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# Studying the Global Climate Changes using Artificial Intelligence: An Overview

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***ABSTRACT***
*Artificial intelligence (AI) can be a powerful tool in addressing some of humanity's biggest challenges named global climate change. Monitoring climate change involves large and ever-evolving data sets. In order to track changes in climatic conditions in real time, address vulnerabilities to reduce them, and provide essential opportunities for humanity to find solutions that can have a positive impact on our planet more quickly, artificial intelligence systems can assist in the analysis of sets of environmental data. Even though AI is only one tool in the difficult analysis of the factors causing climate change, its capacity to handle vast amounts of data, find patterns, and occasionally anticipate data affords us the chance to better comprehend the ecosystem.*

***Keywords:***
*Artificial intelligence; Climate change; Ecology; Nonlinear pattern, Prediction*


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## 1. INTRODUCTION

Governments, environmental experts, and the general public are now paying close attention to global climate change. Recently, there was a considerable improvement in related research across many other fields. The major cause of global climate change is global warming, which has altered the environmental regime in some areas of the earth's surface [1-5]. Multiple observations and experiments have been conducted by numerous researchers across a variety of disciplines, and a vast amount of data has been gathered and studied about climate change [6-9]. In order to produce accurate modeling forecasts regarding the effects of climate changes for the scientific use and legislative initiatives of the government, it is vital to fully utilize this data. In this study, there are a set of terms that must be considered carefully. The word "weather" firstly refers to everything that is occurring outside in a specific location at a specific moment. Wind, temperature, humidity, atmospheric pressure, cloudiness, and precipitation are used to measure it [10].

Thirdly, climate change has been defined as an ongoing change of planet's climate elements, especially one that is brought on by the increase in the average temperature and rainfall. Climate is the cumulative average of the weather across time [8-9]. There are three different ways to look at global warming: (1) there is no climate change and no global warming; (2) global warming and climate change exist, but they are natural, cyclical events unrelated to human activity; and (3) climate change and global warming exist, yet human activity is also a contributing factor. AI is a computer science area which is focused upon the building of the intelligent machines which think and act like people [10-11]. The effectiveness of AI techniques such as genetic algorithms (GAs) and ANNs has been the subject of numerous researches. These tools are used to develop climate data analysis models throughout data training, model calibration, simulation, and the prediction of new data. These models were used in climate change studies like developing models to simulate rainfall-runoff, runoff forecasting, drought forecasting, meteorological data forecasting, and performing numerous other nonlinear hydrological applications linked to water resources studies [12-13]. The ANNs are efficient algorithms that could handle complex nonlinear systems and nonlinear interactions that are challenging to define using mathematical analytical expressions [14-15].

It also has a significant capacity for learning. A three-layer NN model is capable of producing any nonlinear mapping. In theory, an ANN is a useful tool for describing an ecosystem and its numerous features since an ecosystem represents a complicated non-linear system. ANN applications to ecological and global climate changes have advanced quickly. This technique has been used more frequently to study changes in urban air quality, forest ecology, meteorological data forecasting, and hydrology. This study introduces ANNs techniques and covers their recent use in the researches of global climate change and ecology (primarily after 2020). Table 1 shows the scientific published articles that were used as references in this overview study.

**2. Metyhodology**

This article review is written in the style of a traditional survey. However, the reference results are revealed so that the reader may make an informed choice. Although this is not a thorough systematic review, the factors of identifying methodology and study selection are all taken into consideration. Because the topic of this study is important thus, the abstracts included in this survey as part of the discussion.

**3.ARTIFICIAL NEURAL NETWORKS: INTRODUCTION AND CONCEPTS**

The ANNs can be described as mathematical algorithmic models which replicate the neural network behaviors of the animals and distribute information processing in parallel [16-17]. Those networks are reliant upon system complexity by changing a large number of the inter-connected links between the nodes with the aim of processing data. Neural networks are particularly good at establishing (mapping) non-linear relationships in comparison to conventional statistical measures or linear analysis techniques. When training data is evenly distributed throughout the problem space, neural networks frequently generalize very well and are also quite tolerant of data noise. The well-known multi-network backpropagation (BP) technique was developed by psychologists Rumelhart and Mcclelland between 1986 and 1988. One of the most popular methods for NN learning is still this one. The integration of diverse data kinds and sample pixel distribution hypothesis are two areas where this approach falls short [18]. ANNs could be utilized to improve classification performance and address statistical classification's drawbacks. The transfer of the information between every processing unit and layer is governed by the network topology. There are many different neural network topologies available today. Since it can simulate any continuous function, the majority of pertinent studies use a 3-layered backpropagation neural network model [21]Fig. 1.

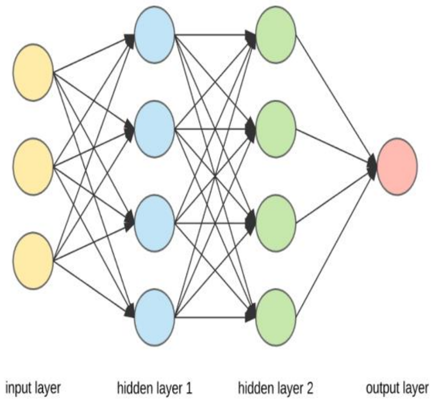


Fig. 1 Neural network topology

Basic neural networks also have consistent training times, and anastomosis is rarely a factor. Training is a crucial part of a neural network. To achieve the necessary precision, training and adjusting are done repeatedly. For data weights, summaries, and when training network systems for pattern recognition, the transfer function f(x) is frequently used.

The output value is then obtained using the conversion function. The input data's ownership category is given the highest weight as the categorization outcome's last step. A NN process could be separated into 2 primary stages to perform the task at hand, much too how the brain works. The learning phase, or the stage of self-improvement, is the initial step [19]. In order to reduce the measure function, a network modifies synaptic weights in accordance with predetermined learning rules. All of the weights can be trained, and the computing unit's state is unaffected. The processing of input data by a neural network and the generation of output data that is consistent with the processed data constitute the second phase of implementation. The connection weights are now fixed, and computation unit had reached a steady state.

## 4. Global climate change applications using artificial neural networks

### 4.1. Climate change and hydrological studies

It is common practice to evaluate the effects of climate change on water supplies using hydrologic models. Numerous studies have found that when hydrologic models are exposed to climatic conditions other than those of the calibration periods, they frequently experience significant performance loss. According to the outcomes they produced, these models were increasingly effective as AI technology advanced [20]. Table 1 shows the references adopted in this study that illustrated the applications of using artificial neural networks in climate change studies. The following references will be a survey of the pertinent most recent studies in this area in this study.

In recent years, ANN applications for climate change and hydrology have advanced. In a work that will be released in 2021 by Reddy et al. [21], the accuracy of multiple data sources will be assessed, and the best source will be selected to model the rainfall-runoff process in a case when data is scarce using AI approaches. In this study, gridded and observed precipitation datasets from the term (TRMM) that mean Tropical Rainfall Measuring Mission were subjected to an absolute homogeneity test. It was discovered that the homogenous observed precipitation data set represents the optimal choice for simulating the rainfall-runoff mechanism in India's Kallada river basin. This research demonstrated the efficacy of (EANN) which means an emotional artificial neural network in simulating the rainfall-runoff process and suggested that it might be a beneficial tool in other water resources engineering fields. The enormous potential of the long short-term memory (LSTM) has recently come to light in studies on rainfall-runoff modeling. But it's not clear how robust the LSTM network is to shifting environmental conditions. Bai et al. in 2021 [22] test robustness regarding the LSTM using 2 basic hydrologic models for predicting runoff under defferint climatic stuations. They descover that the used hydrologic models perform better throughout rainy times compared to dry stuations during calibration periods, however LSTM network performs comparably in all climatic conditions. In the case where they are calibrated during a wet time and validated during a dry time for the periods of validation, the two models perform worse. LSTM performance losses are mostly impacted by the climatic contrast between the validation and calibration periods, whereas the two hydrologic models' performance losses are majorly impacted by climatic stuations regarding the periods of validation. We found as well that the calibration period length is a significant factor that affects relative performance of models. Lengthening the calibration period has little impact on validation performance of both hydrologic models, yet, LSTM network performs better. For runoff simulation, the LSTM network is a suggested method if sufficient calibration data are provided. At the same time, hydrologic models could outperform the LSTM network if there are just some calibration data sets available.

Table 1: Applications of AI moels in climate change studies.

| Reference | Subject area | AI model | Results |
|---|---|---|---|
| **[15]** | Rainfall-runoff forecasting | EANN | It was discovered that the homogenous observed precipitation data set represents the optimal choice for simulating the rainfall-runoff mechanism. |
| **[16]** | Runoff forecasting | LSTM | It was discovered that the used hydrologic models perform better throughout rainy times compared to dry stations during calibration periods, however LSTM network performs comparably in all climatic conditions. |
| **[17]** | Drought evaluating | ANFIS | This study of the long-term meteorological drought found that due to further successive drought levels, it will get worse by 10.1% in the future. |
| **[18]** | Simulating daily stream flow | LSTM, RBF, MLP | The findings show that the semi-conceptual IHACRES model performs significantly worse in stream flow modeling than the best data based model, the used models. |
| **[19]** | Short-term drought forecasting | ARIMA, LSTM | The results show that all the hybrid models outperformed the single model in terms of forecasting drought accuracy |
| **[20]** | Tracking the effects of climate change | BDTR, DFR | This study found that standalone machine learning algorithms can predict rainfall with an acceptable level of accuracy |

The best option for future development urgently depends on an accurate assessment of the drought. The objective of the study presented by Yahya et al. in 2021 [23] was to use a geographic information system (GIS) environment and a fuzzy logic FL process to anticipate and evaluate drought in the Nineveh governorate in northwest Iraq. This study employed primary meteorological data from six stations. Using remote sensing research, changes in vegetation cover were discovered. From 592.3 $km^2$ in 1992 to 487.46 $km^2$ in 2016, the area of the vegetation cover decreased by 17.7%. The Standardized Precipitation Index (SPI) has been simulated as stand-in for drought circumstances by constructing the Adaptive Neuro-Fuzzy Inference System model as an artificially intelligent technique. The model's performance was 82%

when Nash-Sutcliffe coefficient and RMSE were taken into consideration. Yet, a study of the long-term meteorological drought found that due to further successive drought levels, it will get worse by 10.1% in the future. These results were made clearer by the spatial distribution map produced for the long-term drought simulation utilizing GIS as data base to develop future strategies for research region.

Radial basas function (RBF), multi-layer perceptrons (MLP), and long short-term memory models (LSTMs) are used. Also, the IHACRES semi-conceptual rainfall-runoff model has been utilized in order to evaluate AI models with greater accuracy. Momeneh et al. [24] carried out a study in 2022, and the findings indicate that the RBF, ANN, and LSTM models perform better than IHACRES model in simulating daily stream flow for the study area, particularly at the peak flow rate. Although it has performed excellently in medium and calm flows, the IHACRES model has struggled at flow peaks. Additionally, LSTM model outperformed the other models in calibration phase, while ANN and RBF models outperformed the others in verification period when it came to estimating the flow rate. Overall, the findings show that the semi-conceptual IHACRES model performs significantly worse in stream flow modeling than the best data based model, the LSTM model.

Xu et al. proposed in 2022 [25] a hybrid model based on (ARIMA) that's mean an autoregressive integrated moving average model and (LSTM) model in order to improve the accuracy of short-term drought forecasting in China. The accuracy of six drought forecasting models—ARIMA, support vector regression (SVR), (LSTM), (ARIMA-SVR), least square-SVR (LS-SVR), and (ARIMA-LSTM) are analyzed and compared in this study. Utilizing statistical tools like the Nash-Sutcliffe efficiency, the performances of all models were compared (NSE). The results show that all the hybrid models outperformed the single model in terms of forecasting drought accuracy [25].

Parts of the water cycle speed up as evaporation rates grow globally due to global warming; Malaysia is supposed to have a hot environment all year round due to its proximity to the equator. To track the effects of climate change in Malaysia, In order to forecast rainfall data for Tasik Kenyir, Terengganu, Malaysia in 2021, Ridwan et al. used a variety of models and techniques [26]. Overall model performances show that normalization using Log Normal produces better results in all categories except 10-days, where (BDTR and DFR) models are more acceptable than (NNR and BLR) models. It is concluded that two different methods were used with different scenarios and time horizons, and M1 has a higher accuracy than M2 when using BDTR modeling. This study found that standalone machine learning algorithms can predict rainfall with an acceptable level of accuracy; however, more accurate rainfall prediction may be achieved by proposing hybrid machine learning algorithms and incorporating various climate change scenarios [26].

### 3.2. Greenhouse gas emissions and air quality

Given the growth in air pollution levels in metropolitan areas around the world as a result of various human activities, accurate air quality forecasting is essential for public health. Table 2 shows the references adopted in this study that illustrated the role of ANN in analyzing and predicting gas emissions and air quality effects on the environment and eco-system.Air pollution is a serious problem everywhere in the world because of its affects on both the environment and people. The current review discussed by Subramaniam, 2022 [27] in detail the sources and impacts of pollutants on environmental and human health, as well as the current research status on environmental pollution forecasting techniques; this study presents a detailed discussion of the Artificial Intelligence methodologies and Machine learning (ML) algorithms used in environmental pollution forecasting and early-warning systems; additionally, the current work focuses more on Artificial Intelligence techniques (part I).

Despite extensive study and modeling efforts, many prediction systems have overlooked the various impacts that air pollution has on every single citizen. Nam et al. from 2020 [28] produced an energy-efficient ventilation optimization system for the proactive environmental and economic maintenance of subsurface ventilation system for a subway's internal air quality. The system is built on the iterative dynamic programming (IDP) methodology. While the DL model anticipated the subway's environmental conditions for the next 24 hours, AI-iterative dynamic programming sought a fragmented operational plan for ventilation flow rate for an identical operating period.

Table 2: The role of AI in analyzing and predicting gas emissions and air quality.

| Reference | Subject area | AI model | Results |
|---|---|---|---|
| **[21]** | Pollution forecasting | ML | This work focuses on artificial intelligence techniques and early-warning systems. |
| **[22]** | Air quality forecasting | IDP | This study produced an energy-efficient ventilation optimization system for the proactive environmental and economic maintenance of subsurface ventilation system for a subway's. |
| **[23]** | Air pollution prediction | LSTM | The suggested model is very adaptive for predicting air quality conditions at four air quality monitoring stations with high precision levels (90-96%). |
| **[24]** | Ecological quality evaluation | ANFIS, SVR | It has been observed that the simulation procedure yielded more accurate results when the used models were adapted. |
| **[25]** | Greenhouse emissions forecasting | MLP, IoT | The findings of the study demonstrate that the suggested ANN model successfully predicted pollutant gas emissions. This study also showed that cutting greenhouse gas emissions is possible with an IoT-based system. |
| **[26]** | Evaluating urban air quality | PCA | The integration of air pollution models and geographic information system methods holds promise in developing cities. |
| **[27]** | air quality analysis | OANN | This study improving the current artificial neural network model by altering the network's starting weights using a genetic algorithm (GA). |

While maintaining excellent indoor air quality for passengers, Efficiency of energy increased by 8.68%. A proactive, ideal ventilation system for a target subway station's platform demonstrated a decrease of 96 tons of CO2 annually while simultaneously displaying operating cost savings of up to 4217 $ annually, helping to combat climate change.

Schürholz et al. [29], provide a novel context prediction model in 2020 that combines information from an accurate air pollution prediction technique with data from the user's health profile and nearby pollution sources (such as traffic volumes and wildfire occurrences) (using a LSTM deep neural network). Subsequently, with the use of a real-world use case developed in Melbourne urban region, this model has been included into a tool that is referred to as the My Air Quality Index (MyAQI), which is after that applied and assessed in Victoria, Australia. MyAQI data demonstrate that: (i) there is a possibility for predicting air quality conditions at four air quality monitoring stations with high precision levels (90-96%) and (ii) the suggested model is very adaptive to users' particular health condition effects at the same airborne pollutant.

In the year 2021, Nourani et al [30] evaluated the environmental and ecological quality in Iranian cities useing artificial intelligence (AI) and remote sensing (RS) procedures. Ecologists surveyed the sampling sites and supplied background values (EBVs) for the eco-environment of the sites. After that, eco-environmental qualities have been extracted as RS-derived from meteorological variables that had been observed, three AI-based models—the ANN, ANFIS, and support vector regression (SVR)—were utilized in order to identify the link between a target set of well-known EBVs and eco-environmental variables as inputs. Based on results of single models, no model was able to reliably estimate EBV for all regions and classes. To enhance the geographic evaluation regarding EBV, the outputs of many models were after that integrated with the use of three different ways. It has been observed that the Tabriz simulation yielded more accurate results. The more diverse dataset in this kind of climate seems to be the likely reason for Tabriz's higher network performance. The outcomes demonstrated that SVR outperformed ANFIS and ANN models, yet that the models' combining approaches have beensuperior. Combining approaches improved a single AI model's performance during the verification phase by up to 26%.

Bonire and Gbenga 2021 [31] developed a combining model based on the source testing method, artificial neural network (ANN) technique, and the Internet of Things (IoT). This model was used to predict some greenhouse gas emissions for in Abuja province, Nigeria. The predicted emissions gases are carbon dioxide (CO2), carbon monoxide (CO), nitrogen dioxide (NO2), and sulfur dioxide (SO2). This study shows that the emissions of these gases exceed the recommended limit for human health. With a high overall correlation coefficient value that makes it a strong fit for forecasting, the findings demonstrate that the suggested ANN model successfully predicted pollutant gas emissions. This study also showed that cutting greenhouse gas emissions is possible with an IoT-based system.

A geographic information system (GIS) and machine learning techniques were combined in the study by Jasim et al. that conducted in 2020 [32]. In this proposed technique, the principal component analysis (PCA) approach was used to optimize the support vector regression model. The regression model was then integrated with spatial analysis modeling using a grid (100 x 100 m) to produce prediction maps during weekends and workdays throughout the day and at night in a very busy neighborhood of Baghdad, Iraq. The information used in this study was divided into two groups. In the first category, measurements of temperature, humidity, wind speed, wind direction, traffic flow (such as the number of light and heavy vehicles), and carbon monoxide samples taken using portable equipment are made in the field. The information obtained from geographic information system data falls under the second category and includes data on building height, road network, and land use. The proposed model's accuracy is 81%, and the smallest root mean square error was 0.067 ppm. For evaluating urban air quality and developing cities, the integration of air pollution models and geographic information system methods holds promise. Stakeholders and decision-makers use these tools effectively to lay out appropriate plans and strategies to reduce air pollution in metropolitan settings.

Traditional statistical and mathematical models struggle to analyze air quality, meteorological, and traffic variables due to their complexity and non-linear relationships. Machine learning algorithms have recently gained popularity in the field of traffic emissions prediction. The variation and trend of traffic pollutants are influenced by meteorological and traffic variables. In a 2021 an optimized artificial neural network (OANN) was developed by Abdullah et al. [33] this study was carried out in Kuala Lumpur, Malaysia, with the goal of improving the current artificial neural network (ANN) model by altering the network's starting weights using a genetic algorithm (GA). The CO, NO, NO2, and NOx pollution concentrations released by moving cars were predicted using the created model. The OANN model was used to forecast the concentrations of CO, NO, NO2, and NOx pollutants released by cars in Kuala Lumpur, Malaysia. OANN's results were contrasted with Random Forest (RF) and Decision Tree (DT). With the lowest MSE values, the generated OANN model beat the (ANN, RF, and DT) models, according to the results. Officials can utilize the OANN model to help them lessen transportation pollution and protect those who live close to roadways.

### 3.3. Projecting future changes to the vegetation, soil, and forest ecosystems

Since it avoids numerous challenges in processing forest data, like nonlinear and non-normal relations, ANN has lately gained prominence in forest modeling. The measurement of forest biomass is a crucial component of the examination of global change. Table 3 shows the references adopted in this study that illustrated the role of ANN in future changes to the vegetation, soil, and forest ecosystems.

The global land cover is rapidly changing. Shahi et al. used Land Change Modeler (LCM) in a study in 2020 [34] to predict land cover by 2030. Landsat satellite images were used to detect land cover in 1987, 2002, and 2017. A multilayer perceptron technique depend on seven variables were used to develop this model. With a calibration period of 1987–2002, lands cover were modeled for 2017 using the Markov chain, and the land cover map was projected using the generated model. Finally, the lands cover for 2030 were forecasting using the calibration period 2002-2017. The transition of forest lands to other land uses has caused the most change over all historical periods. According to projections, 248 ha of agricultural land will be created in 2030, while 6000 ha of forest area will be turned to pastures.

Jahani et al. [35] developed an MLP artificial neural network model in 2021 to forecast vegetation diversity associated to human activities this study condected in Iran's Lar National Park. As sampling locations with the greatest and least amount of human effect, recreation and restricted zones were chosen. In 210 sample plots, the diversity of the vegetation was quantified by the number of species. Twelve soil and landform variables were also noted and employed in the model's construction. According to sensitivity analysis, the two most important inputs impacting the MLP are human intensity class and soil wetness.

The root of the plant, evapotranspiration rates, and consequently soil water content are all significantly influenced by soil temperature (ST). To understand the quantitative relation between climatic parameters and temperature of the soil, a substantial quantity of study was conducted lately in response to climtic change on a worldwide scale.

Table 3: The role of AI in future changes to the vegetation, soil, and forest ecosystems.

| Reference | Subject area | AI model | Results |
|---|---|---|---|

| | | | |
|---|---|---|---|
| **[28]** | Land cover forecasting | MLP | This work focuses on developing a model based on artificial intelligence techniques for lands cover modeling the remote sensing data were used in the model. |
| **[29]** | Forecasting vegetation diversity | MLP | In 210 sample plots, the diversity of the vegetation was quantified by the number of species. Twelve soil and landform variables were also noted and employed in the model's construction. According to sensitivity analysis, the two most important inputs impacting the MLP are human intensity class and soil wetness. |
| **[30]** | Global climate change evaluating | MLP-NN | The findings indicate that the forestry land usage in SAARC nations will change to varied degrees under each scenario. |
| **[31]** | Soil temperature modeling | ESN | In this study the accuracy of the generated soil temperature models is assessed. The evaluation findings demonstrated that the Deep ESN model performed better than traditional ML methods and could decrease the RMSE accuracy of the old models by (30 to 60 %). |
| **[32]** | Soil and plant degradation | MLP | According to the findings of the sensitivity analysis, the variables most useful in predicting soil and plant cover degradation were the distance from the road, slope, and slope direction in the soil model, and the distance from the road, soil moisture content, and slope direction in the plant model. |
| **[33]** | Understanding soil features | k-NN, SVM | In this study, A proposed method for classifying soil based on macronutrients and micronutrients and predicting the type of crop that can be grown in that soil type using K-Nearest Neighbor (k-NN), Bagged tree (BT), Support vector machine (SVM), and logistic regression (LR). |

Forestry and agriculture are the two main land use types that contribute to global climate change. Because of the rate of growth, such two types of land use are changing throughout time. For South Asian Association for Regional Cooperation (SAARC) nations—a geopolitical union of Bangladesh, Afghanistan, India, Bhutan, Maldives, and Nepal—in the year 2050, Singh et al. analyze the deployment of the MLP-NN in 2020 [36]. The findings indicate that the forestry land usage in SAARC nations will change to varied degrees under each scenario. It has been discovered that as a response to the changing hydro-meteorological elements, hydro-thermal conditions in soil are often changing. In contrast to three conventional ML models, the novel Deep ESN model is used in research by Alizamir et al. [37] from 2021 to forecast ST at depths of (10 cm and 20 cm). To create the Deep ESN model, they merged multiple data sets (daily hydro-meteorological) into 6 unique input combinations. Utilizing three deterministic metrics, the accuracy of the generated soil temperature models is assessed. The evaluation findings demonstrated that the Deep ESN model performed better than traditional ML methods and could decrease the RMSE accuracy of the old models by (30 to 60 %).

Mosaffaei et al. 2020 [38] predict an artificial neural network-based model to deal with soil and plant degradation. Parallel transects were used to sample soil using a systematic random method. Soil profiles were drilled at four different depths from 5 to 20 cm, and the soil texture was assessed using a hydrometer. Two indices (Margalef and Simpson) were used to calculate the diversity and richness of plant species. The artificial neural network model was fed with information from 480 soil profiles, 600 vegetation sample plots, and soil physical characteristics in addition to human and ecological aspects. The proposed models have the following R values for soil texture and biodiversity indices (clay = 0.6960, sand = 0.5657, silt = 0.5913, and Margalef index = 0.5913). According to the findings of the sensitivity analysis, the variables most useful in predicting soil and plant cover degradation were the distance from the road, slope, and slope direction in the soil model, and the distance from the road, soil moisture content, and slope direction in the plant model.

A crucial element in agriculture is the soil. India has many different kinds of soil. To anticipate the kind of crop that can be grown in a specific soil type, knowledge of the features and characteristics of the soil type is necessary. Saranya and Mythili in 2020 [39] used machine learning techniques to provide a flexible way to understand soil features in this case. It is much easier for farmers to predict which crop can be grown in a particular soil type if the soil is classified according to its nutrients. Data mining and machine learning are still new techniques in agriculture and horticulture. In this study, they proposed a method for classifying soil based on macronutrients and micronutrients and predicting the type of crop that can be grown in that soil type using K-Nearest Neighbor (k-NN), Bagged tree (BT), Support vector machine (SVM), and logistic regression (LR).

### 3.4. Dust storms detection

During the previous ten years, dust storms increased in both spatial and temporal dimensions over Middle Eastern countries [13]. Table 4 shows the references adopted in the Dust storm detection.Residents of Iran's south and southwest have suffered incalculable social, economic, and environmental consequences as a result of Middle Eastern dust storms. Amiri et al. in 2020 [40] present a study that uses MODIS data because it offers several benefits, such as usable and accessible spectral bands and high spatial and radiation resolution. Data from (January 18 to January 21, 2018) were used to develop utilizing the model, and data from (January 22 to January 31, 2018) were used to develop an evaluation utilizing the model. Metrological data are acquired concerning the period being studied. The proposed method produced features (ANN input) from the MODIS data after preprocessing the MODIS data and getting ready the field observations. The model was developed using ANN analysis. This model estimates visibility and extracts a dust storm. Visual comparisons between the model and NDDI outputs were made. The constructed model was put to the test using different time data for assessing the efficacy of the suggested method. Visual comparisons between the model and NDDI outputs were made. The accuracy of the suggested method has finally been evaluated by contrasting the model output with the visibility parameter of synoptic stations to highlight its strengths and flaws. The observation root mean squared error for January 18, 19, 20, and 21 is 10%, 15%, 10%, and 10%; for January 26, 2019, and October 28, 2018, it is 20% and 25%, respectively.

Ebrahimi-Khusfi et al. carried out a study in 2021 [41] for forecasting the dust storm index (DSI) between 2000 and 2018 in Iran's arid regions. Their objective was to assess the average as well as the nine ML models' applicability. Those models comprised multivariate adaptive regression splines, SVMs, Cubist, RF, KNN, extreme gradient boosting, genetic programming, and ANNs. The outcomes demonstrated that averaging technique outperformed the other individual models of machine learning in predicting DSI changes throughout all the seasons. For example, the averaging approaches outperformed multivariate adaptive regression splines in the spring, winter, fall, summer, and dusty seasons, respectively, by 39%, 22%, 32%, 28%, and 26%.

Boroughani et al, in 2020 [42] developed a method for producing a dust source susceptibility map (DSSM). In the northeastern Khorasan Razavi Province of Iran, they conducted dust storm tests using statistically-based ML algorithms as well as remote sensing. To identify the origin of dust in the study area by analyzing MODIS images from (2005 to 2016). To locate the dust source, 23 MODIS satellite images have been utilized to create four indices, including BTD2931, BTD3132, NDDI, and the D variable. To train and validate the ML algorithms, 65 dust source sites have been found and categorized as dust source data points. Three statistically based ML algorithms (Frequency Ratio (FR), Weights of Evidence (WOE), and Random Forest (RF)) were used to produce DSSM for the study area. Slope, lithology, soil, geomorphology, NDVI, and distance from rivers were used as conditioning elements to develop this model. They assessed the effectiveness of the models by utilizing the receiver operating characteristic's (ROC) area under the curve (AUC). The WOE and FR algorithms achieved accuracy levels of 83 and 82%, respectively, in terms of AUC success rate (training), while the RF approach provided accuracy levels of 91%. Depending on the AUC prediction rate (i.e. validation), the three models' respective accuracy was 81, 80, and 88% for WOE, FR, and RF.

Airborne dust affects a variety of human endeavors adversely, including and agriculture, aviation. In an investigation, conducted by Berndt et al. in 2021 [43], Known techniques are used to identify dust and aerosols in the atmosphere utilizing remote sensing readings. To assist forecasters and decision-makers in identifying dust at night, false color and Red-Green-Blue (RGB) images with band differences sensitive to dust absorption (Dust RGB) are now employed operationally. Even specialists find it difficult to identify nighttime dust due to picture interpretation's limits, subjectivity, and subtlety.

In this study, a simple random forest (RF) model is utilized to detect nighttime dust using band differences sensitive to dust absorption, dust RGB color components, and infrared data from the Geostationary Operational Environmental Satellite-16 (GOES-16) and Advanced Baseline Imager (ABI).

Table 4: The role of AI in detecting Dust storm events.

| Reference | Subject area | AI model | Results |
|---|---|---|---|
| **[34]** | Dust storm detection | ML | The proposed method produced features (ANN input) from the MODIS data after preprocessing the MODIS data and getting ready the field observations. The model was developed using ANN analysis. This model estimates visibility and extracts a dust storm. |
| **[35]** | forecasting seasonal dust storm index | ML | The outcomes demonstrated that averaging technique outperformed the other individual models of machine learning in predicting DSI changes throughout all the seasons. For example, the averaging approaches outperformed multivariate adaptive regression splines in the spring, winter, fall, summer, and dusty seasons, respectively, by 39%, 22%, 32%, 28%, and 26%. |
| **[36]** | producing dust source susceptibility | ML | In this study a dust source susceptibility map (DSSM) was produced. Statistically-based ML algorithms as well as remote sensing were used to conduct the dust storms and to identify the origin. |
| **[37]** | Airborne dust affecting | RF | Known techniques are used to identify dust and aerosols in the atmosphere utilizing remote sensing readings. In this study, a simple random forest (RF) model is utilized to detect nighttime dust using band differences sensitive to dust absorption. |
| **[38]** | locating dust source sites | ANFES | The findings demonstrate that the ANFIS-DE hybridized model works better than other hybridized models created for dust-storm prediction (AUC=84.1%, 50 TSS=0.73). According to the results, the hybridized ANFIS-DE model is a viable, economical way for quickly locating dust source regions, with advantages for both public health and natural ecosystems where too much dust is a serious problem. |

The RF model accomplishes an Area-Under-Curve (AUC) of 0.97 with a standard deviation of 0.04 for dust scenarios. The model accurately identifies 85% of the pixels in dust photos and 99.96% of the pixels in no-dust images. The training data set's inaccuracy in identifying no-dust pixels as dust is decreased from 45% to 14.5% by including a single null example. The analysis of the dust event that took place on April 13–14, 2019, using the machine learning model, demonstrates the model's ability to detect dust at night when optical dust detection is limited by cooling ground surface characteristics.

Controlling the consequences of this danger depends on locating the dust source regions. Rahmati et al. create a new strategy for locating dust source sites based on hybridized machine-learning algorithms in a 2020 study [44]. Each hybridized model, intended to function as an intelligent system, combines the bat algorithm (BA), the cultural algorithm (CA), and the differential evolution (DE) algorithm with an adaptive neuro-fuzzy inference system (ANFIS). The hybridized model incorporates information from MODIS Deep Blue and the Ozone Monitoring Instrument (OMI), as well as pertinent information from field surveys and dust samples from the study region. Several statistical metrics, such as the true skill statistic (TSS) and the area under the receiver operating characteristic curve (AUC), are used to assess the hybridized models' predictive power (AUC). The findings demonstrate that the ANFIS-DE hybridized model works better than other hybridized models created for dust-storm prediction (AUC=84.1%, 50 TSS=0.73). According to the results, the hybridized ANFIS-DE model is a viable, economical way for quickly locating dust source regions, with advantages for both public health and natural ecosystems where too much dust is a serious problem.

### 3.5. Forecasting runoff using AI

Since water resources in semi-arid and arid regions are susceptible to changes in hydro-climatic factors, particularly under climate change, runoff simulations are more challenging. The references used in the Dust storm detection are displayed in Table 5.

To ensure the security of future water supply in the Karaj River basin, north of Iran, Yoosefdoost et al. calculated input runoff to a dam reservoir in a dry area under changing climatic circumstances in 2022 [45]. ANNs, SVM, genetic expression programming (GEP), as well as the conceptual HYMOD model are the three data mining (DML) technologies they employ. Thirty coupled models participated in Coupled Model Intercomparison Project Phase 5 (CMIP5)'s of three parameters, such as the precipitation and minimum and maximum temperatures, for the 2020–2040 future periods under the extreme RCP8.5 scenario.

Table 5: The role of AI in forecasting runoff.

| Reference | Subject area | AI model | Results |
|---|---|---|---|
| **[45]** | Future water supply | ANNs, SVM | The predicted SVM model was compared to the study period, the mean runoff inflow to the dam reservoir will decline by 25% between 2020 and 2040. (2000–2019). This outcome highlights the need for adopting sustainable adaptation strategies to safeguard the basin's future water resources. |
| **[46]** | Evaluating base flow and surface runoff | ML | Based on the extensive analyses of all models, the base flow and surface runoff values are recommended as inputs to AI-based models for improved stream flow forecast accuracy. |
| **[47]** | Forecastinf rainfall-runoff | SVM, RF | The comparison results showed that the four heuristic techniques performed more accurately than the MLR model. In the training phase, the RMSE (m3/s), R2, NSE, and PBIAS (%) were (6.31, 0.96, 0.94, and 0.20) respectively, while in the testing period, they were (5.53, 0.95, 0.92, and 0.20). For each scenario taken into consideration, the RF predicted daily runoff better than the MARS, SVM, and MLR models. Throughout training, the RF model performed better than the other three models. |
| **[48]** | Identify hydrological impacting elements | XGBoost | It was shown that rainfall at high elevations (or slope) had a bigger impact on runoff than rainfall at low elevations, and that different climatic variables have varying effects on runoff in different sub-basins. The formation of runoff, which is influenced by heavy precipitation, has a clear threshold effect on the mix of land uses (or slope). The results of this study could result in the creation of a fresh approach to runoff factor analysis. |

The SVM model predicted that, compared to the study period, the mean runoff inflow to the dam reservoir will decline by 25% between 2020 and 2040. (2000–2019). This outcome highlights the need for adopting sustainable adaptation strategies to safeguard the basin's future water resources.

Chen et al. created a novel strategy in 2021, outlining four scenarios for evaluating the various contributions of base flow and surface runoff to the accuracy of long-term stream flow forecasting [46]. This was carried out in order to address the problems with water security caused by drought disasters and flooding. Several stream flow sites in the Chinese province of Zhejiang are used to test the developed models. The findings demonstrate that for all twelve months of the year, models based on AI with two predictor variables (surface runoff and basin flow) performed better compared to models with just one predictor. Stream flow and predictions for annual peak and monthly stream flow values are currently more precise. Based on the extensive analyses of all models, the base flow and surface runoff values are recommended as inputs to AI-Based models for improved stream flow forecast accuracy. In a study published in 2022 by Singh et al. [47], In order to forecast rainfall-runoff in the Gola watershed in India, a number of data driven models were applied, including multiple linear regression (MLR), multiple adaptive regression splines (MARS), support vector machine (SVM), and random forest (RF). The analysis of the rainfall-runoff model employed daily rainfall and runoff data for the Gola watershed from 2009 to 2020. The models were evaluated in addition to the numerical comparison. Their model accurcey was assessed using graphical plotting. The comparison results showed that the four heuristic techniques performed more accurately than the MLR model. In the training phase, the RMSE (m3/s), R2, NSE, and PBIAS (%) were (6.31, 0.96, 0.94, and 0.20) respectively, while in the testing period, they were (5.53, 0.95, 0.92, and 0.20). For each scenario taken into consideration, the RF predicted daily runoff better than the MARS, SVM, and MLR models. Throughout training, the RF model performed better than the other three models.

The typical machine learning paradigm is opaque and difficult to understand, which prevents it from being used widely to identify hydrological impacting elements. The interpretability of AL models is enhanced in 2022 by Wang et al [48] using the Interpretable machine learning technique. To ascertain the effect of driving factors on runoff generation, the extreme gradient boosting (XGBoost) approach is applied to data produced by the calibrated Soil Water Assessment Tool (SWAT). After that, the Shapely additive explanations (SHAP) approach is used to understand the XGBoost. The findings demonstrate that XGBoost can imitate SWAT's capability to simulate, and SHAP can read XGBoost to pinpoint the variables affecting runoff formation. It was shown that rainfall at high elevations (or slope) had a bigger impact on runoff than rainfall at low elevations; and that different climatic variables have varying effects on runoff in different sub-basins. The formation of runoff, which is influenced by heavy precipitation, has a clear threshold effect on the mix of land uses (or slope). The results of this study could result in the creation of a fresh approach to runoff factor analysis.

## 4. CONCLUSION

These ANNs have advanced network geometry and a sophisticated design. With some sets of data, they might be able to recreate them with successful outcomes, but with other sets of data, it might have the opposite impact. Because ANNs are not linear, the over-fitness of the data causes this problem. There is no doubt that ANNs' many advantages offer a fresh perspective on the vast possibilities for research into ecological and climatic change. For instance, modal recognition, careful reasoning, strong fault tolerance, distributed knowledge storage, and parallel structure and processing can be used to study new settings and adapt to them. For ensuring reliability and extrapolation criteria, ANNs also require a large number of sample data points. It can be difficult to retrieve such a big volume of measured data at times. Mechanism-based models must still be used, even though ANN models frequently have simulation accuracy that is significantly better than many linear equations. Nonlinear equations and this circumstance are analogous. The ANN model's real advantage is its ability to simulate novel systems or systems which traditional models can't. While it will take time and increased effort to further ANN research, it has immense potential for advancement, much like the human brain. Wavelet analysis, fuzzy systems theory, and the evolutionary computation of genetic algorithms in combination with ANNs have all grown to be significant study areas. Fuzzy logic, for instance, excels at handling structured issues. However, ANNs are better able to manage unstructured data since they can learn directly from the samples themselves.

Environmental studies, their applications, and global climate change forecasts are expanding. ANNs manage complicated problems and simulate nonlinear system behaviors more accurately and quickly than conventional statistical techniques. However, the use of the ANN approach is still in its early stages. It also has problems with its "black box" nature, excessively long training times, and overfitting of the data. ANNs won't totally replace conventional methods. Yet, ANNs will be a helpful tool in researches of ecological change as well as global climate change in the 21 century through fusing such many approaches and technology into a decision-support system.

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# دراسة التغيرات المناخية العالمية باستخدام الذكاء الاصطناعي: نظرة عامة

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***الملخص***

*يمكن أن يمثّل الذكاء الاصطناعي أداة قوية في مواجهة بعض أكبر التحديات التي تشهدها البشرية وهي التغير المناخي العالمي. تشمل عملية مراقبة تغيُّر المناخ مجموعات من البيانات الكبيرة دائمة التطوّر. ويمكن أن تساعد أنظمة الذكاء الاصطناعي في تحليل مجموعات من المعلومات البيئية، وذلك بهدف تتبُّع التغيرات في الظروف المناخية في الوقت الفعلي، ومعالجة نقاط الضعف للحدّ منها، وإتاحة فرص حيوية للبشرية كي تجد حلولاً يمكن أن يكون لها تأثير إيجابي على كوكبنا وبشكل سريع مقارنة بالحلول التقليدية. إنّ الذكاء الاصطناعي ليس سوى أداة واحدة ضمن عملية تحليل أسباب تغيُّر المناخ المعقدة، ولكن قدرته على معالجة كمّ كبير من البيانات واكتشاف أنماط والتنبؤ بالبيانات تتيح لن افرصة لفهم النظام البيئي بشكل أفضل.*

***الكلمات الداله :***

*الذكاء الاصطناعي،التغير المناخي العالمي ,النظام البيئي , الانماط غير الخطية,التنبؤ.*