

DEVELOPING A GRAPHICAL USER INTERFACE (GUI) TO PREDICT THE CONTAMINATION OF GM CORN IN NON-GM CORN



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HIGHLIGHTS

- A GUI tool was developed to predict the adventitious presence in non-GM produce.
- The software calculates tolerance and the probability of GM corn in non-GM corn.
- Predicted probability of contamination ranged from 0.050 to 0.356 at tolerance levels ranging from 0.1% to 5.0%.

ABSTRACT. *The current rate of population growth necessitates the use of viable technologies like genetic modification to address estimated global food and feed requirements. However, in recent years, there has been an increase in resistance against the diffusion of genetic modification technology around the world. Many countries have adopted coexistence policies to allow a certain percentage of adventitious presence in non-genetically modified crops. However, the tolerance percentage for adventitious presence has been a bottleneck to free trade in some cases. It is a challenging task to fix a tolerance percentage considering the level of permeation of genetic modification technology in agriculture. This article introduces a software developed to serve as a decision-making tool to predict the probability distribution of genetically modified (GM) contamination in non-GM grain lot using user inputs such as final quantity of processed corn, overall tolerance level, and moisture content. The output from the software includes the mass of corn in each processing stage, the tolerance level and the probability distribution of potential GM contamination. The software predicted the probability of contamination with adventitious presence at tolerance levels of 5.0%, 3.0%, 1.0%, 0.9%, 0.5%, and 0.1% as 0.05, 0.07, 0.11, 0.12, 0.16, and 0.36, respectively. The predictions from the model were compared to a similar study wherein the effect of tolerance levels incurred in the costs of segregation was studied. The mean absolute percentage error for the predictions was found to be 3.07%. This software can be used as a tool in testing GM contamination in non-GM grain against a desired threshold levels in a grain elevator.*

Keywords. *Corn, Genetic modification, Graphical User Interface (GUI), Threshold level.*

Cultivation of genetically modified (GM) crops has grown from 1.7 million ha in 1996 to 190 million ha in 2017 (Carzoli et al., 2018). Improved yield, disease resistance, and economic gains are major factors that promote the adoption of GM crops. However, in recent years, there have been strong societal concerns over such widespread implementation of GM cropping technology throughout the world. Many developed countries

strongly oppose GM technology and the import of GM products (Bonny, 2003). These rising concerns have forced the policy makers to continuously revise the grain import standards to facilitate the coexistence of GM and non-GM crops in grain production and handling systems.

Nevertheless, it is impossible to completely avoid the unintentional presence of GM material in non-GM grain products (Devos et al., 2009). This has given rise to the concepts of adventitious presence (AP) and tolerance levels. Adventitious presence denotes the level of trace amounts of genetically modified grain allowable in non-GM produce within a specified threshold limit. Thresholds or tolerance levels denote the maximum allowable level of adventitious presence of GM material. This parameter is set by regulatory authorities of different countries. In the United States, the Environmental Protection Agency (EPA), the U.S. Department of Agriculture (USDA), and the Food and Drug Administration (FDA) shares the responsibility of regulation of GM foods (Gostek, 2016). The threshold level for adventitious presence is 5% in the United States, 0.9% in EU, and 0% in Canada (Demont and Devos, 2008). Japan and Hong Kong specify a threshold level of 5% for adventitious presence while South Korea and

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Thailand specify a threshold level of 3%. Several non-GM identity preservation programs for soybeans in Canada prescribe a threshold value of 0.5%. The lowest threshold value that is scientifically feasible for testing GM contamination is 0.1% (Huygen et al., 2004).

Various strategies have been proposed by researchers to reduce the level of adventitious presence in non-GM crops. For non-GM growers, an effective and accurate strategy is important because when the non-GM status of a crop cannot be proven, the crop must be sold at commodity prices rather than at a premium market price. An effective strategy under set tolerance conditions can be the segregation of non-GM and GM crops in the grain elevator to avoid trade disruptions (Wilson and Dahl, 2005). However, the success of this strategy depends on the tolerance level set by different countries. Low and zero tolerance thresholds increase the likelihood of purity but require more testing, higher segregation costs, and an increased number of product failures (Bullock and Desquilbet, 2002; Kalaitzandonakes and Magnier, 2004). Moreover, lower tolerance levels could increase the risk of rejection of grains for non-GM growers and handlers. On the other hand, low and zero threshold policies can lead to cessation of trades between countries and can lead to a huge economic loss. Kalaitzandonakes et al. (2014) studied the potential economic impacts arising from regulatory asynchronicity and zero thresholding in the trade of soybean, soybean meal, and oil between EU and its major suppliers. The study quantified the cost incurred by EU in case of a trade disruption with multiple large trading partners.

Grain handling, as a high-volume, low-margin business, has only a little allowance for increased costs, particularly when the commodity prices are low. In the United States, there is still a small percentage of non-GM crop farmers dependent on feasible coexistence policies to maintain the market value of non-GM crops. The challenge for these growers is to keep AP levels within the threshold, which involves steps like minimizing cross-fertilization between neighboring farms (Demont and Devos, 2008). Several European studies have identified and tested management strategies like temporal and spatial strategies to cut down the adventitious presence to a minimum (Miraglia et al., 2004; Coleno et al., 2009). Use of certified seeds, spatially isolating farms, implementing pollen barriers, scheduling different timing for sowing and flowering periods, cleaning agricultural and material handling machinery, and clustering of fields are some measures that could be taken at the production facilities to lessen the contamination of GM crops in non-GM crops (Devos et al., 2009; Mosher and Hurburgh, 2010).

Science-based coexistence policies should be created to adopt a feasible tolerance level for adventitious presence consistent with the current economic and social limitations. Tolerance level can be mathematically predicted using the probability theory to find an optimal value of threshold level among the alternatives. However, fixing a tolerance level is always challenging since diffusion of GM technology has led to a rise in uncontrollable adventitious presence. The time taken to process a commodity can impact the profitability of agricultural processing industries. Increased processing times can also influence the quality of the final product. So, to minimize the facility downtime and the time

spent by facility managers on evaluating agricultural products, it is important to have an automated software that will give a probabilistic distribution of AP. An automated calculation tool would also enable the facility managers to take precautionary measures to avoid co-mingling of GM-corn with non-GM corn.

The objectives of this work were i) to develop a graphical user interface (GUI) to serve as a decision-making tool to predict the probability distribution of adventitious presence in non-GM produce using user inputs, and ii) to quantify the effect of tolerance levels on the probability of contamination using this software. The purpose of the software is to calculate, at each stage of handling and/or processing, the mass of shelled corn, tolerance level, and the probability of finding GM corn in segregated non-GM corn within a commodity grain elevator.

MATERIALS AND METHODS

MODEL DEVELOPMENT

The developed model has two stages. The first stage was to find the mass of corn in each stage of processing using the inputs from the user. This stage uses a material balance approach to gauge the mass of corn in each processing stage. The second stage uses the mass of corn from the first stage to calculate the probability distribution of GM contamination.

The model included the following assumptions:

1. The scope of this software was limited to handling that occurs in a grain elevator.
2. The processed lot of corn was labeled as non-GM and the probability of finding GM corn was explained using Poisson's approximation to the binomial distribution. One assumption for the model was that any contamination in the incoming lot labelled as non-GM was rare and unintentional. Poisson's distribution is used when the occurrence of an event is considered to be rare. Further, binomial distribution has two possible outcomes which is either true or false. Both of these conditions are present in the model, therefore, the Poisson's approximation to binomial distribution was used.
3. Material handling loss at each processing step was 0.5% (Kenkel, 2008).
4. The desired tolerance percentage was a weighted average of tolerance at each stage of processing.
5. The losses (solids and volatiles) during drying were negligible implying moisture transfer was the major mass transport process during drying.
6. Each handling/processing step had an equal chance of contamination.

MATERIAL BALANCE

The user inputs for this model included the desired mass of processed shelled corn (in bushels), moisture content (wet basis) of the incoming feed and processed corn, and the chosen tolerance in percentage. The typical processing/handling stages in a typical grain elevator in the United States is used in this GUI development (fig. 1). The mass of corn in each processing step was calculated using a material balance

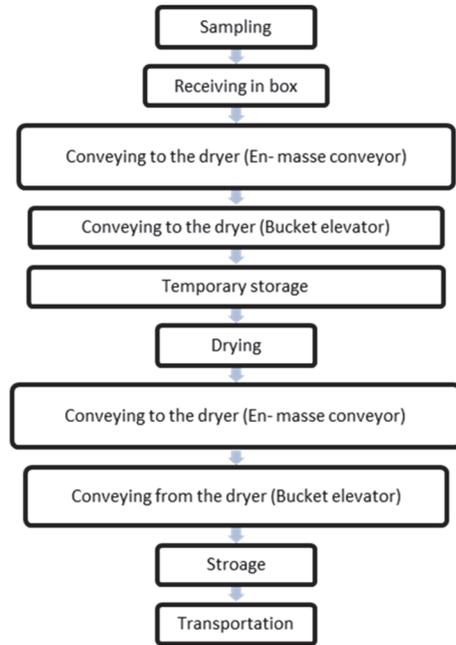


Figure 1. Typical unit handling operations in a corn grain elevator.

equation assuming a loss factor of 0.5%.

$$m_n = m_{n-1} - 0.005 * m_{n-1} \quad (1)$$

where m_n denotes the mass at n stage and m_{n-1} is the mass at the $n-1$ stage in processing.

The solid balance equation was used to assess the mass of corn undergoing the drying process.

$$m_f x_f = m_p x_p, \quad (2)$$

where m_f is the mass of wet grain, x_f is the solids of the wet grain, m_p is the mass of dry grain, and x_p is the solids of the dry grain.

PROBABILITY DISTRIBUTION

The second phase of this GUI development was to calculate the probability distribution of GM contamination in the given non-GM lot of shelled corn. This was estimated using Poisson's approximation to the binomial distribution. Binomial distribution for n trials with x number of successes having p as the probability of success is given by:

$$B(x, n, p) = \frac{n!}{(n-x)!x!} p^x (1-p)^{n-x} \quad (3)$$

If the expected value of the binomial distribution is denoted by $\mu (=np)$, then:

$$p = \frac{\mu}{n} \quad (4)$$

Substituting equation 4 into 3:

$$B(x, n, p) = \frac{\mu^x n!}{x!(n-x)!n^x} \left(1 - \frac{\mu}{n}\right)^n \left(1 - \frac{\mu}{n}\right)^{-x} \quad (5)$$

Evaluating individual terms in equation 5 at the limit $n \rightarrow \infty$, wherein n denotes the number of trials.

$$\lim_{n \rightarrow \infty} \frac{n!}{(n-x)!x!} = \quad (6)$$

$$\lim_{n \rightarrow \infty} \left(\frac{n(n-1)\dots(n-x+1)}{n^x} \right) = 1$$

$$\lim_{n \rightarrow \infty} \left(1 - \frac{\mu}{n}\right)^n = e^{-\mu} \quad (7)$$

$$\lim_{n \rightarrow \infty} \left(1 - \frac{\mu}{n}\right)^{-x} = 1 \quad (8)$$

Substituting equation 6, 7, and 8 in 5:

$$\lim_{n \rightarrow \infty} B(x, n, p) = \frac{\mu^x e^{-\mu}}{x!} \quad (9)$$

where μ is the mean ($= np$) and x (≥ 0) is the number of chances of the experiment being a success denoted by the probability of finding GM corn in the non-GM load.

GUI DEVELOPMENT

The program was written in Java language using libraries Jfreechart (Object Refinery Limited, Hertfordshire, United Kingdom), Commonmath (Apache Software Foundation, Wakefield, Mass.) and JavaFX (Sun Microsystems, Santa Clara, Calif.). The application consisted of methods implemented to calculate the mass of shelled corn in each processing stage as well as to estimate Poisson's probability from the calculated mass of shelled corn. Commonmath library was invoked to estimate the Poisson's probability distribution for the mass of shelled corn in each stage. JFreechart library was used to plot the probability distribution as a line plot. The base of this program was JavaFX whose elements like Textfields, labels, and buttons allow users to interact with the GUI. The program was then exported as a runnable jar and was wrapped up as a packaged installer to distribute the software in windows platform. The algorithm for calculating the mass of shelled corn in each stage of processing is shown in figure 2. The output from this algorithm was used as inputs for calculating the probability of contamination (fig. 3) and the results generated were then plotted using jfreechart library.

RESULTS AND DISCUSSION

DEMONSTRATION OF SOFTWARE

Three input parameters for running the simulation are the final quantity of processed corn, moisture content (initial and final), and the tolerance level in percentage. These parameters were entered into the text fields of the GUI and then the 'calculate' button was clicked to initiate the calculations (fig. 4). To find the probability distribution at any processing stage, the corresponding button for the processing stage must be pressed. The resulting output of the graph can be saved as an image or as a portable document file. The tolerance levels

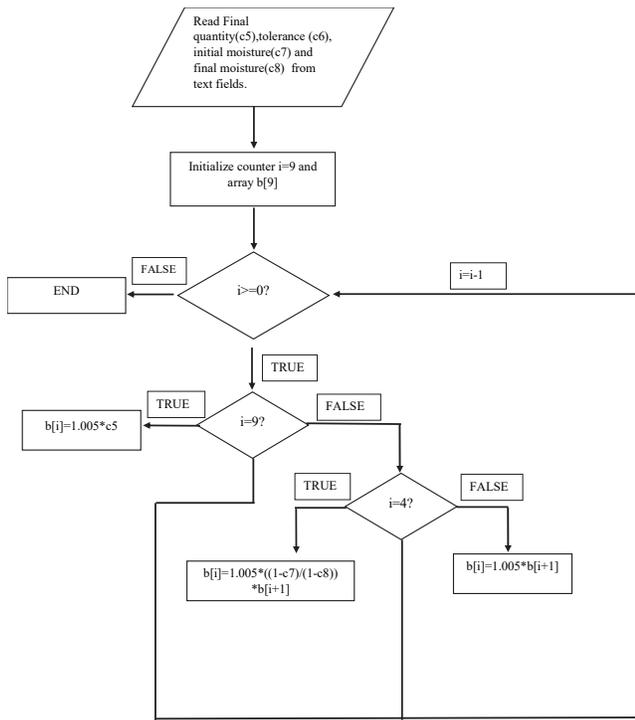


Figure 2. Algorithm for calculating the mass of shelled corn in each processing stage.

and predicted masses can be saved as a text file. To demonstrate the calculation accuracy, several inputs were tested (table 1). Each set of inputs contributed to a unique trial and generated theoretical probabilities which could serve as guidelines to frame management strategies.

Trial 1: The software output of quantity and tolerance level at each stage of processing is presented in table 2. Each processing step has a corresponding mass of corn which can be expected during processing. The tolerance level of each step denotes the maximum permissible level of adventitious presence for the process to attain the desired final tolerance percentage. From figure 4, it could be observed that the probability of finding GM corn in the non-GM lot was approximately 0.12. In conclusion, for the given input variables in Trial 1, there is 11.8% chance of finding GM corn in 12700.59 kg (500 bu) of non-GM corn tested at 0.9% level. In addition, it is evident from figure 5 that the quantity of GM corn that can be expected in the final product during transportation step is approximately 11 kg.

Trial 2: When the input quantity was changed to 10160.47 kg (400 bu) at 0.9% tolerance, it was found that the probability of finding GM contamination in non-GM corn increased to 0.13. The expected amount of contamination in the transportation stage was 9 kg (fig. 6).

Trial 3: In this trial, the quantity simulated was 5080.23 kg (200 bu) at 0.8% tolerance. The output and the

User Inputs	Trial 1	Trial 2	Trial 3
1. Total quantity (kg)	12700.59	10160.47	5080.23
2. Total quantity (bu)	500	400	200
3. Tolerance (%)	0.9	0.9	0.8
4. Moisture of incoming lot (% wet basis)	18	25	19
5. Desired moisture of dried corn	15	18	16

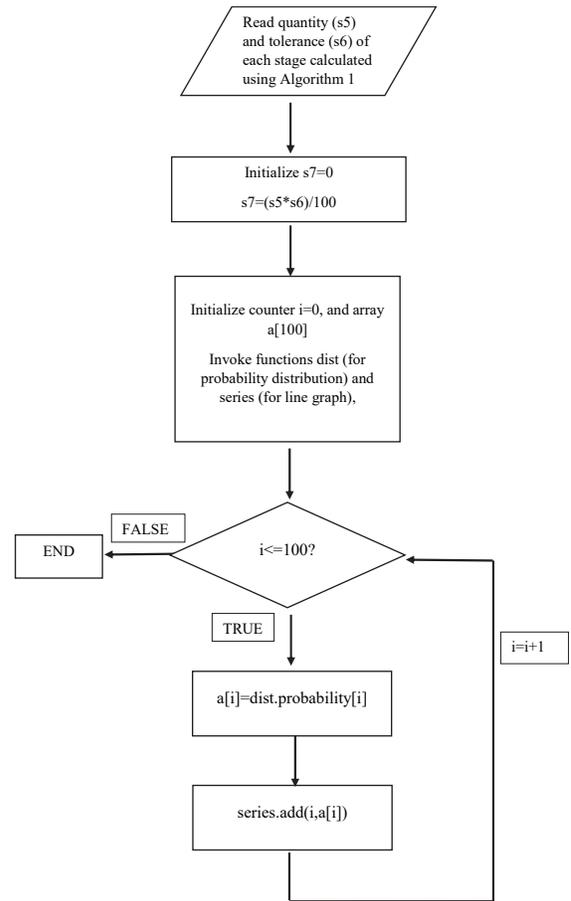


Figure 3. Algorithm for calculating the probability of shelled corn in each processing stage.

probability distribution predicted contamination in the transportation stage at 4 kg of GM corn with a probability of 0.195 (fig. 7). The output screen from trial 3 is shown as figure 8. Therefore, it can be concluded from the trials 1, 2, and 3 that, as the final quantity of processed corn and tolerance level decreases, the chance of contamination increases.

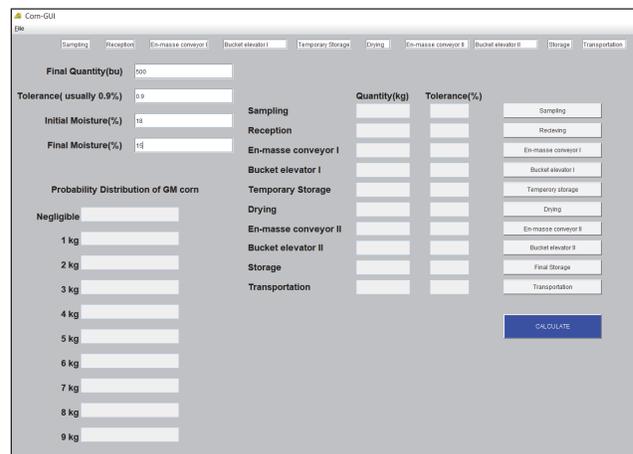


Figure 4. The software interface for entering the inputs.

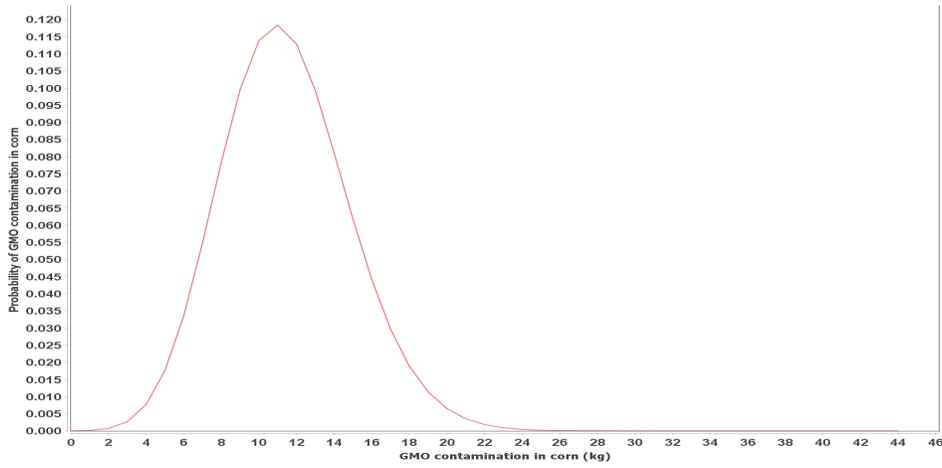


Figure 5. Probability distribution of GM contamination for transportation step based on trial 1 input values.

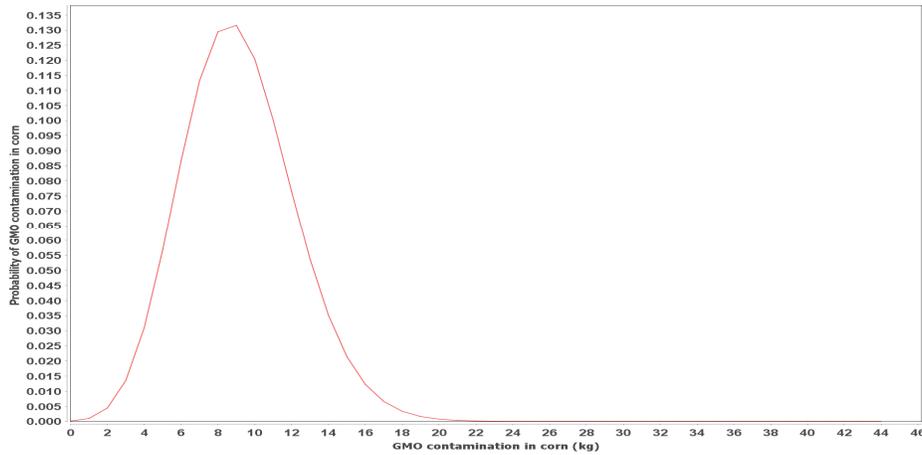


Figure 6. Probability distribution of GM contamination for transportation step based on Trial 2 input values.

EFFECT OF TOLERANCE LEVEL ON PROBABILITY

To quantify the effect of tolerance level on probability, a numerical simulation was conducted with constant inputs and varying tolerance levels as shown in table 3. The tolerance levels assumed in this study were 5.0%, 3.0%, 1.0%,

0.9%, 0.5%, and 0.1%. These assumed tolerance levels represented the legal tolerance levels adopted by different countries. The probability of finding GM contamination in six trials was found to be 0.050, 0.065, 0.112, 0.118, 0.159, and 0.356, respectively. Thus, it is evident that lower tolerances are more likely to correspond with higher probabilities of AP

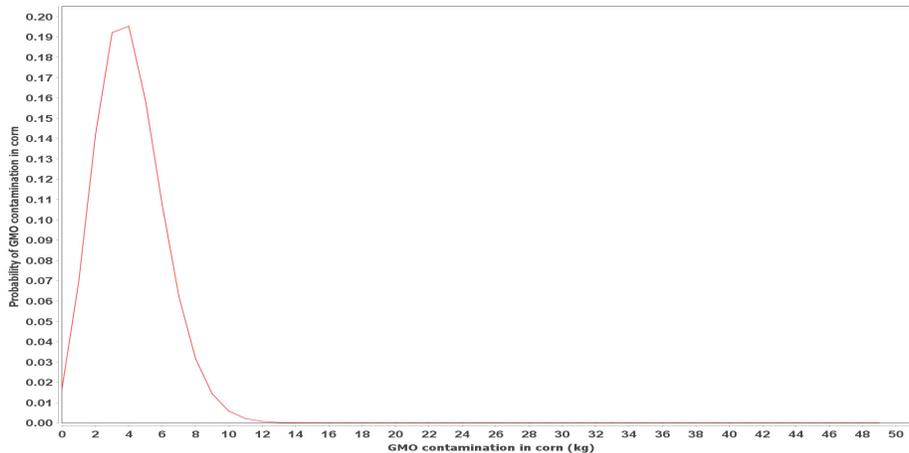


Figure 7. Probability distribution of GM contamination for transportation step based on Trial 3 input values.

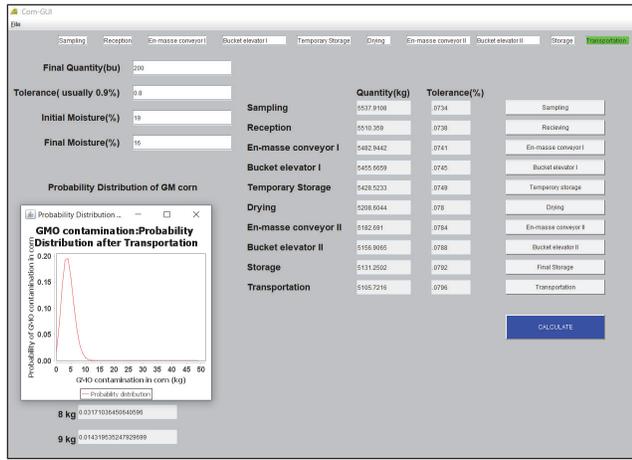


Figure 8. Software output screen for Trial 3 simulations.

contamination. A decrease in tolerance from 5.0% to 3.0% increased the probability from 0.050 to 0.065, which corresponds to a 30% increased chance of AP contamination. The results were found to be in agreement with the observations by Huygene et al. (2004) who compared the effect of changes in tolerance levels with the cost incurred for segregating the grains.

To validate the model, the increase in probabilities of finding AP was compared with costs incurred in the segregation of GM and non-GM wheat (Huygene et al., 2004) when the tolerance level was decreased from 5.0% to 3.0%, 1.0%, 0.5%, and 0.1%. The corresponding increase in cost were 2.38%, 138.09%, 361.90%, and 514.29%.

$$\%PE = \frac{100}{n} \sum_{i=1}^n \frac{|P_i - A_i|}{A_i} \quad (10)$$

The mean absolute percentage error calculated using equation 10 was found to be 3.07%. The variation in percent increase with tolerance levels for both the probability function and the cost incurred with tolerance levels is presented in figure 9. It can be seen from the graph that as tolerance level decreased, the increase cost for segregating correlates with the software predicted percent increase in the probability of AP. A higher chance of contamination with AP at a stringent tolerance level results in higher cost for segregation.

CONCLUSIONS

The GUI developed in this study can be used to test tolerances and predict the probability of contamination of GM corn in non-GM lots. This model forms a theoretical basis for quantifying the expected contamination of non-GM corn with GM corn during different stages of processing/handling. This software can be used by the processors to formulate strategies to prevent contaminations that may lead to trade disputes. In addition, the GUI helps in testing a tolerance level for any select batch of corn processed at a specific moisture content. Thus, the software can be used to assess the possible contamination occurring in ideal conditions at a specified level and can give some insights into the viability of choosing such tolerances. Furthermore, the model has its limitations derived from the assumptions. This current model was constructed based on the assumption that each stage in processing has an equal probability of contamination which is true unless there is some previous history of finding higher levels of contamination at a particular stage of handling. Besides, the model assumed a 0.5% product loss in each stage which can vary depending on the management practices at the elevator. The model presumes that a lot which is marked as non-GM

Table 2. Output results from trial demonstrations.

Processing Step	Trial 1		Trial 2		Trial 3	
	Mass of Corn (kg)	Tolerance Level (%)	Mass of Corn (kg)	Tolerance Level (%)	Mass of Corn (kg)	Tolerance Level (%)
1 Sampling	13838.75	.083	11677.08	.0783	5537.91	.073
2 Reception	13769.90	.083	11618.99	.079	5510.36	.074
3 Wet corn auger conveying	13701.39	.083	11561.18	.079	5482.94	.074
4 Wet corn bucket elevator conveying	13633.22	.084	11503.66	.080	5455.67	.075
5 Temporary storage	13565.40	.084	11446.43	.080	5428.52	.075
6 Drying	13021.51	.088	10417.21	.088	5208.60	.078
7 Dried corn auger conveying	12956.73	.088	10365.38	.088	5182.69	.078
8 Dried corn bucket elevator conveying	12892.27	.089	10313.81	.089	5156.91	.079
9 Storage	12828.13	.089	10262.50	.0891	5131.25	.079
10 Transportation	12764.30	.090	10211.44	.090	5105.72	.080

Table 3. Trial inputs for testing effects of tolerance levels.

User Inputs	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9
1. Total quantity (kg)	12700.59	12700.59	12700.59	12700.59	12700.59	12700.59
Total quantity (bu)	500	500	500	500	500	500
2. Tolerance (%)	5.0	3.0	1.0	0.9	0.5	0.1
3. Moisture of incoming corn	25	25	25	25	25	25
4. Desired moisture of dried corn	15	15	15	15	15	15
Probability of GM contamination	0.050	0.065	0.112	0.118	0.159	0.356

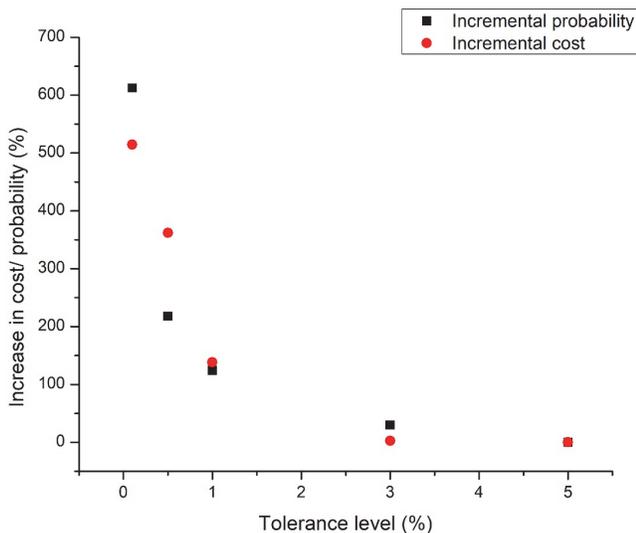


Figure 9. Effect of tolerance levels on probability and cost.

corn could have been contaminated unintentionally and since the quantity of grains under consideration is large enough, the contamination can be predicted using Poisson probability. The model predictions, at different tolerance levels, were well aligned with the cost of segregation with a prediction error of 3.07%. This software can potentially be implemented by the grain handling industry to predict the probabilities of contamination at different tolerance levels.

NOMENCLATURE

m_f	mass of wet corn
x_f	solid content of wet corn
m_p	mass of dry corn
x_p	solid content of dry corn
μ	mean
P	probability
x	number of successes
n	number of trials

ABBREVIATIONS

GUI	graphical user interface
AP	adventitious presence
GM	genetically modified
PE	mean absolute percentage error
Bu	bushels of corn

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