World Mycotoxin Journal, 2022; 15 (2): 101-118

The potential for aflatoxin predictive risk modelling in sub-Saharan Africa: a review

B. Keller[1*], T. Russo[1], F. Rembold[2], Y. Chauhan[3], P. Battilani[4], A. Wenndt[5] and M. Connett[1]

[1]Global Good, 3150 139th Ave SE, Bellevue, WA 98005, USA; [2]European Commission, Joint Research Centre, Via E. Fermi 2749, 21027 Ispra, Italy; [3]Department of Agriculture and Fisheries, 214 Kingaroy Cooyar Road, Kingaroy, QLD 4610, Australia; [4]Department of Sustainable Crop Production (DI.PRO.VE.S.): Università Cattolica del Sacro Cuore, Via Emilia Parmense 84, 29122 Piacenza, Italy; [5]Plant Pathology and Plant-Microbe Biology, School of Integrative Plant Sciences, Cornell University, 334 Plant Science Building, Ithaca, NY 14853-4203, USA; ben.ch.keller@gmail.com

Received: 1 January 2021 / Accepted: 25 May 2021

REVIEW ARTICLE

Abstract

This review presents the current state of aflatoxin risk prediction models and their potential for value actors throughout the food chain in sub-Saharan Africa, with a specific focus on improving smallholder farmer management practices. Several empirical and mechanistic models have been developed either in academic research or by private sector aggregators and processors in high-income countries including Australia, the USA, and Southern Europe, but these models have been only minimally applied in sub-Saharan Africa, where there is significant potential and increasing need due to climate variability. Predictions can be made based on historic occurrence data using either a mechanistic microbiological framework for aflatoxin accumulation or an empirical model based on statistical correlations with climate conditions and local agronomic factors. Model results can then be distributed to smallholders through private, public, or mobile extension services, used by policymakers for strategy or policy, or utilised by private sector institutions for management decisions. Specific agricultural advice can be given during the three most critical points in the phenological cycle: preseason insight including sowing timing and crop varieties, preharvest advice about management and harvest timing, and postharvest optimal practices including storage, drying, and market information. Model development for sub-Saharan Africa is limited by a dearth of georeferenced aflatoxin occurrence data and real-time high resolution climate data; the wide diversity of farm typologies each with significant information and technology gaps; a prevalence of informal market structures and lack of economic incentives systems; and general lack of awareness around aflatoxins and best management practices to mitigate risk. Given advancements towards solving these challenges, predictive aflatoxin models can be integrated into decision support platforms to focus on optimisation of value for smallholders by minimising yield and nutritional losses, which can propagate value throughout the production and postharvest phases.

Keywords: food safety, mycotoxin, dry chain, risk management, smallholder

1. Introduction

Mycotoxins are viewed as one of the most pervasive health risks in the food chain (Kuiper-Goodman, 2004; Wu, 2015), and the specific impacts of aflatoxins in sub-Saharan Africa (SSA) on health and economic systems are an extensive and chronic challenge (Ayalew *et al.*, 2016; Sirma *et al.*, 2018). Aflatoxin exposure in African contexts is generally between 10 to 180 ng/kg body weight per day, significantly higher than values in Europe which are typically between 0 to 4 ng/kg (Liu and Wu, 2010). Health risks associated with high exposure to aflatoxins produced by ascomycetous fungi *Aspergillus flavus* and *Aspergillus parasiticus* (referred to herein as aflatoxin) are numerous, including immune system suppression, risks of cancer and liver cirrhosis, and stunting (Williams *et al.*, 2004). Aflatoxins can occur in diverse food crops and animal feed but maize, groundnuts, tree nuts and spices are most prone to contamination (Pickova *et al.* 2021).

Across the African continent aflatoxin contamination rates can be especially high (Darwish *et al.*, 2014; Hell and

Mutegi, 2011; Mutiga *et al.*, 2014; Wagacha and Muthomi, 2008), with studies showing 90% of maize samples in East Africa and as high as 99% of samples in regions of West Africa, having evidence of high level of aflatoxins in the time periods assayed (Rodrigues *et al.*, 2011). Many challenges currently exist in addressing SSA aflatoxin contamination (Ayalew *et al.*, 2016; Falade, 2018; Okoth, 2016), including:

1. inadequate crop production, harvesting, drying and storage practices;
2. evolving climate conditions conducive to aflatoxin production;
3. institutional capacity, weak governance, and incompatible regulatory frameworks;
4. limited awareness about aflatoxin and mitigation methods;
5. infrastructural deficits;
6. informal market structures;
7. poor access to modern laboratory equipment for monitoring or research.

Aflatoxin production can happen at any stage of the food chain given conditions favouring the fungi to produce toxins, including during pre-harvest, drying, storage, transportation, processing, and handling. The phases of the value chain responsible for controlling aflatoxin producing fungi after harvest maintaining optimal conditions including limited humidity are referred to as the 'dry chain' (Bradford *et al.,* 2018). However, there are also important agricultural practices during field preparation and the growing season to control aflatoxin producing fungi, such as proper tillage, and fertilisation. Figure 1 presents an example map of the phases of production and postharvest illustrating the intervention points that an aflatoxin prediction model could target within the complex value chains in SSA agriculture.

In addition to aflatoxins' impacts on country-level economics or health effects, aflatoxin occurrence has specific economic impacts for SSA smallholder farmers. Smallholders may be restricted from participating in formal markets due to aflatoxin concerns (Njoroge, 2018), make compromises to

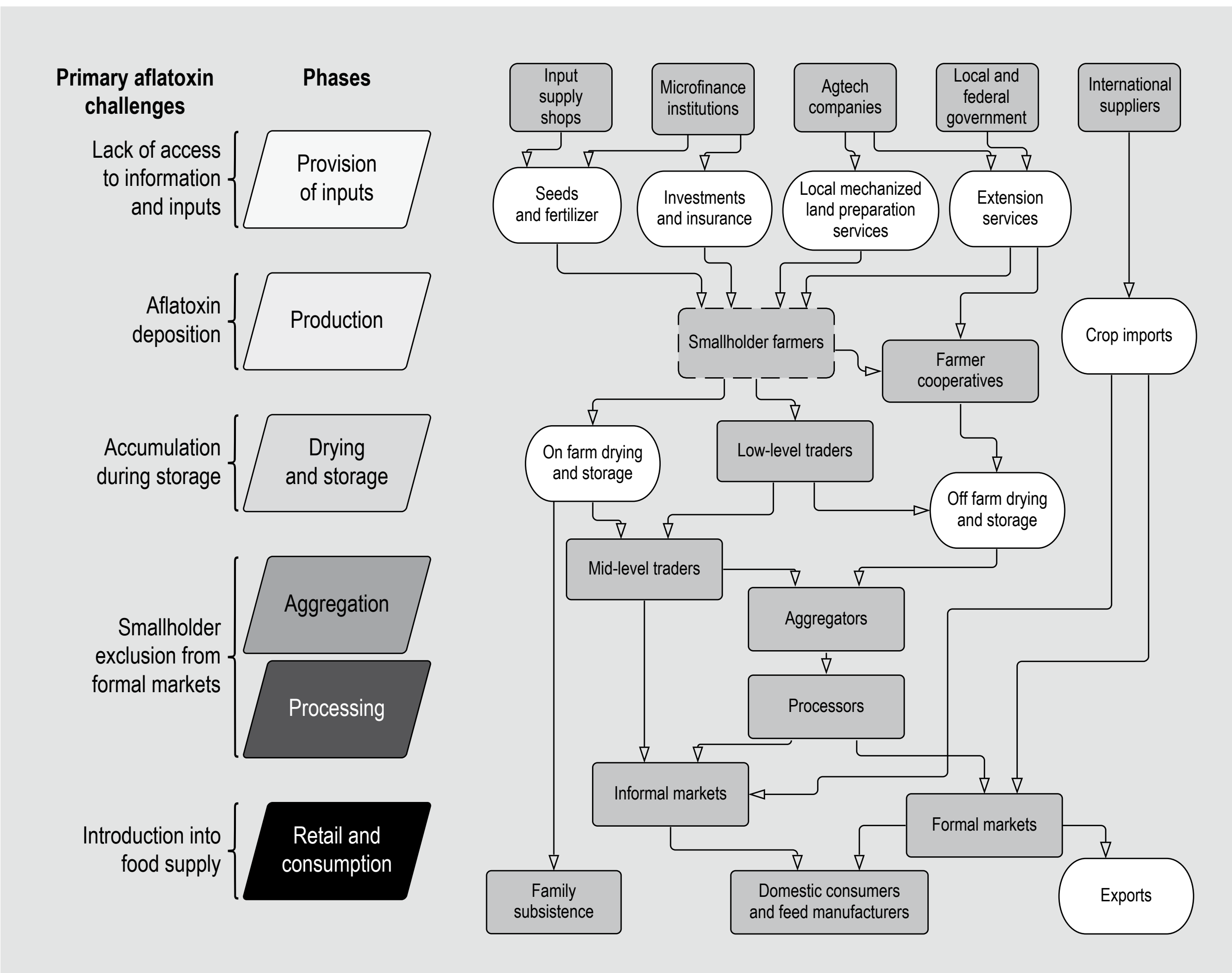

Figure 1. Simplified example maize production and postharvest phases in sub-Saharan Africa focused on smallholder farmers. Shaded and unshaded components in the value chain indicate value actors and processes, respectively, and heavier border weight indicates primary intervention targets for an aflatoxin risk model.

protect themself against postharvest loss by planting an extra portion of crop, only planting in the safest season, and avoiding financial risks such as investing in new technologies (Kohl *et al.*, 2017), and lose productivity due to livestock fed contaminated feed (Peles *et al.*, 2019). Beyond larger goals improved markets and exports, mitigation interventions early in the production and postharvest chain can have significant impacts on farmer food safety and financial stability (Figure 2).

Agriculture in SSA can differ from other regions in factors including strong presence of informal markets with complex value chains, limited information flows, lack of mechanisation, and the prevalence of smallholder and subsistence farms (Ferris *et al.*, 2014). Most smallholder farms (<2 ha) comprise around 60% of the farming population in sub-Saharan Africa (FAO 2015). Smallholder farmers grow a variety of crops through shallow cultivation using hand hoes, often producing an intercropped mix supporting household needs and market sales. Less than 4% of SSA agriculture is equipped with irrigation technologies (Siebert *et al.*, 2010) and fertiliser consumption rates are among the lowest in the world (FAO, 2019).

Technological interventions to address aflatoxin contamination have been developed throughout the production and postharvest phases but have not had widespread adoption in SSA countries due to prohibitive costs, logistical challenges, inadequate incentive systems, and limited access to information (Unnevehr and Grace, 2013). Without widely available and affordable diagnostic tools, health and economic risks can be mitigated instead with early warning and predictive systems to inform agricultural production and postharvest management practices. Several predictive models using known correlations between aflatoxin accumulation and agroecological and biophysical properties have been piloted in Africa, and there is a strong demand for predictive mycotoxin occurrence information by the public and private sectors, but no predictive model is currently applied in an operational way.

We present a review of existing aflatoxin predictive risk models that have current or potential value in SSA. In addition to the model review, we present the context for aflatoxin impacts and management practices in SSA to inform where model output is needed throughout the production and postharvest phases. We conclude with a summary of high priority gaps in aflatoxin modelling for SSA, and briefly discuss the institutional and systems level requirements for enabling models to bring value to smallholder farmers and throughout the agricultural value chain.

2. Aflatoxin risk modelling

Current state of predictive aflatoxin risk models

Risk modelling has the potential to be an effective tool in aflatoxin mitigation for smallholders in SSA. Climate data from remote sensing and meteorological models can be used in mechanistic and empirical models to provide risk assessments to predict the timing, location, and severity of aflatoxin development. These results can then be used to inform interventions with stakeholders across the food chain, working in parallel with other innovations in SSA to improve agricultural management and improve food safety. These relatively simple climatic risk models could support early interventions by helping private and public sector groups allocate resources, deploy extension services, and develop a legislative and market incentive framework to promote best practices throughout the production and postharvest phases.

The predictive variables useful for modelling that have significant correlation to aflatoxin accumulation include climate, soil properties, and agricultural management practices (Table 1). The availability of data related to the primary factors is a prerequisite for modelling to be an effective solution. Continued advancements of remotely sensed data products and climate models can provide high

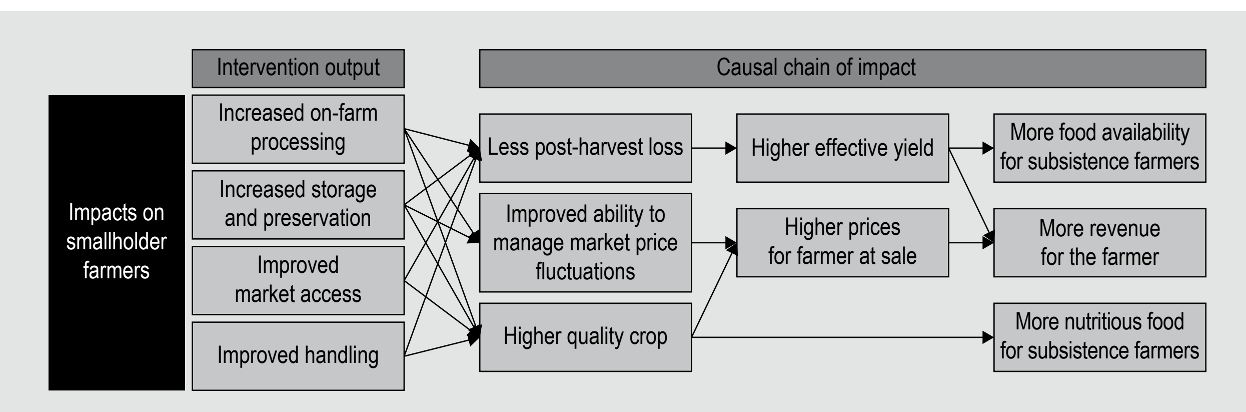

Figure 2. Causal chains in African maize postharvest management, adapted from Rockefeller Foundation (2013).

Table 1. Climatic and preharvest factors influencing aflatoxin production relevant to predictive modelling.[1]

Value in aflatoxin risk modelling	Climatic factors	Soil properties	Other
Primary	rainfall after harvest (1-6) drought stress before harvest (1-6) temperature (1-6)	soil temperature (3,4,5) soil moisture (1,4) soil fertility (4,5)	agronomic practices (3,4,7) sowing / harvest timing (1,5,7) vegetation density (2,4,5)
Secondary	humidity (1,3,4,6) evapotranspiration rates (3) nitrogen stress (3,5) oxygen levels (3,6) co_2 levels (3,6)	substrate composition (1,5) soil organic carbon (5) soil acidity (5,6) exchangeable bases (5) texture (5)	invertebrate vectors (2,3) inoculum load (2,3) crop varieties (1) fungal population (1,5) insect damage (1,2,3,4)

[1] Numbers between brackets refer to the following references: (1) Cotty and Jaime-Garcia (2007); (2) Klich (2007); (3) Hell and Mutegi (2011); (4) Mutiga *et al.* (2014); (5) Smith *et al.* (2016); (6) Tai *et al.* (2020); (7) Kaaya *et al.* (2006).

resolution input data to predict local variability in fungal growth and aflatoxin production (Chisadza *et al.,* 2020).

Several aflatoxin predictive models have been developed based on these climatic and agro-ecological variables, primarily in research or industry in high-income countries (Table 2). Based on their methodology these models can be categorised as either mechanistic, empirical, or hybrid. Mechanistic models account for known biochemical responses of the plant and fungi to various conditions including temperature, rainfall, and soil properties. Empirical models are calibrated by aflatoxin measurements to predict aflatoxin levels based on observed patterns in the training data, often including climatic data as well as satellite derived biophysical indicators, such as normalised difference vegetation index (NDVI). Hybrid models use a combination of mechanistic and empirical methods. It is acknowledged that all models are hybrid at some level since there are always assumptions made about biophysical formation and some amount of statistical analysis is employed, so their categorisation represents only the primary method of prediction.

Models presented in Table 2 have been selected either for their study region in SSA or their applicability to be extended to SSA due to their methodologies and validation with in-situ aflatoxin occurrence datasets.

Existing empirical and mechanistic models have a primary focus on Australia, Southern Europe, and the Southeast USA, with limited case studies in small regions of Africa. Models currently applied in Europe and Australia can be run in an African context when predicting risk from climate factors alone (Van der Fels-Klerx *et al.*, 2016; Warnatzsch *et al.*, 2020). However, consideration of local factors including heterogeneity in farm typologies, cropping systems, and crop calendars must be considered. Validation for both mechanistic and empirical models for SSA has been hindered by limited data on aflatoxin occurrence. Models primarily use field samples of contaminated crops for calibration and validation since it has been shown that extending lab experiments to field conditions doesn't effectively include contextual variability (Probst *et al.*, 2014). The models which have been validated represent 50 to 99% of variation in aflatoxin contamination (Table 2). Mechanistic and empirical modelling approaches are explored here in further detail, as well as decision-support tools and the scope of existing aflatoxin datasets for SSA.

Mechanistic models

Mechanistic models have been shown to be effective in predicting aflatoxin risk, given an advanced understanding of the biophysical crop system as well as the acquisition of aflatoxin occurrence data for defining the functional relationships within the models. The extensive research biology of toxigenesis has been used to derive mathematical functions for the fungal infection cycle, host invasion, and aflatoxin synthesis, specifically regarding the interactive effect of water activity and temperature (Stepman, 2018).

A current leading mechanistic pre-harvest aflatoxin risk prediction model is AFLA-maize (Figure 3) (Battilani and Leggieri, 2015; Battilani *et al.*, 2012, 2013, 2016). Battilani *et al.* (2012) used temperature, relative humidity, and rainfall as input to create predictions for crop phenology and aflatoxin contamination in Europe. The predictions accuracy was 73% for field samples and 68% for validation samples for fields in Italy (Battilani *et al.*, 2013). AFLA-maize was also recently extended to pistachios in AFLA-Pistachio (Kaminiaris *et al.*, 2020), providing a scheme to extend the mechanistic model to other crop types.

Battilani *et al.* (2015) advocated that mechanistic models are better able to be extrapolated to new temporal or spatial bounds, such as applying models built in Europe

Table 2. Selected papers on aflatoxin predictive risk models relevant to sub-Saharan Africa.

Name/description	Aflatoxin dataset (collection dates)	Paper	Location	Type	Accuracy	Crop type	Primary input datasets
CROPGRO	peanut samples from 40 fields (1991-1994)	Craufurd *et al.*, 2006	Niger	empirical	62% of variation	peanut	rainfall, air and soil temperature, radiation and pan evaporation
APSIM + Risk model	1,379 maize samples (1978, 1982 and 1983)	Chauhan *et al.*, 2008	Australia	hybrid	69% of variation	maize	temperature, rainfall, solar radiation, APSIM simulated yield, phenology, and soil water balance
APSIM + Risk model	peanut samples from 21 sowings (2005-2008)	Chauhan *et al.*, 2010	Australia	hybrid	95% of variation	peanut	temperature, rainfall, solar radiation, APSIM simulated yield, phenology, and soil water balance
APSIM + Risk model	five field trials (2011-2012)	Chauhan *et al.*, 2015	Kenya	hybrid	99% of variation	peanut	temperature, rainfall, solar radiation
AVHRR-based	peanut samples from 18 sites (1999)	Boken *et al.*, 2008	Mali	empirical	56% of variation	peanut	NDVI, temperature, crop simulation model
Maxent2	none	Masuoka*et al.*, 2010	Kenya and Mali	empirical	not provided	all	vegetation indices, climate data, elevation, land cover, harvest dates
AFLA-maize	352 maize samples from unique fields (2005 and 2011)	Battilani *et al.*, 2013	Italy	mechanistic	68% of variation (external)	maize	temperature, rainfall, humidity
AFLA-maize	none	Battilani *et al.*, 2016	Europe	mechanistic	future projection	maize, wheat	temperature, rainfall, and solar radiation from general circulation model
Stacked gaussian	small set of field measurements (2012)	Li *et al.*, 2015	USA	empirical	quantified uncertainty	maize	water activity model, interpolated temperature, cropland data, based on a gaussian process
Multi-level modelling	2,466 maize samples from 243 hammer mills (2009-2010)	Smith *et al.*, 2016	Kenya	empirical	multivariate analysis, not predictive	maize	soil conditions, NDVI, rainfall
Spatial Poisson profile regression	measurements from 45 counties (1977-2004)	Yoo *et al.*, 2018	USA	empirical	not a predictive model	maize	weather data, cropscape land cover, NDVI and thermal infrared energy
Drought index (ARID)	Mississippi (13 seasons): Georgia (1977-2004)	Damianidis *et al.*, 2018	USA	empirical	82% accuracy	maize	temperature, precipitation, wind speed, potential evapotranspiration, and solar radiation
Risk in storage	28 maize samples (2015-2016)	Jiang *et al.*, 2019	China	empirical	93.3% accuracy (external)	maize	temperature, storage time, storage conditions
Multivariate regression	84 plots with unique climate conditions (2016-2017)	Chalwe *et al.*, 2019	Zambia	empirical	54% of variation	peanut	ambient temperature, soil temperature and soil moisture content
APHLIS+	none	Rembold *et al.*, 2019	Africa	empirical	unvalidated	all	rainfall (modelled): NDVI, temperature (to estimate evapotranspiration)
AFLA-maize + carryover	none	Van der Fels-Klerx *et al.*, 2019	Ukraine and Netherlands	mechanistic	future projection	maize	temperature sum, climate models, and baseline weather and crop phenology data
AFLA-pistachio	130 pistachio samples (2014-2019)	Kaminiaris *et al.*, 2020	Greece	mechanistic	95.6% of variation	pistachio	phenology model for pistachio, temp, humidity, precipitation

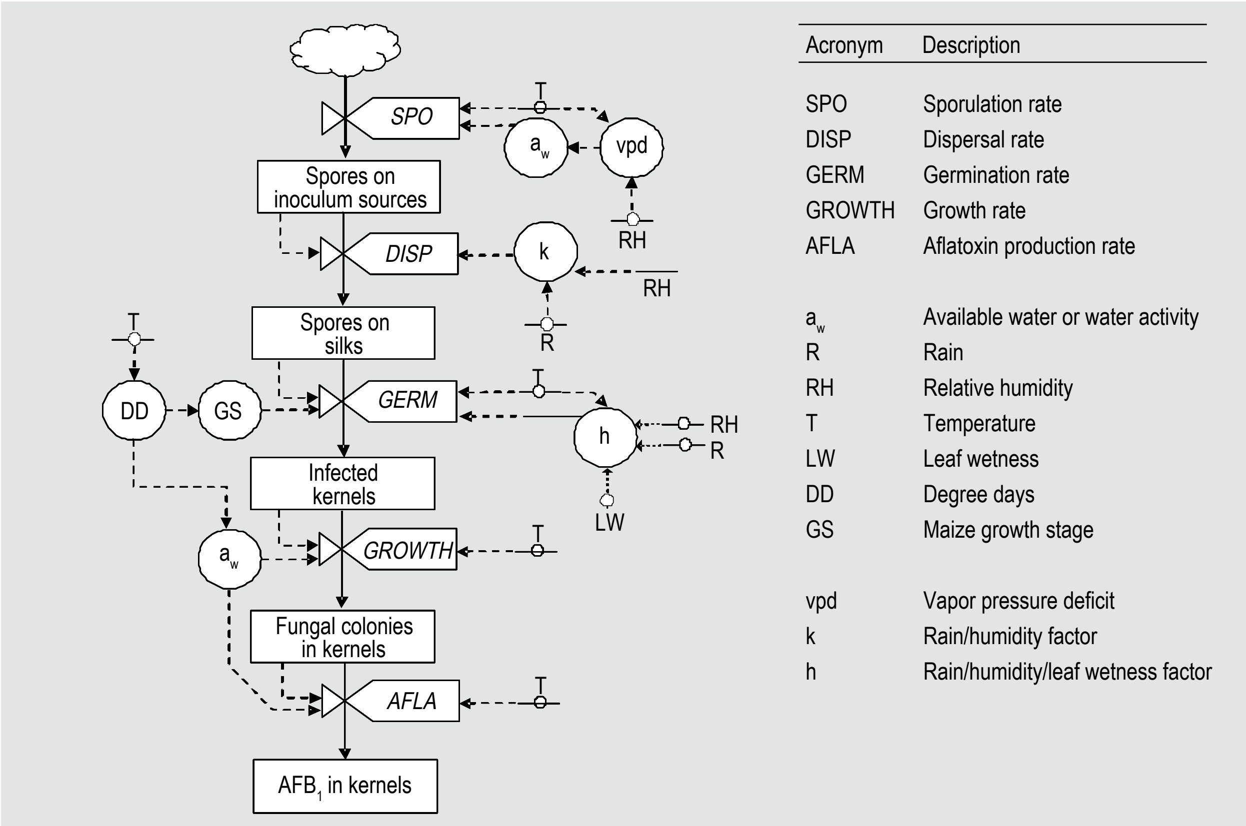

Figure 3. AFLA-maize mechanistic framework, from Battilani *et al.* (2013).

or Australia to SSA, as compared to empirical models which require recalibration in new temporal or spatial domains (Miller *et al.*, 2004; Van der Fels-Klerx *et al.*, 2010). Each factor in Figure 3 can be investigated for its geographic variability, independent of weather conditions, to determine the effectiveness of directly deploying a mechanistic model designed for Europe or Australia in SSA. Factors that vary with weather such as sporulation, dispersal, and germination rates are functions of temperature and humidity conditions (Giorni *et al.*, 2012) so are already effectively represented by the model. Current mechanistic models do not incorporate factors in the cropping system that have more complex relationships with aflatoxin presence, such as soil type, seeding time, cultivar, etc., which would allow models to be more accurate in providing operational decisions (Battilani and Leggieri, 2015). These variables have strong interactions among themselves and therefore the statistical methods typically applied for mechanistic models are not appropriate, and it is therefore useful to move to hybrid models (Leggieri *et al.*, 2021).

Several models have also been developed to assess aflatoxin risk under future climate scenarios (Battilani *et al.*, 2008, 2016; Medina *et al.*, 2015; Ongoma, 2013; Van der Fels-Klerx *et al.*, 2016, 2019), but few have yet been applied over regions of Africa. The mechanistic AFLA-maize model was applied in Malawi, where climate change is expected to shorten maize growing season and make crops more exposed to aflatoxin contamination (Warnatzsch *et al.*, 2020).

Empirical models

Empirical models initially developed for Europe and Australia have begun to be applied to SSA, however these models are constrained by the quantity of georeferenced recalibration data. Machine learning or other multivariate techniques are effective because they can capture complex non-linear relationships between geospatial data and aflatoxin prevalence. Multiple studies have successfully applied empirical models to SSA (Boken *et al.*, 2008; Chalwe *et al.*, 2019; Chauhan *et al.*, 2015; Craufurd *et al.*, 2006; Smith *et al.*, 2016).

One of the leading aflatoxin risk models is integrated with the Agricultural Production Systems Simulator (APSIM) modelling framework (Chauhan *et al.* 2008, 2010, 2013, 2015). Chauhan *et al.* (2008, 2010) first advanced an empirical model for aflatoxin risk for peanuts in Australia, and the ARI predicted by the model explained 95% of variation in measured aflatoxin levels. The model was evaluated using historical climate data and showed a three-fold increase in aflatoxin levels from 1980 to 2007 compared to 1890 to 1980, correlated with decreases in rainfall and increases in ambient temperature. APSIM is used to simulate both pod-yield of peanuts and estimate water deficit (Chauhan *et al.*, 2010). Chauhan *et al.* (2015) extended this approach to predict aflatoxin risk in peanuts in Kenya. For validation Chauhan *et al.* (2015) tested the model for maize hybrids in Kenya with variable conditions including irrigation times and hybrid genotype and showed a linear relationship between aflatoxin contamination and ARI had a R^2 value of 0.99. Figure 4 presents the risk of maize aflatoxin contamination in Kenya for sowing in

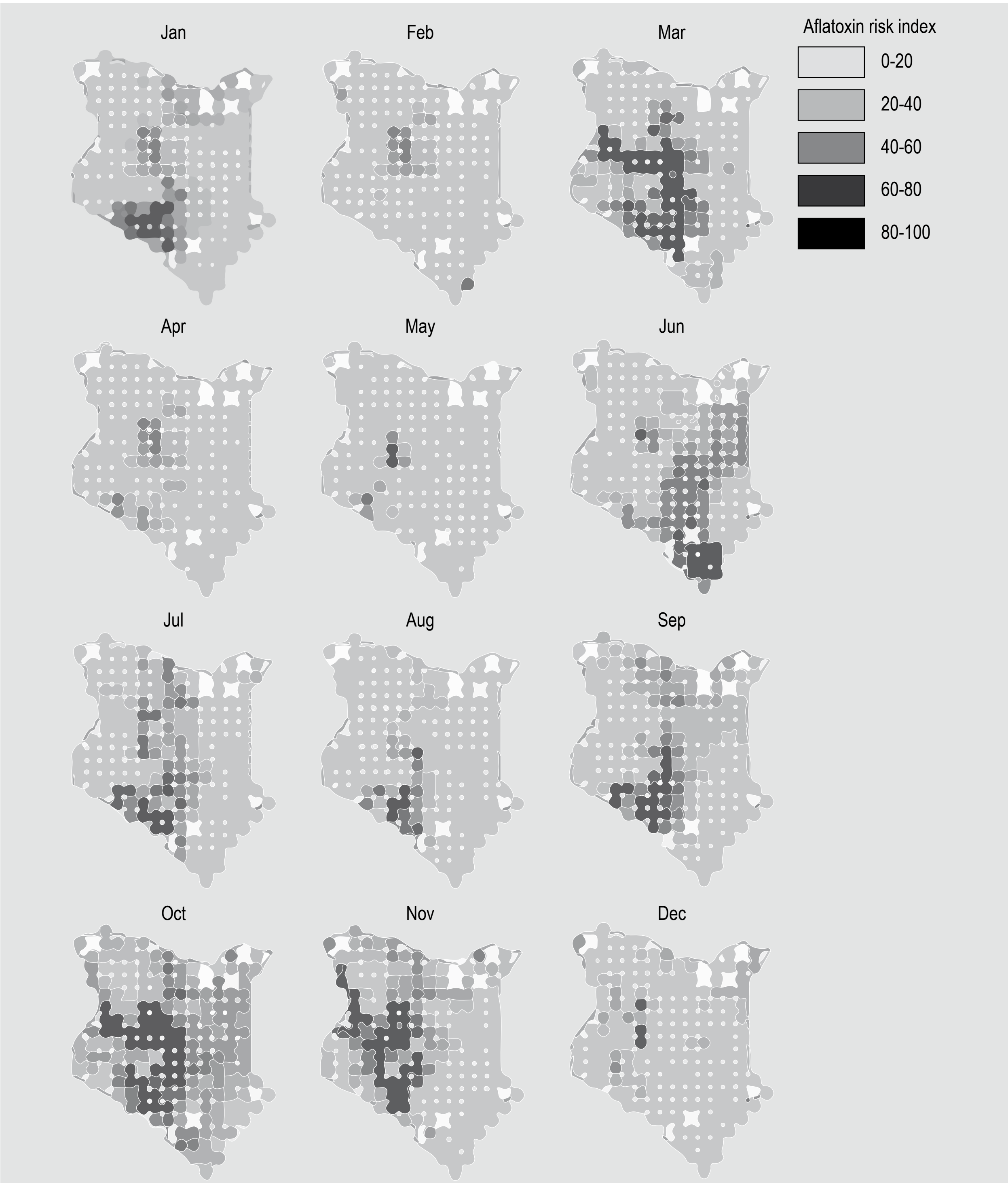

Figure 4. Risk of aflatoxin contamination in maize in Kenya, computed as an Aflatoxin Risk Index (ARI) over a 50 km^2 grid. The model is run based on 12 unique sowing dates, at the start of each month, demonstrating the potential value in determining optimum crop timing to minimise ARI.

different months from the model based on APSIM used by Chauhan *et al.* (2015).

Decision support tools

Decision support tools that translate the outputs of aflatoxin risk models for users can be used at multiple intervention points within the value chain (Figure 1). Several existing decision support systems may be directly applicable to aflatoxin mitigation, or could be extended or replicated to fit the specified purpose, including:

1. early warning maps based on agrometeorological and biomass indicator anomalies – e.g. ASAP (Rembold *et al.*, 2019), APHLIS, GEOGLAM, FAO GIEWS, FEWS NET;
2. aflatoxin information systems – AfricaAims;
3. decision support – e.g. intelligent agricultural systems advisory tool (ISAT) (Rao *et al.*, 2019), GeoFarmer (Eitzinger *et al.*, 2019), MyToolBox (Krska *et al.*, 2016);
4. risk maps in agriculture – e.g. FAMRisk-Map;
5. market information services (MIS) – e.g. M-Farm;
6. weather information services (WIS) – e.g. Ignitia, aWhere;
7. extended crop growth modelling frameworks – APSIM (Keating *et al.*, 2003), DSSAT (Jones *et al.*, 2003).

These tools or services can be used to identify potential user groups, distributors of risk model results, technological barriers to adoption, data limitations, and possible partnerships for scaling a decision support platform. Tools such as the Agricultural Production Systems sIMulator (APSIM) (Holzworth *et al.*, 2014) and DSSAT (Jones *et al.*, 2003) are now being increasingly used to assist farmers in decision making. Other tools are built on top of these frameworks, such as Pl@nteInfo® (Jensen *et al.*, 2000), Yield Prophet (Hochman *et al.*, 2009), Afloman (Chauhan *et al.*, 2010), Aquaman (Chauhan *et al.*, 2013) and Aquacrop (Steduto *et al.*, 2009). Afloman routes silo weather data in Australia through a cluster of computers running APSIM, which uploads peanut aflatoxin model results to be accessed through APSIM website, compiled reports, or through mobile apps accessible by farmers or extension agents (Chauhan *et al.*, 2010). ICRISAT, in partnership with Microsoft India, developed the Sowing App and the Intelligent Agricultural Systems Advisory Tool (ISAT) using cloud-based predictive analytics tools to predict optimal sowing period and other farm management practices and deliver results through SMS to smallholder farmers (Manfre and Laytham, 2018). These integrated solutions are insightful examples of the challenges and benefits of decision-support in aflatoxin management.

ASAP (Anomaly Hotpots of Agricultural Production) was developed by the Joint Research Center of the European Commission as an agricultural early warning system that provides drought conditions warnings for food insecure areas in the world, based on dekadal updates of climate and biophysical data. The system monitors weather and biophysical indicators for anomalies in agricultural areas for all crops. An empirical model was developed to use pre-harvest drought warnings and excessive rainfall around harvest warnings from the ASAP system to provide agro-climatic mycotoxin risk warning maps to APHLIS (African Postharvest Losses Information System) at the province level for allowing more detailed monitoring and for guiding field surveys (Rembold *et al.*, 2019). Combining the climatic warning category dataset computed by APHLIS and the crop calendars from ASAP illustrates occurrence of high-risk conditions over time (Figure 5).

Aflatoxin datasets in Africa

The dearth of aflatoxin occurrence data that exist to recalibrate empirical models and validate all types of models for SSA remains a major challenge in model development. However, some limited aflatoxin datasets do exist for African countries, primarily collected either by private sector processors and aggregators or in small-scale research studies, emphasising the importance of public-private partnerships (Eskola *et al.*, 2019). Five of the research studies identified in this review used field data from African countries (Table 2). Chauhan *et al.* (2015) conducted five maize trials at four Kenyan field stations for validation of an aflatoxin predictive model integrated with APSIM. Smith *et al.* (2016) analysed 2,466 maize samples collected between 2009 and 2010 from 243 hammer mills in Kenya, 60% of which had detectable aflatoxin. Chalwe *et al.* (2019) conducted two years of experiments with peanuts in Zambia with 84 unique climate conditions of ambient temperature and soil temperature and moisture for training of a regression model. Boken *et al.* (2008) collected data for peanut crops from 18 sites in Mali in 1999 with aflatoxin levels from 4.5 to 12.1 μg/kg. Craufurd *et al.* (2006) planted 40 unique fields of peanuts at different experimental conditions in Niger fields between 1991 and 1994.

A promising aflatoxin contamination dataset for aflatoxin model calibration and testing in Africa is being aggregated by the Partnership for Aflatoxin Control in Africa (PACA). PACA has been developing the Africa Aflatoxin Information Management System (AfricaAIMS) to facilitate decision-making for policies, regulations, standards, educational and technological interventions, resource allocation, advocacy and awareness creation by governments and stakeholders. They are aggregating data from several African countries on aflatoxin contamination in food and feed, aflatoxin exposure associated and diseases, consumption of aflatoxin prone foods, rates of child stunting, aflatoxin country standards, and volume of imports and exports of aflatoxin prone foods and export rejections. The PACA dataset has not yet been released, however, and their data partnerships are still being developed.

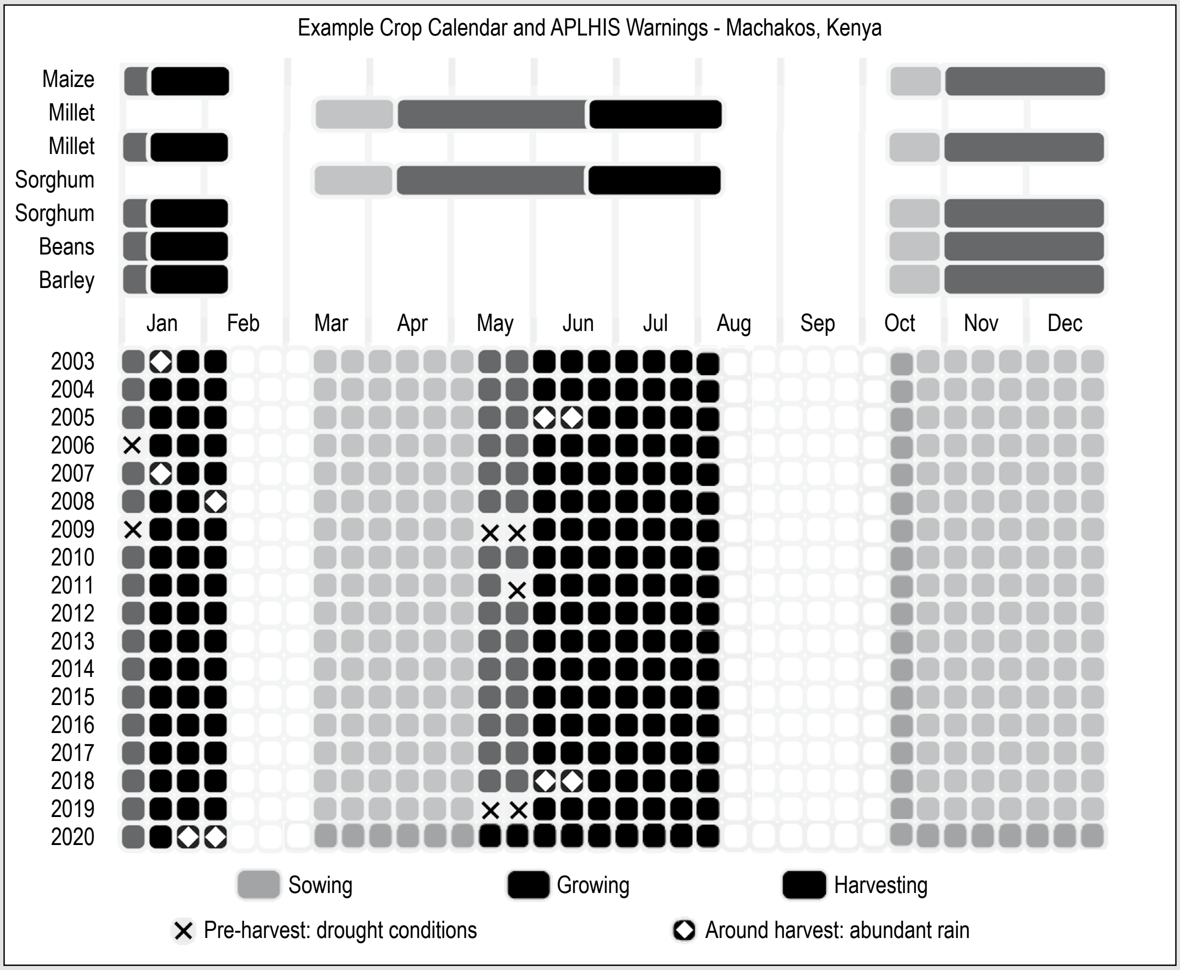

Figure 5. Aflatoxin risk events visualised over dekadal calendars based on APHLIS model and ASAP crop calendars. Two risk sources include abundant rainfall around harvest (◊) and preharvest drought conditions (x).

Multiple datasets exist on the presence of contaminants in food systems, but samples are analysed in food or feed products much removed from the initial conditions of aflatoxin development. The Biomin Mycotoxin Survey currently has a public dataset for five mycotoxins for commercial feed crops in seven African countries. The WHO Global Environment Monitoring System (GEMS) is a food contaminants database with mycotoxin occurrence data in food products collected primarily from private sector organisations and national institutions including 5,400 from the WHO African Region (Miyagishima and Verger, 2016).

Overall, the lack of available African aflatoxin data at the field level impedes the development and testing of models, and scarcity and/or uncertainty in the environmental parameters throughout Africa will also affect model performance and accuracy. Data are especially scarce at the farm-level, and existing data are often georeferenced only broadly by region since testing is conducted at processing facilities and not on-farm, limiting their effectiveness in validating or recalibrating models. Sampling at mills is often used as an effective proxy for human consumption because it is the last point in the value chain before reaching the consumer (Smith *et al.*, 2016). Until testing costs decrease, or market systems incentivise testing, measurements at the farm level will be unlikely to occur without external interventions.

3. Application of predictive aflatoxin risk modelling in sub-Saharan Africa

The applications of predictive risk models in SSA can be grouped into three areas of impact: improved agricultural production and value for smallholders, food safety and public health, and private sector and markets. Activities that mitigate aflatoxin contamination in SSA contribute directly to several of the strategic action areas in the Malabo Declaration on Accelerated Agricultural Growth in Africa, including sustainable agricultural production, market infrastructure, increased resilience to climate variability, and capacity for evidence-based planning (African Union Commission, 2014). Applications of predictive models in African agriculture and postharvest management throughout the production and postharvest phases (Ayalew *et al.*, 2016; Battilani and Leggieri, 2015; Chauhan *et al.*, 2015) include:

1. predict aflatoxin risk before season, during growing season, and at harvest to reduce occurrence with appropriate farming practices;
2. provide real time agricultural practice advice to smallholder farmers through public, private, or digital extension service;
3. guide postharvest processing and storage management practices;
4. map high-risk zones of aflatoxin occurrence for enabling rapid response, guide public extension services, and selectively conduct aflatoxin detection testing;
5. allow private-sector and humanitarian aid organisations to selectively source their crops from low-risk areas to allow the furthering of local purchase program such as the World Food Program Purchase for Progress (P4P) program;
6. improve trade prospects by reducing export related food safety risks.

Many potential methods for distributing predictive model results are available to influence positive management through actionable advice to actors in the food chain. Model results could be distributed to farmers or cooperatives through public extension services run by governmental organisations, private sector multinational food companies who source from these countries, or companies operating mobile weather or market information services to inform farmers about climate and market conditions. Models could also be used primarily at a policy-making or aggregator level for decision-making purposes. The priorities for targeting these groups depend on feasibility given current constraints, as well as role within the production and postharvest phases (Figure 1). It is crucial to deliver model outputs to the proper stakeholders and carefully consider the input and output constraints relative to those user needs and access, as the requirements for accuracy and spatial and temporal resolution will vary based on use case and actionability of results.

The Aflatoxin Control Action Plan by ECOWAS and PACA (Osiru *et al.*, 2014) suggests that real-time mapping of aflatoxin high-risk zones be part of a broader set of methods for addressing aflatoxin in SSA, to allow for the timely and spatially effective deployment of resources and detection systems in high-risk areas. Risk modelling will enable rapid response to outbreaks and the targeting of aflatoxin control methods, but must be accompanied by market development, education, increased testing capacity, and policy and regulatory environment changes. Predictive models can also be employed in very specific segments of the value chain, such as targeting storage contamination in granaries to develop an early warning system (Jiang *et al.*, 2019). Specific intervention strategies are further discussed regarding smallholders, food safety and public health, and private sector and markets.

Improved agricultural production and value for smallholders

It is generally agreed that the highest priority in addressing aflatoxin is building farmer capacity for good agriculture practices (Stepman, 2018). There are three critical points for aflatoxin management in the phenological cycle including: pre-season sowing decisions, the six weeks before harvest during the grain-filling stage, and immediately postharvest for drying and storage (Choudhary and Kumari, 2010; Cotty and Jaime-Garcia, 2007; Hell *et al.*, 2008; Widstrom *et al.*, 2003; Wu, 2015). Modelled aflatoxin risk can be used to identify priority geographies and times for promoting best practices, especially where extension services are limited. Most importantly, recommendations made to smallholder farmers must be actionable given resource and capital constraints. Models could allow farmers' management strategies to be fine-tuned throughout the season based on the seasonal forecasts as they convert weather forecasts into likely crop performance (Hansen, 2005). Models must be updated to account for in-season climate variability which creates the need for continuously shifting management strategies (Bannayan *et al.*, 2003; Booltink *et al.*, 2001; Nnaji, 2001; Phillips *et al.*, 1998). Intervention strategies informed by aflatoxin risk models are presented here based on their chronology in the crop cycle.

Pre-season decisions can be optimised using global climate and phenological models to determine the ideal season timing and investments in the necessary technologies to maximise safe yield. Chauhan (2010) and Chauhan *et al.* (2015) showed that models could be used to design appropriate rotations that might become more relevant in a changing climate. These studies showed that higher yields could be realised by planting crops based on their relative sensitivity to warmer temperatures in conjunction with weather projections. Chauhan *et al.* (2008) proposed a system to predict ARI for maize in Australia that would assist farmers in adjusting sowing time or selecting an appropriate hybrid, based on respective temperature and water stress conditions linked with contamination levels. Given local information on agronomy and agricultural practices, crop timing of both sowing and harvest dates could be predicted through modelling.

Knowledge about aflatoxin presence before harvest would allow farmers to make decisions about what level of maturity to harvest, potentially moving harvest earlier to minimise risk of pre-harvest contamination (Canavar and Kaynak, 2013; Rachaputi *et al.*, 2002). Kaaya *et al.* (2006) showed an increase in aflatoxin levels by a factor of 4 if harvest is delayed 3 weeks from physiological maturity, and by a factor of 7 if delayed by 4 weeks. The trade-off between yield and aflatoxin level must be weighed when considering harvest before physiological maturity. Predictive models could be used to focus on ideal pre-harvest activities that reduce aflatoxin risk. Pre-harvest strategies include avoiding drought stress through irrigation, avoiding nutrition stress with fertiliser, weed and pest control, soil health management, biocontrol, and other in-season activities (Hell and Mutegi, 2011; Munkvold, 2003). Fortunately, most pre-harvest measures that act to reduce aflatoxin incidence are the same practices used to enhance yield (Hell and Mutegi, 2011), so identifying the most effective strategies to minimise risk also maximises input profitability.

Modelling can also inform utilisation of postharvest drying and storage processes that preserve low moisture levels and prevent the proliferation of mycotoxigenic fungi. Risk identification around harvest time could be used by extension agents and farmers making decisions about harvest time and postharvest practices. Postharvest aflatoxin reduction strategies include harvest timing based on maturity and risk, proper drying, sanitation, proper storage in hermetic bags, proper transportation, sorting, cleaning, smoking, and insect management (Hell and Mutegi, 2011; Wagacha and Muthomi, 2008). Food processing procedures to remove aflatoxin include milling, washing, baking, sorting, dehulling, nixtamalisation, ozonation, and UV irradiation (Hell and Mutegi, 2011; Li *et al.*, 2019), but the efficacy of decontamination is limited. Other behavioural methods can also be applied, such as diversifying dietary practices, although this is not possible for many of the poorest individuals (Onyango, 2003). These strategies can all be effectively encouraged by extension services informed by agro-climatic risk factors.

Smallholder farmers are risk averse and often value savings (labour, time, and cost) more than profit, so minimal financial investments with short repayment periods are necessary criteria for interventions (Kohl *et al.*, 2017; Memedovic and Shepherd, 2008). Aflatoxin awareness campaigns supported by agro-climatic risk predictions can be distributed through policy briefs, regional reports, media and social media reports, and through public and private extensions services (Falade, 2018). Increased information access based on model results can allow smallholders to be more strategic with investments while focusing on minimisation of risk.

Food safety and public health

Early-stage risk models can be designed for policymakers who can process high level model results, distribute public extension services, and make policy and regulatory decisions that can positively impact the entire value chain. Local policymakers can address the challenges of the prevalence of informal market structures and lack of economic incentives systems, as well the general lack of awareness around aflatoxins and best management practices. Data on seasonal aflatoxin development at regional-level resolution could be effective in enabling policy and regulations (Rembold *et al.*, 2019). Public extension support is highly variable across country contexts, but is invariably an important factor in raising awareness (Kohl *et al.*, 2017). Equipping extension agents with risk predictions could improve their effectiveness by providing timely and regionally focused actionable advice (Msuya *et al.*, 2017).

The Malabo Declaration, adopted by the African Union at the 2014 Comprehensive Africa Agriculture Development Program, aims to 'develop mechanisms that enhance Africa's capacity for knowledge and data generation and management to strengthen evidence based planning and implementation' (African Union Commission, 2014), and predictive aflatoxin risk modelling can help contribute to the development of strategic policy. Countries typically build networks of trading relationships based on regulatory limits (Falade, 2018), and for the proposed interventions to be effective it will be necessary to support the harmonisation of policies and regulations across trading regions (Okoth, 2016). Enforcing regulatory standards in African countries is difficult for food security reasons, and an estimate by Sirma *et al.* (2018) showed that around 9 million Kenyans would be deprived of the majority of their food supply if standards for cereals were fully enforced. Thus standards need to be enforced relative to local conditions, such as capacity for enforcement, contamination levels, regional standards, use of commodities, and other societal concerns (Sirma *et al.*, 2018). Regulations are typically only enforced in African countries for crops destined for export markets (Ayalew *et al.*, 2016), although most African countries are primarily focused on domestic and regional markets rather than exports (Stepman, 2018). This context is important for understanding the potential market and export incentive structures that would support the proliferation of model use to support improved smallholder management practices.

Private sector and market impacts

Private sector actors with access to aflatoxin risk model outputs could use the information in ways that could either benefit or impair farmers in SSA, depending on their incentives. If private sector organisations are motivated to help farmers improve their practices, they can use model outputs to target development activities as well as purchasing decisions. Private sector actors can provide initial introduction and dissemination of model results, aid in marketing and promotion through private extension services, and set up sustainable production and distribution supply chains (Kohl *et al.*, 2017). Alternatively, unequal dissemination of information in the value chain has the potential to increase the power dynamic between farmers and buyers and ultimately hurt market potential. Currently to reduce the risk of not meeting export and other formal market requirements, many aggregators preclude smallholder farmers from their supplier pool (Falade, 2018). This typically excludes smallholders from participating in formal markets with more reliable and better prices, but potentially could be lessened by modelling regions of low risk and enabling aggregators to purchase from smallholders in low-risk regions.

Aflatoxin risk models could aid in the establishment of these relationships by lowering risk for large aggregators to purchase from farmers in low-risk regions. Two thirds of the value of farm commodities is accrued by the traders in developing countries, and they suffer the most from spoilage losses (Rockefeller Foundation, 2013). Therefore, traders must be considered within any aflatoxin intervention, although the harvesting and storage conditions they receive the goods in are the primary factor controlling fungal growth during transport. Focusing earlier in the supply chain is ideal, especially since it has been shown that the financial cost of investing in storage, drying, and testing systems can be offset by the recovery of postharvest loss (Bradford *et al.*, 2018). A well-integrated holistic process for aflatoxin management is necessary to identify high risk elements in the supply chain (Unnevehr and Grace, 2013).

4. Prospects for implementation of aflatoxin predictive risk modelling in sub-Saharan Africa

Challenges to be addressed

This review has presented the current state of empirical and mechanistic predictive aflatoxin risk models for SSA and has articulated several possible model applications throughout the production and postharvest phases. Although predictive aflatoxin risk models have been successful in high-income country contexts, there are several substantial hurdles that must be overcome in order to extend these approaches to SSA:

1. Scarcity of georeferenced aflatoxin occurrence data and local agricultural practices at the farm level. This will require support of widespread data collection efforts and public-private partnerships for each region and crop of interest.
2. Limitations in real-time high resolution climate data. New modelling and remote sensing approaches can supplement the minimal SSA climate sensor network.
3. Ability for models to generate actionable advice for smallholders. This will require models focused on key decision points with localised recommendations. In order to enable data-driven agriculture in locations where agricultural data are scarce, a model could provide high level information that can be filtered through local contextual knowledge due to the wide diversity of farm typologies in SSA. Before a model that is relevant to local contexts can be developed, it would be necessary to pursue data collection on local factors and growing conditions.
4. Information and technology barriers to accessing decision support and extension services. In order to scale a platform through which smallholders could receive actionable advice based on model results, the parallel advancement of private and public extension alongside mobile decision support platforms will be necessary.
5. Awareness and problem-solving capacity in smallholders, especially regarding their understanding of the economic, health, and livelihood improvements from aflatoxin intervention strategies. Model results can be integrated into community development schemes to address this, in parallel with broader awareness and education programs.
6. Economic incentive system for implementation. Public partnerships will be necessary to establish a market incentive system that can enable adoption of aflatoxin mitigation methods and increase market demand (Kohl *et al.,* 2017; Schreurs *et al.,* 2019). Implementation of incentive systems remains a challenge in informal markets.
7. Capacity development of the extension services (public, private, and digital) responsible for local dissemination of model results. New information technologies can be effective in advancing the efforts of public and private extension, along mobile information service technologies which can be accessed locally by farmer groups.

Pilot studies should be conducted through local extension services in SSA to provide smallholders with model results and management advice. This would enable the identification of primary challenges for scalability, technological barriers to implementation, local awareness mechanisms, and would demonstrate empirical evidence of agronomic and socioeconomic benefits.

Data collection

Aflatoxin occurrence data for each region with similar agro-ecological characteristics is necessary for validation and recalibration since climate interaction varies between regions with shared biophysical parameters (Probst *et al.*, 2014). A framework by IFPRI (Mahuku *et al.*, 2010) for aflatoxin prevalence data collection for maize in Kenya proposed collecting samples throughout the value chain, through production, transportation, storage, and processing. Their recommended data collection points include crop variety, moisture content at harvest, storage period and method, socioeconomic information, grain quantities and sources, agro-ecological zone, management practices, and other information necessary to correlate aflatoxin levels with localised factors. Mahuku *et al.* (2010) proposed that during the season these data should be collected a week before harvest and 15 to 30 days after harvest, and each sublocation should have a local market selected for sample collection from at least five traders. If detailed baseline information on environmental characteristics such as soil properties, agricultural practices, and crop calendar are not known precisely, localised recommendations cannot be effectively distributed to smallholders.

Application of these models and data aggregation would ideally be integrated into a digital platform to improve efficiency, provide real-time monitoring, and support extension service officers with their work. Localised decision-making can be advanced in parallel with data collection schemes on local growing practices, such as digital profiling of smallholder farms through remote sensing techniques using sensor systems operated by local extension services. Deployment of an affordable, standardised testing system connected to a centralised database would also enable other data applications, such as the significant improvement of any modelling system, meta-analysis of aflatoxin patterns, and further development of an information technology infrastructure (Jargot and Melin, 2013; Rosenzweig *et al.*, 2013; Stepman, 2018; Wu *et al.*, 2016).

Proposed modelling approach

Based on the review of existing models and the challenges to their implementations, the authors can provide some recommendations for the development and use of predictive models in SSA. It is encouraged to adopt a modelling approach driven by requirements of model use cases within the value chain and deployed as an integrated solution alongside climate warning and decision-support systems for smallholder and agricultural supply chain risk management. As data collection schemes in SSA become more comprehensive and incentivised, modelling approaches can be increasingly applied to SSA regions sharing biophysical parameters at several stages in the supply chain. Model results will take multiple forms according to the value actor and phase they are applied within and must be designed with the specific application in mind beyond only a risk index.

To leverage the advantages of both approaches a hybrid aflatoxin risk prediction modelling approach is proposed, combining an empirical model trained and recalibrated on data from a new geography while accounting for heterogeneity in agronomic practices, and a mechanistic model based on the infection cycle of *A. flavus*. Mechanistic models are suitable to be applied in different geographic areas without recalibration, although it is a challenge to access data on the diversity of cropping systems which is an important factor in mechanistic models (Battilani *et al.*, 2015). Therefore, empiric approaches are often more appropriate because of their ability to extract non-linear relationships between climatic variables and aflatoxin risk. Empirical models need to be calibrated at the local level with farm-level georeferenced aflatoxin occurrence data because of the heterogeneity in local agricultural practices. A secondary model layer could then produce recommendations from the empirical and mechanistic models, with aflatoxin risk mitigation practices optimised based on nutrition and profit brought to smallholders. These results can then be distributed through public, private, or digital extension services or farmer organisations as presented in Figure 6.

The proposed integrated modelling approach shown in Figure 6 presents a model structure and dissemination pathways for model outputs to be used by government agencies, research institutions, processors, aggregators, and extension services. This framework would allow real-time operation and accessibility through digital information services to extension agents, farmers, aggregators, or policy-makers. This platform would be ideal for accommodating the multiple pathways for distributing information that will be necessary to adequately reach smallholders. Empirical and mechanistic models would take input data from various static or real-time datasets on climate, agronomy, soil properties, and local land use and management information. These models could work in parallel to produce outputs of specific advice on management practices and localised risk maps, and this ensemble model will allow results to be more robust and provide rationale to stakeholders.

Preparing localised risk maps generally assumes that climate is the most significant contributor to variation, but the heterogeneity of local sociocultural realities must also be considered. In addition to the agro-climatic and geospatial risk factors upon which most prediction models are based, there is evidence that farmers' food and crop management behaviours at the household- or farm-level contribute demonstrably to their exposure risk. An exploratory study of household-level risk factors predicted aflatoxin contamination status with 68% sensitivity and 62% specificity in India, illustrating the important role of behavioural factors in modulating risk levels (Wenndt *et al.*, 2020). Future efforts to develop risk prediction models for SSA might consider synergising the predictive potentials of both agro-climatic and household-level factors in order to achieve greater prediction accuracy and to identify locally meaningful solutions. To address unknown local variables, risk maps could also be prepared for multiple different scenarios, and further evidence of the contribution of additional agronomic and management factors should be investigated.

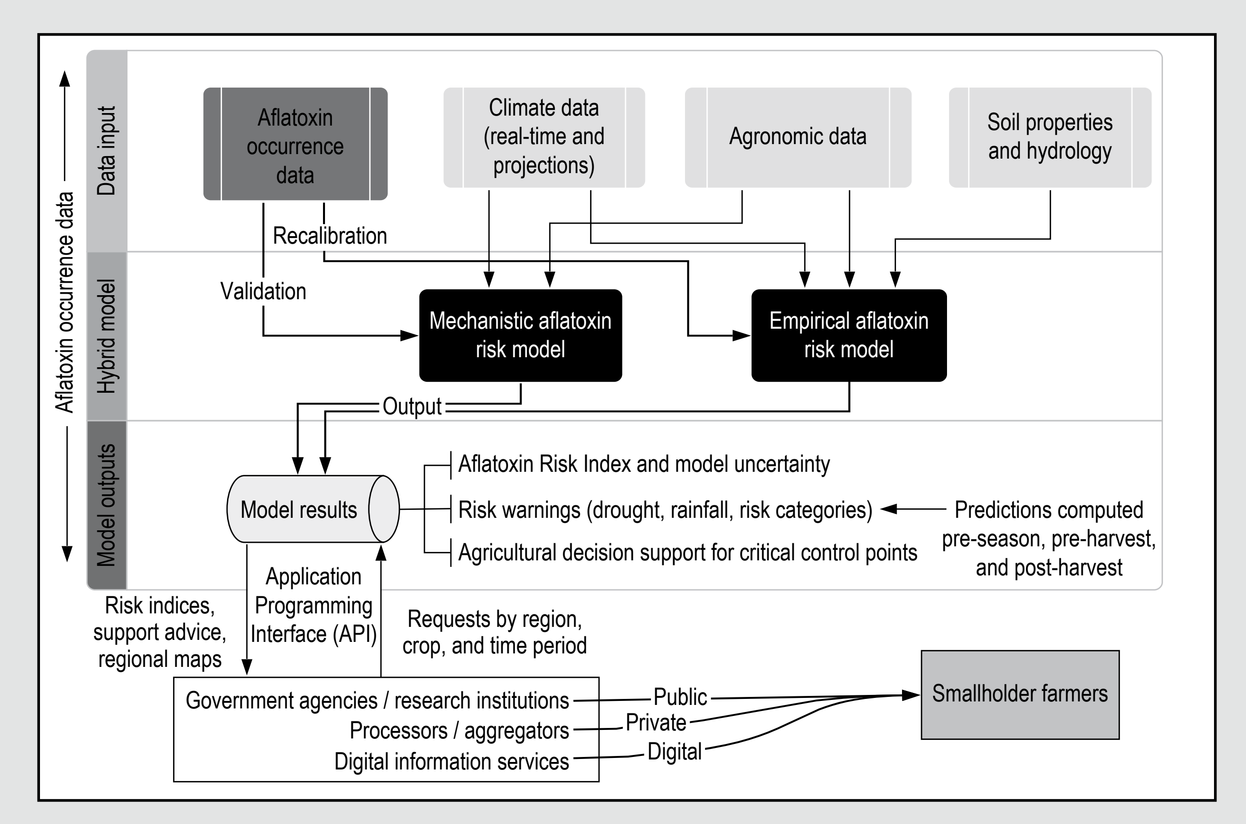

Figure 6. Proposed integrated modelling approach including hybrid risk model results accessible to the various value actors who can optimise distribution of management advice and resources to smallholders.

5. Conclusions

This review of empirical and mechanistic aflatoxin predictive risk models has presented current approaches as well as model applicability in the African agricultural value chain, with an emphasis on improving agriculture practices for smallholder farmers. An analysis of the value chain and aflatoxin management practices in SSA contextualises the forms model output can take within the production and postharvest phases. Although predictive aflatoxin risk models have been successful in high-income country contexts, there are several steps to extend these models to enable provision of actionable advice as early in the SSA value chain as possible. Model validation and recalibration for SSA is limited by a dearth of ground truth data and real-time high resolution climate data, as well as the wide diversity of farm typologies with significant information and technology gaps. Given advancements towards solving these challenges, a hybrid modelling approach is proposed to leverage the benefits of both empirical and mechanistic modelling regarding extending models to new spatial and temporal domains. Alongside extensive data collection schemes and market incentive systems, predictive aflatoxin models can be integrated into decision support platforms to focus on optimisation of value for smallholders by minimising yield and nutritional losses, which can propagate value throughout the production and postharvest phases. Policymakers are a general target, followed by various mid-level actors including private sector organisations providing information and mechanised services, farmer cooperatives, and extension service providers. As models increase in resolution and accuracy and other challenges are addressed in the value chain, the primary target for interventions should be as close as possible to the level of smallholder farmers or farmer groups, who are the primary point of control in aflatoxin mitigation.

Acknowledgements

We would like to thank Elsie Black and Lisa Gilbert for their contributions to this review. Thanks to the project teams from APHLIS and ASAP who facilitated data access used for analysis and visualisation, available at https://www.aphlis.net/ and https://mars.jrc.ec.europa.eu/asap/. The authors would also like to thank the thoughtful suggestions from two anonymous reviewers for improving the quality of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

References

African Union Commission, 2014. Malabo declaration on accelerated agricultural growth and transformation for shared prosperity and improved livelihoods. African Union Commission, Addis Ababa, Ethiopia.

Ayalew, A., Hoffman, V., Lindahl, J. and Ezekiel, C.N., 2016. The role of mycotoxin contamination in nutrition: the nutrition story. IFPRI, Washington, DC, USA.

Bannayan, M., Crout, N.M.J. and Hoogenboom, G., 2003. Application of the CERES-wheat model for within-season prediction of winter wheat yield in the United Kingdom. Agronomy Journal 95: 114. https://doi.org/10.2134/agronj2003.0114

Battilani, P. and Camardo Leggieri, M., 2015. Predictive modelling of aflatoxin contamination to support maize chain management. World Mycotoxin Journal 8: 161-170. https://doi.org/10.3920/WMJ2014.1740

Battilani, P., Barbano, C. and Piva, G., 2008. Aflatoxin B_1 contamination in maize related to the aridity index in North Italy. World Mycotoxin Journal 1: 449-456. https://doi.org/10.3920/wmj2008.x043

Battilani, P., Leggieri, M.C., Rossi, V. and Giorni, P., 2013. AFLA-maize, a mechanistic model for *Aspergillus flavus* infection and aflatoxin B1 contamination in maize. Computers and Electronics in Agriculture 94: 38-46. https://doi.org/10.1016/j.compag.2013.03.005

Battilani, P., Rossi, V., Giorni, P., Pietri, A., Gualla, A., Fels-Klerx, H.J., Booij, C.J.H., Moretti, A., Logrieco, A., Miglietta, F., Toscano, P., Miraglia, M., Santis, B.D. and Brera, C., 2012. Modelling, predicting and mapping the emergence of aflatoxins in cereals in the EU due to climate change. EFSA Supporting Publications 9: 223e. https://doi.org/10.2903/sp.efsa.2012.EN-223

Battilani, P., Toscano, P., Van der Fels-Klerx, H.J., Moretti, A., Camardo Leggieri, M., Brera, C., Rortais, A., Goumperis, T. and Robinson, T., 2016. Aflatoxin B_1 contamination in maize in Europe increases due to climate change. Scientific Reports 6: 24328.

Boken, V., Hoogenboom, G., Williams, J., Diarra, B., Dione, S. and Easson, G., 2008. Monitoring peanut contamination in Mali (Africa) using AVHRR satellite data and a crop simulation model. International Journal of Remote Sensing 29: 117-129.

Booltink, H.W.G., Van Alphen, B.J., Batchelor, W.D., Paz, J.O., Stoorvogel, J.J. and Vargas, R., 2001. Tools for optimizing management of spatially-variable fields. Agricultural Systems 70: 445-476. https://doi.org/10.1016/S0308-521X(01)00055-5

Bradford, K.J., Dahal, P., Van Asbrouck, J., Kunusoth, K., Bello, P., Thompson, J. and Wu, F., 2018. The dry chain: reducing postharvest losses and improving food safety in humid climates. Trends in Food Science and Technology 71: 84-93. https://doi.org/10.1016/j.tifs.2017.11.002

Canavar, O. and Kaynak, M.A., 2013. Prevention of pre-harvest aflatoxin production and the effect of different harvest times on peanut (*Arachis hypogaea* L.) fatty acids. Food Additives and Contaminants Part A 30: 1807-1818. https://doi.org/10.1080/19440049.2013.818720

Chalwe, H., Lungu, I., Mweetwa, A., Phiri, E., Yengwe, J., Njoroge, S., Njoroge, C., Brandenburg, R. and Jordan, D., 2019. Predicting aflatoxin content in peanuts using ambient temperature, soil temperature and soil moisture content during pod development. African Journal of Plant Science 13: 59-69.

Chauhan, Y., 2010. Potential productivity and water requirements of maize-peanut rotations in Australian semi-arid tropical environments – a crop simulation study. Agricultural Water Management 97: 457-464. https://doi.org/10.1016/j.agwat.2009.11.005

Chauhan, Y., Tatnell, J., Krosch, S., Karanja, J., Gnonlonfin, B., Wanjuki, I., Wainaina, J. and Harvey, J., 2015. An improved simulation model to predict pre-harvest aflatoxin risk in maize. Field Crops Research 178: 91-99. https://doi.org/10.1016/j.fcr.2015.03.024

Chauhan, Y., Wright, G. and Rachaputi, N.C., 2008. Modelling climatic risks of aflatoxin contamination in maize. Australian Journal of Experimental Agriculture 48: 358-366.

Chauhan, Y., Wright, G., Rachaputi, R.C.N., Holzworth, D., Broome, A., Krosch, S. and Robertson, M.J., 2010. Application of a model to assess aflatoxin risk in peanuts. The Journal of Agricultural Science 148: 341-351.

Chauhan, Y., Wright, G.C., Holzworth, D., Rachaputi, R.C.N. and Payero, J.O., 2013. AQUAMAN: a web-based decision support system for irrigation scheduling in peanuts. Irrigation Science 31: 271-283. https://doi.org/10.1007/s00271-011-0296-y

Chisadza, B., Mushunje, A., Nhundu, K. and Phiri, E.E., 2020. Opportunities and challenges for seasonal climate forecasts to more effectively assist smallholder farming decisions. South African Journal of Science 116(1-2): 1-5.

Choudhary, A.K. and Kumari, P., 2010. Management of mycotoxin contamination in preharvest and post harvest crops: present status and future prospects. Journal of Phytology 2: 37-52.

Cotty, P.J. and Jaime-Garcia, R., 2007. Influences of climate on aflatoxin producing fungi and aflatoxin contamination. International Journal of Food Microbiology 119: 109-115. https://doi.org/10.1016/j.ijfoodmicro.2007.07.060

Craufurd, P.Q., Prasad, P.V.V., Waliyar, F. and Taheri, A., 2006. Drought, pod yield, pre-harvest *Aspergillus* infection and aflatoxin contamination on peanut in Niger. Field Crops Research 98: 20-29. https://doi.org/10.1016/j.fcr.2005.12.001

Damianidis, D., Ortiz, B.V., Windham, G.L., Bowen, K.L., Hoogenboom, G., Scully, B.T., Hagan, A., Knappenberger, T., Woli, P. and Williams, W.P., 2018. Evaluating a generic drought index as a predictive tool for aflatoxin contamination of corn: from plot to regional level. Crop Protection 113: 64-74. https://doi.org/10.1016/j.cropro.2018.07.013

Darwish, W.S., Ikenaka, Y., Nakayama, S.M.M. and Ishizuka, M., 2014. An overview on mycotoxin contamination of foods in Africa. Journal of Veterinary Medical Science 76: 789-797. https://doi.org/10.1292/jvms.13-0563

Eitzinger, A., Cock, J., Atzmanstorfer, K., Binder, C.R., Läderach, P., Bonilla-Findji, O., Bartling, M., Mwongera, C., Zurita, L. and Jarvis, A., 2019. GeoFarmer: a monitoring and feedback system for agricultural development projects. Computers and Electronics in Agriculture 158: 109-121. https://doi.org/10.1016/j.compag.2019.01.049

Eskola, M., Kos, G., Elliott, C.T., Hajšlová, J., Mayar, S. and Krska, R., 2019. Worldwide contamination of food-crops with mycotoxins: validity of the widely cited FAO estimate of 25%. Critical Reviews in Food Science and Nutrition 60: 2773-2789. https://doi.org/10.1080/10408398.2019.1658570

Falade, T., 2018. Aflatoxin management strategies in sub-Saharan Africa. IntechOpen, London, UK.

Ferris, S., Robbins, P., Best, R., Seville, D., Buxton, A., Shriver, J. and Wei, E., 2014. Linking smallholder farmers to markets and the implications for extension and advisory services. MEAS Brief 4: 13-14.

Food and Agriculture Organization of the United Nations (FAO), 2019. World fertilizer trends and outlook to 2022. FAO, Rome, Italy.

Food and Agriculture Organization of the United Nations (FAO), 2015. The economic lives of smallholder farmers: an analysis based on household data from nine countries. FAO, Rome, Italy.

Giorni, P., Camardo Leggieri, M., Magan, N. and Battilani, P., 2012. Comparison of temperature and moisture requirements for sporulation of *Aspergillus flavus sclerotia* on natural and artificial substrates. Fungal Biology 116: 637-642. https://doi.org/10.1016/j.funbio.2012.03.003

Hansen, J.W., 2005. Integrating seasonal climate prediction and agricultural models for insights into agricultural practice. Philosophical Transactions of the Royal Society of London, Series B 360: 2037-2047. https://doi.org/10.1098/rstb.2005.1747

Hell, K. and Mutegi, C., 2011. Aflatoxin control and prevention strategies in key crops of sub-Saharan Africa. African Journal of Microbiology Research 5: 459-466.

Hell, K., Fandohan, P., Bandyopadhyay, R., Kiewnick, S., Sikora, R. and Cotty, P., 2008. Pre- and postharvest management of aflatoxin in maize: an African perspective. In: Leslie, J.F., Bandyopadhyay, R. and Visconti, A. (eds.) Mycotoxins: detection methods, management, public health and agricultural trade. CABI Publishing, Wallingford, UK, pp. 219-230.

Hochman, Z., Van Rees, H., Carberry, P.S., Hunt, J.R., McCown, R.L., Gartmann, A., Holzworth, D., Van Rees, S., Dalgliesh, N.P., Long, W., Peake, A.S., Poulton, P.L. and McClelland, T., 2009. Re-inventing model-based decision support with Australian dryland farmers. Crop and Pasture Science 60: 1057-1070. https://doi.org/10.1071/CP09020

Holzworth, D.P., Huth, N.I., De Voil, P.G., Zurcher, E.J., Herrmann, N.I., McLean, G., Chenu, K., Van Oosterom, E.J., Snow, V., Murphy, C., Moore, A.D., Brown, H., Whish, J.P.M., Verrall, S., Fainges, J., Bell, L.W., Peake, A.S., Poulton, P.L., Hochman, Z., Thorburn, P.J., Gaydon, D.S., Dalgliesh, N.P., Rodriguez, D., Cox, H., Chapman, S., Doherty, A., Teixeira, E., Sharp, J., Cichota, R., Vogeler, I., Li, F.Y., Wang, E., Hammer, G., Robertson, M., Dimes, J.P.,. Whitbread, A.M., Hunt, J., Van Rees, H., Mcclelland, T., Carberry, P.S., Hargreaves, J.N.G., Macleod, N., Mcdonald, C., Harsdorf, J., Wedgwood, S. and Keating, B.A., 2014. APSIM-evolution towards a new generation of agricultural systems simulation. Environmental Modelling and Software 62: 327-350. https://doi.org/10.1016/j.envsoft.2014.07.009

Jargot, D. and Melin, S., 2013. Characterization and validation of sampling and analytical methods for mycotoxins in workplace air. Environmental Science – Processes and Impacts 15: 633-644. https://doi.org/10.1039/c2em30566f

Jensen, A.L., Boll, P.S., Thysen, I. and Pathak, B.K., 2000. Pl@nteInfo® – a web-based system for personalised decision support in crop management. Computers and Electronics in Agriculture 25: 271-293. https://doi.org/10.1016/S0168-1699(99)00074-5

Jiang, M.P., Zheng, S.Y., Wang, H., Zhang, S.Y., Yao, D.S., Xie, C.F. and Liu, D.L., 2019. Predictive model of aflatoxin contamination risk associated with granary-stored corn with versicolorin A monitoring and logistic regression. Food Additives and Contaminants. Part A 36: 308-319. https://doi.org/10.1080/19440049.2018.1562226

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J. and Ritchie, J.T., 2003. The DSSAT cropping system model. European Journal of Agronomy 18: 235-265. https://doi.org/10.1016/S1161-0301(02)00107-7

Kaaya, A.N., Kyamuhangire, W. and Kyamanywa, S., 2006. Factors affecting aflatoxin contamination of harvested maize in the three agroecological zones of Uganda. Journal of Applied Sciences 6: 2401-2407.

Kaminiaris, M.D., Camardo Leggieri, M., Tsitsigiannis, D.I. and Battilani, P., 2020. AFLA-PISTACHIO: development of a mechanistic model to predict the aflatoxin contamination of pistachio nuts. Toxins 12: 445. https://doi.org/10.3390/toxins12070445

Keating, B.A., Carberry, P.S., Hammer, G.L., Probert, M.E., Robertson, M.J., Holzworth, D., Huth, N.I., Hargreaves, J.N.G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J.P., Silburn, M., Wang, E., Brown, S., Bristow, K.L., Asseng, S., Smith, C.J., 2003. An overview of APSIM, a model designed for farming systems simulation. European Journal of Agronomy 18: 267-288. https://doi.org/10.1016/S1161-0301(02)00108-9

Klich, M.A., 2007. *Aspergillus flavus*: the major producer of aflatoxin. Molecular Plant Pathology 8: 713-722.

Kohl, R., Foy, C. and Zodrow, G., 2017. Synthesis report: review of successful scaling of agricultural technologies. USAID, Washington, DC, USA.

Krska, R., De Nijs, M., McNerney, O., Pichler, M., Gilbert, J., Edwards, S., Suman, M., Magan, N., Rossi, V., Van der Fels-Klerx, H.J., Bagi, F., Poschmaier, B., Sulyok, M., Berthiller, F. and Van Egmond, H.P., 2016. Safe food and feed through an integrated toolbox for mycotoxin management: the MyToolBox approach. World Mycotoxin Journal 9(4): 487-495. https://doi.org/10.3920/WMJ2016.2136

Kuiper Goodman, T., 2004. Risk assessment and risk management of mycotoxins in food. In: Magan, N. and Olsen, M. (eds.) Mycotoxins in food: detection and control. Woodhead Publishing, Cambridge, UK, pp. 3-31.

Leggieri, M.C., Mazzoni, M., Battilani, P., 2021. Machine learning for predicting mycotoxin occurrence in maize. Frontiers in Microbiology 12: 661132.

Li, H., Chowdhury, A., Terejanu, G., Chanda, A. and Banerjee, S., 2015. A stacked gaussian process for predicting geographical incidence of aflatoxin with quantified uncertainties. In: SIGSPATIAL '15: Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems. November 2015. Association for Computing Machinery, New York, NY, USA.

Li, H., Xiong, Z., Gui, D., Pan, Y., Xu, M., Guo, Y., Leng, J. and Li, X., 2019. Effect of ozonation and UV irradiation on aflatoxin degradation of peanuts. Journal of Food Processing and Preservation 43: e13914. https://doi.org/10.1111/jfpp.13914

Liu, Y. and Wu, F., 2010. Global burden of aflatoxin-induced hepatocellular carcinoma: a risk assessment. Environmental Health Perspectives 118: 818-824.

Mahuku, G., Nzioki, H.S., Waliyar, F., Diarra, B. and Kodio, O., 2010. Aflatoxin prevalence data collection sampling framework and methodology. IFPRI, Washington, DC, USA.

Manfre, C. and Laytham, W., 2018. Digitizing the science of discovery and the science of delivery: a case study of ICRISAT. USAID, Washington, DC, USA.

Masuoka, P., Chamberlin, J. and Elias, M., 2010. Modeling the distribution and probability of aflatoxin occurrence using environmental data. Aflacontrol Project, working paper 2. IFPRI, Washington, DC, USA. Available at: https://tinyurl.com/2t6c68k8.

Medina, Á., Rodríguez, A., Sultan, Y. and Magan, N., 2015. Climate change factors and *Aspergillus flavus*: effects on gene expression, growth and aflatoxin production. World Mycotoxin Journal 8: 171-179. https://doi.org/10.3920/wmj2014.1726

Memedovic, O. and Shepherd, A., 2008. Agri-food value chains and poverty reduction: overview of main issues, trends and experiences. UNIDO Research and Statistics Branch Working Paper. United Nations, New York, NY, USA.

Miller, J.R., Turner, M.G., Smithwick, E.A.H., Dent, C.L. and Stanley, E.H., 2004. Spatial extrapolation: the science of predicting ecological patterns and processes. Bioscience 54: 310-320. https://doi.org/10.1641/0006-3568(2004)054[0310:SETSOP]2.0.CO;2

Miyagishima, K. and Verger, P., 2016. Monitoring exposure to food chemicals. WHO Publications, Geneva, Switzerland.

Msuya, C.P., Annor-Frempong, F.K., Magheni, M.N. and Agunga, R., 2017. The role of agricultural extension in Africa's development, the importance of extension workers and the need for change. International Journal of Agricultural Extension 5: 59-70.

Munkvold, G.P., 2003. Epidemiology of *Fusarium* diseases and their mycotoxins in maize ears. European Journal of Plant Pathology 109: 705-713. https://doi.org/10.1023/A:1026078324268

Mutiga, S.K., Were, V., Hoffmann, V., Harvey, J.W., Milgroom, M.G. and Nelson, R.J., 2014. Extent and drivers of mycotoxin contamination: inferences from a survey of kenyan maize mills. Phytopathology 104: 1221-1231. https://doi.org/10.1094/PHYTO-01-14-0006-R

Njoroge, S.M.C., 2018. A critical review of aflatoxin contamination of peanuts in Malawi and Zambia: the past, present, and future. Plant Disease 102: 2394-2406. https://doi.org/10.1094/PDIS-02-18-0266-FE

Nnaji, A.O., 2001. Forecasting seasonal rainfall for agricultural decision-making in northern Nigeria. Agricultural and Forest Meteorology 107: 193-205. https://doi.org/10.1016/S0168-1923(00)00239-2

Okoth, S., 2016. Improving the evidence base on aflatoxin contamination and exposure in Africa: strengthening the agriculture-nutrition nexus. CTA, Wageningen, the Netherlands.

Ongoma, V., 2013. A review of the effects of climate change on occurrence of aflatoxin and its impacts on food security in semi-arid areas of Kenya. International Journal of Agricultural Science Research 2: 307-311.

Onyango, A.W., 2003. Dietary diversity, child nutrition and health in contemporary African communities. Comparative Biochemistry and Physiology Part A 136: 61-69. https://doi.org/10.1016/s1095-6433(03)00071-0

Osiru, M., Aubee, E., Awuah, R., Ayalew, A., Chunga, W., Kimanya, M., Bandyopadhyay, R., Masha, K., Omari, R., Miles, J.P. and Wafukho, S.S., 2014. Aflatoxin control action plan for ECOWAS member states 2014-2024. ECOWAS, Federal Capital Territory, Nigeria.

Peles, F., Sipos, P., Győri, Z., Pfliegler, W.P., Giacometti, F., Serraino, A., Pagliuca, G., Gazzotti, T. and Pócsi, I., 2019. Adverse effects, transformation and channeling of aflatoxins into food raw materials in livestock. Frontiers in Microbiology 10: 2861. https://doi.org/10.3389/fmicb.2019.02861

Phillips, J.G., Cane, M.A. and Rosenzweig, C., 1998. ENSO, seasonal rainfall patterns and simulated maize yield variability in Zimbabwe. Agricultural and Forest Meteorology 90: 39-50. https://doi.org/10.1016/S0168-1923(97)00095-6

Pickova, D., Ostry, V. and Malir, F.A., 2021. Recent overview of producers and important dietary sources of aflatoxins. Toxins 13: 186. https://doi.org/10.3390/toxins13030186

Probst, C., Bandyopadhyay, R. and Cotty, P.J., 2014. Diversity of aflatoxin-producing fungi and their impact on food safety in sub-Saharan Africa. International Journal of Food Microbiology 174: 113-122. https://doi.org/10.1016/j.ijfoodmicro.2013.12.010

Rachaputi, N., Krosch, S. and Wright, G.C., 2002. Management practices to minimise pre-harvest aflatoxin contamination in Australian peanuts. Australian Journal of Experimental Agriculture 42: 595-605. https://doi.org/10.1071/ea01139

Rao, K.P.C., Dakshina Murthy, K., Dhulipala, R., Bhagyashree, S.D., Das Gupta, M., Sreepada, S. and Whitbread, A.M., 2019. Delivering climate risk information to farmers at scale: the intelligent agricultural systems advisory tool (ISAT). CCAFS Working Paper no. 243. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Wageningen, the Netherlands.

Rembold, F., Meroni, M., Urbano, F., Csak, G., Kerdiles, H., Perez-Hoyos, A., Lemoine, G., Leo, O. and Negre, T., 2019. ASAP: a new global early warning system to detect anomaly hot spots of agricultural production for food security analysis. Agricultural Systems 168: 247-257. https://doi.org/10.1016/j.agsy.2018.07.002

Rockefeller Foundation, 2013. Waste and Spoilage in the food chain. Rockefeller Foundation, New York, NY, USA.

Rodrigues, I., Handl, J. and Binder, E.M., 2011. Mycotoxin occurrence in commodities, feeds and feed ingredients sourced in the Middle East and Africa. Food Additives and Contaminants, Part B 4: 168-179. https://doi.org/10.1080/19393210.2011.589034

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G. and Winter, J.M., 2013. The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies. Agricultural and Forest Meteorology 170: 166-182. https://doi.org/10.1016/j.agrformet.2012.09.011

Schreurs, F., Bandyopadhyay, R., Kooyman, C., Ortega-Beltran, A., Akande, A., Konlambigue, M. and Bosch, N., 2019. Commercial products promoting plant health in African agriculture. Burleigh Dodds Science Publishing Limited, Sawston, UK.

Siebert, S., Burke, J., Faures, J.-M., Frenken, K., Hoogeveen, J., Döll, P. and Portmann, F.T., 2010. Groundwater use for irrigation – a global inventory. Hydrology and Earth System Sciences 14): 1863-1880. https://doi.org/10.5194/hessd-7-3977-2010

Sirma, A.J., Lindahl, J.F., Makita, K., Senerwa, D., Mtimet, N., Kang'ethe, E.K. and Grace, D., 2018. The impacts of aflatoxin standards on health and nutrition in sub-Saharan Africa: the case of Kenya. Global Food Security 18: 57-61. https://doi.org/10.1016/j.gfs.2018.08.001

Smith, L., Stasiewicz, M., Hestrin, R., Morales, L., Mutiga, S. and Nelson, R., 2016. Examining environmental drivers of spatial variability in aflatoxin accumulation in Kenyan maize: potential utility in risk prediction models. African Journal of Food, Agriculture, Nutrition and Development 16: 11086-11105.

Steduto, P., Hsiao, T.C., Raes, D. and Fereres, E., 2009. AquaCrop – the FAO crop model to simulate yield response to water: I. Concepts and underlying principles. Agronomy Journal 101: 426-437. https://doi.org/10.2134/agronj2008.0139s

Stepman, F., 2018. Scaling-up the impact of aflatoxin research in Africa. The role of social sciences. Toxins 10: 136. https://doi.org/10.3390%2Ftoxins10040136

Tai, B., Chang, J., Liu, Y. and Xing, F., 2020. Recent progress of the effect of environmental factors on *Aspergillus flavus* growth and aflatoxins production on foods. Food Quality and Safety 4: 21-28.

Unnevehr, L.J. and Grace, D., 2013. Aflatoxins: finding solutions for improved food safety. IFPRI, Washington, DC, USA.

Van der Fels-Klerx, H.J., Burgers, S.L.G.E. and Booij, C.J.H., 2010. Descriptive modelling to predict deoxynivalenol in winter wheat in the Netherlands. Food Additives and Contaminants: Part A 27: 636-643. https://doi.org/10.1080/19440040903571762

Van der Fels-Klerx, H.J., Liu, C. and Battilani, P., 2016. Modelling climate change impacts on mycotoxin contamination. World Mycotoxin Journal 9: 717-726.

Van der Fels-Klerx, H.J., Vermeulen, L.C., Gavai, A.K. and Liu, C., 2019. 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: e0218956. https://doi.org/10.1371/journal.pone.0218956

Wagacha, J.M. and Muthomi, J.W., 2008. Mycotoxin problem in Africa: current status, implications to food safety and health and possible management strategies. International Journal of Food Microbiology 124: 1-12.

Warnatzsch, E.A., Reay, D.S., Leggieri, M.C. and Battilani, P., 2020. Climate change impact on aflatoxin contamination risk in Malawi's maize crops. Frontiers in Sustainable Food Systems 4: 591792. https://doi.org/10.3389/fsufs.2020.591792

Wenndt, A., Sudini, H.K., Pingali, P. and Nelson, R., 2020. Exploring aflatoxin contamination and household-level exposure risk in diverse Indian food systems. PLoS ONE 15: e0240565. https://doi.org/10.1371/journal.pone.0240565

Widstrom, N.W., Guo, B.Z. and Wilson, D.M., 2003. Integration of crop management and genetics for control of preharvest aflatoxin contamination of corn. Journal of Toxicology: Toxin Reviews 22: 195-223. https://doi.org/10.1081/TXR-120024092

Williams, J.H., Phillips, T.D., Jolly, P.E., Stiles, J.K., Jolly, C.M. and Aggarwal, D., 2004. Human aflatoxicosis in developing countries: a review of toxicology, exposure, potential health consequences, and interventions. American Journal of Clinical Nutrition 80: 1106-1122. https://doi.org/10.1093/ajcn/80.5.1106

Wu, F., 2015. Global impacts of aflatoxin in maize: trade and human health. World Mycotoxin Journal 8: 137-142. https://doi.org/10.3920/WMJ2014.1737

Wu, L.X., Ding, X.X., Li, P.W., Du, X.H., Zhou, H.Y., Bai, Y.Z. and Zhang, L.X., 2016. Aflatoxin contamination of peanuts at harvest in China from 2010 to 2013 and its relationship with climatic conditions. Food Control 60: 117-123. https://doi.org/10.1016/j.foodcont.2015.06.029

Yoo, E., Kerry, R., Ingram, B., Ortiz, B. and Scully, B., 2018. Defining and characterizing aflatoxin contamination risk areas for corn in Georgia, USA: adjusting for collinearity and spatial correlation. Spatial Statistics 28: 84-104.