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Article

Modeling Aflatoxin Risk Dynamics in Uganda's Groundnut Value Chain: A System Dynamics Decision Support Approach

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Abstract: Aflatoxin contamination remains a persistent threat to food safety, public health, and trade in Uganda's groundnut value chain, where a large share of household and market samples exceed national and international safety limits. Despite sustained investment in awareness campaigns, improved storage, and biocontrol products, contamination remains high and unevenly controlled, in part because interventions are typically evaluated in isolation and are rarely supported by dynamic tools that capture the feedback, delays, and trade-offs linking climate, farmer behaviour, institutional support, and markets. This study develops and analyses a System Dynamics (SD) decision-support model of aflatoxin risk in the groundnut value chain, framed within an Information Systems view of simulation-based decision support. Causal loop diagrams constructed in Vensim PLE and a stock-and-flow model implemented in STELLA Architect represent the reinforcing and balancing feedback structures governing contamination, including the "Shifting the Burden" archetype. Scenario simulations and a one-at-a-time sensitivity analysis show that symptomatic measures such as awareness campaigns deliver only temporary relief, whereas post-harvest practice quality emerges as the highest-leverage parameter; a realistic mixed-policy scenario that combines moderate investment across practices, awareness, and storage technology drives contamination below regulatory thresholds within the simulated horizon. These findings indicate that durable mitigation in low-resource settings depends on sustained structural investment rather than reactive fixes, and they demonstrate how SD modelling can guide adaptive, evidence-based food-safety policy.

Keywords: System Dynamics modelling; Aflatoxin contamination; Groundnut value chain; Information Systems; Food-safety decision support.

1. Introduction

Groundnut (Arachis hypogaea), also called peanut, is an annual herbaceous legume cultivated across tropical and temperate regions and is valued for its carbohydrates, proteins, lipids, vitamins, minerals, and fiber [1]. Originating in South America, the crop spread to Africa and Asia and is now grown worldwide [2]. In Uganda it is the second most cultivated legume, yielding an average of 0.7 metric tonnes per hectare, behind beans at 1.5 metric tonnes per hectare [3], and it contributes to food security and to the Sustainable Development Goal of zero hunger [4]. With a protein content of 23–25% and an oil yield of 45–52% [5], groundnut is a staple for human consumption and animal feed and an affordable source of dietary protein and income for smallholder farmers [3], [6].

Production and consumption are, however, threatened by aflatoxin, a toxic secondary metabolite produced mainly by Aspergillus flavus and Aspergillus parasiticus [7]. The problem is especially severe in Africa, where climatic conditions favour the growth of aflatoxin-producing fungi [8], affecting both humans and livestock [9]. Of the major aflatoxins in circulation today including AFB1, AFB2, AFG1, AFG2, AFM1, and AFM2, AFB1 is the most carcinogenic as it is associated with liver cancer, malnutrition, and immune suppression [6]. The scale of contamination in the region is substantial: in Uganda roughly 45% of groundnut samples from household stores exceeded the national threshold of 10 ng/g and 53% exceeded the stricter European limit of 4 ng/g, with a maximum recorded level of 1327 ng/g in Iganga district [10]; in Malawi, 93% of commercial groundnut samples exceeded the national 3 μg/kg limit and 72% exceeded the U.S. FDA limit of 20 μg/kg [11].

Several interventions have been deployed against contamination, including awareness campaigns promoting drying to below 10% moisture, sorting of damaged kernels, and hermetic storage to limit fungal growth [12]; biocontrol strategies, such as a rapid PO8-protein screening method that identified strains reducing peanut contamination by 50–80% in field trials [13]; and the work of Uganda's National Agricultural Research Organization (NARO) in public sensitization, research, and dissemination of improved pre- and post-harvest practices [10], [14]. Despite these efforts, progress has been slow and fragmented: limited rural penetration, inadequate funding, weak regulatory enforcement, and insufficient monitoring have undermined impact [15], and most initiatives target short-term symptoms without representing the systemic links among climate, farmer behaviour, institutional support, and market incentives.

The central dilemma is therefore not the absence of technical solutions but the absence of decision-support tools that can anticipate how these solutions interact over time. Aflatoxin contamination is a dynamic problem shaped by feedback loops, delays, and nonlinear responses, yet decisions are still guided largely by static surveys and isolated trials. While systems-thinking and simulation studies exist in adjacent agricultural and environmental domains [16], [17], few feedback-based, simulation-ready decision-support models have been developed specifically for the groundnut aflatoxin system in low-resource settings, a more precise statement of the gap than a blanket claim that dynamic models are lacking. Without such tools, stakeholders cannot readily evaluate the long-term consequences or trade-offs of competing interventions, and responses remain reactive.

To address this gap, the present study develops a System Dynamics (SD) decision-support model of aflatoxin risk in Uganda's groundnut value chain. The contribution is threefold. First, the study provides a feedback-based, simulation-ready SD model tailored to this system, integrating climatic, behavioral, institutional, and technological drivers within a single causal structure. Second, it situates the model within an Information Systems (IS) framing of decision-support systems for data-driven agricultural policy, making explicit how simulation, feedback analysis, and scenario testing function as IS artefacts for evidence-based decision-making. Third, it couples qualitative archetype analysis with quantitative scenario simulation and sensitivity analysis to identify the parameters that offer the greatest policy leverage. Concretely, the study (i) identifies and models the key variables and feedback loops influencing contamination, (ii) simulates and evaluates the effects of alternative intervention strategies over time, and (iii) delivers a scenario-based policy-support tool for sustainable, adaptive mitigation.

The remainder of the paper is organized as follows. Section 2 reviews related work on aflatoxin mitigation strategies and contamination trends and clarifies the distinction between systems thinking and system dynamics. Section 3 describes the methodology, including the modelling tools, the conceptual archetype, and the model equations. Section 4 presents the results and discussion, covering the causal-loop and stock-and-flow structures, the scenario simulations, a mixed-policy scenario, and a sensitivity analysis, followed by model validation and limitations. Section 5 concludes with policy insights specific to Uganda's groundnut system and directions for future work.

2. Review of Related Literature

2.1. Aflatoxin Mitigation Strategies

Aflatoxin mitigation combines physical, chemical, and biological methods. Physical approaches—sorting, dehulling, washing, heat treatment, irradiation, pulsed electric fields, and cold plasma—can reduce aflatoxin by over 90% with limited loss of food quality [18]. Chemical methods neutralize aflatoxins, particularly AFB1, using agents such as citric and lactic acids or ozone, while biological methods deploy non-toxigenic *A. flavus*, beneficial bacteria, and resistant crops to suppress toxin production [19]. These methods are effective individually but show inconsistent efficacy across diverse food matrices, a limitation that systems-level modelling can help address by simulating and optimizing their combined application.

Good Agricultural Practices (GAPs) offer a practical route to managing contamination across production and post-harvest stages through timely planting and harvesting, resistant varieties, field hygiene, proper drying, sorting, clean storage, and moisture control [20]; however, that work does not adopt a dynamic modelling lens capable of representing the time-dependent interactions that govern contamination trends. In Ghana, smallholders combine pre- and post-harvest measures—crop rotation, timely harvesting, kernel sorting, well-aerated storage, composting, weeding, rapid drying, and fumigation—though awareness of seed treatment and supplementary irrigation remains low; adoption is shaped by education, credit access, membership in farmer-based organizations, and proximity to extension services, while pest pressure,

Table 1. Summary of related literature.

Author / Year	Study design / methods	Determinants
Sipos *et al*., 2021 [18]	Review of physical mitigation techniques	Sorting, dehulling, heat, irradiation, cold plasma; >90% efficacy
Alameri *et al*., 2023 [19]	Review of chemical and biological methods	Citric/lactic acid, ozone, non-toxigenic A. flavus, resistant crops
Vranešević & Bagi, 2025 [20]	GAPs assessment	Timely planting/harvesting, resistant varieties, storage/moisture control
Asante *et al*., 2024 [21]	GAPs field study	GAPs, awareness, education, FBOs, extension access
Li *et al*., 2022 [22]	Reactive molecular dynamics	Cold atmospheric plasma; ROS interaction with AFB1
Baidhe *et al*., 2024 [23]	Narrative review; systems-thinking appraisal	Drying–storage integration, sustainable technologies, gender, policy

limited knowledge, and rainfall variability constrain effectiveness [21]. At the molecular scale, reactive molecular dynamics simulations show how cold atmospheric plasma degrades AFB1 through reactions at the C8–C9 bond and cleavage of the difuran and lactone rings, although the speed and multiplicity of the reactive-oxygen-species reactions make individual pathways hard to isolate [22]. System dynamics complements such micro-scale studies by simulating the broader, time-dependent operational interactions that determine whether a technique succeeds at scale.

A systems-oriented appraisal of post-harvest drying and storage in Africa recommends solar and mechanical dryers and hermetic options such as PICS bags and metal silos, and treats drying and storage as interconnected subsystems whose failures—improper moisture content and grain breakage—propagate into storage risk; it advocates integrating sustainable technologies, gender-inclusive practices, financing, and enabling policy so that interventions reinforce rather than isolate one another [23]. The principal challenge such an approach surfaces is coordinating diverse actors, infrastructure, and environmental factors under resource constraints. System Dynamics is well suited to this challenge: by capturing the temporal and systemic nature of contamination, it allows researchers and policymakers to evaluate long-term impacts, locate intervention points, and support data-driven decisions for sustainable risk reduction. Table 1 summarizes the reviewed studies and their determinants.

2.2. Aflatoxin Contamination Trends

Contamination in the groundnut value chain is driven by interrelated variables whose temporal behaviour must be understood to design effective interventions. In Uganda, contamination emerges from the interplay of moisture and temperature, handling practices, storage duration, value-chain stage, awareness and testing, and varietal resistance [24]. Moisture and temperature, particularly during the rainy season and in poorly ventilated storage, trigger sharp seasonal spikes [25], while inefficient drying and handling create U-shaped risk profiles in which contamination dips after harvest and rises again during storage [26]. A study of 105 cereal samples from Kitgum and Lamwo in northern Uganda found total aflatoxin as high as 68 μg/kg, with sorghum averaging 11.8 μg/kg; 46.5% of sorghum samples exceeded the national 10 μg/kg limit and 86.1% exceeded the stricter EU limit of 4 μg/kg [27]. In Kenya, over 70% of milk samples tested positive for AFM1 and more than half exceeded safety limits, with cereal contamination varying markedly by region and season [28]. Encouragingly, the adoption of good agricultural and safe-storage practices, resistant varieties, and biological controls produces downward shifts in contamination, underscoring the value of targeted intervention [18]. Uganda's strategic objective is to hold contamination below national (10 μg/kg) and international (4 μg/kg) limits, which depends on good practices, improved post-harvest handling and storage, broad stakeholder awareness, and the availability of affordable, rapid detection tools [24].

3. Methodology

3.1. Research Design and the Systems Thinking–System Dynamics Distinction

This study employs System Dynamics, the simulation methodology developed by Jay Forrester at MIT to understand the structure and behaviour of complex systems and to identify high-leverage policies for long-term improvement [29]. Because the terms are sometimes used interchangeably, it is worth distinguishing them explicitly: systems thinking is the qualitative conceptual lens that frames a problem holistically in terms of interconnections, feedback, and delays, whereas system dynamics is the quantitative methodology that operationalizes that lens through stocks, flows, and simulation [30], [31]. In this work, systems thinking informs the conceptual structure—how environmental, behavioral, institutional, and technological factors connect—while system dynamics renders that structure computable, enabling scenario testing and sensitivity analysis. SD is selected for its capacity to represent nonlinear interactions, feedback loops, and time delays [32], and the methodology integrates causal mapping, stock-and-flow simulation, literature-based parameterization, and scenario analysis [16].

3.2. Modelling Tools

Vensim PLE was used to construct the Causal Loop Diagrams (CLDs) that capture the qualitative feedback structure, visualizing relationships among variables such as contamination level, farmer awareness, and technology adoption in a form accessible to farmers, consumers, and policymakers. STELLA Architect 8.1.1 was used to build the quantitative stock-and-flow model and its scenario interfaces, enabling simulation of how contamination responds to changes in mitigation levers and contamination drivers over a multi-month horizon relevant to long-term policy.

3.3 Conceptual Model: the "Shifting the Burden" Archetype

The model structure is informed by the "Shifting the Burden" archetype, a systems-thinking pattern in which reliance on symptomatic solutions masks deeper problems and undermines structural improvement [33]. In the aflatoxin context, short-term fixes such as awareness campaigns, reactive testing, and isolated biocontrol applications [18], [19] offer immediate relief but can delay essential structural investment in drying infrastructure, behaviour change, and institutional capacity. As detailed in Section 4.1, this dynamic is represented through balancing and reinforcing loops [17], allowing the identification of leverage points and helping avoid perpetual dependence on quick fixes.

3.4. Model Equations

Each flow in the stock-and-flow model is governed by an equation reflecting the hypothesized causal relationships. The four core flow equations are given below; variables are expressed on normalized scales, and coefficients were chosen to reproduce the observed qualitative behaviour pending field calibration. The contamination inflow rises with humidity and falls as post-harvest practices improve (Equation 1); decontamination scales with technology adoption (Equation 2); training-driven adoption is reinforced by policy support and farmer awareness (Equation 3); and adoption is eroded by cost barriers (Equation 4).

$$\begin{aligned} &\mathit{Contamination\ Rate} \\ &\quad = \mathit{Humidity} \times (1 - \mathit{Postharvest\ Practices}) \times 0.05 \end{aligned} \tag{1}$$

$$\begin{aligned} &\mathit{Decontamination\ Rate} \\ &\quad = 0.01 \times \mathit{Technology\ Adoption\ Rate} \end{aligned} \tag{2}$$

$$\begin{aligned} &\mathit{Training\ Subsidy\ Rate} \\ &\quad = \mathit{Policy\ Support} \times \mathit{Farmer\ Awareness} \times 0.05 \end{aligned} \tag{3}$$

$$\begin{aligned} &\mathit{Abandonment\ Rate} \\ &\quad = \mathit{Technology\ Adoption\ Rate} \times \mathit{Cost\ Barrier} \times 0.02 \end{aligned} \tag{4}$$

These relationships ensure that as awareness grows and policy support strengthens, technology adoption rises, contamination falls, and safe storage improves; conversely, high humidity and weak practices accelerate contamination. Equations 1–4 are intentionally parsimonious; their linear form is a simplification of processes that are, in reality, nonlinear and partly stochastic, a limitation discussed in Section 4.6.

4. Results and Discussion

4.1. System Archetype: Shifting the Burden in Aflatoxin Mitigation

Figure 1 presents the "Shifting the Burden" archetype as a CLD, showing the trade-off between symptomatic and structural responses. At its core, a balancing loop (B1) links rising contamination to the use of symptomatic solutions, which produce a short-term reduction that temporarily lowers contamination and reinforces a sense that the problem is controlled. In parallel, a reinforcing loop (R1) operates as symptomatic use lowers the perceived need for structural action, delaying investment in sustainable mitigation and ultimately sustaining or worsening contamination. A second reinforcing structure (R2) captures the erosion of fundamental solutions, as reliance on symptomatic measures diverts attention and resources from sustainable mitigation and weakens long-term capacity. Finally, a second balancing loop (B2) represents the desired structural pathway, in which rising contamination raises the perceived need for action, promotes sustainable mitigation, and durably reduces contamination.

The central insight is that repeated reliance on short-term fixes introduces a systemic delay in addressing root causes, perpetuating risk. Apparent success after symptomatic gains can mask a worsening underlying problem, leaving the system dependent on quick fixes while contamination accumulates in the background. Breaking the cycle requires a deliberate policy shift toward structural and sustainable interventions, improved storage, farmer education, resistant varieties, and regulatory enforcement, supported by feedback-informed decision tools such as SD modelling.

4.2. Causal Loop Diagram: Contamination Dynamics

Figure 2 shows the CLD of contamination dynamics, integrating environmental, behavioural, and institutional variables through two principal feedback structures. The reinforcing loop, the "contamination spiral," operates when contamination is not mitigated: higher humidity promotes fungal growth and raises aflatoxin levels, which increase market rejection and health risk, reduce farmer income, and thereby limit investment in storage, leading

Table 2. Stock definitions.

Stock	Meaning
Contaminated groundnuts	Volume or proportion of affected harvest
Properly stored groundnuts	Groundnuts kept in safe, aflatoxin-reducing conditions
Farmer awareness level	Proportion of farmers trained or sensitized
Technology adoption rate	Share of farmers using biocontrol or storage technologies

Table 3. Initial stock values and their literature basis. These values are literature-derived priors rather than field-calibrated estimates; see Section 4.6.

Stock	Initial value	Justification	Source
Contaminated groundnuts	40–50%	>50% contamination observed in Uganda	Akullo *et al*., 2025; Okello *et al*., 2010
Properly stored groundnuts	10%	Poor post-harvest practices widespread	Akullo *et al*., 2025; Okello *et al*., 2010
Farmer awareness level	0.20	Most farmers unaware of aflatoxins	Akullo *et al*., 2025; Okello *et al*., 2010
Technology adoption rate	0.10	Adoption <10% despite availability	Akullo *et al*., 2025; Okello *et al*., 2010

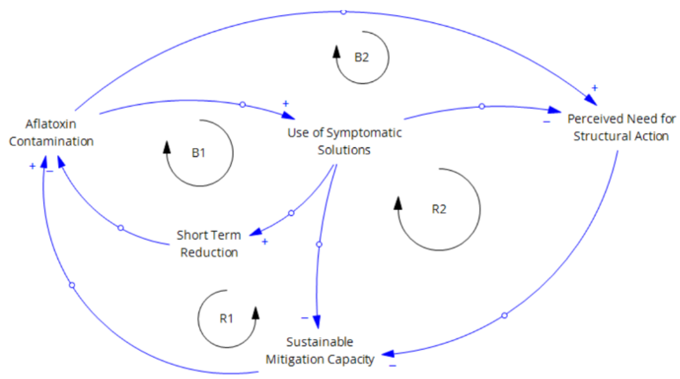

Figure 1. Causal loop diagram representing the "Shifting the Burden" archetype in aflatoxin mitigation.

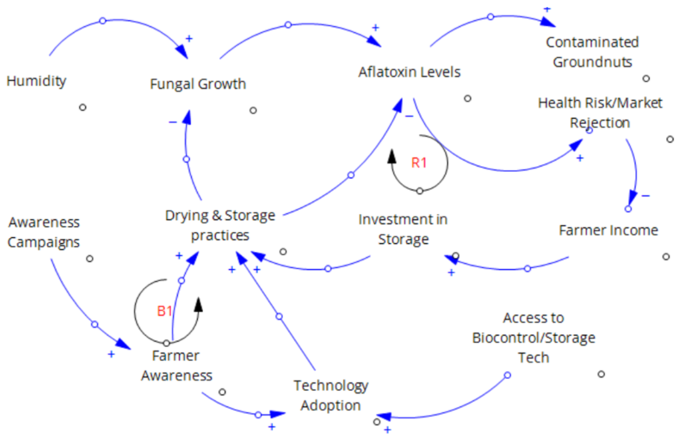

Figure 2. Causal loop diagram for aflatoxin contamination dynamics in Uganda's groundnut value chain.

to poorer drying and storage and further fungal growth. The balancing loop, the "awareness–control loop," counteracts this spiral: awareness campaigns raise farmer awareness, encouraging better drying and storage, which reduces fungal growth and lowers aflatoxin levels. Additional enablers—access to biocontrol and storage technologies—strengthen technology adoption and reinforce the balancing loop. By making these loops explicit, the diagram identifies awareness programmes and post-harvest technology access as the system's primary leverage points for shifting it from a harmful reinforcing trajectory toward a stabilizing one.

4.3. Stock-and-Flow Model

The CLD in Figure 2 was translated into a quantitative stock-and-flow model in STELLA Architect (Figure 3), comprising stocks, flows, converters, and connectors. The four core stocks represent accumulations in the system, as defined in Table 2, and were initialised from recent literature and official guidance, as summarised in Table 3. Contamination was set at 40–50 units (out of 100) following reports of widespread contamination exceeding regulatory thresholds [24], [34]; properly stored groundnuts were set to 10%, reflecting poor post-harvest practice; and farmer awareness and technology adoption were initialised at 20% and 10%, respectively, in line with evidence of limited knowledge and access. The contamination inflow is driven by humidity and poor practices and is offset by a decontamination outflow enhanced by technology adoption; awareness grows through campaigns and decays through forgetting; and adoption is driven by training and eroded by abandonment arising from cost and complexity. The associated converters—humidity, post-harvest practices, policy support, and cost barrier—modulate these flows, as illustrated in Figure 3.

4.4. Baseline Dynamic Behaviour

Running the model from the initialised values produces the time-series behaviour shown in Figure 4. Contaminated groundnuts decline gradually when training is consistent and cost barriers are moderate, while properly stored groundnuts rise steadily as awareness and adoption improve. Farmer awareness grows rapidly in the early months under initial campaigns but tends to plateau unless campaigns are sustained, reflecting the forgetting dynamic. Technology adoption improves more slowly and approaches saturation after roughly 36 months unless policy support is intensified. Together these trajectories

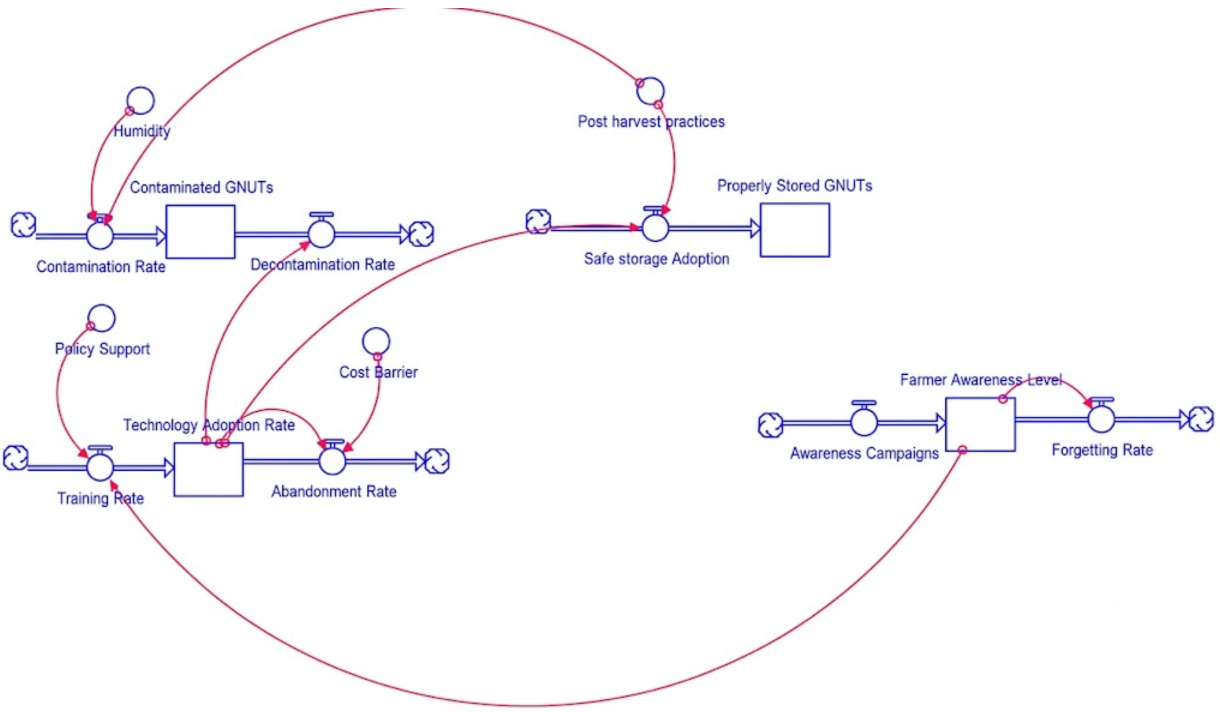

Figure 3. Stock-and-flow model for groundnut aflatoxin contamination in Uganda.

capture the reinforcing dynamic by which rising awareness and adoption translate into more safe storage and less contamination, and they locate the system's leverage at the awareness and subsidy flows.

4.5. Scenario Analysis

Three scenarios were examined. To interpret them correctly, it is important to distinguish the two classes of variable in the model: humidity and poor post-harvest practices act as contamination drivers, whereas awareness campaigns, improved practices, technology adoption, and policy support act as mitigation levers. An earlier framing that grouped awareness campaigns among "growth factors" conflated these classes; the analysis below treats awareness consistently as a mitigation lever, which resolves that inconsistency.

In the first scenario (Figure 5), the contamination driver is held high (humidity at 2.5) while the mitigation levers are held at or near their minimum (post-harvest practices at 0 and awareness campaigns at 0.05). Under these conditions, contaminated groundnuts increase steadily over time, while properly stored groundnuts, farmer awareness, and technology adoption remain low and grow slowly. This reproduces the reinforcing contamination loop and illustrates the consequences of neglecting mitigation, contamination rises rather than falls, consistent with the rising blue trajectory in the figure.

In the second scenario (Figure 6), the contamination driver is suppressed (humidity at 0) and the mitigation levers are raised. Contaminated groundnuts fall sharply over time while farmer awareness and technology adoption rise, demonstrating how strong, integrated mitigation suppresses contamination and promotes safer handling. The contrast between the two scenarios reflects the system's sensitivity to policy choice and to time-delayed effects: unchecked drivers create reinforcing escalation, whereas mitigation levers establish balancing feedback that stabilizes and gradually reduces contamination.

Because real policy rarely operates at either extreme, a third, mixed scenario was simulated with moderate, simultaneous settings across the levers (humidity 0.6, post-harvest practices 0.5, awareness campaigns 0.5, policy support 0.6, cost barrier 0.5). As shown in Figure 7, contamination first holds roughly steady as the reinforcing and balancing influences offset one another, then declines as awareness, adoption, and safe storage accumulate, falling from about 45% to roughly 16% of the harvest by the end of the horizon. Figure 8 compares the contamination trajectory across all three regimes: the growth-dominant case escalates toward saturation, the reduction-dominant case crosses below the national reference limit, and the mixed case follows an intermediate, realistic path. This mixed scenario is the more policy-relevant case, since it shows that even moderate, coordinated investment—rather than maximal effort on any single lever—can move the system toward compliance over time.

4.6. Sensitivity Analysis, Validation, and Limitations

To identify high-impact parameters and probe robustness, a one-at-a-time sensitivity analysis was performed by perturbing each parameter by ±20% about the mixed-scenario baseline and recording the change in steady-state contamination. The resulting ranking (Figure 9) is clear and policy-relevant: post-harvest practice

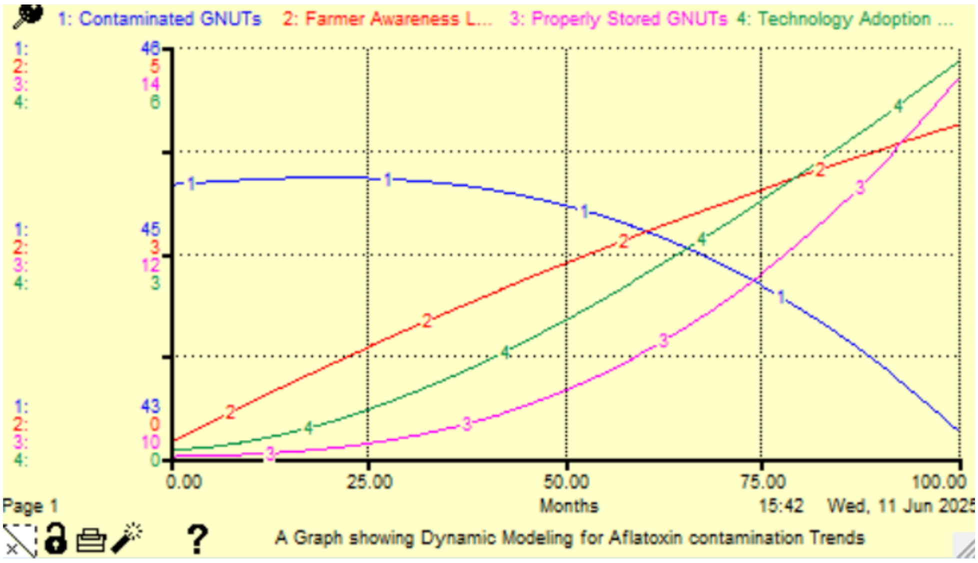

Figure 4. Baseline simulation of the four core stocks over a 100-month horizon.

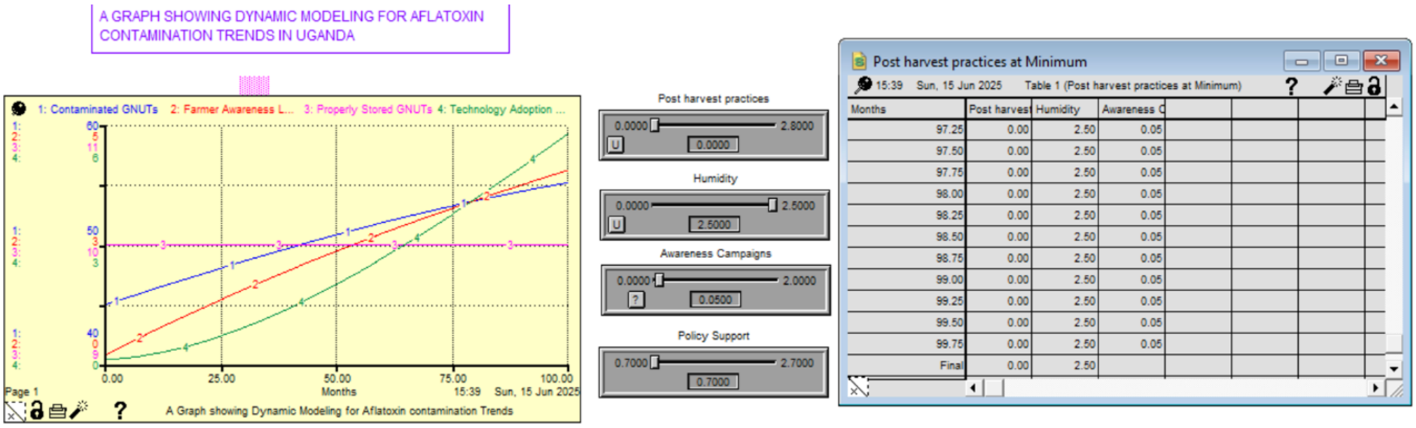

Figure 5. Scenario 1 — contamination driver active, mitigation levers minimal: contamination rises over time. Slider values report the parameter settings.

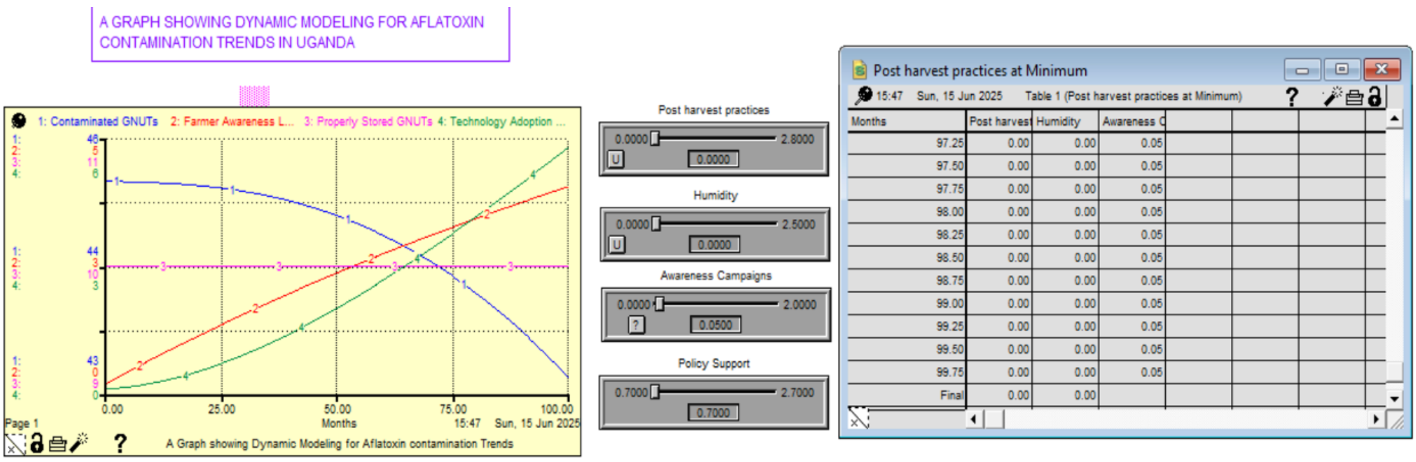

Figure 6. Scenario 2: contamination driver suppressed; mitigation levers active: contamination declines over time.

quality is by far the most influential parameter (elasticity ≈ −1.2), followed by humidity (≈ +0.6), awareness campaigns (≈ −0.4), policy support (≈ −0.3), and cost barrier (≈ +0.1). The dominance of post-harvest practice quality indicates that interventions improving drying and storage behaviour yield the largest marginal reductions in contamination, while the positive humidity coefficient confirms the climatic driver's role and motivates season-targeted action.

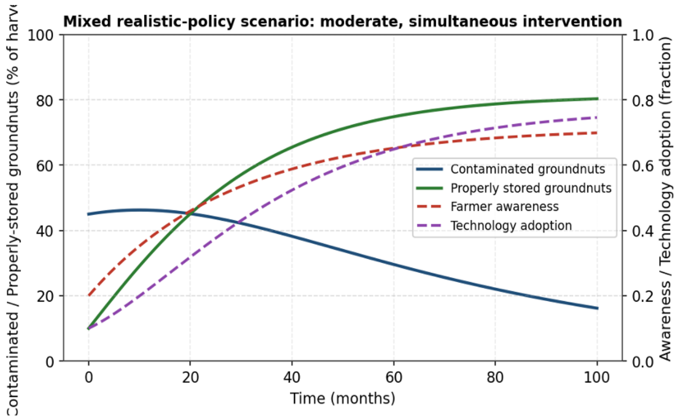

Figure 7. Mixed realistic-policy scenario showing the four core stocks under moderate, simultaneous intervention. Produced by re-implementing the documented model equations.

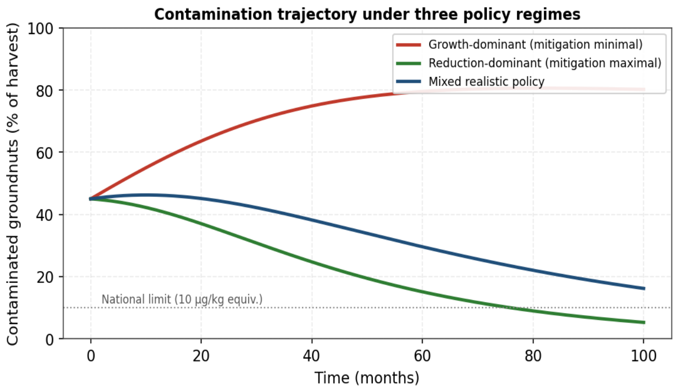

Figure 8. Contamination trajectory under growth-dominant, reduction-dominant, and mixed-policy regimes.

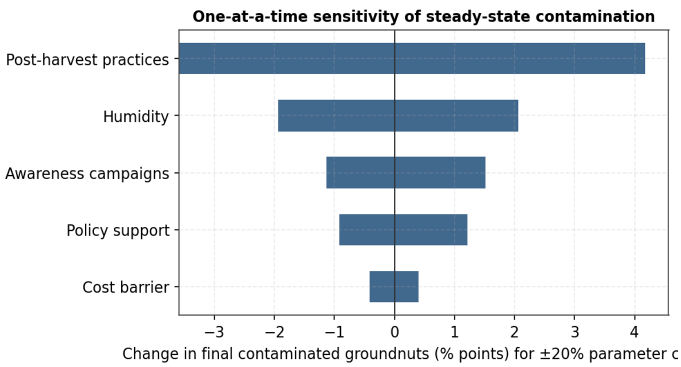

Figure 9. One-at-a-time sensitivity of steady-state contamination to a ±20% change in each parameter.

Model credibility was assessed along three of the dimensions conventional in SD practice. Structurally, the model is grounded in an established archetype and in causal relationships drawn from the reviewed literature, so its feedback structure is consistent with documented mechanisms. Behaviourally, the simulated trajectories reproduce patterns reported empirically—seasonal contamination escalation under neglect, gradual decline under sustained mitigation, rapid early growth and plateauing of awareness, and slow saturating adoption [25], [26]. The sensitivity analysis above provides a first robustness check by showing which parameters most affect outcomes.

Several limitations should temper interpretation and define the agenda for future work. First, initial values and coefficients are literature-derived priors rather than field-calibrated estimates; framing them as definitive parameter estimates would overstate the model's quantitative precision, and primary field calibration is a priority next step. Second, the flow equations are linear and deterministic and therefore approximate processes that are partly nonlinear and stochastic; introducing saturating functions and stochastic forcing would improve fidelity. Third, climatic drivers such as humidity are treated as static or simplified converters, whereas contamination is strongly seasonal and spatially variable; coupling the model to seasonal and geospatial humidity data would strengthen realism. Fourth, the decision-support model remains conceptual: it has not yet undergone stakeholder usability testing, benchmarking against alternative tools, or field deployment, and such evaluation—together with quantitative performance metrics—is required before practical roll-out. Acknowledging these limitations explicitly clarifies the model's current standing as a structured reasoning and scenario-exploration aid rather than a calibrated predictive instrument.

5. Conclusions

This study applied System Dynamics to the persistent problem of aflatoxin contamination in Uganda's groundnut value chain, building causal-loop and stock-and-flow representations in Vensim PLE and STELLA Architect and using them for scenario and sensitivity analysis. A central finding is the operation of the "Shifting the Burden" archetype, in which symptomatic interventions provide temporary relief but delay the structural investments, hermetic storage, early harvesting, and sustained education, that generate the balancing feedback needed to lower contamination durably, echoing empirical findings on integrated post-harvest management.

Beyond restating these principles, the analysis yields several insights specific to Uganda's system. The sensitivity ranking identifies post-harvest practice quality, not standalone awareness messaging, as the dominant leverage point, implying that scarce resources are best directed first toward drying and storage extension and the behaviours that sustain them. Because awareness decays through forgetting, one-off campaigns underperform; awareness must be continuously reinforced to retain its mitigating effect. Because cost barriers and weak policy support drive technology abandonment, financing and subsidy mechanisms are not peripheral but central to sustaining adoption. And because humidity is a strong, seasonal driver, interventions timed to the rainy season and to high-risk districts are likely to outperform uniform, year-round programmes. The mixed-policy scenario further shows that moderate, coordinated investment across these levers can move the system below regulatory thresholds, so Uganda's strategy need not depend on maximal effort in any single domain but on sustained balance across several.

From an Information Systems perspective, the model functions as a decision-support artefact that lets policymakers anticipate long-term effects, locate high-leverage points, and weigh trade-offs before committing resources. Its present value lies in structured scenario exploration rather than calibrated prediction. Future work will pursue field calibration, nonlinear and stochastic formulations, seasonal and geospatial humidity coupling, and stakeholder-based usability testing and benchmarking, advancing the tool from a conceptual framework toward a deployable, data-driven decision-support system for aflatoxin risk management in Uganda and comparable low-resource settings.

6. Declarations

6.1. Author Contributions

Yudaya Nansukusa: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing - Original Draft; **Salama Asikuru:** Writing - Review & Editing, Visualization, Supervision, Project administration; **Umaru Kalyankolo:** Formal analysis, Writing - Original Draft, Investigation, Resources, Data Curation; **Ritah Nafuna:** Formal analysis, Writing, Review & Editing, Visualization, Supervision.

6.2. Institutional Review Board Statement

Not applicable.

6.3. Informed Consent Statement

Not applicable.

6.4. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.5. Acknowledgment

Not applicable.

6.6. Conflicts of Interest

The authors declare no conflicts of interest.

7. References

[1] S. Çiftçi and G. Suna, "Functional components of peanuts (*Arachis hypogaea L.*) and health benefits: A review," *Future Foods*, vol. 5, 2022. https://doi.org/10.1016/j.fufo.2022.100140.

[2] Y. Gelaye and H. Luo, "Optimizing Peanut (*Arachis hypogaea L.*) Production: Genetic Insights, Climate Adaptation, and Efficient Management Practices: Systematic Review," *Plants*, vol. 13, no. 21, 2024. https://doi.org/10.3390/plants13212988.

[3] J. O. Akullo *et al*., "Aflatoxin contamination in groundnut and maize food products in Eastern and Northern Uganda," *Cogent Food & Agriculture*, vol. 9, no. 1, 2023. https://doi.org/10.1080/23311932.2023.2221015.

[4] R. Pretorius, M. Nicolau, L. B. A. Salvia, J. Mazutti, K. Shulla, A. M. Motta, J. Pohlman, *Sustainable Development Goal 2: Zero Hunger — Teacher's Manual*. 2023. https://www.researchgate.net/publication/382998018.

[5] C. O. Ojiewo *et al*., "Advances in crop improvement and delivery research for nutritional quality and health benefits of groundnut (*Arachis hypogaea L.*)," *Frontiers in Plant Science*, vol. 11, pp. 1–15, 2020. https://doi.org/10.3389/fpls.2020.00029.

[6] T. Omara *et al*., "Aflatoxins in Uganda: An encyclopedic review of the etiology, epidemiology, detection, quantification, exposure assessment, reduction, and control," *International Journal of Microbiology*, vol. 2020, 2020. https://doi.org/10.1155/2020/4723612.

[7] M. Ahmad, Z. Han, and Q. Kong, "Aflatoxin in peanuts and maize: An overview on occurrence, regulations, prevention, and control methods," *World Mycotoxin Journal*, vol. 16, no. 2, pp. 99–114, 2023. https://doi.org/10.3920/WMJ2022.2786.

[8] Y. Gelaye, "Systematic review on aflatoxin contamination in Ethiopia: Current status and implications," *Studies in Fungi*, vol. 9, 2020. https://doi.org/10.48130/sif-0024-0013.

[9] B. Dabuo, E. W. Avogo, G. O. Koomson, M. Akantibila, and D. A. Gbati, "Aflatoxins: Toxicity, occurrences and chronic exposure," in *Aflatoxins — Occurrence, Detection and Novel Detoxification Strategies*, 2022. https://doi.org/10.5772/intechopen.105723.

[10] J. P. Sserumaga, J. M. Wagacha, M. Biruma, and C. K. Mutegi, "Contamination of groundnut (*Arachis hypogaea L.*) with Aspergillus section Flavi communities and aflatoxin at the post-harvest stage," *Food Control*, vol. 128, p. 108150, 2021. https://doi.org/10.1016/j.foodcont.2021.108150.

[11] K. Magamba *et al.*, "Aflatoxin risk management in commercial groundnut products in Malawi (Sub-Saharan Africa): A call for a more socially responsible industry," *Journal of Consumer Protection and Food Safety*, vol. 12, no. 4, pp. 309–316, 2017. https://doi.org/10.1007/s00003-017-1129-6.

[12] S. Bonkoungou *et al.*, "Mitigation of aflatoxin contamination of maize, groundnut, and sorghum by commercial biocontrol products in farmers' fields across Burkina Faso, Mali, Niger, and Togo," *CABI Agriculture and Bioscience*, vol. 5, no. 1, pp. 1–21, 2024. https://doi.org/10.1186/s43170-024-00313-3.

[13] M. Gu *et al*., "Approach for quick exploration of highly effective broad-spectrum biocontrol strains based on PO8 protein inhibition," *npj Science of Food*, vol. 7, no. 1, pp. 1–8, 2023. https://doi.org/10.1038/s41538-023-00210-5.

[14] S. K. Mutiga *et al*., "Integrated strategies for durable rice blast resistance in sub-Saharan Africa," *Plant Disease*, vol. 105, no. 10, pp. 1–22, 2021. https://doi.org/10.1094/PDIS-03-21-0593-FE.

[15] C. A. Chilaka *et al*., "Mycotoxin Regulatory Status in Africa: A Decade of Weak Institutional Efforts," *Toxins*, vol. 14, no. 7, art. No. 442, 2020. https://doi.org/10.3390/toxins14070442.

[16] K. Naeem, A. Zghibi, A. Elomri, A. Mazzoni, and C. Triki, "A literature review on system dynamics modeling for sustainable management of water supply and demand," *Sustainability*, vol. 15, no. 8, pp. 1–24, 2023. https://doi.org/10.3390/su15086826.

[17] S. Bogra "Applying system dynamics modeling for assessing environmental-economic sustainability of regional agriculture: An application for the Free State, South Africa," *Research Square preprint*, 2023. https://doi.org/10.21203/rs.3.rs-3282804/v1.

[18] P. Sipos *et al.*, "Physical and chemical methods for reduction in aflatoxin content of feed and food," *Toxins*, vol. 13, no. 3, pp. 1–17, 2021. https://doi.org/10.3390/toxins13030204.

[19] M. M. Alameri *et al*., "Aflatoxin contamination: An overview on health issues, detection and management strategies," *Toxins*, vol. 15, no. 4, pp. 1–16, 2023. https://doi.org/10.3390/toxins15040246.

[20] N. Pavković, M. Vranešević, F. Bagi, R. Iličić, "Implementation of biotechnical measures for the control and prevention of aflatoxin contamination in maize production," *Contemporary Agriculture*, vol. 74, no. 1-2, pp. 86-97, 2025. https://doi.org/10.2478/contagri-2025-0011.

[21] I. S. Asante, M. Aidoo, S. Prah, B. O. Asante, and C. K. Sackey, "Managing aflatoxin contamination threats in groundnut (Arachis hypogaea L.) production in Ghana: The role of adoption of management strategies," *Journal of Stored Products Research*, vol. 107, p. 102335, 2024. https://doi.org/10.1016/j.jspr.2024.102335.

[22] S. Li, X. Yao, X. Wang, S. Tian, and Y. Zhang, "Reactive molecular dynamics simulation on degradation of aflatoxin B1 by cold atmospheric plasmas," *Innovative Food Science and Emerging Technologies*, vol. 80, p. 103101, 2022. https://doi.org/10.1016/j.ifset.2022.103101.

[23] E. Baidhe, C. L. Clementson, J. Senyah, and A. Hammed, "Appraisal of post-harvest drying and storage operations in Africa: Perspectives on enhancing grain quality," *AgriEngineering*, vol. 6, no. 3, pp. 3030–3057, 2024. https://doi.org/10.3390/agriengineering6030174.

[24] J. O. Akullo *et al.*, "A comprehensive review of aflatoxin in groundnut and maize products in Africa: Prevalence, detection and mitigation strategies," *Journal of Food Quality*, vol. 2025, no. 1, 2025. https://doi.org/10.1155/jfq/2810946.

[25] P. Villers, "Food safety and aflatoxin control," *Journal of Food Research*, vol. 6, no. 2, p. 38, 2017. https://doi.org/10.5539/jfr.v6n2p38.

[26] B. Teutsch and L. Kitinoja, "100 under $100: Tools for reducing postharvest losses," *The Postharvest Education Foundation*, 2019. https://worldveg.tind.io/record/73168?v=pdf.

[27] R. Echodu, G. Maxwell Malinga, J. Moriku Kaducu, E. Ovuga, and G. Haesaert, "Prevalence of aflatoxin, ochratoxin and deoxynivalenol in cereal grains in northern Uganda: Implication

for food safety and health," *Toxicology Reports*, vol. 6, pp. 1012–1017, 2019. https://doi.org/10.1016/j.toxrep.2019.09.002.

[28] S. J. K. Sirma and J. Kigen, "Assessment of risk to human health associated with aflatoxins in the Kenyan dairy value chain," M.S. thesis, Univ. of Nairobi, Nairobi, Kenya, 2020. http://erepository.uonbi.ac.ke/handle/11295/153744.

[29] J. D. Sterman, "System dynamics: Systems thinking and modeling for a complex world," in *Proc. ESD Internal Symposium*, Cambridge, MA, USA, 2002. http://hdl.handle.net/1721.1/102741.

[30] J. W. Forrester, "System dynamics, systems thinking, and soft OR," *System Dynamics Review*, vol. 10, no. 2–3, pp. 245–256, 1994. https://doi.org/10.1002/sdr.4260100211.

[31] E. Iacovidou, J. N. Hahladakis, and P. Purnell, "A systems thinking approach to understanding the challenges of achieving the circular economy," *Environmental Science and Pollution Research*, vol. 28, no. 19, pp. 24785–24806, 2021. https://doi.org/10.1007/s11356-020-11725-9.

[32] A. Fowler, "Systems modelling, simulation, and the dynamics of strategy," *Journal of Business Research*, vol. 56, no. 2, pp. 135–144, 2003. https://doi.org/10.1016/S0148-2963(01)00286-7.

[33] M. Branz, A. Farrell, M. Hu, W. Liem, and E. Ballard, "*System archetypes*," Social System Design Lab, St. Louis, MO, USA, vol. 1.07, pp. 1–62, 2021. https://doi.org/10.7936/c89k-d163.

[34] D. K. Okello *et al*., *Management of Aflatoxins in Groundnuts.* Entebbe, Uganda: National Agricultural Research Organisation (NARO), 2010. https://nru.uncst.go.ug/server/api/core/bitstreams/83fe2d88-127a-4363-bd1b-248e369d41cc/content.