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Neutrosophic Logic-Based Crop Yield Prediction and Risk Assessment using Least Squares Regression

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Abstract: Agriculture faces significant challenges due to climate change and unpredictable environmental factors, which impact crop yields and threaten food security. This study proposes a novel approach to crop yield prediction and risk assessment using neutrosophic logic and least squares regression. By integrating these methods, we aim to improve accuracy in predicting crop losses under uncertain conditions. The model classifies crops based on profitability and environmental risks, utilizing the independence test to evaluate the relationships between crop attributes. Our approach leverages deep learning techniques, such as restricted Boltzmann machines (RBM), to enhance the analysis of crop data and provide farmers with actionable insights for decision-making. The results demonstrate that the proposed method effectively estimates crop yield damage with the ability to assess risk under varying conditions, such as extreme weather. This approach can help farmers optimize crop management strategies, minimize losses, and improve overall productivity. Future work will explore the application of this method to other crops and farming systems to expand its utility.

Keywords: Neutrosophic Logic; Crop Yield Prediction; Deep Learning; Agricultural Risk Assessment; Least Squares Estimation; Restricted Boltzmann Machines; Climate Impact; Precision Agriculture.

1. Introduction

Agriculture, a crucial component for global survival and energy, has significantly evolved with urbanization and mechanization, despite the challenges posed by climate change and shifts in agricultural practices in regions like India and Canada [1] (Figure 1). In India, paddy field labor presents significant ergonomic challenges for workers, often leading to musculoskeletal issues and increasing the risk of non-fatal occupational accidents [2] (Figure 2). Experts are exploring ergonomic solutions to mitigate these risks, focusing on worker safety, education, and the implementation of safety measures in labor-intensive sectors like rice farming [3].

The increased frequency and severity of natural disasters, such as floods, cyclones, and droughts from 2019 to 2023, have exacerbated pre-existing challenges in agriculture (Figure 3). These disasters, including those in the Atlantic hurricane seasons, have caused substantial financial losses for farmers and disrupted the agricultural value chain [4]. In addition to environmental disasters, pest infestations and disease outbreaks have contributed to significant agricultural production losses, costing farmers billions globally [5] (Figure 4).

Technological advancements in agriculture, such as AI, remote sensing, and machine learning, are helping mitigate these risks and improve crop yield prediction [11] (Figure 5). Farmers now rely on precise tools for yield forecasting and decision-making, which have become essential in optimizing productivity and reducing environmental impact [6]. Emerging methods such as transfer learning and ensemble learning have been applied to integrate various data sources, enhancing yield prediction accuracy and enabling better resource management [12].

This paper explores a novel fuzzy logic-based approach for predicting uncertain crop yields, focusing on the least squares estimation technique. It aims to address the gaps in traditional forecasting methods and develop more robust, adaptable models for diverse agricultural settings. The format of this paper includes an introduction to the topic, a detailed discussion of the proposed methodology, an evaluation of experimental results, and a conclusion summarizing the findings.

2. Uncertainty Crop Estimation using Neutrosophic Logic

Single Crop Neutrosophic logic is the integration of fuzzy, intuitionistic, para-consistent, and intuitionistic reasoning to agriculture. It makes use of the usual unit interval and True, Indeterministic, and False subsets of [0, 1+].

i. $0 \leq T+I+F < 3$ when each of the three elements is autonomous.
ii. $0 \leq T+I+F<2$ identify the circumstance in which the first two components are interconnected while the third is not dependent on the others.
iii. $0\leq T+I+F \leq 1$ when each of the three variables is related.

There is a possibility of incomplete information (sum < 1), para-consistent and conflicting information (sum > 1), or complete information (sum = 1) when three or two of the components T, I, and F are independent. In a similar vein, in the event where T, F, and I are all reliant on one another, there is a chance for either whole knowledge (sum = 1) or partial knowledge (sum< 1).

The three factors used to calculate the yield of a single crop in agriculture are:

i. In reality, farmers are content with crop output as long as they make a profit (T).
ii. The unpredictable nature of the indeterministic state refers to farmer crop loss brought on by climate change (I).
iii. The claim that the government does not have the authority to approve crop yields because there are insufficient water resources in the designated area is untrue (F).

3. Estimate the Crop for Independence Test

Let A be a normal random vector of the crop in agriculture, for instance, paddy [10]. The variables of crop components like profit or loss are independent if they are uncorrelated. i.e.., Cov (A_i, A_j) = 0 then they are uncorrelated so the two attributes' components A_i and A_j are independent. In this section, the unexpected extraordinary properties like damage of risk in the following two cases are used for consistency reliability:

i. Compare the total expenditure on crops and check whether the selling rate of the crop belongs to paddy or not. In this case, if they are not uncorrelated then all investment of paddy belongs to one particular crop. i.e., Cov (A_i, Aj) ≠ 0 and $A_i, A_j \in C$ (A_i, A_j are from Paddy) which means that they are independent and there is a relation between these paddies.
ii. After succeeding from step 1, subtract the expenditure of the crop on estimated crop bags, which is going to be either profit or loss [1]. This test case the independence property between investment on paddy and check whether the selling rate of crop i.e.., Cov (X_i, Xj) ≠0, if any one type of crop is not independent of inputs (investment on paddy, which means it is the target inference for the input i_m.

4. Restricted Boltzmann Machines

Restricted Boltzmann Machines (RBMs) have been instrumental in various agricultural advancements, particularly in integrating smart technologies for more efficient crop management. Agriculture, which encompasses soil cultivation, crop production, livestock rearing, and product marketing, often demands significant land-clearing efforts [1] (Table 1). The introduction of IoT-based smart crop monitoring systems has revolutionized this field by gathering data from sensors placed in agricultural zones. These systems collect critical real-time information, such as soil moisture, temperature, and rainfall data, allowing farmers to optimize farming practices and increase crop yields [2] (Table 2). Furthermore, IoT provides enhanced capabilities for integrating real-time weather data into agricultural decision-making, enabling farmers to improve crop fertility and manage resources more efficiently. Weather forecasting is vital, as accurate predictions can significantly impact crop yields by allowing for better planning and reduced costs [3] (Table 3).

Additionally, integrating real-time data into supply chain management strategies enhances the logistics of moving perishable goods, improving productivity and reducing spoilage. The cultivation of crops in specific geographic regions depends on several factors, including labor availability, technological access, soil topography, and climate [4] (Figure 1). RBMs play a crucial role in analyzing these growth factors across eight distinct agricultural zones.

RBMs, which are essential to deep learning models like Deep Belief Networks (DBNs), are used in various applications such as dimensionality reduction, classification, regression, and feature learning [5] (Figure 2). These deep learning techniques consist of a bias unit and two layers: the visible layer and the hidden layer, facilitating both forward and backward learning phases. The unique ability of RBMs to process large datasets and extract meaningful patterns makes them valuable for agricultural applications. The figure below illustrates the role of RBMs in crop monitoring and yield prediction systems.

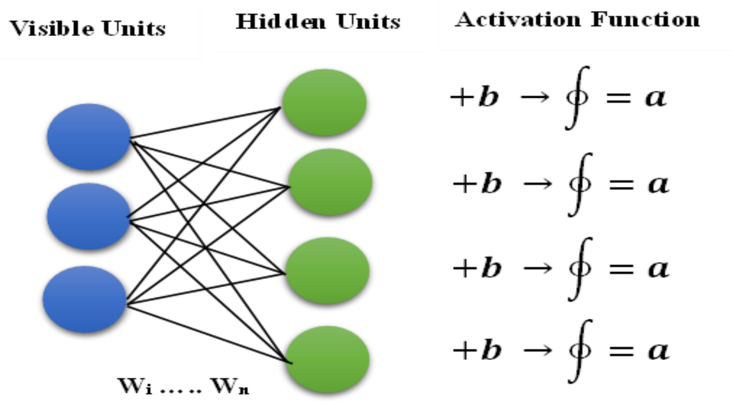

Figure 1. Restricted Boltzmann Machines.

5. Crop Attributes Estimation Procedure on RBM

The accurate risk assessment in agriculture relies on crop parameter estimation, which involves minimizing expenditure and selling prices using a point estimate.

Step 1. Let x_1 be an initial point and Δ be the step size. Compute $x_2 = x_1 + \Delta$.
Step 2. Evaluate $f(x_1)$ $and f(x_2)$.
Step 3. $if\ f(x_1) > f(x_2), let\ x_3 = x_1 + 2\Delta; Else\ let\ x_3 = x_1 - \Delta, Evaluate\ f(x_3)$.
Step 4. Determine $F_{min} = min(f_1, f_2, f_3) and\ X_{min}\ is\ the\ point\ x_i\ that\ corresponds\ to\ F_{min}$.
Step 5. Use points $x_1, x_2,$ and x_3 to calculate $\bar{x}$.
Step 6. Are $\left|F_{min} - f(\bar{x})\right|$ and $|X_{min} - \bar{x}|$ Small? If not, go to Step 7. Else the optimum is the best of the current four points and terminate.

Step.7. Save the best point and bracket it, if possible, otherwise save the best three points. Relabel them according to $x_1 < x_2 < x_3$ and go to Step 4.

6. A Single Crop Developing the Machine Learning Model's Process

The crop farming development process for a machine learning model involves the following steps:

i). Initial Single Crops Farming Dataset: The first crop dataset, consisting of targets and input variables, serves as the foundation for our machine learning system.

ii). Exploratory Crops Data Analysis (EDA): Understanding the agricultural dataset through EDA is essential before starting to build a model. Methods Regression analysis and fuzzy-based independent tests aid in finding patterns and connections in the agricultural data. This phase allows us to gain insights into the distribution of crop data, identify outliers, and potentially identify significant features.

iii). Single Crops Data Preparation and Cleaning: First, any flaws or inconsistencies are removed from the various single crop farming records by cleansing. Following that, the collection of data ensures that the agricultural information is pertinent and properly classified. Lastly, unnecessary features are found and removed to improve the dataset's quality and create a pre-processed farmer single crops dataset.

iv). Single-Crop Features Engineering: Adding new single-crop features or changing existing ones is part of this critical step in enhancing the model's performance. Among the methods used in crop cultivation are:

- Developing Interaction of Crop Features: The process involves combining crop features to identify connections.
- Normalization and Scaling of Each Crop: The process of normalization and scaling each crop ensures that every feature contributes equally to the model.
- Encoding Categorical Variables of Each Crop: The process involves encoding the categorical variables of each crop, thereby providing a numerical representation of the diverse crop data.
- Every Crop Reduction in Dimensionality: The process of reducing the dimensionality of farmer's crop data while preserving most of the variance using transformation techniques.
- Each Crop Data Splitting: The pre-processed Crops dataset is crop data split into 80% for training and 20% for testing, with the test set evaluating the model's performance and the training set for development.
- Crops Farming Data Model Training: The training set undergoes learning techniques like Neutrosophic Logic-based Independent Test and Regression, with parameters adjusted through hyperparameter optimization and key variables identified through feature selection.
- Various Crops data Cross-validation: Differential Crops information to make sure the model is reliable and generalizable, cross-validation techniques are used to assess the model's performance on various subsets of the training set.
- Evaluation of Crops Farming Models: The performance of crop farming models is evaluated using metrics like R2, MSE, and RMSE for classification and regression jobs, using a 20% test set.
- Every Crop Farming Evaluation of Performance: The evaluation of crop farming performance involves comparing expected output values to actual test set values to ensure the model's effectiveness in generalizing to fresh, untested data.

These procedures will help us create a solid machine-learning model that reliably forecasts results from farmers' different crop input data.

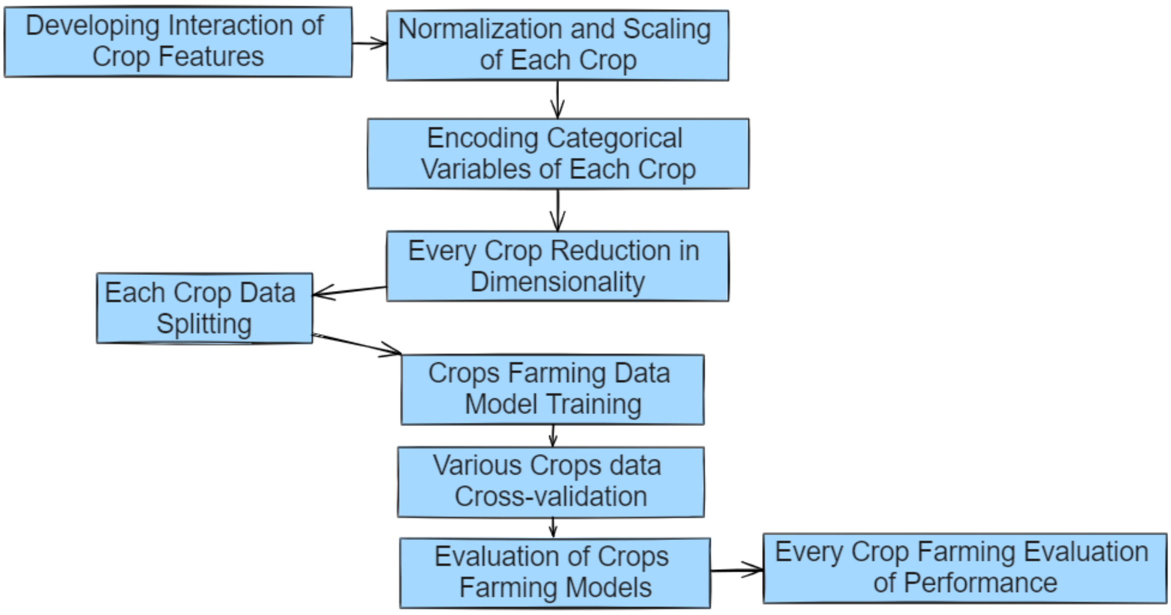

Figure 2. Developing a process for the machine learning model.

7. Least Square Risk Estimation of Crop

The estimation of various crop parameters is crucial for accurate risk prediction in the agricultural sector [11, 12]. Unbiased regression, a statistical methodology, estimates the value of one variable (such as spending) from the value of another variable (such as crop yield) using mathematical and visual methods. In this study, the risk of crop failure is evaluated using an algebraic approach known as least squares estimation. This method determines the best possible mean value of one variable corresponding to the mean value of another. The normal equation can be solved to provide the coefficients for the rice risk identification model from the single-crop data set, represented by the equation Y=a+bX (Figure 1).

Regression equation of y on x:

$$\sum y = b\sum x + Na$$
$$\sum xy = b\sum x^2 + a\sum x$$

Regression equation of x on y:

$$\sum x = b\sum y + Na$$
$$\sum xy = b\sum y^2 + a\sum y$$

In this case, it is simple to compute the values of a and b to find the value of y for any given value of x or x for any given value of y. The aforementioned normal equations are used to determine the values of a and b.

8. Experimental Results

The results of a separate experiment predicting farmers' crop yields using a fuzzy algorithm were analyzed, with crop diversification among farmers gauged by performance metrics and losses for those employing Least Squares estimation on Restricted Boltzmann Machines (RBMs). The experiment focused on a sample of 160 farmers, collecting data from regions where crops such as rice, bananas, coconuts, turmeric, and other produce were cultivated [1].

Farmers' crop productivity and yield outcomes either increased or decreased based on various factors, including environmental conditions. For instance, heavy rains in 2023 caused significant agricultural damage. The regression analysis used crop yield damage (y) as the dependent variable, with independent variables such as crop weight (x1), investment amount (x2), and the number of crops harvested (x3), to predict losses and productivity. The experiment's primary goal was to assist farmers in evaluating crop losses due to environmental impacts, such as diseases, pests, climate change, natural catastrophes, and human activities.

By comparing yields from damaged crops against healthy crops, farmers could identify areas where interventions were needed. A specific case involved a farmer with 6 acres of land in the Undi Mandalam village, where regression analysis using Least Squares estimation assessed crop loss. The results revealed that external factors like heavy rain directly impacted the yield, and the regression model provided insights into how variables such as crop weight and investment amount could predict potential losses [2].

Table 1. Dataset of different crops Undi Mandalam village.

S.No.	Crops Names	Damage (y)	Crop Weight (100kgs)/Quintal (x_1)	Invest Amount(x_2)	Received(x_3)
1	Rice	15000	25	10000	15000
2	Banana	12000	50	30000	18000
3	Turmeric	15000	50	10000	14000
4	Kandha	13000	60	33000	22000
5	Coconut	14000	10	11000	24000
6	Coco	12000	30	10500	15000
Total		81,000	220	1,04,500	1,08,000

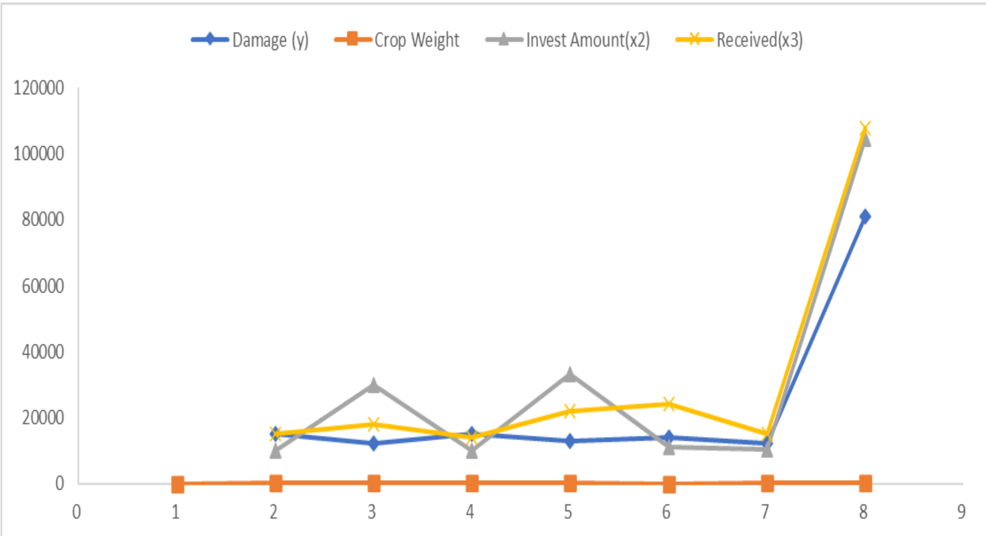

Figure 3. Input variables of different crops.

Here, n=6. Substitute the Harvesting data from the following Table 1, in the normal equations:

$\sum y = N b_0 + b_1 \sum x_1 + b_2 \sum x_2 + b3 \sum x_3$

$\sum x_1 y = b_0 \sum x_1 + b_1 \sum x_1^2 + b_2 \sum x_1 x_2 + b_3 \sum x_1 x_3$

$\sum x_2 y = b_0 \sum x_2 + b_1 \sum x_1 x_2 + b_2 \sum x_{2i}^2 + b_3 \sum x_2 x_3$

$\sum x_3 y = b_0 \sum x_3 + b_1 \sum x_3 x_1 + b_2 \sum x_2 x_3 + b_3 \sum x_{3i}^2$

So that,

$81{,}000 = 6b_0 + 220 b_1 + 104500 b_2 + 108000 b_3$

$3005000 = 220 b_0 + 10{,}225 b_1 + 4655000 b_2 + 3985000 b_3$

$1369000000 = 104500b_0 + 4655000b_1 + 2420250000 b_2 + 1977500000 b_3$

$1425000000 = 108000b_0 + 3985000b_1 + 1977500000b_2 + 2030000000b_3$

Solving we get

$b_0 = 18211.882$

$b_1 = 60.3507262$

$b_2 = -0.10716$

$b_3 = -0.281017$

Thus, the required regression plane is $y=18211.882+60.3507262x_1+(-0.10716)\ x_2$. Estimate:

i). For a Rice Crop damage of per acre (x_1=25 and x_2=10000), the damage incurred in rupees is y (x_1=25, x_2 = 10000) = 18211.882+60.3507262*25+(-0.10716)*10000=19718.5-1071.6.y=18646.9. The estimated rupee value for Rice Crop damage per acre is y=18646.9.

ii). For a Banana Crop damage per acre (x_1=50 and x_2=30000), the damage incurred in rupees is y (x_1=50, x_2=30000) =18014.61. The estimated rupee value for Banana Crop damage per acre is y=18014.61 so on.

a) Estimation of Crops for Independence Test Using Regression Model: The output includes multiple correlation values, coefficient of determination, adjusted R Square, and standard error, indicating the correlation between response and predictor variables. The statistical test known as analysis of variance compares the means of several groups using one or two independent variables. It also divides the overall variability into factors that are random and systematic and ascertains the impact of independent variables on dependent variables.

Table 2. Regression statistics.

Regression Statistics	
Multiple R	0.973059
R Square	0.946843
Adjusted R Square	0.683554
Standard Error	3828.583
Observations	6

Analysis of Variance is a statistical method that disperses variance among several sources and compares group averages. It is comparable to multiple two-sample t-tests. It can be applied to one-way or two-way analyses to ascertain changes in the dependent variable in Table 3 below.

Table 3. Analysis of variance

ANOVA					
	df	SS	MS	F	Significance F
Regression	2	1.04E+09	5.22E+08	35.62439	0.008122
Residual	4	58632185	14658046		
Total	6	1.1E+09			

Table 4. The intercept represents the difference between the response variable's mean and the product of the slope and the explanatory variable's mean.

	Coefficients	Standard Error	t-Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
Invest Amount (x_2)	-0.09399	0.172275	-0.5456	0.614341	-0.5723	0.384319	-0.5723	0.384319
Received(x_3)	0.807326	0.188107	4.291852	0.012727	0.285058	1.329593	0.285058	1.329593

Table 5 Linear regression involves a residual, which represents the difference between the actual and predicted value (y-ŷ) at a specific point, and a least-squares model minimizes the sum of these residuals.

Table 5. Probability outputs.

Probability Output	
Percentile	Damage (y)
8.333333	12000
25	12000
41.66667	13000
58.33333	14000
75	15000
91.66667	15000

Figure 4 shows the x-axis denotes the investment of a crop, and the y-axis indicates the residual of crop investment.

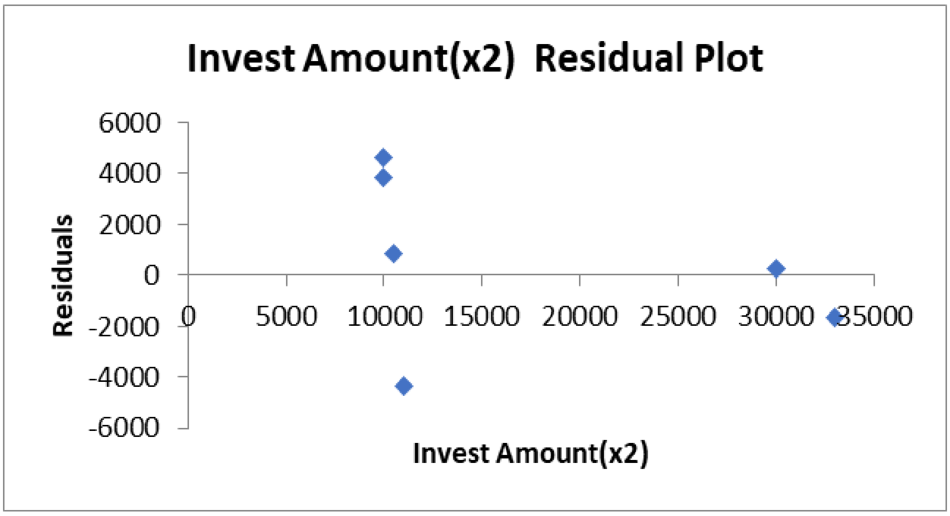

Figure 4. Two Variables residual plots of different crops.

Figure 5 shows the x-axis denotes investment in the crop, and the y-axis indicates the damage to the crop.

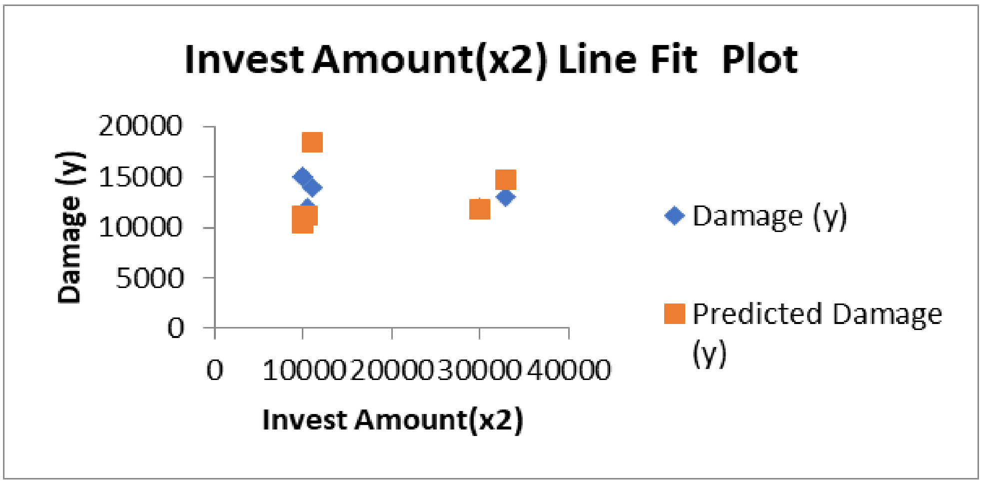

Figure 5. Invest amount plot.

Figure 6 shows that the x-axis denotes predicted damage and the y-axis shows damage.

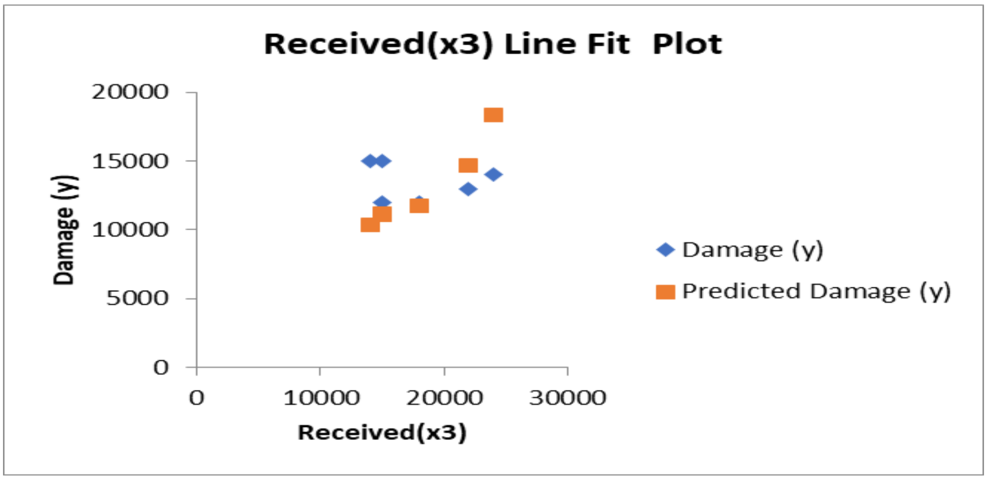

Figure 6. Received amount of Plots of different crops.

Figure 7 shows are y-axis residuals of different crops and the x-axis denotes the received amounts of different crops.

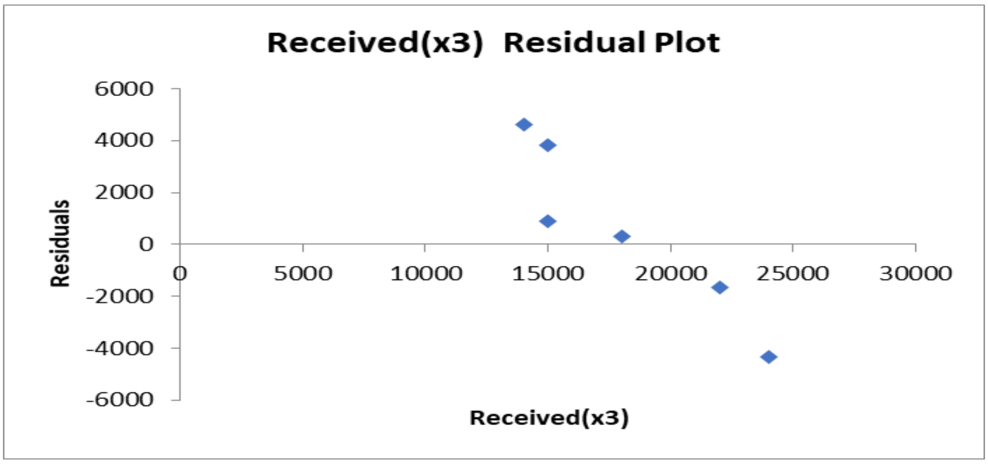

Figure 7. The residual of the received amount of different crops.

Table 6. Residual output of different crops.

Residual Output			
Observation	Predicted Damage (y)	Residuals(X3)	Standard Residuals(X3)
1	11169.96	3830.045	1.225212
2	11712.07	287.9275	0.092107
3	10362.63	4637.37	1.483472
4	14659.4	-1659.4	-0.53083
5	18341.89	-4341.89	-1.38895
6	11122.96	877.0411	0.280561

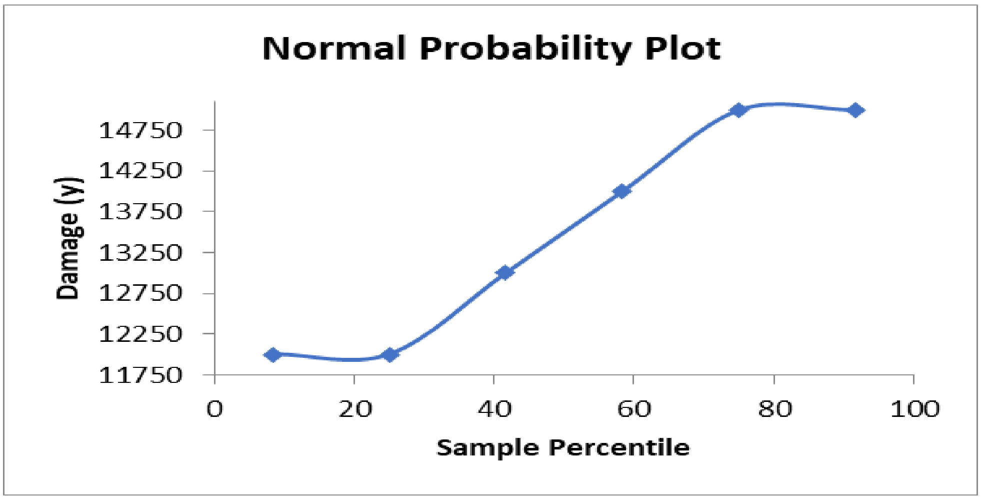

Figure 8. Probability Plot of different crops.

The p-value in a regression model indicates the degree of evidence contradicting the null hypothesis, with a low p-value indicating a statistically significant relationship between variables and responses.

b) Crop growers use artificial intelligence for tasks like crop forecasting, and assessing precision and accuracy as key indicators of observational error.
Single Crops Farming Accuracy: The "Rand index" is a statistical measure that compares pre- and post-test probability estimates for single crop farming performance accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where FN = False negative, TN = True negative, FP = False positive, and TP = True positive.

$$Accuracy = \frac{1 + 90}{1 + 90 + 1 + 8} = 0.91$$

The model demonstrated its effectiveness in class-imbalanced crop data, with a 91% accuracy rate in loss prediction for 100 farmers, despite only correctly estimating one out of nine samples.
Single Crops Farming Precision: Precision in single-crop farming refers to the percentage of accurately classified occurrences or samples, determined by a specific formula.

$$Precision = \frac{TP}{TP + FP}$$

where FN = False negative, FP = False positive, and TP = True positive.
Based on a yield dataset from 160 farmers, the model predicts the ambiguity of single-crop farming with 105 correct predictions and 55 false positives. True Positives (TP) and False Positives are used to obtain the accuracy value for single-crop farming (FP). The Single Crops Farming Precision is calculated as follows:

$$Precision = \frac{105}{105 + 55} = 0.66$$

Therefore, the precision of the Single Crop Farming model is 0.66.

9. Conclusion

The agricultural industry faces threats from pests, diseases, extreme weather, and market fluctuations. To increase productivity, smallholder farmers should grow a variety of crops. In 2023, heavy rain damaged harvesting, affecting farmers' livelihoods. Crop loss is estimated using least square regression analysis on several plots in a neutrosophic logic and independent test. An independent test using deep learning and neuromorphic logic suggests the yield productivity range of crops cultivated on a farmer's 6 acres. In the experiment, a lone farmer estimated crop damage per acre for rice and other crops by applying least squares estimation and neutrosophic logic techniques to predict crop risk.

Declarations

Ethics Approval and Consent to Participate

The results/data/figures in this manuscript have not been published elsewhere, nor are they under consideration by another publisher. All the material is owned by the authors, and/or no permissions are required.

Consent for Publication

This article does not contain any studies with human participants or animals performed by any of the authors.

Availability of Data and Materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare no competing interests in the research.

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Author Contribution

All authors contributed equally to this research.

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