants are subjected to different temperatures and water activity to assess their impacts on aflatoxin contamination. Results from these laboratory experiments provide insight to further field-related studies where other environmental factors; soil characteristics, and farm management like irrigation and fertilizer usage, can be used to have reality in assumptions and more accurate results. [21] and [22] used findings from laboratory to estimate the relationship between aflatoxin contamination and environmental factors. They both used the Barinyi model [30] to study the growth rate of growth of *Aspergillus flavus* and the production rate of aflatoxin production. [22] used the Gaussian model and polynomial equations to estimate aflatoxin production at various temperatures and water activity. The model was validated using the root mean square error (RMSE) calculated using predicted and observed concentrations of *Aspergillus flavus*. The developed model showed good performance with R^2 of 0.859 and 0.605 for *Aspergillus flavus* growth and aflatoxin production, respectively. On the other hand, [22] used logistic regression models to predict aflatoxin production. The model was able to correctly predict 89.4% of the cases and was seen as useful.

Logistic regression is one of the approaches used in predictive modelling of the impacts of climate change on aflatoxin contaminations. The main characteristic of logistic regression is that the dependent variable is a binary variable (having two categories) in this case: 1 if the aflatoxin contamination exceeds the given limit and 0 if otherwise. The study by [31] used logistic regression models to assess the probability of exceeding a given threshold of 20μg/kg (dependent variable) given a set independent variable (drought index, soil characteristics, and maize hybrid). The results revealed that the drought index can be used to predict aflatoxin contamination.

Another study by [25] used logistic regression to estimate the relation between weather data and aflatoxin occurrences and concentration in maize during the 2013 growing season in Tanzania and Kenya. Using statistical approaches: Logistic regression and machine learning techniques: support vector machine and random forest the study used weather data as predictors of aflatoxin concentration in maize samples collected from Tanzania and Kenya. The results showed that low rainfall and high temperature during the early stage of maturity of the maize plant increases the chance of occurrence and high concentration of aflatoxin.

Crop modelling frameworks have also been used to model climate risk on aflatoxin contamination. [32] and [33] developed a model for the climate risks on aflatoxin concentration in maize. Temperature and moisture were used as input in the Agricultural Production Systems Simulator (APSIM) modelling framework [34] to produce the aflatoxin risk index (ARI). In validating the model, field data on aflatoxin contamination were regressed with the aflatoxin risk index (ARI) showing significant results R^2 of 0.69 for the rainfed location and R^2 of 0.62 for the irrigated locations. Furthermore, the study revealed that locations with both dry and hot climates had higher risk of aflatoxin compared to locations with either hot or dry climates.

Aflatoxin contamination is a spatial-temporal phenomenon as it depends on both location and time. Predictive models need to be developed or validated in each region before being used. Data on crop physiology, soil characteristics, weather and climate and farm management like irrigation and fertilizer application are necessary for modelling to have a more accurate and valid prediction of aflatoxin contaminations. Table 1 shows a summary of different studies conducted on aflatoxin contamination.

Table 1: Summary of different studies conducted on aflatoxin contamination.

Study (Source)	Location	Objective	Methods (Models) used
[27]	NA	To analyse the dynamics of aflatoxin in feeds and foods in plants, animals and humans.	System of ordinary differential equations
[28]	NA	To control the risk of aflatoxin using probiotics.	System of ordinary differential equations
[21]	South Korea	To predict aflatoxin production of *Aspergillus flavus* under various temperatures and water activity.	Barinyi model [30] Gaussian Model and polynomial equations
[22]	Spain and Iran	Analyse *Aspergillus flavus* growth and accumulation of aflatoxin in pistachio nuts under the climate change scenario.	Barinyi model [30] and Logistic regression
[20]	Italy	To develop a model (AFLA-maize) for aflatoxin concentration in maize using weather data.	Logistic regression
[29]	Aegina Islands, Greece	To predict aflatoxin contamination in pistachio nuts (AFLA-Pistachio).	AFLA-maize model [20]
[1]	Netherlands	Analysing the impacts of climate change in aflatoxin B1 on maize and aflatoxin M1 in milk by combining models already available models and data on aflatoxin in maize and dairy milk for cows.	AFLA-maize model [20] Aflatoxin simulation model [33] Carryover simulation model [18]
[32]	NA	To develop a model for climate risks on aflatoxin concentration in maize.	APSIM model [34]
[25]	Tanzania and Kenya	Estimating the relationship between weather data and aflatoxin occurrences and concentration in maize during the 2013 growing season in Tanzania and Kenya.	Logistic regression Machine learning techniques
[8]	Malawi	Assess the impacts of climate change on the growth cycle of maize in Malawi. Predict the impacts of climate change on aflatoxin contamination in Malawi.	AquaCrop model [35] AFLA- Maize model [20]
[33]	Kenya	To develop an improved model from the [32] model.	APSIM model [34]
[31]	Mississippi and Georgia, USA	To assess whether the drought index can be used to predict aflatoxin contamination in maize.	Logistic regression

3. DISCUSSION

In assessing the impacts of climate change on aflatoxin contamination, five models have been used directly or as base models in most of the reviewed articles, as shown in Table 1. These five models are discussed in this section with their inputs and expected outputs. Most of these models have been developed and validated in Europe calling for further studies in other geographical areas.

3.1 Afla-maize model

Afla-maize model is a logistic regression model to estimate the probability of aflatoxin concentration exceeding the given level (5µg/kg for Europe). It consists of a binary dependent variable with a set of one or more independent variables. The independent variables are the climate variables, soil characteristics, and crop characteristics [20]. The probability P is given by equation 1.

$$P = \frac{1}{1 + exp^{-(C+B_1x_1+\ B_1x_1+\ldots+\ B_nx_n)}} \tag{1}$$

Where C, B_1, B_2, …, B_n are parameters to be estimated and x_1, x_2, …,x_n are independent variables. The probability values P range from 0 to 1 with $P > 0.5$ meaning that aflatoxin contamination will exceed 5 µg/kg while $P >\ 0.5$ means that aflatoxin contamination will not exceed 5 µg/kg. The Afla-maize model has been applied in other studies like [1,8,29] due to its strengths in predicting aflatoxin contamination. However, soil and crop characteristics were not included in this study leading to uncertainty in its prediction.

3.2 Baranyi model

The Baranyi model describes the growth rate of moulds and bacteria under different temperatures and water activity [30]. Although the model is primarily made to model the growth rate of bacteria [21], the studies by [21-23] used this model to describe the growth rate of *Aspergillus flavus* as shown in Equations 2 and 3.

$$y = y_0 + \mu_{max}A - ln\left(1 + \frac{[exp(\mu_{max}A)-1]}{exp(y_{max}-y_0)}\right) \tag{2}$$

$$A = t + \left(\frac{1}{\mu_{max}}\right) ln[exp(-\mu_{max}t) + exp(-\mu_{max}\lambda) - exp(-\mu_{max}t - \mu_{max}t)] \tag{3}$$

Where y is the colony diameter, y_0 is the initial colony diameter, y_{max} is the maximum colony diameter, μ_{max} is the maximum specific colony growth rate of the colony, λ is the lag phase and t is time in days. One of the the assumptions of Baranyi model is that the growth rate of fungi or bacteria is independent of the environment [30]. This assumption is an oversimplification because environmental factors have a significant contribution to fungi growth.

3.3 Logistic regression

Most of the studies in this review have used logistic regression to estimate the probability of aflatoxin production given the set of independent variables: moisture content (%mc) or water activity (a_w) and Temperature (T) [22,25,30]. The format of the logistic regression model is as shown by Equation 4 where P is the probability of aflatoxin production.

$$Logit\ P = ln\left(\frac{P}{1-P}\right) = b_0 + b_1\%mc + b_2T + b_{11}\%mc^2 + b_{22}T^2 + b_{12}\%mcT + b_3 time \quad (4)$$

Where mc is the moisture content, T is temperature, P is the probability of aflatoxin production. Logistic regression models use time series data (climate variables) and it is difficult to include data on soil characteristics. Thus, logistic regression models miss an important soil component that could improve their performance.

3.4 Aflatoxin simulation model

The aflatoxin risk index (ARI) of [33] is calculated based on the temperature dependency factor ($Aflo\_temp\_factor$). The temperature dependency factor is obtained from the mean temperature (T_{mean_aflo}), optimal temperature (T_{opt_aflo}) for *Aspergillus flavus*, minimum temperature (T_{min_aflo}) and maximum temperature (T_{max_aflo}) as shown by equations 5 to 8.

$$ARI = \sum Aflo\_risk \times 10 \quad (5)$$

$$\sum Aflo\_risk = Aflo\_risk + (1 + Aflo\_temp\_factor) \quad (6)$$

Where, when $T_{mean\_aflo} \geq T_{min\_aflo}\ and\ \leq T_{opt\_aflo}$

$$Aflo\_temp\_factor = \frac{T_{mean\_aflo} - T_{min\_aflo}}{T_{opt\_aflo} - T_{min\_aflo}} \quad (7)$$

When $T_{mean\_aflo} > T_{opt\_aflo}\ and\ < T_{max\_aflo}$

$$Aflo\_temp\_factor = \frac{T_{max\_aflo} - T_{mean\_aflo}}{T_{max\_aflo} - T_{opt\_aflo}} \quad (8)$$

The Aflatoxin Simulation Model assumes that the growth and aflatoxin production depends on the temperature and time spent in drought conditions only. The model does not include other climate factors such as temperature and humidity that might have a significant contribution to the growth of fungi growth and aflatoxin production.

3.5 Pitt model

The Pitt mathematical model [24] has been used by many researchers as a base model to predict aflatoxin contamination due to climate and environmental factors. The model incorporates a different combination of temperatures to determine aflatoxin contamination as indicated in equation 9.

$$f_T = A \times exp\left\{-\left[\frac{\alpha^2}{(T-T_{min})} + \frac{\alpha^2}{(T_{max}-T)}\right]\right\} \quad (9)$$

Where f_T is the relative toxin formation, T_{min} is minimum temperature, T_{max} is maximum temperature, α is the shape parameter and A is the scaling parameter. However, the Pitt model does not include other climate factors, such as temperature and humidity, which might have a significant contribution to fungi and aflatoxin production.

4. CONCLUSIONS

Modelling the impacts of projected climate change on aflatoxin contamination is of great importance for proper mitigation strategies to be adopted. However, modelling requires adequate data on climate variables, crop characteristics, soil properties, and aflatoxin contamination cases. The inaccessibility of these data has been reported to be an obstacle in many regions for modelling purposes [8,20]. The study recommends the following:

i) Models that involve many input variables like Afla-maize model [20] have shown good performance in predicting aflatoxin contamination in maize. More research is needed to develop site-specific models that incorporate climate factors, soil properties, and crop characteristics to determine aflatoxin contaminations in the crops currently and in future.

ii) Since in most areas data for aflatoxin contamination and the associated factors are not available for modelling purposes. We recommend that surveillance should be done on susceptible crops and aflatoxin contamination data should be gathered, stored and be easily available to researchers. This will help in model development and study how fungi and aflatoxin contamination behaves in different regions under different climates.

iii) The accuracy of available predicting models needs to be improved through continuous field trials and validation. Since most of the models are geographically dependent, they also need to be validated in other areas to be accurate. When the prediction capability of models is high, policymakers will be motivated to use them in decisions, making them an important tool.

iv) Most of the available models have been developed and validated in European countries. The study recommends each region to have its studies according to the crop characteristics and projected climate of the given area for better and more accurate results.

FUNDING

This study is funded by the TANIPAC Project under Tanzanian Ministry of Agriculture.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

REFERENCES

[1] H.J. Van der Fels-Klerx, L.C. Vermeulen, A.K. Gavai, et al. Climate change impacts on aflatoxin B1 in maize and aflatoxin M1 in milk: A case study of maize grown in Eastern Europe and imported to the Netherlands, PLoS ONE. 14 (2019), e0218956. https://doi.org/10.1371/journal.pone.0218956.

[2] C.A.F. Oliveira, C.H. Corassin, About the Authors, in: Research in the Sociology of Work, Elsevier, 2003: pp. 291–294. https://doi.org/10.1016/S0277-2833(03)11013-8.

[3] G. Carla, S. Souza, V. Feddern, et al. Aflatoxins: Contamination, analysis and control, in: R.G. Guevara-Gonzalez (Ed.), Aflatoxins - Biochemistry and Molecular Biology, InTech, 2011. https://doi.org/10.5772/24902.

[4] M. Mushtaq, B. Sultana, F. Anwar, M.Z. Khan, M. Ashrafuzzaman, Occurrence of Aflatoxins in Selected Processed Foods from Pakistan, Int. J. Mol. Sci. 13 (2012), 8324–8337. https://doi.org/10.3390/ijms13078324.

[5] A. Kamala, C. Shirima, B. Jani, et al. Outbreak of an acute aflatoxicosis in Tanzania during 2016, World Mycotoxin J. 11 (2018), 311–320. https://doi.org/10.3920/wmj2018.2344.

[6] S.Z. Iqbal, S. Nisar, M.R. Asi, et al. Natural incidence of aflatoxins, ochratoxin A and zearalenone in chicken meat and eggs, Food Control. 43 (2014), 98–103. https://doi.org/10.1016/j.foodcont.2014.02.046.

[7] J. Boonen, S.V. Malysheva, L. Taevernier, et al. Human skin penetration of selected model mycotoxins, Toxicology. 301 (2012), 21–32. https://doi.org/10.1016/j.tox.2012.06.012.

[8] E.A. Warnatzsch, D.S. Reay, M. Camardo Leggieri, et al. Climate change impact on aflatoxin contamination risk in Malawi's maize crops, Front. Sustain. Food Syst. 4 (2020), 591792. https://doi.org/10.3389/fsufs.2020.591792.

[9] F. Wu, J.D. Groopman, J.J. Pestka, Public health impacts of foodborne mycotoxins, Annu. Rev. Food Sci. Technol. 5 (2014), 351–372. https://doi.org/10.1146/annurev-food-030713-092431.

[10] European Commission, Commission Regulation (EC) No. 165/2010 of 26 February 2010, amending Regulation (EC) No. 1881/2006setting maximum levels for certain contaminants in foodstuffs as regards aflatoxins, Official J. Eur. Union, 50 (2010), 8–12.

[11] Y.Y. Gong, M. Routledge, M.E. Kimanya, et al. Building an Aflatoxin Safe East African Community Technical Policy Paper 8 Aflatoxin Standards for Food Knowledge Platform 2015 Situational Analysis East Africa Region; International Institute for Tropical Agriculture: Dar es Salaam, Tanzania, 2015.

[12] F. Abel Mgandu, M. Mkandawile, M. Rashid, Modelling the impacts of climate change on water level fluctuations in water resources in Tanzania: A case study of Mtera dam, Int. J. Math. Sci. Comput. 6 (2020), 22–32. https://doi.org/10.5815/ijmsc.2020.03.03.

[13] M. Hulme, Climate change, concept of, Int. Encyclopedia Geography: People Earth, Environ. Technol. (2017), 1–6. https://doi.org/10.1002/9781118786352.wbieg0343.

[14] F. Wu, D. Bhatnagar, T. Bui-Klimke, et al. Climate change impacts on mycotoxin risks in US maize, World Mycotoxin J. 4 (2011), 79–93. https://doi.org/10.3920/wmj2010.1246.

[15] R.R.M. Paterson, N. Lima, How will climate change affect mycotoxins in food? Food Res. Int. 43 (2010), 1902–1914. https://doi.org/10.1016/j.foodres.2009.07.010.

[16] G. Perrone, A. Gallo, A.F. Logrieco, Biodiversity of Aspergillus section Flavi in Europe in relation to the management of aflatoxin risk, Front. Microbiol. 5 (2014), 377. https://doi.org/10.3389/fmicb.2014.00377.

[17] A. Medina, A. Rodriguez, N. Magan, Effect of climate change on Aspergillus flavus and aflatoxin B1 production, Front. Microbiol. 5 (2014), 348. https://doi.org/10.3389/fmicb.2014.00348.

[18] H.J. Van der Fels-Klerx, C. Liu, P. Battilani, Modelling climate change impacts on mycotoxin contamination, World Mycotoxin Journal. 9 (2016), 717–726. https://doi.org/10.3920/wmj2016.2066.

[19] N. Magan, A. Medina, D. Aldred, Possible climate-change effects on mycotoxin contamination of food crops pre- and postharvest, Plant Pathol. 60 (2011), 150–163. https://doi.org/10.1111/j.1365-3059.2010.02412.x.

[20] P. Battilani, M. Camardo Leggieri, V. Rossi, et al. AFLA-maize, a mechanistic model for Aspergillus flavus infection and aflatoxin B1 contamination in maize, Computers Electron. Agric. 94 (2013) 38–46. https://doi.org/10.1016/j.compag.2013.03.005.

[21] S. Lee, Y. Yoon, D.M. Kim, et al. Mathematical models to predict kinetic behavior and aflatoxin production of Aspergillus flavus under various temperature and water activity conditions, Food Sci. Biotechnol. 23 (2014), 975–982. https://doi.org/10.1007/s10068-014-0132-2.

[22] S. Marín, A.J. Ramos, V. Sanchis, Modelling Aspergillus flavus growth and aflatoxins production in pistachio nuts, Food Microbiology. 32 (2012), 378–388. https://doi.org/10.1016/j.fm.2012.07.018.

[23] W. Mousa, F.M. Ghazali, S. Jinap, et al. Modelling the effect of water activity and temperature on growth rate and aflatoxin production by two isolates of Aspergillus flavus on paddy, J. Appl. Microbiol. 111 (2011), 1262–1274. https://doi.org/10.1111/j.1365-2672.2011.05134.x.

[24] R.E. Pitt, A descriptive model of mold growth and aflatoxin formation as affected by environmental conditions, J. Food Protect. 56 (1993), 139–146. https://doi.org/10.4315/0362-028x-56.2.139.

[25] B.A. Temba, R.E. Darnell, A. Gichangi, et al. The influence of weather on the occurrence of aflatoxin B1 in harvested maize from Kenya and Tanzania, Foods. 10 (2021), 216. https://doi.org/10.3390/foods10020216.

[26] T. Dövényi-Nagy, C. Rácz, K. Molnár, et al. Pre-harvest modelling and mitigation of aflatoxins in maize in a changing climatic environment-a review, Toxins. 12 (2020), 768. https://doi.org/10.3390/toxins12120768.

[27] H.I. Kademi, I.A. Baba, F.T. Saad, Modelling the dynamics of toxicity associated with aflatoxins in foods and feeds, Toxicol. Rep. 4 (2017), 358–363. https://doi.org/10.1016/j.toxrep.2017.05.009.

[28] H.I. Kademi, F.T. Saad, B.H. Ulusoy, et al. Mathematical model for aflatoxins risk mitigation in food, J. Food Eng. 263 (2019), 25–29. https://doi.org/10.1016/j.jfoodeng.2019.05.030.

[29] M.D. Kaminiaris, M. Camardo Leggieri, D.I. Tsitsigiannis, et al. AFLA-PISTACHIO: Development of a mechanistic model to predict the aflatoxin contamination of pistachio nuts, Toxins. 12 (2020), 445. https://doi.org/10.3390/toxins12070445.

[30] J. Baranyi, T.A. Roberts, A dynamic approach to predicting bacterial growth in food, Int. J. Food Microbiol. 23 (1994), 277–294. https://doi.org/10.1016/0168-1605(94)90157-0.

[31] D. Damianidis, B.V. Ortiz, G.L. Windham, et al. Evaluating a generic drought index as a predictive tool for aflatoxin contamination of corn: From plot to regional level, Crop Protect. 113 (2018), 64–74. https://doi.org/10.1016/j.cropro.2018.07.013.

[32] Y.S. Chauhan, G.C. Wright, N.C. Rachaputi, Modelling climatic risks of aflatoxin contamination in maize, Aust. J. Exp. Agric. 48 (2008), 358-366. https://doi.org/10.1071/ea06101.

[33] Y. Chauhan, J. Tatnell, S. Krosch, et al. An improved simulation model to predict pre-harvest aflatoxin risk in maize, Field Crops Res. 178 (2015), 91–99. https://doi.org/10.1016/j.fcr.2015.03.024.

[34] B.A. Keating, P.S. Carberry, G.L. Hammer, et al. An overview of APSIM, a model designed for farming systems simulation, Eur. J. Agronomy. 18 (2003), 267–288. https://doi.org/10.1016/s1161-0301(02)00108-9.

[35] T. Foster, N. Brozović, A.P. Butler, et al. AquaCrop-OS: An open source version of FAO's crop water productivity model, Agric. Water Manage. 181 (2017), 18–22. https://doi.org/10.1016/j.agwat.2016.11.015.