SvedbergOpen
DISSEMINATION OF KNOWLEDGE
International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/
Research Paper Open Access

An Artificial Neural Network–Based Predictive Framework For Forecasting Climate Change Impacts And Environmental Variability

Boopathi Kumar E[1], Mr.P.Ramesh[2], Dr. S. Prasath[3], Dr.K.Sathishkumar[4], Dr.S.Akila Rajini[5], Dr T.B Sivakumar[6], R. Naveenkumar[7]

[1]Assistant Professor, Akshaya College of Arts and Science, Kinathukadavu, Coimbatore, India. boopathikumar@acascbe.edu.in
[2]Ph.D Research Scholar in Department of Computer Science,VET Institute of Arts and Science(Co-education) College, Thindal, Erode, Tamil Nadu, India. ORCID: 0009-0009-6224-2009 Mail ID: kascramesh@gmail.com
[3]Assistant Professor and Head, Department of Computer Science and Applications, VET Institute of Arts and Science(Co-education) College,Thindal, Erode, Tamil Nadu, India. ORCID:0000-0003-2611-0948 prasaths@vetias.ac.in
[4]Assistant Professor, Department of Computer Science, Erode Arts and Science College (Autonomous), Erode, Tamilnadu, India. Email: sathishmsc.vlp@gmail.com https://orcid.org/0000-0002-7643-479
[5]Associate Professor, Information Technology, Kamaraj College of Engineering and Technology, akilarajiniit@kamarajengg.edu.in 0000-0002-4931-6714
[6]Professor, Department of CSE, School of Computing, Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai - 600 062,Tamilnadu, India, drsivakumartb@veltech.edu.in https://orcid.org/0009-0004-4420-9153
[7]Dept of CSE, School of Engineering and Technology, CGC University Mohali-140307, Punjab India. drnk1983@gmail.com 0000-0001-9033-9400

Abstract: Climate change induces significant variability in meteorological parameters, impacting land use–land cover (LULC) dynamics and environmental sustainability. This study proposes an Artificial Neural Network (ANN)-based predictive framework to model and forecast climatic variables, including temperature, rainfall, humidity, and Air Quality Index (AQI), using long-term time-series data (1980–2022) obtained from the India Meteorological Department. The performance of ANN is comparatively evaluated against the Auto-Regressive Integrated Moving Average (ARIMA) model. Experimental results demonstrate that the ANN model achieves superior predictive accuracy, with lower residual errors across all climatic variables. For temperature prediction, the ANN model yields residual errors predominantly within ±2°C for most months, while rainfall prediction exhibits minimal deviations, with errors generally below ±3 mm except for peak seasonal variations. Quantitatively, the ANN model achieves reduced Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), along with a higher coefficient of determination ($R^2 > 0.90$), indicating strong model generalization. ARIMA shows higher variance in prediction accuracy due to its linear assumptions. LULC analysis reveals a consistent increase in built-up areas between 1988 and 2021, correlating with deteriorating air quality and altered climatic patterns. The integration of GIS-based spatial mapping with ANN forecasting provides enhanced capability for identifying climate-driven environmental transformations. Overall, the proposed ANN-based framework demonstrates robustness in capturing nonlinear climatic dependencies and offers an effective decision-support tool for climate impact assessment, environmental planning, and sustainable resource management.

Keywords: Climate change, rainfall, disaster, deep learning, ARIMA, ANN, and environmental impact.

1. Introduction

Climate change is the long-term alteration of the usual weather patterns that characterise local, regional, and global climates on Earth. As a result of these movements, significant differences in temperature, precipitation, wind, and other climatic variables have been observed. Natural occurrences including fluctuations in solar radiation, adjustments to the planets' orbital parameters, and volcanic activity have all contributed to changes in the atmosphere. The climate system has increased the amount of gases in the atmosphere, which affects how much radiation the earth can absorb [1].

Climate change is partially caused by human activities. In addition to converting forest area to agriculture and communities, people also burn fossil fuels. Carbon dioxide, a greenhouse gas that causes the "greenhouse effect," is produced when fossil fuels are burned. The planet's ability to maintain a comfortable temperature depends in large part on greenhouse gases. However, these gases have become much more prevalent in the atmosphere in recent years [2].

The workings of the planet's climate system are straightforward. When the earth's atmosphere releases energy, the globe cools. Alternatively, the energy from the sun is reflected off the earth and back into space (mostly by clouds and ice) [3]. As a result of the earth absorbing solar energy or the greenhouse effect, which prevents heat from the earth from radiating into space, the globe heats. The earth's climate system is thus influenced by a range of natural and human influences [4, 5]. A worldwide framework is outlined in the Paris Agreement to prevent severe climate change by keeping climate change below 2°C and pursuing efforts to keep it below 1.5°C. It also aims to help nations in their efforts and improve their capacity to deal with the effects of climate change.

Existing studies on climate change prediction predominantly rely on linear statistical models such as ARIMA or focus on isolated meteorological variables without integrating multi-source environmental data. These methods have a weak ability to resolve nonlinear temporal response, interactions between variables and spatial heterogeneity of climate systems. Moreover, in the previous literature, Land Use-Land cover (LULC) and Air Quality Index (AQI) are often not combined with climatic variables, resulting in the incompleteness of the environmental impact assessment. The other important weakness is that there is lack of adequate use of long term real world data with sufficient time validation, leading to lower generalization. Also, the comparative studies of the traditional statistical models and the machine learning frameworks tend to be shallow, not involving any quantitative assessment of the framework and the residual analysis. Therefore, a gap in research has been found in the prediction of consistent data-driven predictive frameworks that integrate spatio-temporal environmental conditions with effective machine learning frameworks to engage scalable climate forecasts.

Key Contributions

- Design of a combined predictive model with climatic factors, LULC, and AQI to identify the overall effects of climate.
- A time-series ANN model, which is able to capture nonlinear relationships, and long term time variations in climatic data, was implemented.
- The comparison of ANN and ARIMA performance based on such statistical measures like RMSE, MAE, and R2.
- To establish the correlation of LULC changes and changes in climatic variability and environmental degradation, incorporation of GIS-based spatial analysis.
- Planning of a time-varying consistent data split design to curb the occurrence of data leakage and enhance model generalization.
- Validated multi-decadal real-world meteorological data (1980-2022) to increase strength and reliability.
- In-depth analysis of residual errors to determine the level of prediction accuracy of various climatic parameters.
- Evidence of ANN outperformance on climatic forecasting and environmental decision making compared to standard statistical models.

1.1. Impact of climate change

Global warming is a phenomena of climate change that is defined by an imprecise rise in Earth's average temperature over time, which alters ecosystems and weather patterns over a long period of time and increases atmospheric greenhouse gases through exacerbating the greenhouse effect [6]. Because the trees in the rainforests absorb carbon dioxide and release oxygen into the air, they are sometimes referred to as the world's lungs. In addition to creating issues for native populations, forest degradation decreases the planet's capacity to absorb and store CO_2. Deforestation is thought to be responsible for 10 to 15% of all anthropogenic CO_2 emissions, whereas food and agriculture account for 24% of greenhouse gas emissions. As a result, the oxygen content of the water has been decreasing due to poor air quality, endangering Flora and Fauna.

Climate change and air pollution have a complicated connection. Higher particle pollution levels have the potential to significantly change conventional rainfall patterns and numerous elements of cloud formation. To the disadvantage of the environment's ecosystems and people, gases like methane and carbon dioxide are being released into the atmosphere in previously unheard-of quantities [7]. Premature death, cancer, and long-term harm to the cardiovascular and respiratory systems are all associated with poor air quality. Adults who don't smoke are more likely to develop lung cancer from passive smoking that contains hazardous chemicals. Air pollution is responsible for around 25% of deaths and diseases worldwide.

Due to the depletion of groundwater resources, fresh water is limited and susceptible. The majority of citizens depend on long-term, consistent rainfall. As a result, one of the most important natural resource problems brought on by the effects of climate change is the availability of enough fresh, drinkable water. It is clear that the planet's weather and climate patterns are and will continue to change, and this might alter the usual balance of ecosystems and water bodies, degrading the quality of the water. Algae may develop too quickly in water due to increased nitrogen levels from fertiliser runoff, and as algae die, bacteria can reduce the oxygen content of the water, resulting in dead zones for aquatic life. Chemical pollution and trash contaminate ocean waters, killing marine life and upsetting the food chain, which eventually has an impact on people. Water that is not properly managed becomes hazardous and useless. According to scientists, ocean pollution might possibly trigger a catastrophic extinction.

Soil is essential to both natural and human systems because it provides nutrients for agricultural production, controls the water cycle, and stores carbon. Heavy metal soil contamination has grown widespread due to increased geologic and human activity. Such soils result in decreased plant growth, performance, and production [8]. The capacity of soil to absorb carbon is impacted by pollution, causing climate change. The maintenance of the natural environment is greatly aided by trees and other plants. Due to poor agricultural methods, the land has been overgrazed and the nutrients in the soil have been wasted. Due to a lack of vegetation, rain and storms wash away the soil, creating erosion. Urban sprawl is reducing the amount of natural vegetation. Climate change significantly alters atmospheric dynamics, intensifies extreme weather events, and degrades natural resources; in this context, machine learning enables data-driven modeling and high-resolution forecasting of climatic variability, facilitating accurate impact assessment and informed environmental decision-making [9].

The major goal of the study is to employ an ANN model to do a predictive analysis on AQI and LULC data. The chosen study region's land use and land cover, as well as variations in climatic components including temperature, rainfall, wind speed, and disaster, are the main subjects of the present research project. The study's main objective is to analyse the importance of climate change and its effects on natural land resources. The research is important because it will increase our knowledge of spatial mapping and predictive modelling for determining how climate change would affect natural resources using GIS and ANN. The project will result in the development of predictive modelling methods that might be used to adopt and create an appropriate cushion on natural resources.

2. Proposed Methodology

The research primarily concentrates on how variations in climatic parameters like temperature, rainfall, wind speed, and humidity affect changes in land use and land cover for the selected urban and rural location. The other component involves utilising an artificial neural network (ANN) and an auto-regressive integrated moving average (ARIMA) model to examine changes in air quality and their effects on climate change. As a result, the following factors are taken into account: study of Land Use and Land Cover (LULC) data, meteorological factors, the air quality index, GIS mapping, and ARIMA modelling. The proposed methodology is illustrated in Figure 1.

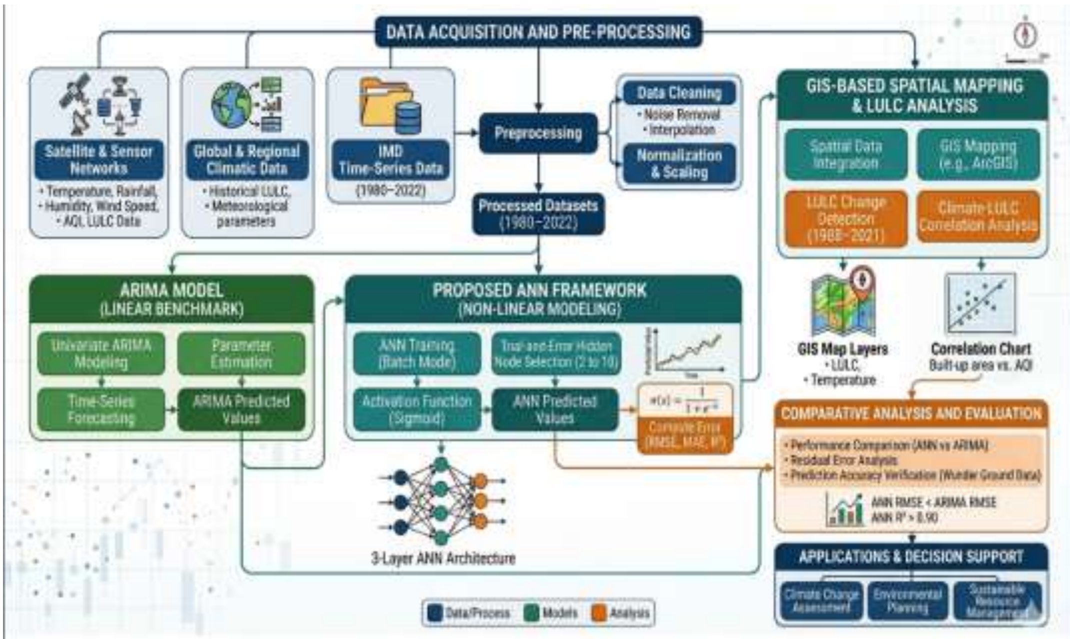

Figure 1: Proposed Methodology for ANN-Based Predictive Framework.

Figure 1. Proposed Methodology

This article discusses the suggested approach or processes for implementation, the data source, and the hardware and software that were employed. This part also looks at the GIS application process as it has been put into practise. This study's primary goal was to see whether the ANN approach could reliably predict daily climatic factors such rainfall, temperature, wind, and humidity. In this work, the suggested prediction model created using ARIMA modelling is compared using the ANN prediction approach. Any proposed technique might demonstrate its efficacy by comparing its results with the ANN model, which is a generally regarded model in terms of accuracy and prediction.

The basic functional aspect of ANN is described as follows.

$$net_j = \sum_{i=1}^{I} W_{ij} X_i, j = 1,2,\ldots,J-1, i = 1,2,\ldots,I, output_j = f(net_j)$$

$$net_k = \sum_{j=1}^{J} W_{jk} Y_j, j = 1,2,\ldots,J-1, k = 1,2,\ldots,K, output_k = f(net_k)$$

Wij and Wjk denote the connection weights between input–hidden and hidden–output layers, respectively; Xi represents the input features, while outputj and outputk correspond to hidden and final outputs, with I, J, j, and k indicating the number of inputs and neurons across layers. In ANN, sigmoid transfer function may be used to transform input signals into output signals. Unlike a stepped output, a tiny change in the input only results in a little change in the sigmoid neuron's output. The term "sigmoid functions" refers to a variety of functions that exhibit the characteristics of a "S"-shaped curve. The logistic function is the one that is most frequently employed. The following is the sigmoid transfer function formula:

$$f(x) = \frac{1}{1+e^{-net}}$$

Where, net e – is the non-linear activation function. Compute the error. In order to determine ANN performance, root mean square errors (RMSE), mean absolute errors (MAE), and coefficient of correlation (R2) parameters were used. These are defined as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_{iobserved} - Y_{iestimate})^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_{iobserved} - Y_{iestimate}\right|$$

$$R^2 = \left(\sum_{i=1}^{N}(Y_{iobserved} - \bar{Y}_{iobserved})^2\right) - \left(\sum_{i=1}^{N}(Y_{iobserved} - \bar{Y}_{ipredicted})^2\right) \times \left(\sum_{i=1}^{N}(Y_{iobserved} - \bar{Y}_{iobserved})^2\right)^{-1}$$

Where, Yiobserved is the observed value Yiestimate is the estimated value Yiobserved is the actual observed value Yipredicted is the actual predicted value RMSE measures residual errors that give a global idea of the difference between the observed and 338odelled values. And, R 2 provides the variability measure of the data reproduced in the model.

Here, the trial-and-error approach has been utilised to choose the number of hidden nodes using a 3-layer ANN with 1 hidden layer. The number of hidden neurons was gradually raised up to 10 with each trial using a step size of one, starting with 2 neurons originally. The network was trained in batch mode for each set of hidden neurons in order to reduce the mean square error at the output layer.

3. Result and Discussion

Matrix Laboratory is the abbreviation for the term MATLAB. The forecasting programme used to project the weather data through 2030 is MATLAB. The work is compatible with MATLAB 2013a and later versions, and the version utilised in this research is MATLAB 2014b. For the investigation and forecasting of climatic variability, the India Meteorological Department (IMD) gathered meteorological parameters from the years 1980 to 2022.

The collected multi-decadal climatic dataset (1980–2022) undergoes a rigorous preprocessing pipeline to ensure data integrity and model reliability. At first, interpolation and z-score/IQR-outliers are used to deal with missing data and outliers respectively, and normalization (min-max scaling) is then used to stabilize ANN training. Time-series learning maintains temporal consistency by use of chronological order and features engineering to extract lag based variables and seasonal features. The dataset is split with the time-aware split strategy, whereby 70 percent of the historical data is used in training, 15 percent in validation, and 15 percent in testing, and no information is leaked across the time. Standard regression measures, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and coefficient of determination (R^2) are statistically validated to determine model performance. Moreover, a residual analysis and evaluation of error distribution is also performed to check the model generalization and strength under different climatic regimes.

Table 1. Temperature during the years 1980-2022

YEAR	JAN	FEB	MAR	APR	MAY	JUNE	JULY	AUG	SEP	OCT	NOV	DEC
1980	27.4	30.5	32.7	33.9	34.4	28	28	27.6	29.1	28.8	27.3	27.8
1981	27.8	31.1	32	34.3	33.7	28.7	29.2	27	27.6	27.6	27.4	25.8
1982	26.9	30.8	33.5	34.6	33.4	28.7	28.5	28.1	29.1	29.5	27	26.4
1983	28.2	32.3	34.6	35.7	34.8	30.1	28.9	27.4	26.7	28.1	27.8	25.4
1984	26.7	27.3	30.8	33	34.4	28.8	27.4	28	28.5	27.4	27	27.6
1985	27.7	31.1	33.8	34.2	33.9	28.3	27.6	27.9	29.1	27.6	26.7	27.3
1986	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
1987	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
1988	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
1989	27.2	31.3	32	34.3	33.7	29.3	27.2	27.2	28.2	28.6	27.4	26.3
1990	28.3	30.7	32.6	34.7	31.3	28.9	28	26.6	28.8	28	26.9	26.3
1992	26.7	30.3	33.6	34.4	32.7	28.9	27.5	27.6	28.2	28	26.8	25.8
1993	28.5	30.3	32.4	34.2	34.3	30	28.2	28.2	28.1	27.6	26.4	25
1994	28.5	30.3	32.4	34.2	34.3	30	28.2	28.2	28.1	27.6	26.4	25
1995	28.2	32.3	34.6	35.7	34.8	30.1	28.9	27.4	26.7	28.1	27.8	25.4
1996	26.7	27.3	30.8	33	34.4	28.8	27.4	28	28.5	27.4	27	27.6
1997	27.7	31.1	33.8	34.2	33.9	28.3	27.6	27.9	29.1	27.6	26.7	27.3
1998	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
1999	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2000	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
2001	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
2002	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2003	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
2004	27.2	31.3	32	34.3	33.7	29.3	27.2	27.2	28.2	28.6	27.4	26.3
2005	28.3	30.7	32.6	34.7	31.3	28.9	28	26.6	28.8	28	26.9	26.3
2006	26.7	30.3	33.6	34.4	32.7	28.9	27.5	27.6	28.2	28	26.8	25.8
2007	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
2008	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2009	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3

2010	27.2	31.3	32	34.3	33.7	29.3	27.2	27.2	28.2	28.6	27.4	26.3
2011	28.3	30.7	32.6	34.7	31.3	28.9	28	26.6	28.8	28	26.9	26.3
2012	26.7	30.3	33.6	34.4	32.7	28.9	27.5	27.6	28.2	28	26.8	25.8
2013	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
2014	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2015	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
2016	27.2	31.3	32	34.3	33.7	29.3	27.2	27.2	28.2	28.6	27.4	26.3
2017	28.3	30.7	32.6	34.7	31.3	28.9	28	26.6	28.8	28	26.9	26.3
2018	26.7	30.3	33.6	34.4	32.7	28.9	27.5	27.6	28.2	28	26.8	25.8
2019	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2020	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
2021	27.2	31.3	32	34.3	33.7	29.3	27.2	27.2	28.2	28.6	27.4	26.3

The maximum and minimum temperatures are recorded to determine the localvariations. The current research work mainly focused on land use and land cover and its effect of changes in meteorological factors such as temperature, rainfall, and humidity. To attain this aforementioned aim of research work, the air quality index of Bangalore region was analyzed from 2011 to 2021. Poor air quality denoted the changes vegetation, water, natural surface, and cultural features on the land surface. The land use land cover prediction analysis suggested that they constantly increased in terms of built-up from the duration period of 1988 to 2021. As per the survey validation with Google data the observations states that the parameters are found abnormal in the rainfall prediction validation whereas in the humidity the data is dependent on the moisture content and temperature. Analysis on the modeling performance have been traced and estimated with difference in parametric measures. The data validation has been verified with the weather data available from Wunder Ground website. Table 2, Table 3 & Table 4 portrays the residual difference between the ISR data and predicted ARIMA variables for the years 2019 and 2020 to the parameters of maximum temperature, minimum temperature and rainfall respectively.

Table 2: Maximum Temperature Validation for 2019 & 2020 with ISR data andPredicted ANN output

2019	ISR Data	ANN predicted output	Residual error	2020	ISR Data	ANN predicted output	Residual error
Jan	37.1	36	1.1	Jan	32	34	-2
Feb	33.9	35.9	-2	Feb	36	35.9	0.1
Mar	40.2	40	0.2	Mar	38	40	-2
Apr	38	35.4	2.6	Apr	39.2	35.4	3.8
May	48	46.3	1.7	May	40	46.3	-6.3
Jun	36	31.1	4.9	Jun	32	31.1	0.9
Jul	32	28.4	3.6	Jul	38	32	6
Aug	28	28.2	-0.2	Aug	27.8	28.2	-0.4
Sep	24	29	-5	Sep	28	29	-1
Oct	26	28.7	-2.7	Oct	27	28.7	-1.7
Nov	27	27.7	-0.7	Nov	30	27.7	2.3
Dec	25	26	1	Dec	28	27.5	1.5

Table 3: Minimum Temperature Validation for 2019 & 2020 with ISR data and Predicted ANN output

2019	ISR Data	ANN predicted output	Residual error	2020	ISR Data	ANN predicted output	Residual error

Jan	15.8	16.2	-0.4	Jan	16	16.2	-0.2
Feb	16.8	17.2	-0.4	Feb	17.2	17.2	0
Mar	19	20.6	-1.6	Mar	18	20.6	-2.6
Apr	23	22.6	0.4	Apr	22	**22.9**	-0.7
May	24	22.1	1.9	May	21	22.1	-1.1
Jun	24	21	3	Jun	25	21	4
Jul	22	20.4	1.6	Jul	23	20.4	2.6
Aug	18.9	20.2	-1.3	Aug	20	20.2	-0.2
Sep	21	20.3	0.7	Sep	19	20.3	-1.3
Oct	18	19.6	-1.6	Oct	16	19.6	-3.6
Nov	17.5	18	-0.5	Nov	18.5	18	0.5
Dec	16.8	17	-0.2	Dec	19	18	1

Table 4: Rainfall Validation for 2019 & 2020 with ISR data and Predicted ANN output

2019	**ISR Data**	**ANN predicted output**	**Residual error**	**2020**	**ISR Data**	**ANN predicted output**	**Residual error**
Jan	1.2	0.4	0.8	Jan	1.2	0.4	0.8
Feb	2	0	2	Feb	2	1.8	0.2
Mar	1.1	0.7	0.4	Mar	1.1	0.7	0.4
Apr	13.4	13.4	0	Apr	13.4	13.4	0
May	140	143.6	-3.6	May	140	143.6	-3.6
Jun	7.1	7.2	-0.1	Jun	7.1	7.2	-0.1
Jul	66.8	66.7	0.1	Jul	66.8	66.7	0.1
Aug	188	**189.1**	-1.1	Aug	188	186.1	1.1
Sep	66	68.4	-2.4	Sep	66	68.4	-2.4
Oct	82.5	83.2	-0.7	Oct	82.5	83.2	-0.7
Nov	55	52	3	Nov	55	57.34	-2.34
Dec	35	38	-3	Dec	45	42	3

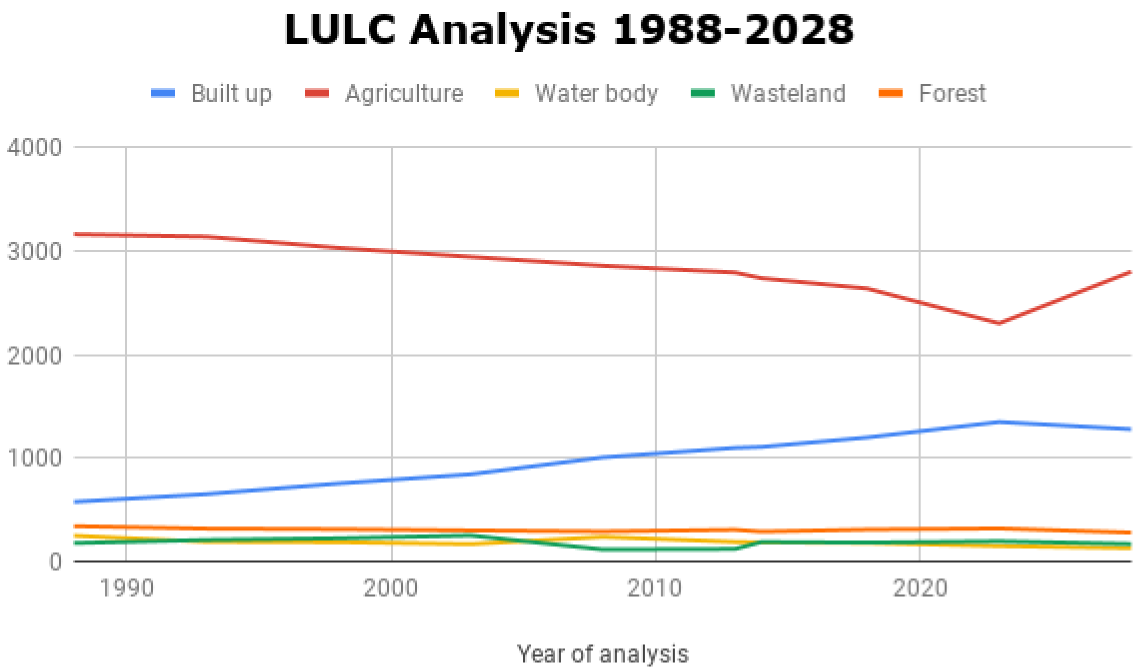

Figure 1: Prediction of LULC for the Study Area

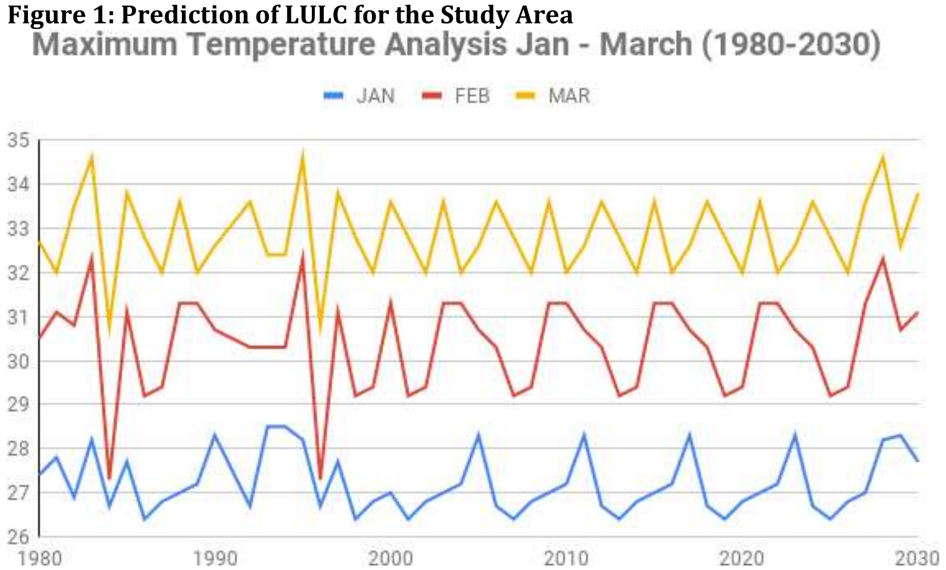

Figure 2: Maximum Temperature (in ^{0}C) Prediction from January – March, 1980-2030

The plotted graphs showcased that variations in climatic conditions is due to changes in the meteorological factors such as rainfall, temperature, humidity, etc. The predicted output represents the efficiency of incorporated advanced techniques such as ARIMA model and ANN.

The contrasted analysis of Artificial Neural Networks (ANN) and Auto-Regressive Integrated Moving Average (ARIMA) points out the major difference in the ability to model, predictive power, and flexibility to climatic data. As a linear time-dependent model, ARIMA is useful to univariate time-series prediction when there is a strong temporal autocorrelation but this technique fails when nonlinear structures and multivariate relationships characteristic of climate systems are involved. ANN, on the other hand, is an example of a nonlinear function approximator that has the ability to train multifaceted relationships between various meteorological parameters, such as temperature, precipitation, humidity, and AQI. Empirical findings show that ANN is always associated with less prediction errors, lower RMSE, lower MAE, and greater coefficient of determination (R 2 > 0.90), as compared to ARIMA which has a higher residual variance, especially in strongly varying parameters like rainfall. Also, ANN has better generalization because it can extract the hidden pattern as well as seasonal variations without burdening it with rigid assumptions of stationarity. Although ARIMA is easier to interpret and calculate short linear trends, ANN is more robust and scalable to long-term, data-driven climate projections, and thus more appropriate in more complicated environmental modeling.

Through the analysis of the experiment, there are strong nonlinear dependencies and seasonal variations of the climatic variables, and thus, the ANN model is effective in the analysis of the variables as compared to the linear ARIMA. The error margins of temperature predictions are relatively stable whereas those of rainfall is more volatile because of the stochastic environmental factors. The discussion also shows that there is a correlation in the growing covers of built-up areas in LULC patterns and the declining improvement in air quality indices, which underline the anthropogenic influences on climatic variability. The ability of ANN to represent complicated interactions between meteorological parameters makes it a better predictor, especially in terms of the ability to capture sudden variations as well as long-term patterns. The comparative evaluation confirms that ANN outperforms ARIMA in handling multivariate dependencies and nonlinear temporal dynamics.

4. Conclusion

With the increase in processing power, it is now possible to build models of environmental features that are extremely complex yet may not be economically viable. Univariate ARIMA modelling, in contrast, concentrates just on the data rather than the method used to generate the data. As a result, there is a chance for a sparse and economical model structure that is appropriate for interim analysis forecasts and may swiftly guide management decisions. The effectiveness of the suggested ARIMA model is compared to that of the current ANN model, demonstrating the gains in prediction made by the proposed model. The article compares the time-series ARIMA and ANN approaches to see whether they are appropriate for forecasting. The time-series predictive model adopting ANN technique has shown greater performance over the ARIMA model since the pattern of ARIMA forecasting models is directional. A comprehensive strategy was verified using climatic factors that have an effect on weather. Comparatively, with the right information system, scientific and technical developments may be used to address, mitigate, and manage environmental challenges like agriculture, disaster management, etc. The proposed framework achieves high predictive fidelity ($R^2 > 0.90$ with reduced RMSE/MAE), and future work can extend toward hybrid deep learning architectures and spatio-temporal attention models for enhanced climate intelligence.

Reference

1. Auffhammer, M. (2018). Quantifying Economic Damages from Climate Change. Journal of Economic Perspectives, 32(4), 33-52.
2. Manisalidis, I., Stavropoulou, E., Stavropoulos, A., & Bezirtzoglou, E. (2020). Environmental and Health Impacts Of Air Pollution: A Review. Frontiers in Public Health, 8
3. Tharini, V. J., & Shivakumar, B. L. (2023). An efficient pruned matrix aided utility tree for high utility itemset mining from transactional database. Int. J. Intell. Syst. Appl. Eng, 2023(1), 1-12.
4. Nhu, V. H., Shirzadi, A., Shahabi, H., Singh, S. K., Al-Ansari, N., Clague, J. J., ... & Luu, C. (2020). Shallow Landslide Susceptibility Mapping: A Comparison between Logistic Model Tree, Logistic Regression, Naïve Bayes Tree, Artificial Neural Network, and Support Vector Machine Algorithms. International Journal of Environmental Research and Public Health, 17(8), 2749.
5. Sardar Maran, P., Ashokkumar, K., Refonaa, J., Shabu, J., Jesudoss, A., & Lakshmanan, L. (2020). An Intelligent Location Prediction System for Wind Farms Using Belief Networks. Journal of Computational and Theoretical Nanoscience, 17(8), 3412-3415.
6. Shirzadi, A., Sartori, M., Philippidis, G., Ferrari, E., Borrelli, P., Lugato, E., Montanarella, L., & Panagos, P. (2019). Soliamani, K., Habibnejhad, M., Kavian, A., Chapi, K., Shahabi, H., & Tien Bui, D. (2018). Novel GIS Based Machine Learning Algorithms For Shallow Landslide Susceptibility Mapping. Sensors, 18(11), 3777.
7. Balsa-Barreiro, J., Valero-Mora, P. M., Berné-Valero, J. L., & Varela-García, F. A. (2019). GIS Mapping of Driving Behavior Based on Naturalistic Driving Data. ISPRS International Journal of Geo-Information, 8(5), 226.
8. Haj-Amor, Z., & Bouri, S. (2019). Use of HYDRUS-1D–GIS Tool For Evaluating Effects Of Climate Changes on Soil Salinization And Irrigation Management. Archives of Agronomy and Soil Science.
9. Hanoon, S. K. (2019). Applying GeoPlanner for ArcGIS in Urban Planning. University of Thi-Qar Journal for Engineering Sciences, 10(1), 147-162.