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Araştırma Makale/ Research article

Estimation of Climate Change Parameters for Agricultural Economy Efficiency with Machine Learning Methods

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ABSTRACT
Climate change threatens economies worldwide by disrupting food and water supplies, necessitating complex statistical models to forecast crop yields. Turkey, heavily reliant on agriculture, requires economic analyses of the intricate links between climate variability and resource availability to mitigate climate change impacts through effective policies. Recent predictive modeling incorporating meteorological data demonstrates the feasibility of anticipating monthly precipitation in Türkiye. The study demonstrates the effectiveness of using monthly relative humidity and average temperature data from 1970 to 2021 for precise precipitation predictions by applying artificial neural networks. The study's conclusions have important ramifications for raising agricultural output. Accurate monthly precipitation estimates enable stakeholders to make well-informed decisions on the development of grain crops, improving agricultural practices and raising sector productivity overall.

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Introduction

The growing strain on the planet's limited resources emphasizes how important it is to have long-term plans for anticipating climate change, especially when it comes to promoting economic expansion. These days, climate data is essential to everything from international relations to hydrology to economic planning, healthcare, especially in industrialized countries, and agricultural and resource management [1]. As a result, there's an increasing need to use cutting-edge approaches, including machine learning techniques, to create prediction models meant to reduce the dangers related to climate change. These predictive models serve as invaluable tools, elucidating the requirements of both producer and user communities, thereby facilitating informed decision-making processes.

These forecasting models are quite useful since they clarify the needs of the production and user communities, which helps with well-informed decision-making. About 80 million people in Turkey depend on agriculture for their fundamental necessities, making it an essential sector of the national economy. That's why many studies have been done on agricultural economics [2-4].The extensive use of machine learning in predictive analytics has led to a revolution in recent years [5, 6].

Many methodologies fall under this umbrella, such as random forest, artificial neural networks, naive bayes, multi linear regression, and K-nearest neighbor. These advanced analytical procedures enable identifying historical rainfall patterns that are predictive of drought. The drought of 2021 caused a concerning 17.6% slump in wheat production in Turkey, from 20.5 million tons in 2020 down to 17.6 million tons. This alarming downward trend points to significant declines in broader grain production as well, with overall output dramatically plunging 14.3% year-over-year to just 31.9 million tons in 2021, according to data from the Turkish Statistical Institute [7].

Machine learning has become a powerful tool for accurate prognostication across a variety of domains, including health [8], animal husbandry [9], agriculture [10], sports [11], economy [12], and industry [13].

This research sets out on a critical exploration, proving the effectiveness of machine learning in predicting rainfall, a critical component determining the incidence of droughts.

Using a dataset that includes 624 data points from the Konya General Directorate of Meteorology [14] covering Turkey's 12-month relative humidity, average temperature, and precipitation records from 1970 to 2021, this study uses three different machine learning techniques: radial basis function, multiple linear regression, and

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artificial neural networks. Among the models that have been studied, artificial neural networks stand out as the most effective in making predictions.

The rest of the paper is organized as follows: in the next section we describe the effect of clmate change on agriculture and economy. In Section 3 we introduce preceding related work. In section 4 we expose the research method followed. In Section 5 and 6, we present the used software and performance criteria and finding obtained, respectively. The paper ends with a conclusions.

The Effect Of Climate Change On Agriculture And Economy

Rising sea levels, altered precipitation, and increasing temperatures signify climate change, posing a major threat to Earth. More frequent and intense extreme weather also surfaces in the short-term from unpredictable weather patterns. Greenhouse gas emissions, chiefly from burning fossil fuels, livestock production, rice cultivation, and nitrogen fertilizers, drive climate change. Like a greenhouse, these gases trap solar radiation in the atmosphere [15]. Figure 1 shows agriculture's outsized role, generating nearly half of all emissions. Industry and transportation also contribute substantially as the other major greenhouse gas emitters at 23% and 17% of total emissions, respectively.

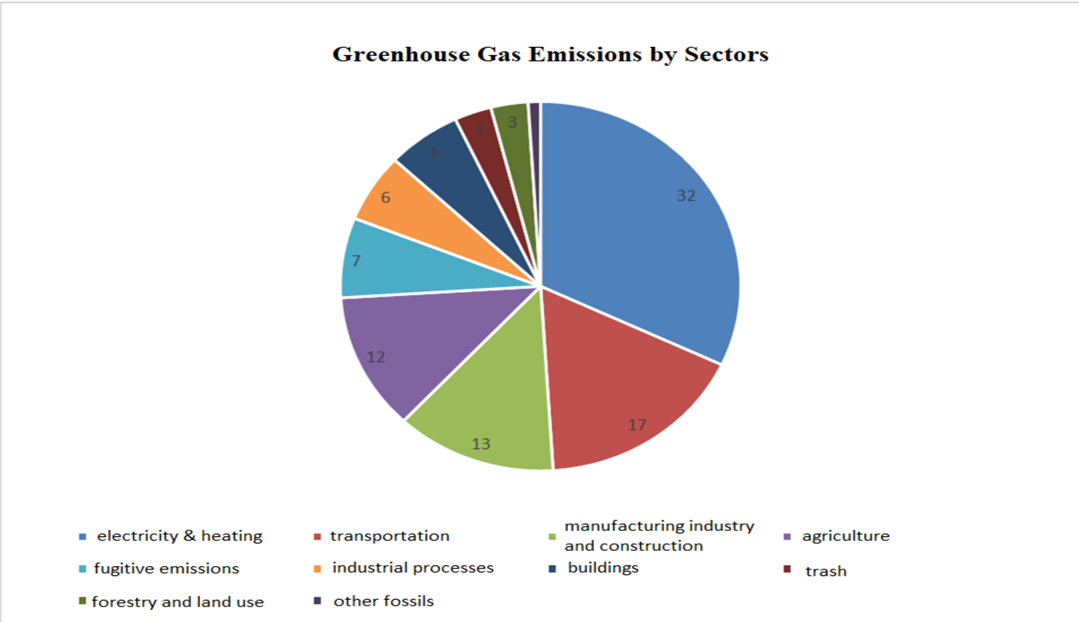

Fig 1 Greenhouse Gas Emissions by Sectors (2019) [10]

The average sea level has risen due to the melting of glaciers in Greenland and the Arctic, but within the past 100 years, weather patterns have gotten more unpredictable and extreme weather events have been more destructive, raising the sea level by 4.10–20 centimeters.

Although in 2011 the average amount of greenhouse gas emissions per person in high-income countries was ten times that of poor countries, in 2013 China surpassed the European Union (EU) by 6.8 tons with 7.2 tons of carbon per person [16].

Digital technology integration has promise for reducing the impact of climate change. Energy management techniques can be updated with the use of robotics, artificial intelligence (AI), sensors, and Internet of Things (IoT) devices. This will increase energy efficiency in all industries. To achieve the UN's sustainable development goals, it is especially important to recognize the possible negative effects of these technologies on the labor force and the production of electronic waste.

Figure 4 shows observations that show a partial decline in wheat production in Turkey throughout time, with the drought in 2021 being especially noteworthy. Therefore, in addition to deploying sensor technology for optimal irrigation techniques, it is necessary to use cutting-edge approaches like artificial intelligence and machine learning for precise rainfall and temperature projections.

Production quantity graphs also show the price pattern suggested by the spider web theory, which is that prices vary according to supply quantities from prior years. Turkey's annual production of barley varies from year to year, however it has been declining since 2019.

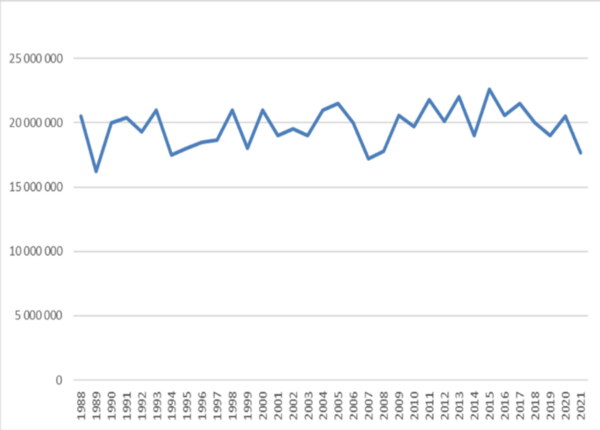

Fig 2 Türkiye Wheat Production (Ton) [17]

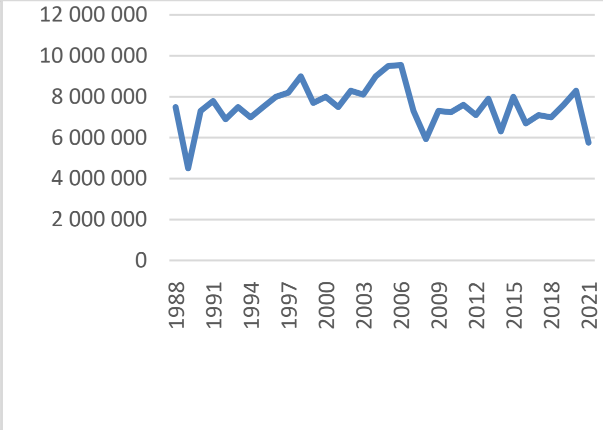

Fig 3 Türkiye Barley Production (Ton) [17]

The General Directorate of Meteorology's analysis of relative humidity statistics from 1970 to 2021 reveals a consistent drop in humidity levels over time, as seen in Figure 4. Simultaneously, analysis of temperature data for Türkiye from 1970 to 2021 shows a significant 1-degree rise in average temperature, from 13.5 to 14.5 degrees Celsius (Figure 5).

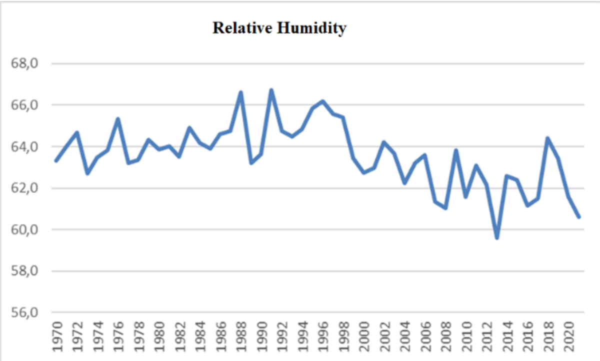

Fig 4 Annual Average of Monthly Humidity Values in Türkiye (1970-2021)

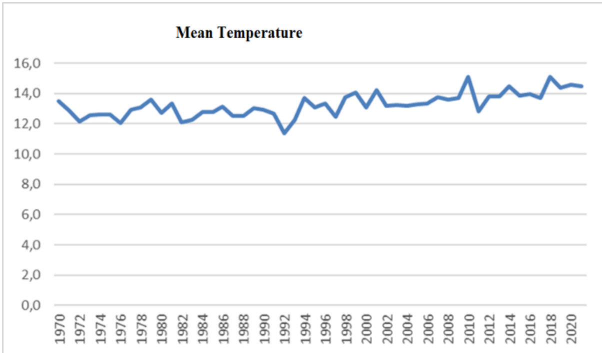

Fig 5 Annual Average of Monthly Temperature Values in Türkiye (1970-2021)

The observed patterns of decreasing humidity levels, rising average temperatures, and notable variations in maximum and lowest temperatures across the study period highlight the importance of precisely assessing climate change parameters. These kinds of discoveries play a critical role in shaping policy interventions and adaptive solutions meant to lessen the negative effects of climate change.

Digital technologies can lead to climate change mitigation. Energy management and energy efficiency can be raised in all industries with the use of sensors, the Internet of Things, robotics, and artificial intelligence. However, when considering the United Nations sustainable development goals, its detrimental effects on the workforce and the quantity of electronic waste it produces also have an adverse effect.

Literature Review

In the study [18], the Penman-Monteith method combined with an Artificial Neural Network (ANN) predicted the impact of climate change on evaporation rates in Cyprus's Kyrenia and Larnaca regions through 2050. The results show ANN's efficiency in forecasting future evaporation, with R2 coefficients ranging from 0.8959 to 0.9997 for Kyrenia and 0.8633 to 0.9996 for Larnaca.

Previous research, including [19], demonstrates ANN's superiority in predicting energy demand over simpler methods like linear regression. However, these studies didn't employ optimization methods to assess climate change's effects on hydropower and energy demand [20].

[21] found that ANN provides accurate predictions for energy efficiency, with a determination coefficient of 60.99%, indicating reliable results.

The study on California's energy demand [22] showed that climate change, particularly temperature variations, could significantly affect electricity consumption and costs.

[23] explored climate change's impact on hydroelectric energy, energy demand, and the supply-demand balance using an ANN and the Enhanced Electromagnetic Field Optimization (IEFO) algorithm. Their research forecasts a notable decrease in hydroelectric production due to temperature rises and changing precipitation patterns, by up to 14,765 MW in future scenarios.

In [24], the authors have developed artificial intelligence models with rapid decision-making ability to understand the impact of climate change on water resources. The study involves predicting evaporation in the Karaidemir Dam in Turkey with artificial neural networks (ANN). Daily meteorological data covering the irrigation season are provided for a 30-year reference period. Bayesian Regularization (BR), Levenberg-Marquardt (L-M) and Scalar Conjugate Gradient (SCG) learning algorithms were used. The results obtained revealed that the ANN model has statistically high performance in prediction with few input parameters.
The authors made the following claims in [25]:
i. Global drylands, where 38% of the world's population resides, present significant challenges such as low water productivity and scarcity.
ii. There are fields that are over- or under-irrigated due to incorrect irrigation techniques.
iii. Smart irrigation models can be developed that take into account soil characteristics, climate change, plant responses to water scarcity and weather changes. vi. Algorithms such as artificial intelligence and deep learning (fuzzy logic, expert systems, artificial neural networks and hybrid intelligent systems) can be used for models.
v. Model predictive irrigation systems will offer high water use efficiency.
The literature makes clear that various machine learning algorithms have been used to create smart models incorporating climate change characteristics for a variety of uses. They made an effort to forecast how evaporation rates, energy consumption, and water supplies will be affected by climate change. On the other hand, no research on agricultural economic efficiency has been located. In order to maximize agricultural economic efficiency, this research focuses on using machine learning algorithms to estimate monthly rainfall.

Methods

Artificial neural network

A neural network is a computational structure inspired by the study of biological neural processing. The purpose of Artificial Neural Networks (ANN) is to find the relationship between input and output values by performing internal calculations [26]. ANN operates in two stages: training and testing. During training, input and output data sets are used to adjust the network's parameters. Artificial neural networks typically comprise three layers: input layer, output layer, and one or more hidden layers, each containing numerous interconnected neurons (Figure 6)

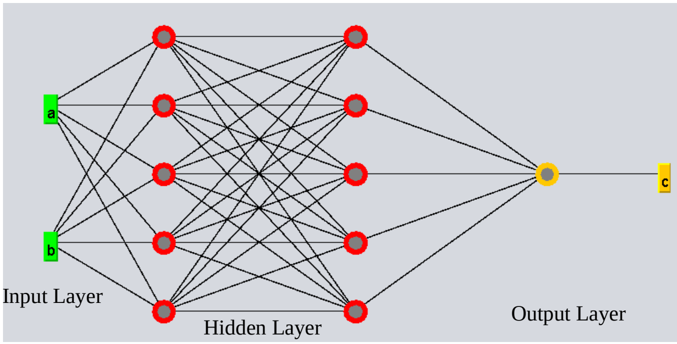

Fig 6 Architecture of Artificial Neural Network

Radial basic function

The function utilized in a radial basis neural network describes any real-valued function whose output relies solely on the distance of its input from an origin. The radial basis neural network (RBF) shares structural similarities with a multilayer perceptron. However, the RBF is constrained to feature precisely one hidden layer (see Figure 7). Within artificial neural networks, a radial basis function serves as the activation function. The Gaussian variation of this function is a widely adopted alternative. A Gaussian formula with one-dimensional input can be expressed as:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (1)$$

Here, x denotes the input, μ represents the mean or center of the Gaussian, and σ is the standard deviation controlling the width of the function's peak. The Gaussian function assigns higher weights to inputs closer to the center, gradually decreasing as the distance from the center increases, capturing the radial nature of the function.
This activation function enables the radial basis neural network to effectively model complex relationships within data, making it suitable for various tasks such as function approximation, classification, and regression.

Additionally, its single hidden layer architecture contributes to faster training and simpler optimization compared to deeper neural networks.

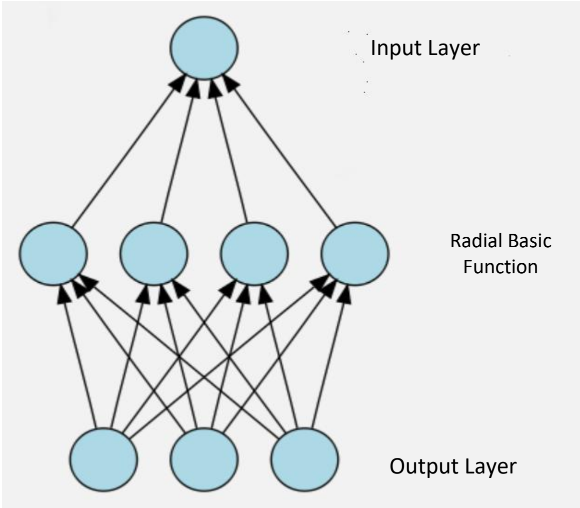

Fig 7 Architecture of Radial Basic Function

Multi linear regression

Multiple linear regression (MLR) refers to a statistical technique that uses two or more independent variables (input) to predict the outcome of a dependent variable (output). Its purpose is to model the linear relationship between inputs and output(s). It is expressed by equation 2.

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_{3+} \dots . b_n x_{n+} \epsilon \tag{2}$$

Here, y is the predicted variable, b_0 is constant term, b_i 's (i=1,2…n) are the regression coefficients and ϵ is the model's error term.

Data collecting

The Konya General Directorate of Meteorology provided the data used in the models. Sixty-four data points covering the twelve-month period from 1970 to 2021 are included in total. These data, which were gathered monthly over a 52-year period, include measures of relative humidity, average temperature, and precipitation amounts. Given the comprehensive nature of these data, which cover all seasons over this extended period, they were deemed sufficient for capturing potential seasonal variations. Relative humidity and average temperature serve as the input parameters, while precipitation amount serves as the output parameter. The training and simulating subsets of the proportion were 75–25%, respectively. The training data-set was divided into three subsets (training 70%, testing 15% and validation 15%). Table 1 presents a detailed overview of the input and output parameters along with their respective statistics.

Table 1 Data ranges and statistic

Parameters	Data Statistic		
	Ranges	Mean ± S.D.	Unit
Input Layer Average Relatively Humidity	2.00 – 70.00	21.71 ± 11.05	gr/m^3
Average Temperature	-26.5 – 15.40	-0.93 ± 8.86	^{0}C
Output Layer Average Rainfall	0.00 – 24	27.57 ± 27.39	mm

Used software and performance criteria

The models developed in this study were tested and simulated using Weka 3.8.5 software, developed by the University of Waikato in Hamilton, New Zealand. Various configurations of layers and neuron parameters were explored to determine the optimal architecture for the developed ANN models. Several methods exist for evaluating the performance of models generated through different machine learning techniques. As certain performance criteria are commonly employed across various studies[27]), they were likewise adopted in this research. Specifically, Root Mean Squared Error (RMSE) and Coefficient of Determination (R^2) were utilized as performance metrics. The formulations for these performance measures are provided below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(Y_{exp,i} - Y_{prd,i})^2} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{1}^{n}(Y_{prd,i}-Y_{exp,i})2}{\sum_{i=1}^{n}(Y_{prd,i}-Y_m)2} \tag{4}$$

Y_{prd} is the predicted data, Y_{exp} is measured data and Y_m is the the total number of data.

For RMSE, the sum of the squares of the differences (i.e. errors) between the Actual Values and Predicted Values is divided by the number of observations and then the square root is taken. When adding errors, errors are squared to prevent positive and negative values from canceling each other out. However, to prevent swelling caused by this process and to make more accurate measurements, square roots are taken.

RMSE is used to quantify the difference between a machine learning model's anticipated and actual value. The range of the RMSE value is 0 to ∞. When the RMSE value is 0, it means that the model has successfully memorized the dataset and has made no mistakes. The model is considered more successful the closer the RMSE is near 0.

In a similar vein, the closer the R^2 value is to 1 (100%), the more successful the prediction is considered. However, a score of 100% indicates that the model might be overfitting the data, which compromises the model's dependability when R^2 is used as the machine learning performance criterion.

Findings

In this study, 624 datasets—the statistical details of which are given in Table 1—were used in an attempt to determine the quantity of rainfall that occurs on average each month in Türkiye. These datasets were acquired from the Konya General Directorate of Meteorology and span the years 1970–2021. Three different machine learning methods were employed for this purpose.

Artificial neural network findings

Various ANN models were created with different hidden layers and neuron numbers to predict Turkey's monthly average rainfall. The feedforward backpropagation algorithm, featuring a single hidden layer and neuron, demonstrated the best efficiency in estimating the average rainfall. Figure 8 displays the most suitable ANN model of graph comparing the estimated values of the model with the actual values.

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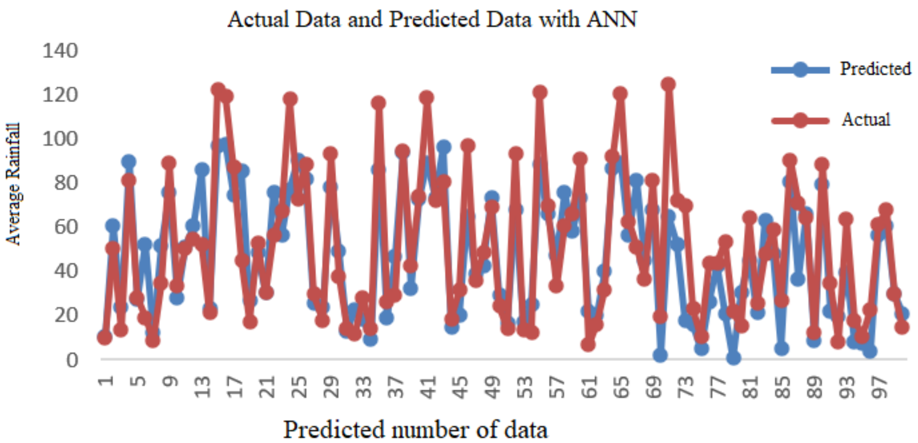

Fig 8 Actual Data and Predicted Data with ANN

The performance criterion results of the ANN model are presented in Table 2.

Table 2 Performance of ANN

Model	RMSE	R^2
ANN	18.20	0.67

Radial basis function findings

Observations indicate that the findings of RBF do not outperform those of artificial neural networks. The R^2 value for ANN is 0.67, whereas for RBF it is 0.54. This means that while ANN achieved a 67% success rate in prediction, RBF's prediction success rate was 54%. Figure 9 displays a graph comparing RBF prediction results with actual values, while Table 3 presents RBF performance based on performance criteria.

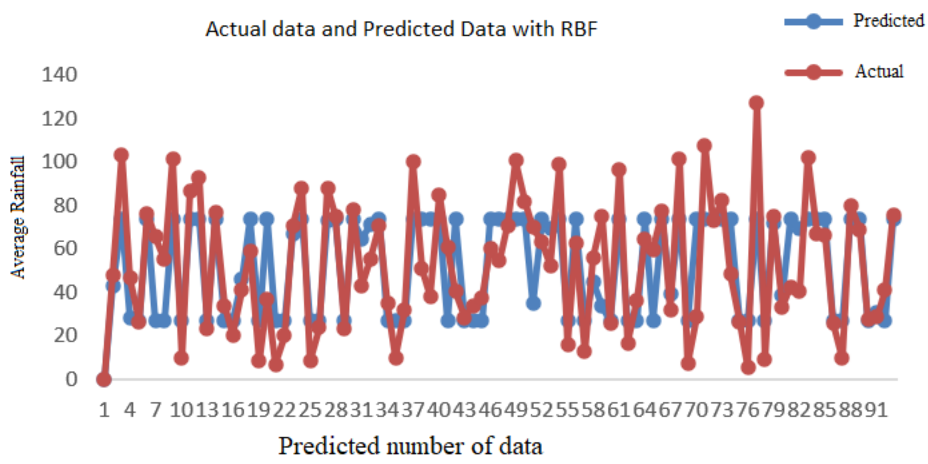

Fig 9 Actual Data and Predicted Data with RBF

Table 3 Performance of RBF

Model	RMSE	R^2
RBF	20.29	0.54

Multiple linear regression findings

MLR findings showed similar success to ANN performance. The coefficient of determination was 0.67 in both machine learning methods. The graph comparing the prediction results of the MLR with the actual data is presented in Figure 9. The performance criteria table is also shown in table 4. Figure 9 displays a graph comparing the prediction results of the MLR with the actual data, while Table 4 presents the performance criteria.

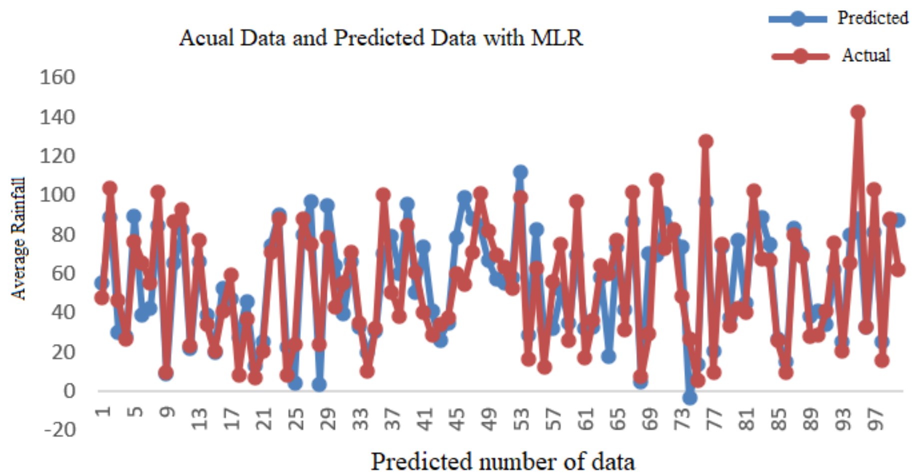

Fig 9 Actual Data and Predicted Data with MLR

Table 4 Performance of MLR

Model	RMSE	R^2
MLR	17.25	0.67

Conclusion

Climate change, resulting from increased levels of greenhouse gases, is the most critical global environmental issue today. This phenomenon occurs over many centuries. The results show that calculating climate change characteristics is important, as evidenced by the considerable changes in maximum and lowest temperatures, the 1 degree increase in average temperature, and the decrease in humidity between 1970 and 2021. The root mean square error (RMSE) and coefficient of determination (R^2) between the measured and predicted outcome variables were used as performance metrics to assess the study's outcomes. R2 for the MLR and ANN models is 0.67. Because of this, it was discovered that the ANN and MLR models created in this study were more successful and palatable than the RBF model. The average amount of rainfall may be successfully estimated using the ANN and MLR approaches. It was determined that grain growers and decision makers may utilize it as a valuable tool for evaluating performance. Also the model we built can be made more accurate and more broadly applicable by using data that can be gathered from various places and climate conditions. To improve prediction accuracy and dependability, a variety of machine learning techniques, including the deep learning algorithm, can be applied. Furthermore, models that use real-time data have the ability to produce more dynamic predictions and can respond swiftly to sudden changes in the climate through the integration of various sensors within the framework of the Internet of Things. The energy, water resource management, aviation and transportation, and healthcare industries can all benefit from using climate change characteristics. Planning public health initiatives and creating disease control plans can be aided by forecasting the production of renewable energy sources (solar, wind), managing water better during droughts, maximizing agricultural water use, minimizing the impact of weather on flight safety and efficiency, and anticipating the spread of diseases brought on by climate change (e.g., malaria, dengue fever).

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