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FarmTrend Insights: Harnessing Regression-Fuzzy Models for Farmer Economic Predictions

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Abstract

India, often referred to as an agricultural country, has 52% of its population engaged in agriculture. The agricultural sector's prosperity is heavily dependent on regional climatic conditions. Adverse weather events significantly impact farmers' economic stability, exacerbating existing pressures and contributing to high rates of farmer suicides. This paper proposes a novel solution: the integration of regression-fuzzy models for predicting the economic conditions of farmers. By utilizing historical weather data spanning the past decade, this model aims to forecast economic fluctuations and mortality rates among farmers. The primary objective is to reduce the mortality rate by providing accurate predictions based on weather impacts on crop production, specifically focusing on Kharif and Rabi seasons. Through the application of fuzzy clustering and rule generation, the model classifies farmers' economic conditions and assesses the influence of weather on their production. This approach offers actionable insights to enhance economic resilience and mitigate distress in the agricultural sector.

Keywords: agriculture, economic prediction, fuzzy logic, K-means clustering, regression-fuzzy model, weather impact, farmer mortality, crop production.

1. Introduction

Most Asian countries, including India, are heavily dependent on agriculture, which plays a crucial role in their economies. In India, agriculture is a primary livelihood for a significant portion of the population. As an agricultural nation, India relies on this sector for about seventy percent of its workforce. Agriculture not only supports various industries by providing food, wood, raw materials, and shelter [1] but also sustains the flow of food and money necessary for basic needs and economic stability. Adequate stock and flow of resources, alongside secure access to income-generating activities and assets, are vital for offsetting risks, easing shocks, and meeting contingencies [2].

According to Hurst, Termine, and Karl, Indian agriculture, like global agriculture, faces numerous challenges in the coming decades, necessitating increased food production to support growing and affluent populations. The rural economy in India is plagued by economic issues, diseases, and limited farming diversification. Livelihood diversification is essential for economic stability, food security, and improved incomes for rural farming communities [3].

India, being an agrarian country, has around 60% of its population reliant directly or indirectly on agriculture. Alarmingly, farmer suicides constitute 11.2% of all suicides in India [4]. Researchers and activists have identified several causes for this distress, including monsoon failures, high debt burdens, genetically modified crops, governmental policies, public mental health issues, personal matters, and family problems [5]. In 2014, the National Crime Records Bureau of India reported 5,650 farmer suicides [4], with the highest number recorded in 2004, when 18,241 farmers took their own lives. Over a decade, the farmer suicide rate in India has fluctuated between 1.4 to 1.8 per 100,000 people.

This paper primarily focuses on the weather factors influencing farmers' economic conditions. The author has compiled two sets of data for computational experiments, using weather data from the past ten years. Based on this data, the authors predict mortality rates among farmers, aiming to reduce these rates caused by uncertain weather conditions. The study classifies farmers' economic conditions and assesses the weather's impact on their crop production, particularly during the Kharif and Rabi seasons. By analyzing these conditions, the authors aim to forecast and ultimately reduce the mortality rate among farmers.

The structure of this paper is as follows: Section 2 analyzes the literature review, Section 3 analyzes the study region and details the data collected from 2004 to 2014. Section 4 discusses the tests applied to this data. Section 5 presents and verifies the Regression-Fuzzy model, including fuzzy clustering. Finally, Section 6 summarizes and concludes the study.

2. Literature Review

The impact of climate change on agriculture has been a critical area of research, with various studies highlighting its effects on crop yield, agricultural productivity, and farmer livelihoods. This literature review synthesizes key findings from previous studies and situates the current work within this context.

Aggarwal, Kumar, and Pathak (2010) examined the impacts of climate change on the growth and yield of rice and wheat in the Upper Ganga Basin. Their study provided empirical evidence on how rising temperatures and changing precipitation patterns adversely affect staple crop production, which directly impacts farmers' economic conditions.

Arora (2019) discussed sustainable solutions to counteract the negative effects of climate change on agriculture. This study emphasized the need for adaptive strategies, such as improved crop varieties and better water management practices, to sustain agricultural productivity under changing climatic conditions

Arshad and Shafqat (2012) focused on food security indicators and techniques for sustainable agriculture in Pakistan. They highlighted the importance of adopting innovative agricultural practices to enhance food security and support farmer livelihoods amid climate challenge .

Barve, Kumar, and Viswanathan (2021) explored the relationship between weather variability, agricultural productivity, and farmer suicides in India. Their findings underscored the severe socio-economic consequences of climatic fluctuations, linking poor harvests to increased farmer suicides.

Chakraverty (2022) edited a comprehensive volume on the application of soft computing techniques in interdisciplinary sciences, including agriculture. This work demonstrated the potential of fuzzy logic and heuristic models in addressing complex agricultural problems.

Das (2011) examined the public health implications of farmers' suicides in India, attributing these tragic events to the financial stress caused by crop failures and debt burdens exacerbated by climatic uncertainties.

De Salvo, Begalli, and Signorello (2013) provided a literature review of analytical models measuring the effects of climate change on agriculture. Their review highlighted the diversity of modeling approaches and the importance of selecting appropriate models to accurately capture the multifaceted impacts of climate change on agricultural systems.

Gadgil (1995) offered an early perspective on climate change and agriculture in India, identifying critical areas for research and policy intervention to mitigate adverse effects on crop production and food security.

Gupta, Rana, and Kansal (2020) compared various heuristic techniques, including those used in agricultural contexts, emphasizing the efficiency and applicability of these methods in solving complex optimization problems like crop planning and resource allocation.

Karimi, Karami, and Keshavarz (2018) discussed the impacts of climate change on agriculture in Iran and adaptive responses. Their study highlighted the need for localized adaptation strategies to ensure agricultural sustainability under climate stress.

Kumar (2016) investigated the role of modeling in achieving food security by assessing the impacts of climate change on crop yields. This work underscored the importance of predictive models in planning and decision-making processes to enhance food security.

Lakhiar et al. (2018) reviewed intelligent sensor techniques in agriculture, demonstrating the potential of these technologies in monitoring and controlling agricultural systems to improve productivity and resilience against climate variations.

Mehrabi and Ramankutty (2019) examined the synchronized failure of global crop production, emphasizing the interconnected nature of agricultural systems and the potential for widespread crop failures due to global climatic events.

Ng, Soong, and Teh (2021) discussed the application of machine learning in food security and sustainability, highlighting the potential of advanced computational techniques to address complex agricultural challenges and enhance sustainability.

Ngandee et al. (2021) assessed rice yield prediction models based on big data analytics, demonstrating how data-driven approaches can improve supply chain decision-making and enhance agricultural productivity.

This comprehensive review of the literature reveals a broad consensus on the significant impacts of climate change on agriculture and the need for innovative modeling approaches to predict and mitigate these effects. The current study builds upon this foundation by developing a Regression-fuzzy heuristic model that integrates fuzzy logic and regression analysis to provide nuanced predictions of farmers' economic conditions based on weather and crop production data.

3. Data Collection and Analysis

The paper analyzes the daily weather data: minimum and maximum temperature, minimum and maximum relative humidity, rainfall, precipitation, wind speed, sea level pressure and dew point recorded from 2004 to 2014 for New Delhi, Ghaziabad and the adjoining regions are taken for the study.

3.1 Characterization of agriculture in the study area

Wheat and Cereals, which are grown in the Rabi season, are the significant yield around here. Rice and Maize are developed during the Kharif season. The region under rice fluctuated from 24 to 56 thousand hectares in various areas and the region under wheat differed from 110 to 287 thousand hectares [6]. Kharif crops are planted with the start of the primary first rain towards the finish of May in the southern province of Kerala during the coming southwest rainstorm season. As the monsoon season moves towards the north India, the planting dates differ for the Kharif and Rabi at July in north Indian states. These yields are subject to the amount of rainwater also its planning. To an extreme, excessively little or at wrong time might endanger or destroyed the entire year's endeavors. Rabi crop follows to farming the yields planted in winter and gathered in the spring. It is the spring harvest (otherwise called the "winter crop") in Indian subcontinent. The Rabi crops are processed between the months mid-November to April. The fundamental Rabi crop is wheat [7].

3.2 Data Collection

The weather knowledge for last ten years (2004 to 2014) was collected and analysed. The data was collected of the past 10 years of the subsequent 3 major parameters: Average Mean Temperature, Average Humidity and Average Wind Speed.

3.2.1 Average Mean temperature: From the temperature information of 2004 to 2014 , the mean average temperature of the region throughout Kharif season (June to September) raged from 34.1821^{0}C to 29.3636^{0}C. Thus, the temperature data being normal seeing the temperature data it has been analyzed that New Delhi from 2004 to 2014 have received average temperature equal to 27.41^{0}C (81.35^{0}F) [17].

Fig 1 shows the graph showing the year-wise average temperature of past 10 years (2004-2014). The graph shows the temperature difference from 24.8910^{0}C to 26.2271^{0}C from 2004 to 2014.Fig 2 shows the Time Series plot of Annual Average Temperature of all the months. The maximum temperature increase is during the Kharif season that from June to September. There is a sharp drop in temperature during the Rabi season that is from September to October.

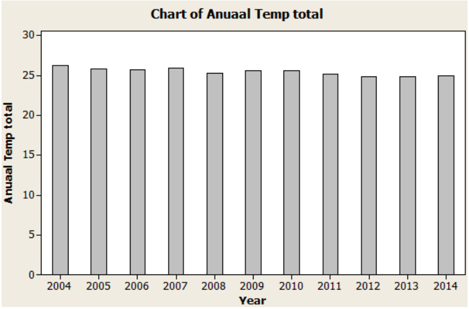

Fig 1 shows Year-wise average temperatureat New Delhi (in ^{0}C) from 2004 to 2014.

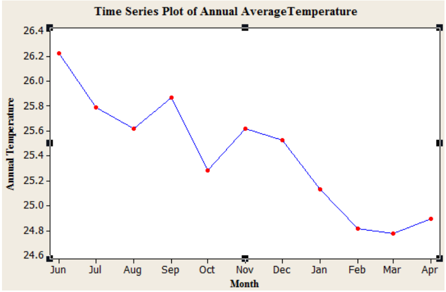

Fig 2 shows Time Series plot of Annual Average Temperature at New Delhi (in ^{0}C) from 2004 to 2014.

3.2.2 Average Humidity: Fig 3 shows the graph showing the year-wise average humidity at New Delhi from 2004 to 2014. The graph shows the difference in humidity being 57.206625% to 59.546075% from 2004 to 2014. Fig 4 shows the Time Series plot of Annual Average Humidity showing the average annual humidity of all the months. The region experienced maximum annual humidity from March to April and the minimum from November to December [17].

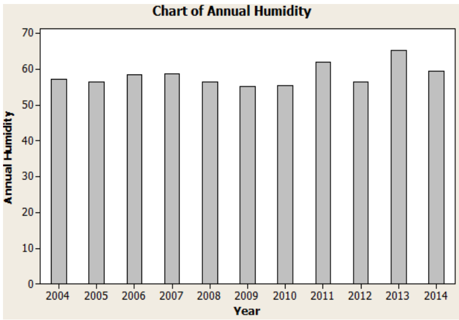

Fig 3 shows Year-wise average humidity of day at New Delhi (in %) from 2004 to 2014.

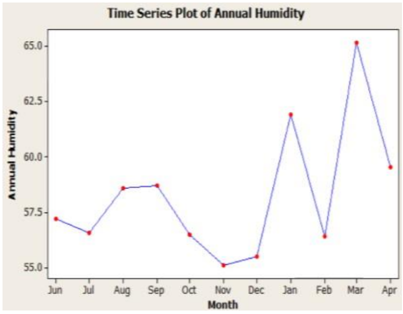

Fig 4 shows Time Series plot of Annual Average Humidity at New Delhi (in %) from 2004 to 2014.

3.2.3 Average Wind Speed: Fig 5 shows the graph showing the year-wise average wind speed at New Delhi from 2004 to 2014. The graph shows the speed difference from 8.053285 km/h to 7.827349167 km/h from 2004 to 2014. Fig 5 shows the Time Series plot of Annual Average Humidity showing the average annual wind speed of all the months. The maximum beingfrom August to September and the lowest from June to July [17].

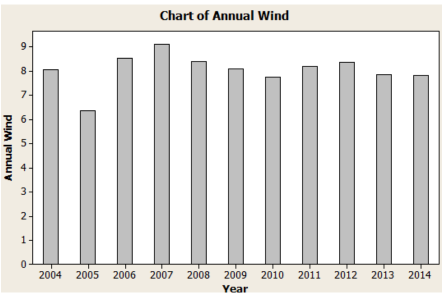

Fig 5 shows Year-wise average wind speed of day at New Delhi (in km/h) from 2004-2014.

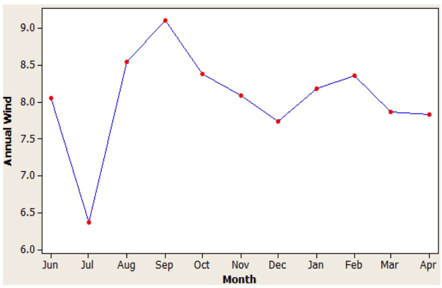

Fig 6 shows Time Series plot of Annual Average Wind Speed at New Delhi (in km/h) from 2004-2014.

3.2.4. Production of Rabi and Kharif crops: The further analysis has been done, the data has been refined for Kharif and Rabi seasonsseparately. The average temperature, average wind and average humidity of each of these categories are separated. Two major crops each season are taken into consideration. For the Kharif season- Rice and Maize and for the Rabi Season-Cereals and Wheat. The yearly productions of each of these crops have been taken into consideration. Hence the data is collected for the yearly production of rice, maize, wheat and cereals for the Kharif and Rabi season [19, 20]. The yearly production is in terms of milliontons.

3.2.5. Standard Mortality Rate:It is the measure to calculate the Absolute number of suicides happened. Henceforth similar number of suicides could have an alternate significance on the grounds that the quantity of farmer is unique. As such, it might just happen that in two years similar number of ranchers has ended it all however in the second year the complete number of ranchers is lower than in the first. This should truly intend that from an overall perspective the suicides were higher in the subsequent year. So, one requirements a relative estimation to check the seriousness of the issue. For that reason scientists gauge number of suicides per 1,00,000 populace. This number is called self-Mortality Rate death rate (SMR). We have gathered the beyond 10 years of rancher's SMR [18].

4. Statistical Analysis

The Kharif season starts in June and is the time of the year when in rice is sown in the study region. From the time series plot graph it is noticed that the month of June has experienced the highest temperature in the last 10 years among all the other months. However there has been an increase in temperature in the month of June since 2004 to 2014.
The Rabi season starts in the month of November and last in April.

4.1 The Hypothesis

Null Hypothesis
H_0: Temperature wind and Humidity data do not affect the production of crops
Alternate Hypothesis
H_1: Temperature wind and Humidity data affect the production of crops

4.2 Chi-Square Test Analysis

Table 1. Chi-Square test results for the Kharif and Rabi season respectively

Kharif season	**Rabi season**
The test shows: • Mean value obtained is 25.41. • The standard deviation 0.4741. • The P-Value of 0.2	The above test shows: • Mean value obtained is 25.41. • The standard deviation 0.4741. • The P-Value of 0.2

The p-value >0.05 means that we reject the null hypothesis and accept the alternate hypothesis that the data is normal. Hence in our case the null hypothesis is rejected and alternate hypothesis is accepted. Therefore,these shows:
Temperature wind and Humidity data affect the production of crops.

5. Regression Fuzzy based Model(Regro-Fuzzy)

5.1 Regression Test Analysis

Table 2. Regression Test Variables for the Kharif and Rabi season respectively.

	Kharif season	**Rabi season**
Dependent variables	SMR (per 1,00,000 persons)	SMR (per 1,00,000 persons)
Independent variables	temperature, humidity, wind, rice production, maize production	temperature, humidity, wind, wheat production, cereal production
Obtained R	0.961	0.987
Obtained R Square	0.924	0.974

The "R" section addresses the value of R, the numerous relationship coefficients. R can be viewed as one proportion of the nature of the expectation of the reliant variable. For this situation, SMR.The acquired values of R in all the cases esteem demonstrates a decent degree of expectation. The "R Square" segment addresses the R^2 esteem (likewise called the coefficient of determination), which is the extent of fluctuation in the reliant variable that can be clarified by the autonomous factors (actually, it is the extent of variety represented by the relapse model far more than the mean model). Our worth of 0.924 and 0.974 shows that our free factors clarify 92.4% and 97.4% of the changeability of our reliant variable individually. Anyway the "Changed R Square" (adj. R^2) precisely reports the information.

5.2 Statistical significance

The F-ratio in the ANOVA table1 tests whether the overall regression model is a good fit for the data. The table2 shows that the independent variables statistically significantly predict the dependent variable

- $F(5,4) = 9.679$, for Kharif season
- $F(5,4) = 29.988$, for Rabi season

5.3. Proposed Model

The general form of the equation to predict SMR from Temperature, Humidity, Wind and Production is described in Table 3. Using the proposed model The SMR value has been calculated and shown in Table 4 and Table 5 for Kharif and Rabi season respectively.

Table 3. It showsthe Proposed Model for Kharif and Rabi season.

Kharif season	**Rabi season**
SMR=14.122-(.048xtemp) -(.017xhumidity) +(.192x wind) -(.170 x maize_production) -(.037 x rice_production). ……………(**1**)	SMR=7.751+(.332xtemp)-(.040xhumidity)+(.079 x wind)-(.065 x wheat_production)-(.013 x cereal_production). ……………(**2**)
where, temp denotes temperature in ^{0}C, humidity denotes humidity in %, wind denotes wind speed in km/h, maize_production denotes production of maize in million tonnes, rice_production denotes production of rice in million tonnes.	where, temp denotes temperature in ^{0}C, humidity denotes humidity in %, wind denotes wind speed in km/h, wheat_production denotes production of wheat in million tonnes, cereal_production denotes production of cereal in million tonnes.

Year	Temperature(^{0}C)	Humidity (%)	Wind Speed(km/h)	Rice Production (million tons)	Maize Production (million tons)	SMR	Calculated SMR
2004	30.0054	63.7129	8.0462	83	14	7.70	7.66
2005	29.6530	68.5331	6.4675	92	15	7.15	6.88
2006	29.1691	64.1732	8.2016	93	15	7.04	7.18
2007	30.1522	60.6143	8.6994	97	19	6.77	6.51
2008	28.8436	64.8304	8.2097	99	20	6.60	6.19
2009	29.6059	61.8035	7.9871	89	17	6.60	7.05
2010	28.5218	78.1777	7.8511	80	22	6.39	6.26
2011	28.7159	71.1938	8.5328	105	23	5.57	5.43
2012	28.7250	69.7508	8.0938	105	22	5.41	5.43
2013	28.8936	76.2428	7.4946	107	24	4.58	4.80

Table 4. It shows the value of SMR calculated using the proposed model for Kharif season.

Table 5. It shows the value of SMR calculated using the proposed model for Rabi season.

Year	Temperature(^{0}C)	Humidity (%)	Wind Speed(km/h)	Rice Production (million tons)	Maize Production (million tons)	SMR	Calculated SMR
2004	20.4110	62.0405	6.1447	69	33	7.70	7.73
2005	19.7319	62.4225	5.0716	69	34	7.15	7.36
2006	20.1772	64.4235	6.7624	76	34	7.04	7.14
2007	19.3968	61.2255	7.2818	79	41	6.77	6.80
2008	19.9341	56.9792	7.3388	81	40	6.60	7.03
2009	19.8331	59.5903	6.1287	81	34	6.60	6.85
2010	19.9390	54.8645	5.9607	87	43	6.39	6.57
2011	19.2173	63.6872	6.5610	95	42	5.57	5.51
2012	18.4198	59.3623	6.7426	94	40	5.41	5.55
2013	18.7054	71.6633	6.5655	96	43	4.58	4.95

Figs 7 and 8 show theHistogram graphs for Kharif and Rabi season respectively. The graphs have a mean of 3.69 and -0.48 respectivelyand a standard deviation of 0.66 and 0.66respectively. This shows that our model for the SMR ratio deviates by 0.66 from the mean in both cases.

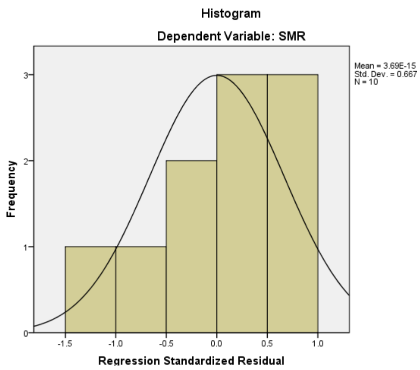

Fig 7 shows Histogram showing the result of the regression test of Kharif season

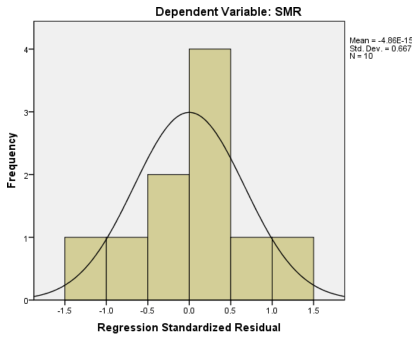

Fig 8 shows Histogram showing the result of the regression test of Rabi season

5.4 Result Verification

Thus below is the comparison of the observed and calculated value of SMR of Kharif and Rabi season.

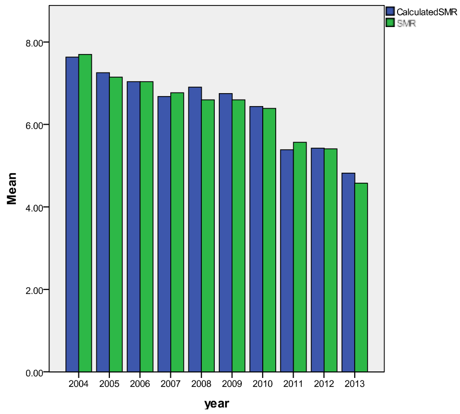

Fig 9 showsComparison of observed and calculated SMR for Kharif season

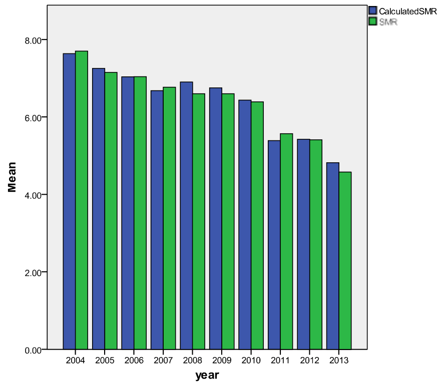

Fig 10 showsComparison of observed and calculated SMR for Rabi season

5.5 Regro-Fuzzy Clustering

5.5.1 Normality testing

The Table6 below presents the results from two well-known tests of normality, namely the Kolmogorov-Smirnov Test and the Shapiro-Wilk Test.

We can see from table 6 that the dependent variable, "SMR",is normally distributed as our sig value is greater than 0.05.Hence our data is normal.

Table 6. It shows the results of Normality test on SMR data

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
SMR	.204	10	.200*	.945	10	.604

a. Lilliefors Significance Correction

*. This is a lower bound of the true significance.

5.5.2. K Means Cluster Analysis

This method endeavours to recognize somewhat homogeneous gatherings of cases in view of chosen qualities, utilizing a calculation that can deal with huge quantities of cases. by this method the calculation requires determining the cluster of groups. Group enrolment can be saved, distance data, and various cluster by unsupervised. Alternatively, a variable can be indicated whose values are utilized to name case to case result. While all these things are opportunistic (the system attempts to frame bunches that do vary), the overall size of the insights gives data about every factor's commitment to the partition of the groups.

Table 7. This shows the fuzzy cluster centres SMR data

	Cluster				
	1	2	3	4	5
SMRValue	7.70	7.10	4.58	6.59	5.49
Economic Status	very high	High	moderate	low	very low

Table 8. This shows the fuzzy cluster centres of the Average Production of crops data of Kharif season and Rabi season.

	Cluster				
	1	2	3	4	5
Production_avg of Kharif season	48.65	51.07	54.23	57.83	65.45
Production_avg of Rabi season	51.06	54.87	59.66	65.14	69.48
Production Status	very low	low	moderate	high	very high

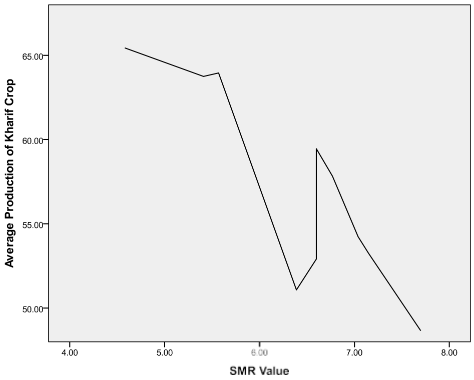

Fig 7 shows Line Graph showing the Average production of crops of Kharif season vs the SMR value

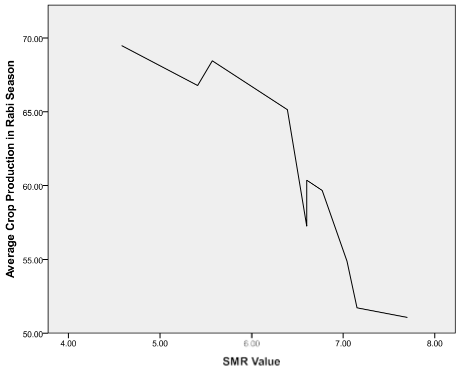

Fig 8 shows Line Graph showing the Average production of crops of Rabi season vs the SMR value.

Table 9. This shows Fuzzy rules and its analysis for the SMR value and Production of crops of Kharif season and Rabi season

S. No	Fuzzy Rule	Analysis
1.	IF SMR is very low AND Production_avg is very high THEN Economic Condition is Very Good.	If the farmer suicide rates are very low and the average production of crops is very high, then the Economic Condition of farmers is considered Very Good.
2.	IF SMR is low AND Production_avg is high THEN Economic Condition is Good.	If the farmer suicide rates are low and the average production of crops is high, then the Economic Condition of farmers is considered Good.
3.	IF SMR is moderate AND Production_avg is moderate THEN Economic Condition is Medium.	If the farmer suicide rates are moderate and the average production of crops is moderate then the Economic Condition of farmers is considered Medium.
4.	IF SMR is high AND Production_avg is low THEN Economic Condition is Poor.	If the farmer suicide rates are high and the average production of crops is low then the Economic Condition of farmers is considered Poor.
5.	IF SMR is very high AND Production_avg is very low THEN Economic Condition is Very Poor.	If the farmer suicide rates are very high and the average production of crops is very low then the Economic Condition of farmers is considered Very Poor.

6. Results and Discussion

The results of this study confirm the successful development and implementation of the Regression-fuzzy heuristic model, which provides a powerful predictive tool for assessing the economic conditions of farmers. The model integrates fuzzy clustering techniques and regression analysis, allowing for a comprehensive and nuanced evaluation of the impact of weather factors on farmers' economic stability.

6.1 Fuzzy Clustering of SMR Values and Crop Production

The study used historical data to create fuzzy clusters of Soil Moisture Retention (SMR) values and the average production of crops. These clusters are detailed in Table 7 and Table 8:

Table 7: Defines fuzzy clusters for SMR values along with their corresponding statuses.

Table 8: Defines fuzzy clusters for average crop production along with their corresponding statuses.

These clusters provide a structured approach to categorize the data, facilitating the generation of fuzzy rules that are essential for the prediction process.

6.2 Fuzzy Rules for Economic Prediction

Based on the fuzzy clusters, fuzzy rules were established as shown in Table 9. These rules form the backbone of the Regression-Fuzzy Model, enabling it to predict the economic conditions of farmers accurately. The rules take into account the interplay between SMR values and crop production, providing a detailed and precise forecast of economic outcomes.

6.3 Predictive Accuracy and Economic Insights

The application of the Regression-fuzzy heuristic model has shown promising results in predicting the economic conditions of farmers. By analyzing weather data and crop production over the past decade, the model has demonstrated the following:

6.3.1 Accurate Predictions: The model successfully predicts economic fluctuations by assessing the impact of weather conditions on crop yields. This predictive accuracy is critical for developing proactive strategies to mitigate economic risks faced by farmers.
6.3.2 Economic Classification: The model effectively classifies farmers' economic conditions based on fuzzy rules derived from historical data. This classification helps in understanding the various economic scenarios farmers might face under different weather conditions.

6.3.3 Mortality Rate Reduction: One of the primary objectives of this research is to reduce the mortality rate among farmers by providing timely and accurate economic predictions. The model's ability to forecast economic distress linked to uncertain weather conditions can inform policy measures and support systems aimed at alleviating farmer suicides.

The Regression-fuzzy heuristic model successfully predicts farmers' economic conditions by using fuzzy clusters and rules based on historical weather data and crop production. This model accurately forecasts economic fluctuations and mortality rates, offering valuable insights for policymakers to develop targeted interventions and support systems. By addressing economic risks associated with adverse weather conditions, the model aims to enhance the economic resilience of the agricultural sector, thereby reducing farmer mortality rates.

The Regression-fuzzy heuristic model provides a promising tool for predicting the economic conditions of farmers, but its use should be considered within the broader context of agricultural economics. The model's reliance on historical weather data and crop production highlights the need for continuous updates and integration of new data to maintain its accuracy. The nuanced understanding of economic conditions offered by the model can inform better decision-making and policy development.

Further research and development are necessary to address the model's current limitations and expand its applicability. By incorporating additional economic variables, conducting real-world validation, and expanding its geographical scope, the model can become an even more valuable asset for supporting farmers and enhancing the resilience of the agricultural sector. Integrating the model into policy frameworks will ensure that its insights are effectively translated into actions that benefit the farming community.

7. Conclusion

The development of the Regression-fuzzy heuristic model marks a significant step forward in predicting the economic conditions of farmers by integrating regression analysis and fuzzy logic. By leveraging fuzzy clustering and rule generation, the model provides nuanced predictions based on crop production and Soil Moisture Retention (SMR) values, offering a sophisticated tool for assessing the impact of weather factors on farmers' economic stability.

The results indicate that the model can accurately classify and predict economic conditions, which can inform policy measures and support systems aimed at mitigating economic risks. However, it is important to recognize the limitations and areas for improvement. The model's accuracy is contingent on the quality and comprehensiveness of the input data. Therefore, while the current model provides valuable insights, its predictions should be interpreted with caution and in conjunction with other economic and agricultural indicators.

In summary, while the Regression-fuzzy heuristic model offers promising capabilities for predicting economic conditions, its results should be interpreted as part of a broader analysis. Future enhancements will focus on improving the model's robustness and practical applicability, contributing to more informed decision-making and better support for the agricultural sector.

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