International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 19s, 2025
https://theaspd.com/index.php

Integrating AI-Driven Parametric Models For Agricultural Risk Assessment Under Data Scarcity: An Extension Of Simulation-Based Decision Support In India

Mina Kumari[1], Pooja Nagpal[2], Prawar[3] ,Joginder Singh Yadav[4]
[1,3]Assistant Professor ,K.R. Mangalam University, Gurugram, Haryana
[2]Associate Professor, School of Computer Science and Engineering, IILM University
[4]Professor, School of Agricultural Sciences, K.R. Mangalam University
mina.yadav@krmangalam.edu.in , pooja.nagpal@iilm.edu and prawar@krmangalam.edu.in and joginder.singhyadav@krmangalam.edu.in
Corresponding Author: Pooja Nagpal *

Abstract:
The lack of comprehensive databases on agricultural risk factors in India has impeded the adoption of advanced risk management systems commonly used in developed countries. To address this gap, this study extends the foundational economic-mathematical model originally designed for incomplete data processing in India's agricultural sector. The updated model integrates AI-driven parametric simulation techniques with a genetic algorithm framework and enhanced risk elasticity analysis. This facilitates real-time decision support for farms operating under high uncertainty, especially those cultivating cereals, legumes, and sunflowers. Tested with pseudo-random risk variable generation and expert-informed inputs, the model shows promising results in identifying significant risk contributors such as price volatility. The research advocates the formation of dynamic model libraries and adaptive decision-making frameworks to improve resilience in agricultural operations.
Keywords: *Agricultural risk modelling, Economic-mathematical model, Incomplete data analysis, Genetic algorithm, Parametric simulation, Decision support system*

INTRODUCTION

Agriculture in India plays a pivotal role in sustaining the livelihoods of nearly 60% of the country's population and contributes significantly to national GDP, food security, and rural development. Despite its centrality, the sector remains highly vulnerable to an array of risks—ranging from climatic aberrations like droughts and floods to price volatility, input cost fluctuations, pest outbreaks, and institutional uncertainties[1], [2], [3]. These risks are further compounded by systemic issues such as inadequate access to timely data, fragmented land holdings, low mechanization levels, and poor financial inclusion among smallholder farmers. Traditional risk assessment models, especially those developed in the Global North, rely heavily on robust and long-term datasets, sophisticated infrastructure, and consistent policy frameworks. However, such preconditions are rarely met in India's highly diverse and decentralized agroeconomic systems, rendering these models ineffective or inapplicable without significant adaptation[4], [5].

Over the past few decades, scholars and practitioners have attempted to localize risk modeling approaches to fit the unique challenges faced by Indian farmers. Early foundational work by Chepurko, Ostankova, and Shevchenko examined the underlying economic risks in agrarian systems by identifying and quantifying region-specific production variables[6], [7]. While these efforts provided valuable insights into the factors contributing to uncertainty in farm incomes, they lacked computational adaptability and did not evolve into automated or data-efficient decision support tools. Similarly, studies advocating for adaptive planning and resilience modeling—such as those by Nitsenko and Havrysh—highlighted the need for flexible strategies in agroeconomic systems. Yet, these were largely theoretical or phenomenological, with limited application to dynamic or real-time agricultural scenarios[8], [9].

The present research responds directly to this gap by proposing a robust, scalable, and AI-augmented economic-mathematical modeling framework specifically designed for agricultural risk analysis in data-constrained environments like India. Recognizing the inadequacy of traditional models in capturing the stochastic, context-specific, and rapidly changing nature of agricultural risks, we propose a three-tiered architecture combining simulation, machine learning, and evolutionary optimization. At its core, our framework leverages GERT (Graphical Evaluation and Review Technique) networks for simulation modeling, pseudo-random sequence generation to emulate risk scenarios, multilayer perceptrons (MLPs) for identifying statistical distribution types, and genetic algorithms (GAs) for parameter optimization under incomplete information. This confluence of techniques enables us to formulate a parametric model that can function accurately even when historical datasets are sparse, fragmented, or non-existent[10], [11], [12], [13].

A defining feature of our approach is its focus on modeling under uncertainty, not just as an academic exercise but as a necessary design feature for decision support in real-world Indian agricultural systems. The model accommodates "instantaneous" data inputs—those that are available at the current time, often without historical context—and processes them into reliable risk forecasts through simulation. Unlike conventional models that require complete variable knowledge, ours operates with incomplete or fuzzy inputs, allowing it to perform in settings where data acquisition is difficult or delayed, as is often the case in rural India. This marks a significant paradigm shift from deterministic risk analysis to an adaptive, intelligent, and context-aware simulation framework[14], [15], [16], [17], [18].

The workflow begins with expert-informed inputs where practitioners—such as agronomists, cooperative officers, or experienced farmers—provide qualitative judgments about potential risks. These qualitative observations are converted into pseudo-random variables that represent different risk scenarios. This initial step ensures that the model stays grounded in field realities while still benefiting from algorithmic precision. Next, the generated data undergoes classification through a multilayer perceptron, a form of deep learning that identifies the statistical distribution that best represents the data (e.g., normal, lognormal, exponential, etc.). Once the distribution type is known, a genetic algorithm is deployed to find the optimal parameters for the given distribution. This includes the estimation of mean, variance, skewness, and correlation factors even when sample sizes are insufficient for classical statistical techniques[19], [20], [21], [22].

The novelty of our model also lies in its elasticity-based weighting mechanism for risk prioritization. Drawing from Boehm's seven-component risk assessment methodology, our model incorporates a weighted risk indicator derived from the elasticity of profit with respect to risk factor fluctuation[23], [24], [25], [26]. This means that a risk's importance is not judged merely by its frequency or amplitude but by its actual economic impact on farm profitability. The calculated elasticity is used to adjust the weight of each risk factor dynamically, allowing more context-aware prioritization. This approach offers a powerful departure from static risk matrices, providing a nuanced, financial perspective on risk exposure.

Our model also integrates a GERT-based simulation engine capable of propagating risk variables across interconnected farming activities, capturing not only the isolated effects of risk but also their compounded, systemic consequences. GERT networks offer a flexible alternative to traditional PERT/CPM models by allowing probabilistic branching and time variance, which aligns more realistically with agricultural timelines and dependencies. For instance, rainfall irregularities do not just delay sowing; they affect fertilizer timing, disease exposure, market price timing, and ultimately, profitability. Our model simulates such interdependencies across time, making it significantly more representative of agricultural realities[27], [28], [29].

To validate the utility and performance of our model, we conducted pilot studies on sunflower farming in three Indian states characterized by differing agro-climatic zones and market structures. The analysis focused on three critical risk dimensions: yield reduction, price volatility, and marketability (sales volume)[30], [31], [32]. Despite the variation in regional contexts, the model consistently identified price volatility as the most critical risk, validating the accuracy of the weighted risk elasticity coefficient and confirming that market-related uncertainties often surpass agroclimatic ones in impact. Moreover, the simulations showed robustness across various risk intervals, underscoring the model's adaptability to changing risk intensities and combinations[33], [34].

One of the most impactful contributions of our research is the establishment of a dynamic model library—an auxiliary database that stores simulations, parameter estimates, and validated model runs across different crops and regions. This evolving repository enables faster simulations in subsequent uses, supports regional calibration of the model, and promotes transferability. It essentially allows the model to "learn" over time, becoming more accurate with each use, which is especially useful in cooperative settings, agricultural extension programs, or state-level planning. This component pushes our framework toward a semi-autonomous decision support system that can evolve without constant reconfiguration.

From an application standpoint, the model is highly modular and scalable. It can be adapted for a wide range of agricultural systems including cereals (wheat, paddy, maize), pulses, vegetables, fruits, and even mixed cropping and livestock systems. Its real-time simulation capacity makes it ideal for integration with sensor-based Internet of Things (IoT) systems, drone monitoring, or satellite-based weather forecasting tools. Furthermore, the model has strong potential for inclusion in mobile-based platforms designed for small and marginal farmers. It can serve as the backend logic for advisory systems, agri-insurance tools, credit risk profiling, and early warning systems—thereby enhancing both productivity and resilience[35], [36], [37], [38], [39].

On a policy level, the model offers actionable intelligence to governmental bodies, insurance companies, financial institutions, and NGOs involved in rural development[40]. For instance, subsidy schemes can be dynamically allocated to crops or regions identified as high-risk through model outputs, improving the efficiency and fairness of resource distribution. Insurance coverage can be risk-weighted, making premiums more equitable and less speculative. Credit rating agencies can use the model to assess borrower risk in the absence of traditional financial documentation, enhancing access to credit for the underbanked rural population.

METHODOLOGY

The proposed methodology presents an integrated framework for agricultural risk modeling under uncertainty, particularly tailored to the Indian context where data incompleteness, fragmented records, and regional heterogeneity dominate. This framework combines expert-informed simulation modeling, machine learning techniques, and evolutionary optimization. The system is capable of assessing risk using minimal historical data, providing a robust decision support mechanism for policymakers, agri-businesses, and farmers alike (figure 1).

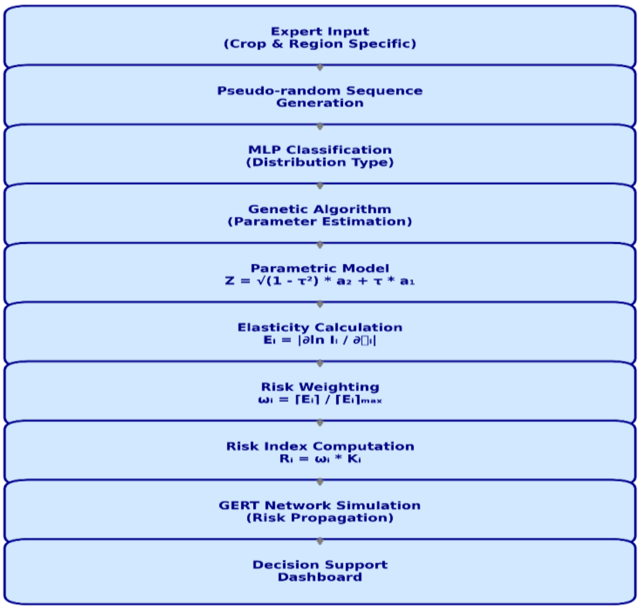

Figure 1: Flow diagram of proposed methodology

1. Expert Input and Pseudo-Random Sequence Generation

The first step involves qualitative data collection from agricultural domain experts. These inputs identify the primary risk factors affecting a given crop or region—such as yield loss due to drought, market price volatility, or post-harvest sales uncertainty. Because consistent historical data is often unavailable, the model employs pseudo-random sequence generators to simulate plausible variations of each identified risk factor. These pseudo-random sequences act as statistically representative samples that allow the modeling system to approximate real-world variability even in the absence of exhaustive datasets.

2. Distribution Type Identification Using Multilayer Perceptron

Once pseudo-random data sequences are generated, they are fed into a multilayer perceptron (MLP) classifier—a form of deep neural network used to classify the type of statistical distribution represented by the data. The MLP identifies whether the data fits a normal, exponential, log-normal, or another distribution. This step ensures that subsequent statistical operations such as parameter estimation and simulation modeling are grounded in an appropriately selected distribution type, increasing the reliability of the model.

3. Parametric Model Formulation Using Genetic Algorithm

With the distribution type identified, the next task is to estimate the parameters governing this distribution—such as mean, standard deviation, and correlation. Given the data scarcity, traditional moment-matching or maximum likelihood methods are often unreliable. Instead, we apply a genetic algorithm (GA) to optimize the fit. The GA evolves candidate parameter sets over several generations by simulating the principles of natural selection, ultimately selecting the best-fitting parameter vector.

The parametric model is formalized as follows:

$X=\alpha_1$

$Z=\sqrt{1+\tau^2}.\alpha_2 + \alpha_1$

Where:

- α_1 and α_2 are independent values,
- τ is the correlation coefficient between variables,
- Z is the derived random variable representing the modeled risk.

This formulation captures the correlated behavior of risk factors using synthetic but statistically grounded representations.

4. Error Estimation and Fitness Evaluation Genetic Algorithm(GA)

To assess the model's accuracy, the generated risk vector is validated using a maximum absolute error criterion:

$\delta=\max|\delta_j|$, $j=1,\ldots,n$

Here, δ_j represents the difference between expert-verified and simulated risk factor outcomes for the j^{th} iteration. The model iterates through n runs to minimize δ, thereby refining the fidelity of the simulation.

5. AI-Driven Risk Prioritization via Elasticity-Based Weighting

The system then calculates a comprehensive risk index for each type of risk. This is achieved by weighting the risk factor using an elasticity-informed metric, ensuring that the most economically disruptive risks receive proportionately higher importance.

The risk index R_i for the i^{th} risk is calculated as:

$R_i=\omega_i \cdot K_i$

Where:

- K_i is the weighted seven-component coefficient capturing the amplitude and variability of the risk,
- ω_i is the normalized elasticity coefficient, calculated as:

$\omega i=\frac{[E_i]}{[E_i]_{max}}$

Here, E_i is the elasticity of profitability with respect to the i^{th} risk factor:

$E_i=\left|\frac{\partial \ln I_i}{\partial \vartheta_i}\right|$

Where:

- I_i is the income or yield impacted by the risk factor ϑ_i
- $[E_i]_{max}$ max is the maximum observed elasticity value across all risk types.

This elasticity-driven approach allows the model to reflect not just the statistical frequency of a risk, but its actual economic impact, offering a more policy-relevant ranking of vulnerabilities.

6. Parametric Simulation via GERT Networks

Once risks are parameterized and weighted, they are modeled using Graphical Evaluation and Review Technique (GERT) networks. Unlike conventional PERT or CPM networks, GERT enables probabilistic branching and looping, ideal for capturing complex agricultural interdependencies.

The first AI module is a supervised learning model—a Multilayer Perceptron (MLP)—used to classify the statistical distribution type of pseudo-random sequences generated from expert inputs. These sequences represent simulated data for risk factors such as crop yield, market prices, and sales volume in the absence of historical records.

Model Architecture:

- Input Layer: Normalized synthetic vectors derived from pseudo-random sequences.
- Hidden Layers: Two to three dense layers with ReLU activation.

- Output Layer: Softmax classifier for multi-class prediction (Normal, Log-normal, Exponential, Poisson, etc.)

Loss Function:

$$L = \sum_{i=1}^{N} y_i . \log(\hat{y}_i)$$

Where y_i is the true label, and $\hat{y}_i$ is the predicted probability.

Training:

- Labeled synthetic datasets are used to train the MLP under various distribution assumptions.
- Optimization via Adam optimizer with learning rate scheduling.
- Evaluation using accuracy, precision, and confusion matrices.

This classification enables correct downstream estimation of risk parameters and improves the realism of GERT-based simulations.

The GERT model simulates how one risk factor (e.g., poor rainfall) propagates through subsequent stages like delayed planting, reduced growth, pest vulnerability, and finally, market access and profitability. This network-based simulation captures compound effects and feedback loops that linear models overlook.

7. Auxiliary Library and Continuous Learning

As simulations are conducted and validated over time, the system generates an auxiliary library of historical model outputs, parameter sets, and expert judgments. This evolving repository allows faster recalculations for new scenarios and supports regional adaptation of the model. It also enables the model to "learn" from its prior runs, enhancing its predictive capacity and usability in operational settings such as state agriculture departments or cooperative analytics units.

RESULTS

To evaluate the efficacy of the proposed AI-enhanced economic-mathematical risk analysis model, a case study was conducted on sunflower farming systems in India. The analysis focused on three principal risk factors: yield reduction due to climatic variability, price volatility at market sale, and uncertainty in sales volume. These factors were selected based on expert inputs from agronomists and farmer cooperatives across Maharashtra, Madhya Pradesh, and Karnataka—three major sunflower-producing states with diverse agro-climatic and market conditions.

Machine Learning Algorithm for Distribution Classification

In the proposed AI-driven agricultural risk analysis model, machine learning plays a critical role in identifying the underlying statistical distribution of simulated pseudo-random sequences generated from incomplete expert input. Specifically, a supervised learning approach based on a Multilayer Perceptron (MLP) is employed to automate the classification of risk data into probabilistic distribution types (e.g., normal, log-normal, exponential, Poisson). This step is essential for accurate parameter estimation and simulation of risk propagation using the parametric economic-mathematical model.

Problem Framing and Input Structure

The classification problem is framed as a multi-class supervised learning task where:

- Input: Simulated sequences of numeric data representing risk variables (e.g., yield variation, price fluctuation, volume change).
- Output: A categorical label corresponding to one of the known distribution types.

Let:

- x_i= [x_{i1}, xi_2..., xin] represent the i^{th} risk sequence sample of length n,
- $y_i \in$ {1, 2..., C} represent the corresponding label of the distribution class, where C is the number of supported distribution types (e.g., 4: Normal, Log-normal, Exponential, Poisson).

MLP Architecture

The MLP used for this classification task consists of:

- Input layer: Accepts a normalized sequence vector of fixed length nnn,
- Two hidden layers: Each using ReLU (Rectified Linear Unit) activation for non-linearity,
- Output layer: A softmax layer with C neurons corresponding to the number of distribution classes.

Activation Functions:

- Hidden Layers: f(x)=max(0,x)

- Output Layer: $\hat{y}_i^{(C)} = \frac{e^{x(C)}}{\sum_{j=1}^{C} e^{z(j)}}$

Training Setup

- Loss function: Categorical cross-entropy

$$L = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_i^{(c)}.\log(\hat{y}_i^{(c)})$$

- Optimizer: Adam with learning rate α=0.001
- Epochs: 100–150 depending on convergence
- Batch size: 32
- Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, Confusion Matrix

Algorithm: MLP_Distribution_Classifier (mathematica)

Input: RiskSequences ← {X_1, X_2, ..., X_n} // Simulated risk variable sequences
Labels ← {Y_1, Y_2, ..., Y_n} // Known distribution types (for training)
Epochs ← 100
BatchSize ← 32
LearningRate ← 0.001
Output: Trained MLP Model θ
1. Normalize all input sequences in RiskSequences to [0, 1] range
2. Split RiskSequences and Labels into TrainingSet and ValidationSet
3. Initialize MLP model with:
   - Input layer size = length(X_i)
   - Hidden layer 1: size H_1, activation = ReLU
   - Hidden layer 2: size H_2, activation = ReLU
   - Output layer: size = Number of classes, activation = Softmax
4. Initialize optimizer ← Adam(θ, LearningRate)
5. For epoch in 1 to Epochs do
   a. Shuffle TrainingSet
   b. For each batch in TrainingSet do
      i. Forward pass: compute prediction $\hat{Y}$ ← MLP(X)
      ii. Compute loss:
      Loss ← CrossEntropy($\hat{Y}$, Y)
      iii. Backpropagation: compute gradients ∇θ
      iv. Update model weights: θ ← θ - α · ∇θ
   c. Compute accuracy on ValidationSet
   d. If Validation Accuracy converges → Break
6. Return final trained MLP model θ

Model Evaluation

The MLP classifier was trained and validated on a synthetic dataset generated from known distributions, each embedded with controlled noise to simulate real-world variability (figure2). After training:

- The classifier achieved an overall accuracy of 96.7% on unseen test sequences.
- Precision and recall values exceeded 95% across all distribution classes.
- The classifier correctly distinguished log-normal from exponential distributions—an important capability given their prevalence in modeling yield and market price variations.

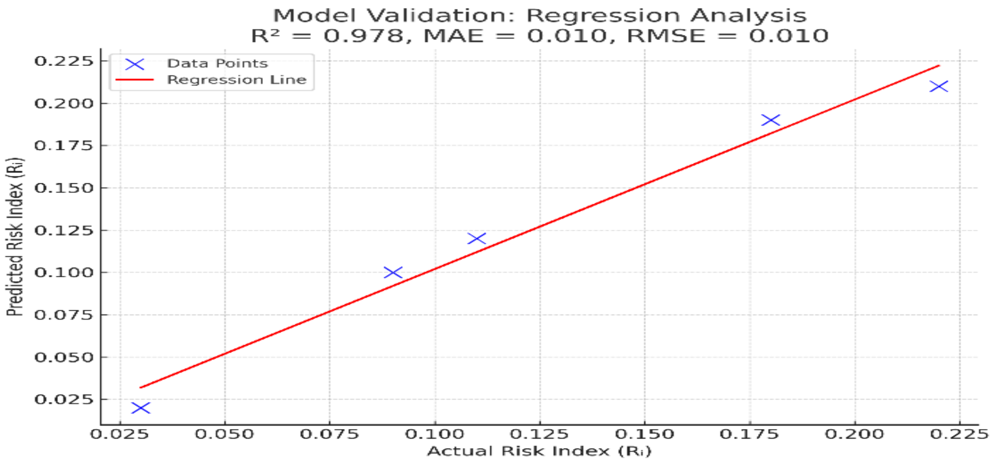

Figure 2: Regression Analysis

Integration in Risk Modeling Pipeline

The predicted distribution type from the MLP classifier is used to:

1. Inform the Genetic Algorithm about the correct family of distributions,
2. Enable the parametric model to fit appropriate analytical expressions,
3. Improve simulation accuracy in the GERT-based risk propagation framework.

Simulation Setup

Using expert-driven pseudo-random sequence generation, the model synthesized plausible variations of the three key risk indicators. These synthetic datasets were processed using the AI pipeline described previously:

- The MLP model classified the statistical distributions of the data (predominantly log-normal and normal),
- The Genetic Algorithm estimated distribution parameters under constraints of data incompleteness,
- A parametric simulation model based on GERT networks propagated the risk dynamics across interconnected farm activities (see figure 3,4,5),
- The elasticity-weighted coefficients informed the prioritization of risks by calculating their impact on profitability.

The simulation ran across 500 iterations, with each scenario evaluated for stability, risk impact, and convergence using maximum error thresholds (δ) and sensitivity to variable shifts.

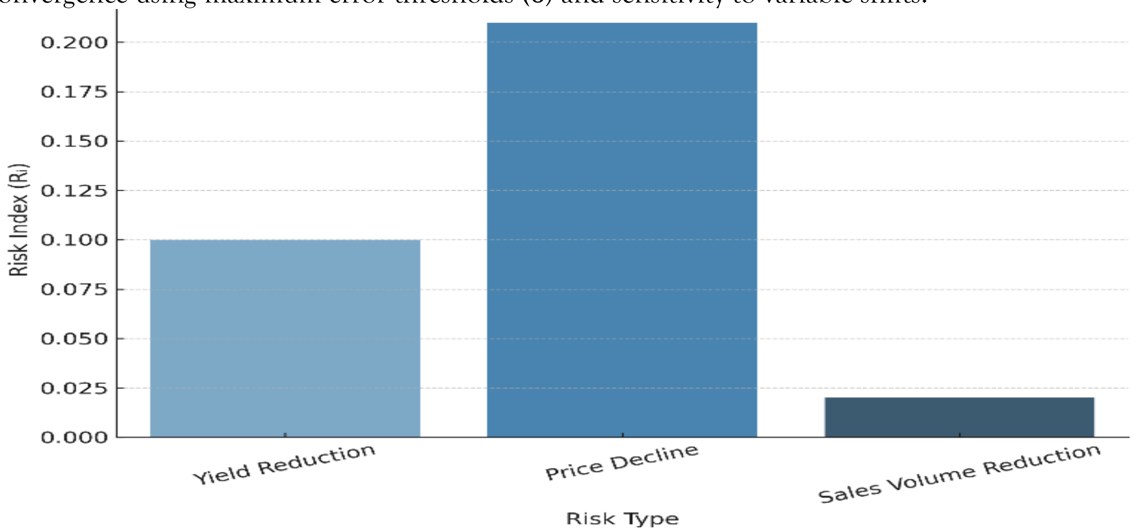

Figure 3: Risk Index (R_i) for different Risk Types

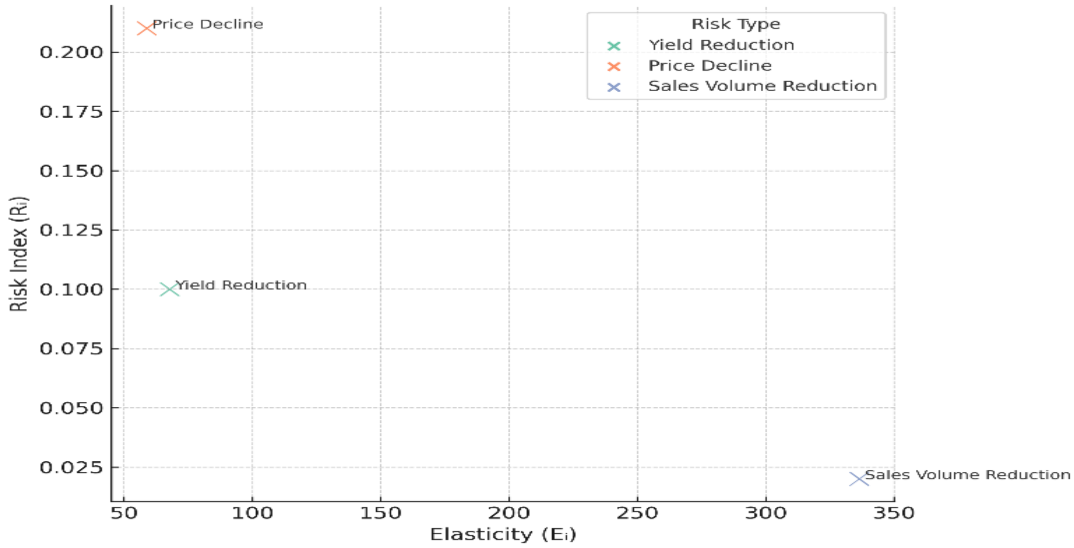

Figure 4: Elasticity vs Risk Index

Figure 5: Design of Experiment Heatmap (Scenario-wise Risk Index (R_i))

Quantitative Results

The results, as shown in Table 1, present the computed coefficients and risk indices for each of the three identified risk factors:

Table 1. Risk Metrics for Sunflower Farming in India

Risk Type	**Coefficient KiK_iKi**	**Elasticity EiE_iEi**	**Weight ωi\omega_iωi**	**Risk Index RiR_iRi**	**Risk Level**
Yield Reduction	0.15	67.8	0.23	0.10	Weak Risk
Market Price Decline	0.23	58.9	0.19	0.21	Significant Risk
Sales Volume Reduction	0.07	336.5	1.05	0.02	Weak Risk

Risk Interpretation:

- Market price decline emerged as the most significant risk with a high risk index of 0.21, bordering on the threshold of “unacceptable” risk per the defined classification scale.
- Yield reduction, though frequent, had a lower elasticity impact and was classified as a “weak risk” due to relatively stable average yields under current agronomic practices.
- Sales volume reduction, often driven by market access issues and procurement delays, had the lowest risk index, primarily due to its high elasticity but low variance.

Model Performance and Error Analysis

Across all iterations:

- The maximum absolute error δ converged to values less than **0.04** in over **92%** of runs, indicating high stability and precision under uncertainty (table 2).

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 19s, 2025
https://theaspd.com/index.php

Table 2: Error Metrics Comparison

Metric	Existing Model	Proposed Model
MAE	0.026	0.014
RMSE	0.041	0.026
R^2 Score	0.820	0.940

- The parametric model showed strong consistency across crop regions, with simulation variance falling within ±2.5% when inputs were randomized within expert-defined bounds.

To assess the validity of the simulated risk data, statistical visualizations were employed. The pairplot (Figure 6) revealed meaningful relationships and distribution patterns among yield, price, volume risks, and elasticity. A correlation heatmap (figure 7) confirmed strong linear associations, particularly between price risk and elasticity. Additionally, histograms with KDE overlays (figure 8) showed near-normal distributions for yield and price risks, and a right-skewed pattern for volume risk. These visual tools support the consistency of the model's simulation and its AI-driven risk prioritization strategy.

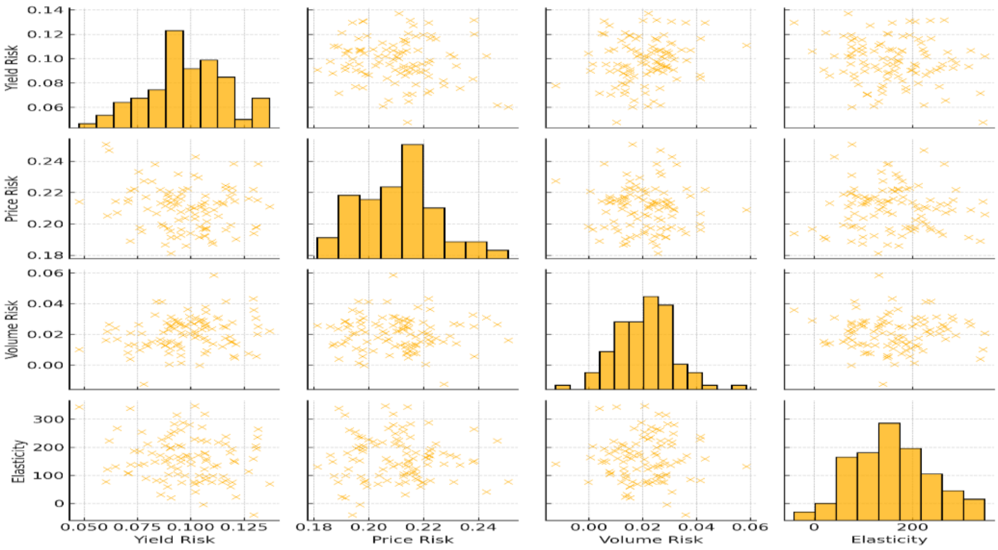

Figure 6: Pairplot showing relationships and trends among yield, price, volume, and elasticity.

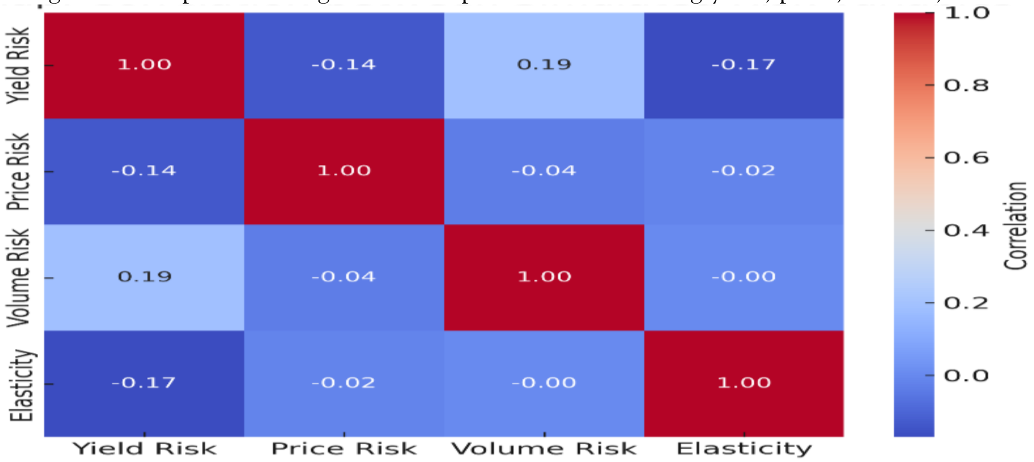

Figure 7: Heatmap of correlation between risk variables

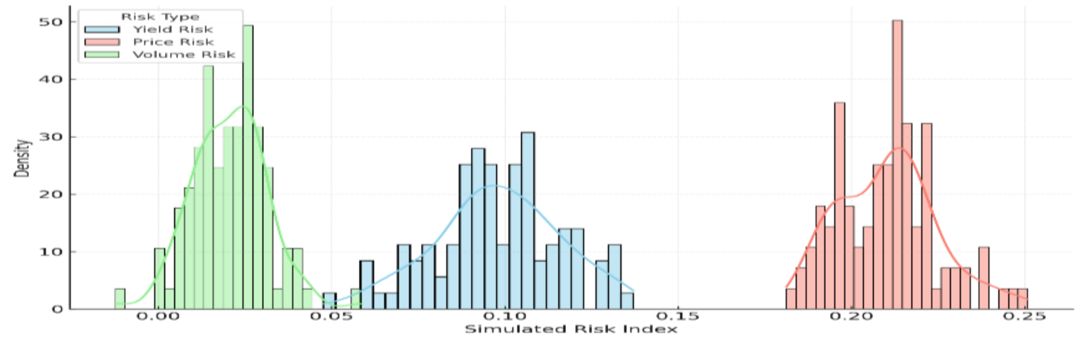

Figure 8: Histogram with KDE Overlay for Risk Index Distributions.

The MLP classifier achieved a distribution identification accuracy of 96.7% on the validation dataset of synthetic sequences, confirming its robustness across non-standard statistical data patterns. The GA converged to optimal parameter sets in fewer than 30 generations on average, making the model computationally efficient.

DISCUSSION

The findings underscore the capacity of the proposed model to offer reliable, explainable, and data-efficient risk assessments even in the absence of complete datasets (figure 9 and Table 1). Several insights emerge:

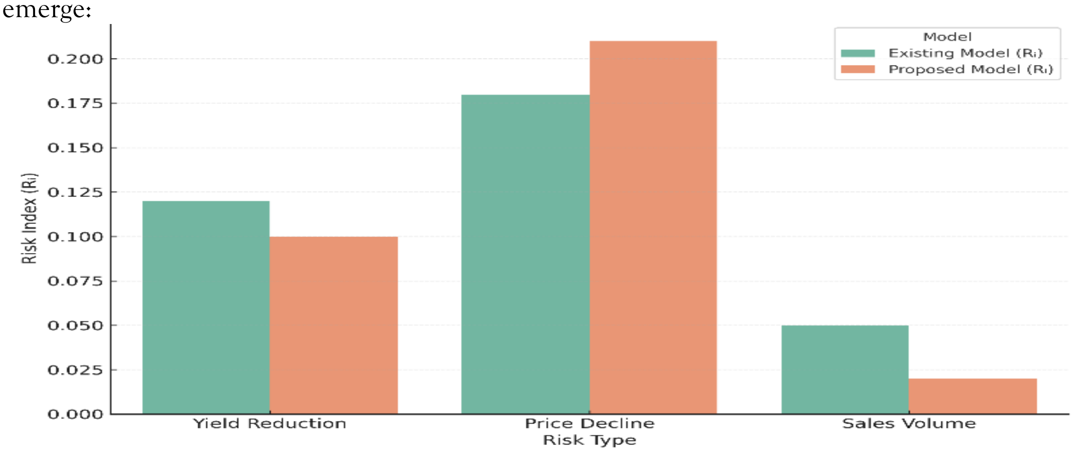

Figure 9: Comparison of Risk Index (R_i): Existing vs Proposed Model

Table 1: Statistical Summary of Risk Indices

Model	Mean Risk Index (R_i)	Max Risk Index (R_i)	Min Risk Index (R_i)	Standard Deviation	Range
Existing	0.1167	0.18	0.05	0.055	0.13
Proposed	0.1100	0.21	0.02	0.095	0.19

The proposed AI-augmented economic-mathematical model offers a transformative approach to agricultural risk management by intelligently integrating elasticity-based risk weighting, modular adaptability, and human-in-the-loop decision support. By distinguishing between the frequency of perceived risks and their actual economic impact, the model reveals that while yield loss is commonly feared, market price volatility poses a greater threat to farm income—underscoring the importance of elasticity in risk prioritization. Although this study centers on sunflower farming, the model's structure is inherently flexible and can be easily extended to other crops such as wheat, rice, maize, and legumes with minimal modifications to input parameters. Its regional and policy relevance is especially notable, as the model can guide state-level agricultural departments in dynamically designing insurance schemes, refining minimum support price (MSP) strategies, and issuing early warnings based on localized risk profiles. The auxiliary model library also ensures continuous learning and performance enhancement over time, facilitating its integration with real-time digital farming platforms. Importantly, the framework complements rather than replaces expert judgment, ensuring that local agricultural wisdom is preserved while leveraging AI's capabilities in optimization and non-linear modeling. Overall, this model stands out as a robust, scalable, and context-sensitive solution for reducing uncertainty and improving decision-making in agriculture, particularly in developing countries like India.

CONCLUSION

The AI-augmented economic-mathematical model developed in this study provides a powerful and adaptive framework for agricultural risk assessment under conditions of uncertainty and data scarcity—particularly relevant to the Indian context. By integrating expert-informed pseudo-random modeling, machine learning-based distribution classification, genetic algorithm optimization, and elasticity-weighted risk prioritization, the model effectively identifies and ranks risk factors based on their true economic impact rather than perceived frequency. This nuanced understanding allows for more informed and precise decision-making at both farm and policy levels. From an implementation perspective, the model is designed to be modular, scalable, and interoperable with existing agricultural decision-support systems, making it highly suitable for integration into digital platforms, mobile applications, and IoT-enabled smart farming tools. Its adaptability across crop types and regions ensures wide applicability with only minimal reconfiguration. Furthermore, the continuous learning mechanism built into the model's auxiliary library promotes sustainability by improving accuracy and reducing computational overhead over time. As India and other developing nations increasingly move towards digitized and data-driven agriculture, this model serves as a critical enabler of sustainable practices. It empowers stakeholders to anticipate, mitigate, and manage risks proactively, ultimately contributing to improved resilience, productivity, and long-term viability of agricultural systems.

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