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Review article

Soft computing paradigm for climate change adaptation and mitigation in Iran, Pakistan, and Turkey: A systematic review

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ABSTRACT

This systematic review examines the application of artificial intelligence (AI), including machine learning (ML) and deep learning (DL), for climate change adaptation and mitigation in Iran, Pakistan, and Turkey. These three nations—key Economic Cooperation Organization (ECO) members and a nexus between Europe and South Asia—are experiencing diverse environmental challenges due to varying climatic conditions. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, we conducted a comprehensive search in the Scopus database, ultimately identifying 76 relevant articles out of an initial 492. Although some articles utilized multiple techniques, classical ML methods appeared in approximately 37.3 % of the studies, neural network paradigms in about 57.5 %, and optimization or meta-heuristic algorithms in around 5.0 %. Regarding thematic focus, about 33.3 % of the articles addressed water resource management, 22.2 % focused on climate prediction, 11.1 % on land and agriculture, 9 % on ecosystem modeling, and 24.2 % on natural disaster preparedness and response. The analysis reveals a growing but uneven body of research utilizing AI across the ECO countries. By highlighting successful applications, identifying key gaps—such as limited cross-border collaboration and inconsistent data availability—and proposing a framework for more integrated research, this review aims to guide future initiatives that leverage AI's potential to improve climate resilience and sustainability in the region.

1. Introduction

Climate change is a global crisis with localized impacts that demand tailored solutions [1]. Particularly vulnerable to these changes, countries like Turkey [2], Iran [3], and Pakistan [2] are founding members of the Economic Corporation Organization (ECO) and also considered as Euro-South Asian Gateway, facing unique climatic impacts by their geographical and socio-economic frameworks. As traditional approaches to climate change mitigation and adaptation become increasingly insufficient, innovative solutions involving intelligent soft computing algorithms such as machine learning (ML) and deep learning (DL) have shown promising potential [4]. These technologies offer unparalleled capabilities in processing vast and complex datasets to derive actionable insights, making them indispensable tools in combating climate change effects more effectively. Meanwhile, Iran, Turkey, and Pakistan are situated in a region where climatic extremes are common, ranging from arid deserts to fertile plains, exposing them to a range of environmental

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stressors from water scarcity [5] to extreme weather events.

Global evidence demonstrates how AI and ML can enhance the understanding and managing climate-related hazards. For example, frequency ratio and ensemble modeling approaches have enhanced landslide susceptibility mapping in Himalayan regions by more effectively capturing the complex interactions among geomorphological, climatic, and environmental factors compared to standalone methods (Chowdhuri et al., 2020; [6]; Pal & Chowdhuri, 2019). Multi-hazard frameworks that integrate future climate and land-use projections have further advanced the protection of cultural heritage sites and informed sustainable environmental strategies discussed by Saha et al. (2021). Beyond landslides, optimization modeling combined with ML has guided interventions for mitigating gully erosion shown by Saha, Pal, Arabameri et al. (2021), while ML-driven analyses have illuminated how changing land use and climate patterns heighten flood vulnerabilities (Pal et al., 2022). Additionally, a study by Roy et al. (2022) shows that MaxEnt and ANN models have identified drought-prone areas, offering valuable insights for agricultural resilience and policy recommendations. These studies collectively highlight that advanced AI and ML methodologies can refine hazard assessments, guide resource planning, and inform policy-making, underscoring their potential applicability to the diverse and underexplored challenges facing Iran, Turkey, and Pakistan.

Despite the critical need, the application and research into these technologies remain fragmented and underexplored within these countries. This review paper seeks to bridge this gap by providing a comprehensive analysis of the current and potential applications of ML and DL in climate change mitigation and adaptation strategies in Turkey, Iran, and Pakistan. Through this examination, the paper aims to highlight successful models, identify areas requiring further research, and propose a collaborative framework for regional environmental resilience.

2. Methodology

This review aimed to comprehensively investigate the various AI and ML techniques employed for climate change adaptation and

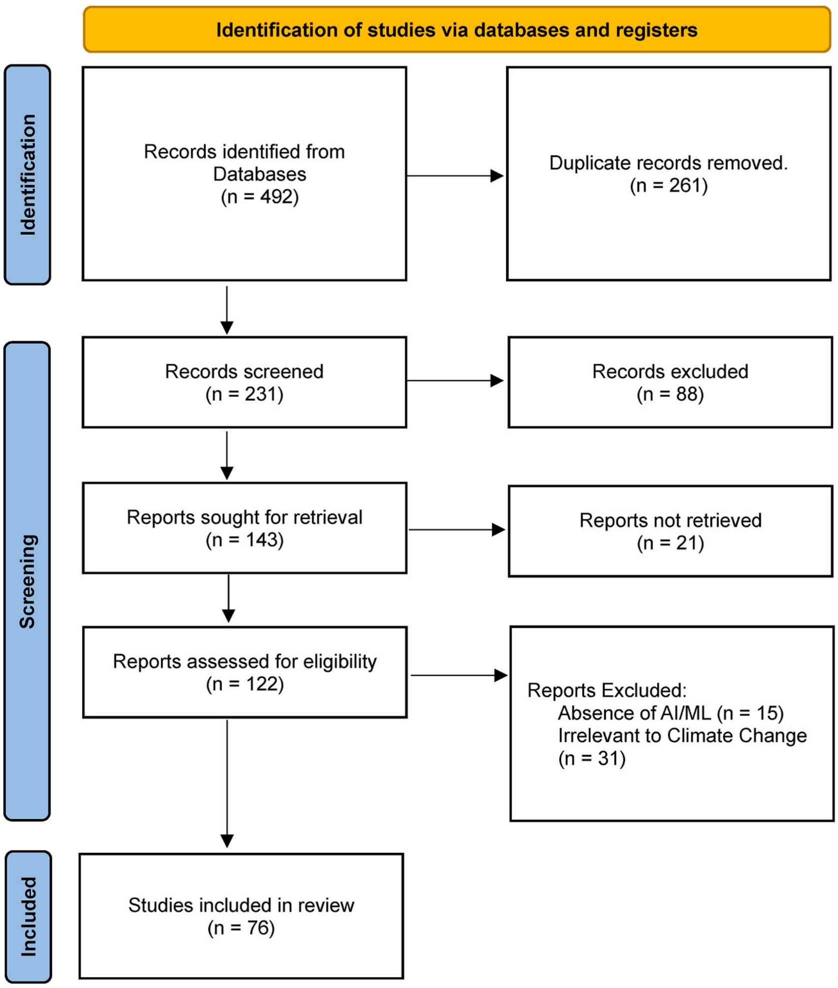

Fig. 1. Systematic diagram according to PRISM statement.

mitigation strategies in Iran, Turkey, and Pakistan, adhering to the guidelines outlined in the PRISMA statement. Extensive research was conducted using the Scopus database, employing a carefully selected set of keywords, including "Iran", "Turkey", "Pakistan", "Climate Change", "Climate Change Adaptation", "Climate Change Mitigation", "Artificial Intelligence", "Machine Learning", "Deep Learning", "ANN", "Artificial Neural Network", "Convolution Neural Network", "CNN", "LSTM", and others. These keywords were applied in the title, abstract, and keywords of papers. Boolean search commands, including "AND" and "OR", were utilized to retrieve relevant literature while ensuring the elimination of any duplicate entries. Subsequently, the search results underwent a series of steps following the PRISMA model for systematic reviews, including identification, screening, eligibility, and inclusion processes.

Fig. 1 depicts the systematic diagram illustrating the review process conducted in accordance with the PRISMA Statement. The initial stage involved identifying relevant research sources, resulting in the retrieval of 492 papers containing the specified keywords with various Boolean settings. Subsequently, 261 duplicate articles were eliminated during the first part of the screening process, leaving 231 papers for further consideration. Careful exclusion of 88 records took place, as they did not align with the purpose of the review. Furthermore, 21 articles were removed due to restricted access. The full text of the remaining 122 articles was thoroughly reviewed, leading to the exclusion of 15 articles lacking AI/ML techniques and 31 articles deemed irrelevant to the climate change problem. Consequently, a final set of 76 articles remained, which were considered for the systematic review. The population under investigation encompassed the climate change challenges faced by Turkey, Iran, and Pakistan, while the interventions explored were the diverse AI/ML approaches employed to address these challenges. The key outcome of interest revolved around the effectiveness and impact of these interventions in enhancing climate change adaptation and mitigation strategies in the respective countries and finding the research gap for more recent advancements in AI algorithms.

The collected papers were systematically categorized into five primary research areas for effective organization and analysis: 1) Water Resources Management, 2) Climate Prediction, 3) Land and Agriculture, 4) Ecosystem, 5) Natural Disasters. These research areas were meticulously selected to establish a comprehensive understanding of the extensive array of AI/ML techniques employed in the context of climate change adaptation and mitigation. The literature review also revealed the prominence of specific algorithmic or model categories (Table 1), namely: 1) Classical Machine Learning, 2) Neural Network Paradigm, and 3) Optimization and Meta-Heuristic Algorithms. The systematic categorization and identification of algorithmic or model categories enhances our understanding of the diverse applications of AI/ML techniques in climate change adaptation and mitigation. The distribution of papers across different regions (Fig. 2) and research fields and AI/ML techniques (Fig. 3) are presented in below:

Fig. 2 illustrates t the distribution of research papers in Iran, Pakistan, and Turkey across various climate change adaptation fields. The focus is on the application of soft computing techniques in water resources management, climate prediction, land and agriculture, ecosystems, and natural disaster management. Meanwhile, Fig. 3 represents the number of papers in each research field categorized by

Table 1
Overview of cited studies on machine learning applications in climate change adaptation and mitigation across various research fields.

Research Fields	Techniques		
	Classical Machine Learning	Neural Network Paradigm	Optimization and Meta-Heuristic Algorithms
Water Resources Management			
Evapotranspiration	[8,15]	[8,15,36]	
Groundwater	([7,37]; [18,19]; [16,17,20,67,68])	([37,69]; [18]; [16,17,20,70,71])	[17]
Rivers		[41,42,44,52]	
Streamflow Prediction		[43,72,73]	
Lakes		[74,75]	
Water Demand		[76]	
Surface Runoff		[77]	
Water Reservoir		[78]	
Climate Prediction			
Temperature	[9]	[39,45,46,53,79]	[45]
Precipitation	[9,10,21]	[39,47–49,79]	[21]
Climate Zones	[80]		
Global Warming	[22,23]	[22,23]	
Hydrological Cycle		[50]	
Land and Agriculture			
Virtual Water Content	[11]	[11]	[11]
Crop Yield	[11]	[11,51,52]	[81]
Land Use Change		[53,54]	
Soil Erosion Risk		[55,56]	
Ecosystem			
Biodiversity	[24–27]	[24–26]	
Forest	[12]	[58]	
Natural Disasters			
Floods	([31]; [29]; [28,30])	[31,40]	
Wildfire Disasters	[82]	[60]	
Heatwave	[63]	[63]	
Drought	[13,14,32,33,83]	[14,32,33,59,83]	
Landslide	[35]		
Disaster Preparedness		[62]	
Dust Phenomenon		[61]	

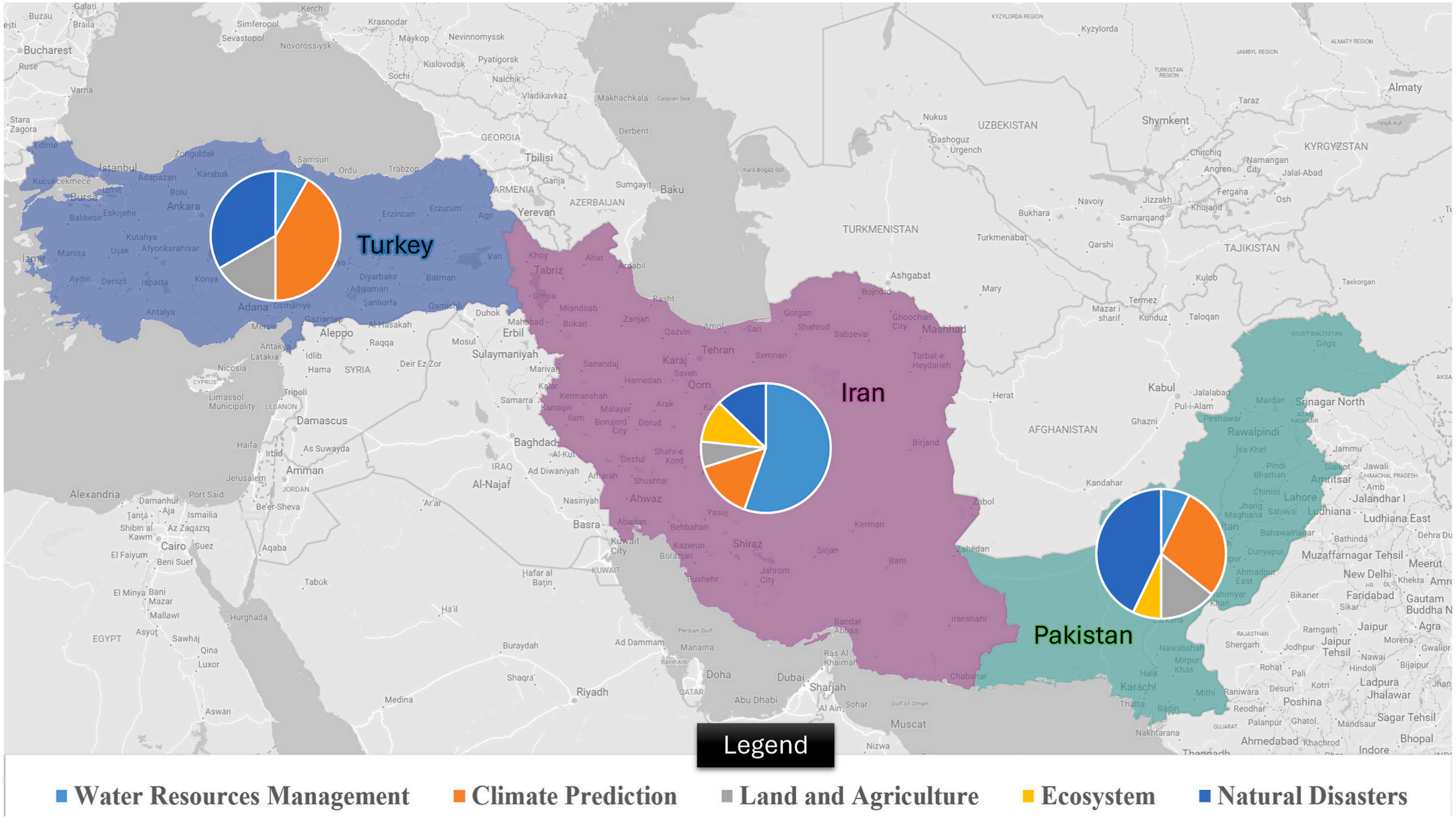

Fig. 2. Distribution of research papers on climate change adaptation in Iran, Pakistan, and Turkey across various fields: a focus on soft computing applications.

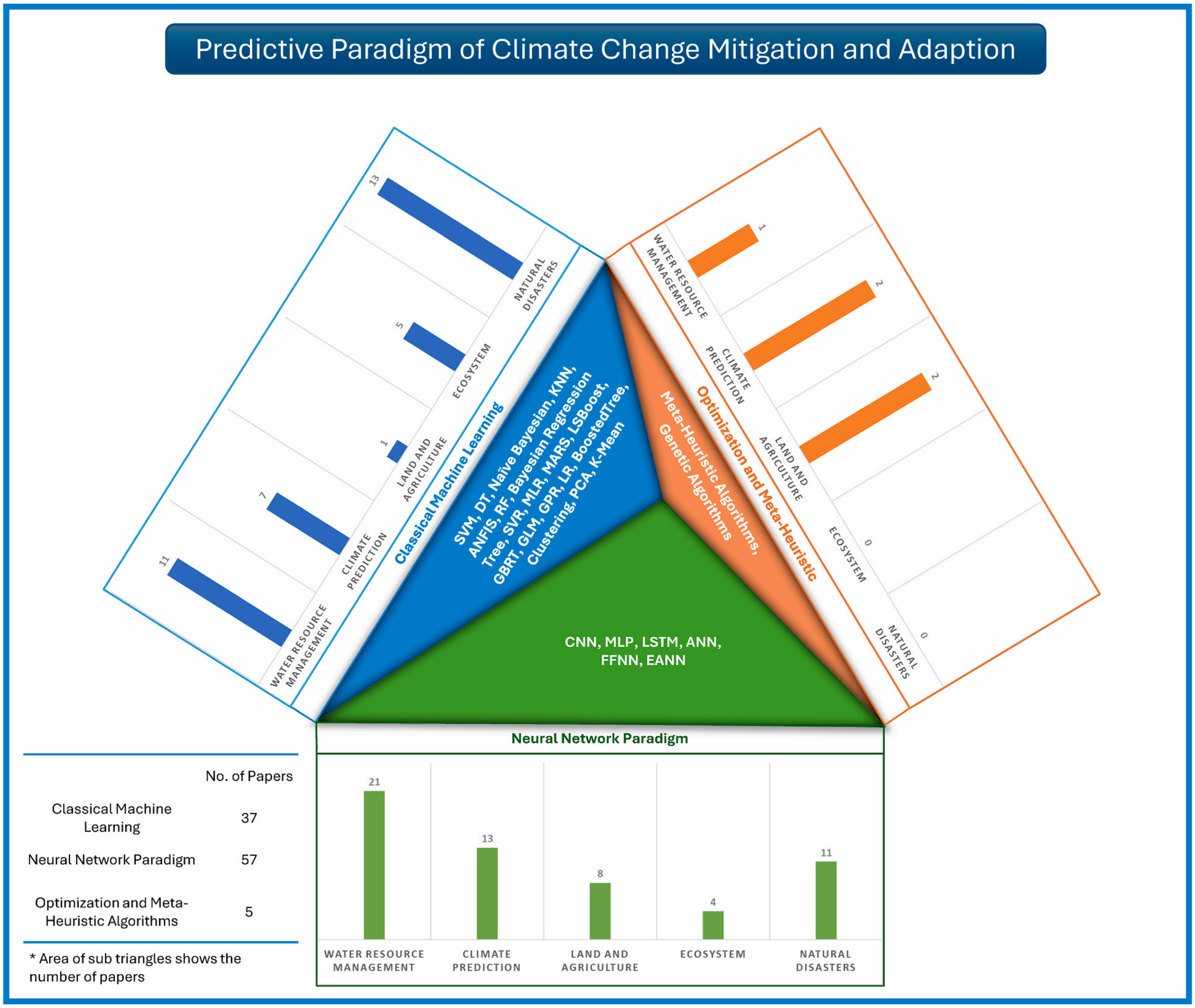

Fig. 3. Synopsis of paper distribution: AI/ML algorithm deployment in various climate change adaptation research fields.

the specific AI/ML techniques employed. It provides a quantitative overview of the distribution and utilization of different techniques across various domains. This research study is delineated by distinct objectives: firstly, the encapsulation of principal AI and ML algorithms; secondly, the discernment of focal points within the domain of Climate Change Adaptation research; and thirdly, the identification of latent features necessitating prospective investigation to enhance the application of AI and ML for bolstering climate change adaptation strategies.

2.1. *Modeling methods*

In this section, we investigate the majorly used AI/ML-based modeling methods for Climate Change Adaptation and Mitigation.

2.1.1. *Classical machine learning*

Classical machine learning, including supervised and unsupervised learning techniques, utilizes annotated and unannotated datasets to instruct algorithms and facilitate precise outcomes. Our comprehensive systematic literature review revealed a multitude of scholarly works employing diverse algorithms to address challenges in various domains, such as Water Resources Management [7,8], Climate Prediction [9,10], Land and Agriculture [11], Ecosystem [12], and Natural Disasters Management [13,14].

Water Resource Management: In the field of water resource management, there is a strong focus on using classical ML models to understand and predict groundwater levels and evapotranspiration, especially under changing climate conditions. Various ML techniques, such as Linear Regression (LR), Multiple Liner Regression (MLR), Multivariate Adaptive Regression Spline (MARS), M5, Random Forest (RF), and Least-squares boost (LSBoost), have been employed to forecast future evapotranspiration. In this regard, Kadkhodazadeh et al. [15] and Modaresi & Araghi [8] have explored predicting evapotranspiration and analyzing its uncertainties.

Their findings indicate that among these techniques, LSBoost and RF have shown superior performance, particularly in terms of Root Mean Square Error (RMSE) and Pearson Correlation Coefficient (R).

Furthermore, the application of ML techniques for predicting fluctuations in groundwater levels has seen a significant surge in recent years. These techniques are being leveraged to investigate the impact of climate change on groundwater levels. Notably, Nourani et al. [16] advocate for using ensemble models over individual ML techniques, emphasizing that each ML model can extract different features from the dataset. This suggestion is echoed by Ebrahimi et al. [7], who compared Support Vector Regression (SVR) and MODFLOW, a physics-based 3-dimensional model, to highlight the efficacy of ML models in enhancing decision-making speed in groundwater management.

Additionally, there is a growing interest in hybrid techniques, which combine ML with other methods for more nuanced analysis. For instance, Zeydalinejad and Dehghani [17] demonstrated the efficacy of hybrid meta-heuristic approaches, such as Wavelet-Support Vector Regression (WSVR) and innovative gunner-SVR (AIG-SVR), in simulating aquifer responses to climate changes. These approaches significantly outperformed standalone models, with WSVR achieving exceptional accuracy, highlighting its robustness in groundwater level prediction under varying climate scenarios. Similarly, Jeihouni, Mohammadi et al. [18,19] employed a wavelet-based preprocessing step with the Nonlinear Autoregression Exogenous Model (NARX) to enhance prediction accuracy for groundwater levels in Iran’s Shabestar Plain, demonstrating that hybrid techniques like wavelet-NARX outperformed traditional methods. Panahi et al. [20] further showcased the benefits of combining machine learning with advanced activation functions, such as Radial Basis Function Neural Networks (RBFNN), which excelled in predicting groundwater fluctuations with superior accuracy metrics. These hybrid methodologies not only integrate the strengths of individual techniques but also effectively capture complex, nonlinear interactions in climate parameters such as temperature, precipitation, and evaporation. As a result, they provide more reliable and nuanced predictions, particularly in regions with scarce data. This growing body of research underscores the importance of leveraging hybrid techniques to address multifaceted challenges in climate change adaptation and water resource management.

In summary, the collective evidence within water resource management highlights the growing importance of using diverse ML algorithms, hybrid techniques, and ensemble models. These approaches emerge as pivotal approaches to tackling the challenges of climate change, offering nuanced and robust solutions for sustainable water resource management practices.

Climate Prediction: The global rise in temperature and shifting precipitation patterns have significantly impacted environmental sectors worldwide. In response, classical ML models such as SVM, Gradient Boosted Regression Trees (GBRT), Principal Component Regression (PCA), Group Method of Data Handling (GMDH), Gene Expression Programming (GEP), and Greedy Search Algorithms have been employed for climate change modeling and the downscaling of climate variables across various applications.

Central to these efforts are recent studies like those by Guven and Pala [21] and Asadollah et al. [9], which focus on the statistical downscaling and future projection of Global Circulation Model (GCM) outcomes, particularly concerning precipitation and temperature. Guven and Pala [21] research identifies SVM as the most effective downscaling method they tested, outperforming GEP and GMDH. Similarly, Asadollah et al. [9] have studied Iran’s climate regions, finding GBRT to be more favorable than SVR for their purposes.

In addition to these studies, the prediction of Greenhouse Gas (GHG) emissions, a crucial factor in mitigating the effects of global warming, is being advanced through the use of SVM [22] and DT along with neural networks [22,23]). These methods are instrumental in modeling and predicting GHG emissions more accurately.

In general, the focus of these studies is on downscaling GCMs to local or regional scales. Techniques like GMDH, SVM, and GEP are particularly used for statistical downscaling. This approach allows for more accurate predictions at finer spatial resolutions, vital for effective climate change mitigation strategies.

Crop Yield: In the prediction of crop yields and virtual water content (VMC) patterns under varied climate change conditions, classical ML approaches such as SVM, Genetic Programming (GP), and neural networks have been employed [11]. Notably, the SVM model demonstrates superior performance compared to GP and neural networks in forecasting both VMC and crop yields.

Ecosystem: Researchers exploring the applications of classical ML algorithms have found intriguing prospects in assessing the impact of climate change on biodiversity and forest habitats. These studies employ various methods and models to understand and predict the repercussions of climate change across different scenarios.

For instance, Mirhashemi et al. [12] utilized a Bayesian Additive Regression Tree (BART) to model the potential habitat of Oaks Forest under both present and future climatic conditions. This approach indicates the growing use of sophisticated ML techniques in habitat modeling.

In the domain of biodiversity research, Hamidi et al. [24] have applied General Linear Models (GLM) and neural networks to investigate the effects of climate change on biodiversity in the Hyrcanian Forest. Their study is part of a broader trend of integrating diverse ML models to capture the complexity of ecological systems.

An interesting approach to mitigating uncertainty in climate change research is the use of ensemble models. For example, Makki et al. [25] and Morovati et al. [26] employed an ensemble model combining GLMs, Gradient Boosting Machine (GBM), MARS, SVM, Maximum Entropy, and RF to assess the effects of climate change on the Garra rufa fish species and the Asian black bear, respectively. Ensemble models are generally favored in this context due to their ability to reduce overfitting and enhance generalization.

Additionally, a predictive habitat suitability study for the Indian Hog Deer was conducted by Azeem et al. [27], employing dimension reduction techniques such as Pearson’s correlation, multi-collinearity reduction, and PCA. This study exemplifies using advanced statistical methods in conjunction with ML algorithms to refine predictions.

Throughout these studies, diverse environmental variables are considered to provide a comprehensive understanding of the impacts of climate change on various species and habitats. The integration of multiple ML techniques and models reflects the complexity and multifaceted nature of climate change research in the field of biodiversity and forest habitats.

Natural Disasters: ML technologies have become crucial in the multifaceted approach to climate change mitigation. They enhance our ability to predict, prevent, and respond to a range of natural disasters, including floods, wildfires, heatwaves, storms, droughts, and landslides. Among these, the prediction and management of floods have seen significant advancements. Techniques such as spatio-temporal mapping by Janizadeh et al. [28], remote sensing by Avand et al. [29], and dynamic rainfall variables analysis by Pham et al. [30] have been pivotal. These studies have employed various ML modeling techniques, including K-Nearest Neighbour (KNN), advanced RF, GBM, Extreme Gradient Boosting (XGB), and Bayesian Generalized Linear Model (GLMBayes), often in ensemble forms, to predict areas susceptible to flooding.

Additionally, the research by Anaraki et al. [31] emphasizes the importance of downscaling and decomposition of precipitation and temperature data. In this context, methodologies like KNN, Least Squares Support Vector Machines (LSSVM), and Wavelet Transform (WT) have been applied to specific tasks related to downscaling and decomposition processes.

The forecasting of droughts has also been a significant focus, with methodologies such as ANFIS and SVMs being extensively employed. This is highlighted in the works of Khan et al. [32] and a comprehensive review by Soylu Pekpostalci et al. [14]. These models leverage patterns observed during past droughts and large-scale climatic patterns. Additionally, Fooladi et al. [13,33] have proposed using RF and GBM techniques for meteorological and hydrological drought prediction in conjunction with remote sensing, adapting to various climate change scenarios. Furthermore, assessing water quality in aquifers during drought conditions has been advanced by employing PCA for spatiotemporal impact assessment, as demonstrated by Feizizadeh, Abdollahi, and Shokati [34]. This diversification of methodologies contributes to a more nuanced understanding of drought prediction across different contexts.

Lastly, the future susceptibility of landslides, categorized as natural disasters, has been modeled using tree-based algorithms like Boosted Trees (BT), RF, and Extremely Randomized Trees (ERT), as proposed by Ref. [35]).

In summary, the effectiveness of these models varies depending on the dataset and problem specifics, but ensemble models and tree-based algorithms have been frequently used and perform well in predicting flood and landslide risks under changing environmental conditions.

2.1.2. Neural network paradigm

In the domain of neural computing, a variety of models such as Convolutional Neural Networks (CNN), Multilayer Perceptron (MLP), Long Short-Term Memory networks (LSTM), Artificial Neural Networks (ANN), Feedforward Neural Networks (FFNN), and Evolving Artificial Neural Networks (EANN) play crucial roles in processing and interpreting intricate environmental data. These technologies are instrumental in analyzing and forecasting a broad spectrum of environmental phenomena. They excel particularly in areas related to water, such as evapotranspiration [36], groundwater dynamics [37], and streamflow prediction [38], as well as in studying biodiversity in ecosystems [25], climate prediction [39], and natural disasters [40]. The integration of these diverse research fields with advanced neural computing models enhances our comprehensive understanding of the environment, fostering informed decision-making for sustainable development and disaster readiness. This collaborative integration of various disciplines and technological innovations supports effective management and conservation strategies.

Water Resources Management: In recent years, the application of neural network techniques in water resources management has become increasingly prevalent, addressing a range of challenges. These techniques are particularly successful in forecasting parameters like potential evapotranspiration, reservoir evaporation, groundwater levels, and future runoff, especially under climate change scenarios.

In the field of evapotranspiration forecasting, Modaresi and Araghi [8] employed a hybrid LR-ANN model that relies on CMIP6 mean temperature data. This model uses the LR approach for downscaling and bias correction, while the ANN estimates mean potential evapotranspiration based on observed temperatures. Similarly, Ahi et al. [36] conducted a study using an ANN model to forecast reservoir evaporation, considering various climate change scenarios and parameters like temperature, sunshine duration, solar intensity, and wind speed.

Groundwater level prediction has also seen significant advancements. Nourani et al. [16] utilized a FFNN for downscaling GCM variables, employing both autoregressive and non-regressive input combinations. Additionally, ANFIS is used for groundwater modeling, while LSTM models simulate groundwater levels using downscaled climate variables from GCM scenarios. In a comparative study, Panahi et al. [20] examined the performance of ANFIS against ANNs with a Radial Basis Function (RBF), finding that RBFNNs outperformed ANFIS. Further, Ghazi et al. [37], and Zeydalinejad and Dehghani [17] used NARX and ANNs with wavelet transformations for groundwater modeling under different climate pathways.

Regarding surface runoff forecasting, ANNs have been widely applied to model future runoff and flood events in Iran's rivers, as shown by studies from Baghanam et al. [41], Rahmati et al. [42], and Sheikhbabaei et al. [43]. A comparative analysis between ANNs, IHACRES, and SWAT was conducted by Moghadam et al. [44], evaluating their performances using metrics like RMSE, MAE, Nash-Sutcliffe Efficiency (NSE), and R2.

In summary, neural network techniques, particularly when employed in ensemble configurations or combined with wavelet transform or RB Function, are the preferred choice for accurately predicting water-related phenomena in response to climate change. However, the effectiveness of specific techniques may vary based on the characteristics of the aquifer, data availability, and the complexity of climate interactions, highlighting the need for tailored approaches in each study area.

Climate Prediction: The global rise in temperature and shifting precipitation patterns are profoundly affecting environmental sectors worldwide, prompting a growing interest in employing neural network techniques. These techniques are increasingly used to enhance our understanding and predictions of climate-related phenomena, such as climate prediction, temperature modeling, precipitation pattern analysis, global warming assessments, and the study of the hydrological cycle.

In recent years, neural networks have notably contributed to the significant task of statistical downscaling, as highlighted by

Niazkar et al. [45]. Focusing on northwest Iran, studies by Baghanam et al. [39] demonstrate the efficacy of neural network techniques in assessing climate change impacts on regional climate patterns and associated risks. These studies involved comparing three statistical downscaling techniques: the Long Ashton Research Station-Weather Generator (LARS-WG), the statistical downscaling model (SDSM), and ANNs. The findings indicated that while the ANN model excelled in predicting temperature changes, the SDSM was superior in precipitation predictions. Furthermore, research by Rahimi et al. [46] investigated modeling uncertainty in late spring frost risk predictions, utilizing SDSM and ANN methods alongside GCM data. The models showed better simulation of averages than variances, with SDSM indicating more significant changes in frost risk zones.

Similarly, Shahani et al. [47] employed a hybrid approach combining LARS-WG6 and rainfall-runoff modeling with CNN to project future precipitation patterns and assess their impact on river flow across different climates in Iran. The method accurately captured the complex interactions between climate variables and hydrological responses by integrating predicted meteorological data with CNN-based runoff models. This approach provides valuable insights for water resource management and adaptation strategies. Adib and Ghafari Rad [48] introduced a novel integrated method for generating Intensity-Duration-Frequency (IDF) curves based on climatic scenarios, combining probability distributions and ANN for accurate projections. This is crucial for understanding changes in rainfall intensity. Additionally, Modarres et al. [49] explored future extreme rainfall changes in northern Iran using six GCMs and ANNs, emphasizing the potential decrease in maximum rainfall and alterations in the frequency and intensity of extreme events. Finally, Nguyen et al. [50] presented an approach integrating traditional GCMs with LSTM networks for climate forecasting, demonstrating the LSTM model's superior accuracy in climate projections and its potential for precise climate forecasting.

In brief, these studies collectively underscore the pivotal role of advanced modeling techniques, particularly neural network-based algorithms, in enhancing the precision and reliability of classical models for climate change impact assessments across diverse regions.

Land and Agriculture: Climate change drastically impacts land and agricultural productivity, with countries like Pakistan, Turkey, and Iran particularly affected. In the realm of environmental sustainability and climate change impact assessment, neural networks have emerged as a critical tool for deciphering complex relationships and forecasting essential variables.

The study conducted by Arefinia et al. [11] is particularly noteworthy, as it applies ANN to predict the geographical variations in virtual water content and crop yields across eastern provinces of Iran. This research also undertakes a comparative analysis of three data mining approaches, including ANN, and interestingly notes the superior performance of SVM in achieving the highest NSE and lowest RMSE. Despite these comparative results, ANN's efficacy in offering valuable insights into virtual water content and crop yield patterns under different climate change scenarios is underlined in the study.

In the Aidoghmoush basin, Iran, a study by Jafari et al. [51] employs ANNs as a key component in modeling reservoir inflow projections. The integration of ANNs with the Hargreaves-Samani (HS) method allowed the development of operational rules to manage uncertainties arising from climate change, achieving impressive reliability rates of 93 % and 95 % for future water supply predictions. Similarly, the economic impacts study by Aghapour Sabbaghi et al. [52] relies on an ANN rainfall-runoff model to assess the biophysical impacts of climate change on water resources and crop yields. Here, the ANN model is integrated into a hydro-economic spatial equilibrium model and a positive mathematical programming (PMP) model, aiding in the simulation of adaptive strategies and changes in agricultural patterns in response to climate-induced water scarcity.

Additionally, the interconnected and bidirectional relationship between land use change and climate change is brought to light. Two significant studies exemplify the use of neural networks in this domain. Arabacı and Kuşçu Şimşek [53] focus on the urban environment, specifically the recently constructed Istanbul Airport area, using ANNs to simulate and predict thermal changes. The accuracy of these predictions, up to 97 % within a 300-m range, is a testament to the effectiveness of ANNs in capturing the impact of land-use changes on urban climates. Conversely, the study by Singh et al. [54] explores this relationship in the South Asian Association for Regional Cooperation (SAARC) nations, using MLP to project future Agriculture, Forestry, and Other Land Use (AFOLU) under various climate change scenarios. The MLP models, with their ability to capture nonlinear responses, provide a robust framework for assessing the dynamics of land use changes across the SAARC nations, thereby assisting policymakers in crafting sustainable land management strategies.

Lastly, in the context of soil erosion risk assessment amid climate change, neural network approaches, particularly ANNs and MLPs, have proven instrumental in enhancing predictive capabilities and understanding complex interactions. Aslan et al. [55] utilize ANN to predict future soil erosion risks by forecasting erosivity index (EI) values across different clusters in Turkey. Incorporating meteorological data and clustering techniques into the ANN model highlights increased risk in southern and western Turkey. In a similar endeavor, Aslam et al. [56] employ MLP, in conjunction with the Revised Universal Soil Loss Equation (RUSLE), to assess soil erosion in Pakistan's Chitral district. This combination allows for modeling future land cover changes and evaluating soil erosion rates, thus offering valuable insights for sustainable development and watershed conservation.

In conclusion, the widespread and effective use of neural network approaches, particularly ANNs and MLP models, is a unifying theme across these studies. Combined with traditional agricultural methods and models, these neural network approaches are pivotal in addressing the multifaceted problems associated with climate change, environmental sustainability, and land management.

Ecosystem: Integrating neural network approaches is invaluable in biodiversity conservation and climate change impact assessment. This is evidenced by numerous studies focusing on different ecological aspects. Hamidi et al. [57] utilized ANNs alongside Generalized Linear Models (GLMs) to evaluate the effects of climate on biodiversity in Iran's Hyrcanian Forest. Their findings highlighted the superior predictive capabilities of ANNs in modeling species richness and evenness. Likewise, Makki et al. [25] applied a combination of modeling techniques, including ANN, to predict the impact of climate change on Garra rufa, a prevalent fish species in southwestern Iran. Their work demonstrated ANN's efficacy in species distribution modeling, leading to accurate predictions under various climate scenarios. Additionally, Morovati et al. [26] utilized ANN and other tools to assess habitat suitability and connectivity for the Asian black bear in southern and southeastern Iran, further emphasizing the role of neural networks in understanding species

Table 2
Current research, challenges, and gaps in various subfields of water resources management, climate prediction, land and agriculture, ecosystems, and natural disasters.

Area	Subfields	Challenges	Current Studies	Study Gap
Water Resources Management	Evapotranspiration	o Forecasting evapotranspiration under different climate change conditions. oDownscaling of available data to enhance the spatiotemporal resolution.	oUtilizing classical models like MLR, MNLR, MARS, RF, and LSBoost to forecast evapotranspiration and performance evaluation using RMSE and R coefficient [15]. oUse of hybrid model of LR and ANN based on CMIP 6 [8].	oLSTM and RNNs can be used to model temporal patterns in meteorological data [84]. oCNN models can be employed for feature extraction from remote-sensing satellite images [85] oUsing metaheuristics and genetic algorithms can also help with feature selection while dealing with high-dimensional datasets [86].
	Groundwater	oPredicting fluctuation in groundwater levels under the impact of climate change oIdentifying the most vulnerable areas to changes in groundwater availability due to climate variability. oIncorporating data from different sources to improve predictions.	oEnsemble and hybrid models should be used using meta-heuristic algorithms instead of classical techniques alone [16]. oDrawing the comparison between ML models with MODFLOW model [7]. oDownscaling of GCM variables using various kinds of neural networks [16]. oLSTM model to simulate groundwater levels using downscaled climate variables[16].	oGenetic algorithms can calibrate hydrogeological models, ensuring that the parameters are adjusted to match observed groundwater level data [87]. oIntegrating satellite imagery and remote sensing data can provide additional information for modeling groundwater levels using computer vision algorithms [88]. oIntegration of physics based numerical and machine learning models [89].
	Runoff/Streamflow	oPredicting river discharge, runoff patterns, and streamflow behavior under different climate scenarios based on historical data. oRecognizing patterns to indicate potential changes in river behavior or extreme events impacted by climate change. oCalibrating hydrological models, reducing the time and resources required to fine-tune models for specific regions.	oClimate change impacts on prediction of future runoff using ANN to understand the variability of river flow regime [41]. oDownscaling and bias correction using ANN of data [73].	oTransfer learning could be used for streamflow and runoff prediction in data-sparse regions [91,92]. oUtilization of integrated methodologies using CNN, LSTM or any other advanced deep learning-based models to predict streamflow and runoff [38,93].
	Lakes	oModeling predictions for various climate change impacts on lakes, such as changes in water temperature, nutrient levels, and algal blooms. oModeling species distribution to predict the distribution and abundance of aquatic species in response to climate change. oIntegrating and analyzing diverse datasets from sources like satellite imagery, water quality monitoring stations, and ecological surveys.	oDeep learning, especially different structures of LSTM was being used to fuse the data from multiple sources to understand the impact of climate on lake dynamics [75]. oANN's and other techniques like SVM and multiple Regression are widely employed to simulate lake water level fluctuations [74].	oIncorporation of enhanced deep learning approaches to assess or predict lake water quality [94,95] oUsing machine learning, finding the impact of climate change on lakes aquatic ecosystems [96].
Climate Prediction	Temperature & Precipitation	oEnhancing the spatial resolution of climate model outputs to provide more localized and accurate forecasts. oPredicting future climate conditions over varied geographic and climatic zones.	oMachine learning techniques, including artificial neural networks, multi-gene genetic programming, and ensemble models like Gradient Boosting Regression Trees, are used to enhance the accuracy and reliability of climate change predictions [9,45] oStatistical downscaling models such as LARS-WG, SDSM, and ANN are employed to evaluate and improve the precision of temperature and precipitation forecasts for detailed regional climate assessments [39].	oEnhancement of interpretability could be the direction for future research using the fusion of statistical methodologies with machine learning algorithms[97]. oIntegration of ML with traditional physical models can accelerate calculations and enhance real-time analysis and forecasting through techniques like model parallelization and the development of faster surrogate models [90].
Land and Agriculture	Crop Yield	oCoping with Uncertainties in agricultural water supply under climate change oIntegrating economic impacts of climate change on water resources and agriculture oPredicting effective climate change indicators on crop yield.	oOptimization algorithms like particle swarm optimization are used to derive robust reservoir operation rules under climate uncertainties [51]. oBiophysical and economic impact simulation using GCMs, ANN, HE-SEMZ, PMP [52].	oExplainability of deep learning models used to predict the crop yield can address the "black box" nature [98]. oTo increase the scalability of predictive machine learning models, transfer learning can help find patterns in regions with less data availabilities [99,100]

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Table 2 (*continued*)

Area	Subfields	Challenges	Current Studies	Study Gap
			oStatistical downscaling, genetic algorithm to assess impact on agricultural yield [81].	oEnhance transparency, integrate diverse remote sensing data, and develop data augmentation strategies to improve deep learning models for crop yield prediction and mapping [101].
	Land Use Change	oIntegrating diverse climate change scenarios (RCPs) to accurately predict their impact on dynamic and complex land use systems and vice versa.	oEmployment of the Multilayer Perceptron Neural Network to predict dynamic land use changes under various climate scenarios [54]. oUse of ANN and novel texture transfer method to predict thermal changes in urban areas due to land use modifications [53].	oConvolution Neural networks along with different conventional ML models can improve the predictive accuracy of land use change [102]. oIntegration of remote sensing and census data to deal with inconsistencies in the data [103].
	Soil Erosion Risk	oPredicting future soil erosion under different climate change scenarios and land cover changes.	oIntegrating different models (RUSLE, MLP, Markov chain, climate models) to accurately predict future soil erosion using complex data and uncertainty in climate and land-cover changes [56]. oAssessment of effects of climate change on soil erosion risk by using ANN and clustering methods [55].	oCombining advanced deep neural networks like LSTM with RUSLE model to forecast soil erosion probability [104]. oTackling the uncertainty of soil erosion modeling using high resolution and aggregated DEMs [105].
Ecosystem	Biodiversity	oQuantifying the impacts of climate change on species distribution; uncertainty in model predictions.	oUtilized ANN and other ensemble models, which showed better skills in predicting species richness and evenness [24,26]	oMany models struggle with the appropriate scales of analysis. There is a gap in linking fine-scale biological processes with larger-scale climate models. This includes addressing how microclimate and local habitat features interact with broader climatic trends[106].
	Forest/Vegetation	oPredicting habitat and tree growth responses to variable future climate scenarios.	oEmployment advanced machine learning models like Bayesian additive regression trees and multilayer perceptron networks, coupled with multiple climate scenarios to accurately project changes in forest habitats and growth [12,58]	oUsing Remote Sensing data with CNN-LSTM coupling to perform spatiotemporal analysis for forest change under climate change [107].
Natural Disasters	Floods	oPredicting flood risk accurately under different climate scenarios with high spatial variability. oIntegrating and merging large-scale climate models with localized land-use changes and historical flood data.	oUtilization of diverse ML algorithms (like KNN, RF, ERT) and ensemble methods to enhance predictive accuracy and manage uncertainties in model outcomes [30] oHybrid modeling approaches use a combination of metaheuristic algorithms, decomposition methods, and ML to enhance the accuracy and reliability of flood risk and frequency predictions [31].	oPhysics-based deep learning for flood modeling includes advancing Physics Informed NNs to generalize across boundary conditions and improving neural operators' scalability and adaptability for complex flood scenarios [108]. oData augmentation for flood modeling includes improving the training stability of GANs and enhancing the precision of VAE-generated synthetic data to support robust flood predictions [108].
	Drought	oPredicting complex dynamics such as drought impacts on agricultural productivity and aquifer quality under changing climate conditions remains a significant hurdle. oIntegrating diverse data sources like remote sensing and ground measurements effectively, particularly in regions with limited data availability.	oUtilizing fusion-based frameworks and ensemble machine learning models to improve the accuracy and reliability of drought predictions and their impacts on crop yields [33]. oGIS-based spatial analysis combined with multivariate statistical methods to effectively assess and manage water quality in drought-affected areas [34].	oUtilizing state-of-the-art deep learning models with explainability to predict and understand the predictivity of a model [109]. oIncorporating remote sensing data with deep learning models to get spatiotemporal patterns of drought under various climate change seniors [110].
	Landslide Susceptibility	oIntegrating diverse and heterogeneous datasets (e.g., topographical, geological, seismic, and climatic variables) to improve predictive accuracy. oModeling landslide susceptibility under changing climatic conditions, especially projected storm rainfall intensity and frequency increases.	oPredicting landslide susceptibility using decision tree-based models (BT, RF, ERT) under changing climate and LULC conditions, demonstrating ERT's superior predictive performance [35].	oTesting and validation hybrid landslide susceptibility models in diverse terrains for broader applicability [111]. oEnhancing the precision of landslide susceptibility models by integrating high-resolution, real-time climate and land-use change data [6].

responses to climate change. Exploring the potential applications of neural network regimes further, researchers are uncovering promising avenues for assessing climate change influences on forest habitats and biodiversity. By employing diverse methods and models, these studies aim to understand and predict climate change consequences under different scenarios.

In addition to understanding the complex dynamics of climate change impacts on forest ecosystems, Bayat et al. [58] presented a compelling study on tree growth responses in the Hyrcanian Forest of northern Iran. Focusing on tree diameter increment, a critical factor in determining forest volume and production, they employed MLP and linear mixed-effect models. This study explored the interplay between various biotic and abiotic factors, including diameter at breast height, basal area, elevation, aspect, slope, precipitation, and temperature. A key finding was the MLP model's superior performance over the linear mixed-effect model, highlighting the effectiveness of neural network approaches in predicting tree diameter increment. This research offers valuable insights into sustainable forest management in the context of climate change, showcasing the importance of neural network models in deciphering ecological responses to environmental changes.

Collectively, these studies underscore the significance of neural network methodologies in enhancing our ability to predict and mitigate the impacts of climate change on biodiversity and species distribution patterns.

Natural Disasters: Neural network technologies are crucial in the multifaceted approach to climate change mitigation. These technologies significantly enhance our ability to predict, prevent, and respond to various natural disasters, including floods, wildfires, heatwaves, storms, droughts, and landslides. In the domain of hydrological studies, particularly in investigating the repercussions of climate change on flood frequency, the incorporation of neural network methodologies is prominent. Notably, there have been substantial advancements in the prediction and management of floods through the application of neural networks.

Loyeh and Bavani [40] conducted an in-depth analysis of the Ghareh Sou basin, comparing maximum instantaneous flood estimates under stationary and non-stationary conditions. They utilized the Variable Infiltration Capacity (VIC) model to generate daily runoff and assessed the effectiveness of various methods, including ANN, in transforming daily discharge into maximum instantaneous floods. Similarly, Anaraki et al. [31] introduced an innovative framework integrating neural network methods for flood frequency analysis, utilizing metaheuristic algorithms and ANN. Conducted in the Karun-3 Basin of southwest Iran, their research demonstrates the superior performance of specific machine learning algorithms in downscaling precipitation and temperature.

Moreover, the collective body of research on drought monitoring and forecasting in Turkey and Pakistan reflects a dynamic landscape marked by diverse methodologies and a discernible shift toward advanced techniques. Soylu Pekpostalci et al. [14] conducted a comprehensive review, revealing a predominant focus on meteorological drought and an emerging trend toward machine learning, particularly neural networks, for short-term predictions. Contributions such as Katip [59] and Fooladi et al. [33] in meteorological drought modeling further underscore the increasing role of advanced methodologies, particularly neural network approaches, in addressing drought complexities.

The literature also encompasses diverse applications of neural network approaches in addressing climate-related challenges in the Mediterranean region, Turkey, Iran, and Pakistan. Studies by Gürsoy et al. [60], Moghanlo et al. [61], Rana et al. [62], and Khan et al. [63] showcase the growing prominence and efficacy of neural network approaches in various climate challenges, offering valuable insights for climate change adaptation and disaster risk reduction strategies.

In summary, the literature underscores the pivotal role of neural network approaches in various domains of climate change challenges. These networks excel in water resources management, climate prediction, land and agriculture, ecosystems, and natural disaster management. They provide accurate forecasts for evapotranspiration, reservoir evaporation, groundwater levels, surface runoff, temperature modeling, precipitation pattern analysis, virtual water content, crop yields, reservoir inflow projections, soil erosion risks, biodiversity shifts, species distributions, forest growth responses, flood frequency analysis, and drought monitoring. The literature highlights neural networks as indispensable tools for understanding, predicting, and mitigating climate change impacts.

2.1.3. Metaheuristic algorithms

Meta-heuristic approaches have emerged as powerful tools in the area of climate change impact assessment, particularly in the context of hydrological and agricultural systems. The studies conducted by Guven and Pala [21], Zeydalinejad and Dehghani [17], and Niazkar et al. [45] underscore the significance of meta-heuristic algorithms in enhancing the predictive capabilities of statistical downscaling models. Guven and Pala [21] employed the GEP for downscaling precipitation in the Göksun River basin. In the assessment of aquifer response to climate change, Zeydalinejad and Dehghani [17] employed meta-heuristic algorithms such as wavelet-support vector regression (WSVR) and innovative gunner-support vector regression (AIG-SVR), revealing high proficiency in modeling groundwater levels. Additionally, Niazkar et al. [45] innovatively applied multi-gene genetic programming (MGGP), a meta-heuristic approach, for downscaling daily temperatures at Dogonbadan, Iran, showcasing its effectiveness compared to traditional methods. The use of these meta-heuristic approaches signifies a paradigm shift in addressing the complexities of climate change impact studies, offering robust solutions for improved accuracy and reliability in future projections.

3. Discussion: current trends and challenges

In the comprehensive review on climate change mitigation and adaptation, Table 2 categorizes challenges, current research, and gaps in subfields like water management, climate prediction, and natural disasters. It highlights the broad use of advanced ML/DL techniques such as ANNs, LSTMs, and CNNs to enhance prediction accuracy and regional adaptability. Key gaps include the integration of diverse data sources, improving model interpretability, and local customization. The adoption of hybrid models for groundwater forecasts underscores a shift towards integrating ML with physical models, reflecting a trend towards sophisticated, data-driven approaches in environmental research. This underscores the need for improved computational models that combine empirical data with dynamic environmental processes for better real-world applicability.

The above table shows that the widespread adoption of these techniques is hindered by issues related to interpretability, scalability, and data integration. In the context of evapotranspiration, while classical and hybrid models have shown potential, their ability to generalize across different regions and climatic conditions remains limited. Similarly, relying on ensemble and hybrid models in groundwater management introduces complexities in model calibration and validation, particularly when integrating diverse data sources. For runoff and streamflow prediction, the accuracy and reliability of ML models in data-sparse regions are questionable, with transfer learning offering potential solutions, albeit with limitations. In the study of lakes, DL models like LSTM networks have effectively captured temporal patterns, but they often overlook the complex ecological interactions at play.

Climate prediction models face challenges in balancing spatial resolution with computational efficiency, and the integration of ML with traditional physical models, while promising, adds complexity. In environmental sciences, the "black box" nature of DL models poses significant barriers to policymakers' adoption, and the integration of economic impacts with climate predictions remains underexplored. To address this issue, techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) have been developed to enhance the interpretability of complex models [64]. They provide insights into how individual features contribute to the model's predictions, enabling a better understanding of the decision-making process and fostering greater confidence in its predictions.

Hybrid models, which integrate ML with traditional physical models, are gaining prominence in climate science due to their ability to enhance predictive accuracy and computational efficiency. For example, NeuralGCM, a hybrid model developed by Google DeepMind, combines physics-based components with ML techniques to outperform traditional models in medium-range weather forecasts and decadal climate predictions while reducing computational costs [65]. Similarly, hybrid hydroclimatic forecasting systems utilize data-driven methods to integrate predictions from dynamical models, improving the prediction skill of variables such as rainfall and streamflow [66]. These approaches address the limitations of purely data-driven or physics-based models by leveraging their strengths, leading to more robust and reliable climate projections. However, challenges remain in effectively combining these methodologies, particularly in ensuring the interpretability and scalability of the resulting models. Future research should focus on developing standardized frameworks for hybrid modeling, enhancing data integration techniques, and improving model transparency to facilitate their adoption in climate change mitigation and adaptation strategies.

Soil erosion modeling faces challenges in dealing with high uncertainty and variability in input data, while ecosystem models struggle to link fine-scale biological processes with larger-scale climate patterns. Finally, in natural disaster prediction, ML and hybrid models improve accuracy but often struggle with data integration and merging large-scale climate models with localized data.

Overall, while ML and DL techniques have propelled the field forward, future research must address these study gaps by developing more robust, transparent, and scalable models. These models should not only achieve high predictive accuracy but also provide actionable insights that can effectively guide decision-making in water resources management, particularly in the face of climate change.

4. Conclusions

This review has systematically explored the integration of advanced AI technologies, particularly ML and DL, in addressing climate change adaptation and mitigation across key environmental sectors in Iran, Pakistan, and Turkey. The findings underscore the transformative potential of AI in tackling complex climate challenges, with applications in water resource management, groundwater prediction, runoff/streamflow analysis, and climate forecasting. Techniques such as CNNs, LSTMs, and hybrid models have demonstrated significant improvements in data processing and predictive accuracy. However, the adoption of AI in these regions remains at an early stage, with notable gaps in scalability, data integration, and localized modeling.

Our study reveals critical challenges, including the scarcity of localized, high-resolution data, the complexity of integrating diverse data sources, and the need for models that reflect region-specific environmental conditions. Addressing these challenges requires interdisciplinary collaborations that merge expertise in environmental science with advancements in AI. Moreover, enhancing model interpretability and transparency will be essential to build trust among stakeholders and policymakers.

The implications of this research extend beyond the ECO region. The methodologies and insights discussed here can serve as a blueprint for other regions facing similar environmental and climatic challenges. Promoting open access to data, fostering collaborative research frameworks, and developing robust, scalable AI models are essential steps toward global climate resilience.

By leveraging the synergy between AI and traditional scientific approaches, ECO member countries can not only enhance their climate resilience but also contribute valuable knowledge to the global fight against climate change. This research serves as a call to action for scientists, policymakers, and the international community to collectively harness AI's transformative potential for a sustainable future.

CRediT authorship contribution statement

Muhammad Talha: Writing – review & editing, Writing – original draft. **A. Pouyan Nejadhashemi:** Writing – review & editing, Methodology, Conceptualization. **Kieron Moller:** Methodology.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT 4o to improve readability and language. After using this tool/

service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] F. Wang, J.D. Harindintwali, K. Wei, Y. Shan, Z. Mi, M.J. Costello, S. Grunwald, Z. Feng, F. Wang, Y. Guo, X. Wu, P. Kumar, M. Kästner, X. Feng, S. Kang, Z. Liu, Y. Fu, W. Zhao, C. Ouyang, J.M. Tiedje, Climate change: strategies for mitigation and adaptation, Innov. Geosci. 1 (1) (2023), https://doi.org/10.59717/j.xinn-geo.2023.100015.
[2] D.Y. Ulku, Analyzing vulnerability and resilience of Turkey to climate change, Sci. Res. Essays 9 (11) (2014), https://doi.org/10.5897/sre2013.5716.
[3] M.R. Mansouri Daneshvar, M. Ebrahimi, H. Nejadsoleymani, An overview of climate change in Iran: facts and statistics, Environ. Syst. Res. 8 (1) (2019), https://doi.org/10.1186/s40068-019-0135-3.
[4] T. Ladi, S. Jabalameli, A. Sharifi, Applications of machine learning and deep learning methods for climate change mitigation and adaptation, Environ. Plan. B Urban Anal. City Sci. 49 (4) (2022), https://doi.org/10.1177/23998083221085281.
[5] J. Liu, H. Yang, S.N. Gosling, M. Kummu, M. Flörke, S. Pfister, N. Hanasaki, Y. Wada, X. Zhang, C. Zheng, J. Alcamo, T. Oki, Water scarcity assessments in the past, present, and future, Earth's Future 5 (Issue 6) (2017), https://doi.org/10.1002/2016EF000518.
[6] I. Chowdhuri, S.C. Pal, R. Chakrabortty, S. Malik, B. Das, P. Roy, K. Sen, Spatial prediction of landslide susceptibility using projected storm rainfall and land use in Himalayan region, Bull. Eng. Geol. Environ. 80 (7) (2021), https://doi.org/10.1007/s10064-021-02252-z.
[7] R.S. Ebrahimi, S. Eslamian, M.J. Zareian, Groundwater level prediction based on GMS and SVR models under climate change conditions: case Study—Talesh Plain, Theor. Appl. Climatol. 151 (1–2) (2023) 433–447, https://doi.org/10.1007/s00704-022-04294-z.
[8] F. Modaresi, A. Araghi, Projecting future reference evapotranspiration in Iran based on CMIP6 multi-model ensemble, Theor. Appl. Climatol. 153 (1–2) (2023) 101–112, https://doi.org/10.1007/s00704-023-04465-6.
[9] S.B.H.S. Asadollah, A. Sharafati, S. Shahid, Application of ensemble machine learning model in downscaling and projecting climate variables over different climate regions in Iran, Environ. Sci. Pollut. Control Ser. 29 (12) (2022) 17260–17279, https://doi.org/10.1007/s11356-021-16964-y.
[10] S. Kumari, M.O. Raza, A. Kumari, Performance evaluation of machine learning algorithms for rainfall prediction using dimensionality reduction techniques, in: 2023 4th International Conference on Computing, Mathematics and Engineering Technologies: Sustainable Technologies for Socio-Economic Development, 2023, pp. 2023–Janua, https://doi.org/10.1109/iCoMET57998.2023.10109001. *ICoMET 2023*.
[11] A. Arefinia, O. Bozorg-Haddad, K. Ahmadaali, J. Bazrafshan, B. Zolghadr-Asli, X. Chu, Estimation of geographical variations in virtual water content and crop yield under climate change: comparison of three data mining approaches, Environ. Dev. Sustain. 24 (6) (2022) 8378–8396, https://doi.org/10.1007/s10668-021-01788-0.
[12] H. Mirhashemi, M. Heydari, O. Karami, K. Ahmadi, A. Mosavi, Modeling climate change effects on the distribution of oak forests with machine learning, Forests 14 (3) (2023), https://doi.org/10.3390/f14030469.
[13] F.A. Prodhan, J. Zhang, T.P. Pangali Sharma, L. Nanzad, D. Zhang, A.M. Seka, N. Ahmed, S.S. Hasan, M.Z. Hoque, H.P. Mohana, Projection of future drought and its impact on simulated crop yield over South Asia using ensemble machine learning approach, Sci. Total Environ. 807 (2022), https://doi.org/10.1016/j.scitotenv.2021.151029.
[14] D. Soylu Pekpostalci, R. Tur, A. Danandeh Mehr, M.A. Vazifekhah Ghaffari, D. Dąbrowska, V. Nourani, Drought monitoring and forecasting across Turkey: a contemporary review, Sustainability 15 (7) (2023), https://doi.org/10.3390/su15076080.
[15] M. Kadkhodazadeh, M.V. Anaraki, A. Morshed-Bozorgdel, S. Farzin, A new methodology for reference evapotranspiration prediction and uncertainty analysis under climate change conditions based on machine learning, multi criteria decision making and Monte Carlo methods, Sustainability 14 (5) (2022), https://doi.org/10.3390/su14052601.
[16] V. Nourani, A.H. Ghareh Tapeh, K. Khodkar, J.J. Huang, Assessing long-term climate change impact on spatiotemporal changes of groundwater level using autoregressive-based and ensemble machine learning models, J. Environ. Manag. 336 (2023), https://doi.org/10.1016/j.jenvman.2023.117653.
[17] N. Zeydalinejad, R. Dehghani, Use of meta-heuristic approach in the estimation of aquifer's response to climate change under shared socioeconomic pathways, Groundwater Sustain. Dev. 20 (2023), https://doi.org/10.1016/j.gsd.2022.100882.
[18] E. Jeihouni, S. Eslamian, M. Mohammadi, M.J. Zareian, Simulation of groundwater level fluctuations in response to main climate parameters using a wavelet–ANN hybrid technique for the Shabestar Plain, Iran, Environ. Earth Sci. 78 (10) (2019), https://doi.org/10.1007/s12665-019-8283-3.
[19] E. Jeihouni, M. Mohammadi, S. Eslamian, M.J. Zareian, Potential impacts of climate change on groundwater level through hybrid soft-computing methods: a case study—Shabestar Plain, Iran, Environ. Monit. Assess. 191 (10) (2019), https://doi.org/10.1007/s10661-019-7784-6.
[20] G. Panahi, M.H. Eskafi, A. Rohani, A. Faridhosseini, S.R. Khodashenas, Prediction of groundwater level fluctuations under climate change based on machine learning algorithms in the Mashhad aquifer, Iran, J. Water Clim. Change 14 (3) (2023), https://doi.org/10.2166/wcc.2023.027.
[21] A. Guven, A. Pala, Comparison of different statistical downscaling models and future projection of areal mean precipitation of a river basin under climate change effect, Water Supply 22 (3) (2022), https://doi.org/10.2166/WS.2021.372.
[22] I. Ulku, E.E. Ulku, Forecasting Greenhouse gas emissions based on different machine learning algorithms, Lecture Notes Netw. Syst. 505 (2022), https://doi.org/10.1007/978-3-031-09176-6_13. LNNS.
[23] M. Kayakuş, Forecasting carbon dioxide emissions in Turkey using machine learning methods, Int. J. Glob. Warming 28 (3) (2022), https://doi.org/10.1504/ijgw.2022.126669.
[24] S.K. Hamidi, M. de Luis, C.P.A. Bourque, M. Bayat, R. Serrano-Notivoli, Projected biodiversity in the Hyrcanian Mountain Forest of Iran: an investigation based on two climate scenarios, Biodivers. Conserv. (2022), https://doi.org/10.1007/s10531-022-02470-1.
[25] T. Makki, H. Mostafavi, A. Matkan, H. Aghighi, Modelling climate-change impact on the spatial distribution of Garra Rufa (Heckel, 1843) (Teleostei: Cyprinidae), Iran. J. Sci. Technol. Trans. A-Science 45 (3) (2021), https://doi.org/10.1007/s40995-021-01088-2.
[26] M. Morovati, P. Karami, F.B. Amjas, Accessing habitat suitability and connectivity for the westernmost population of Asian black bear (Ursus thibetanus gedrosianus, Blanford, 1877) based on climate changes scenarios in Iran, PLoS One 15 (11 November) (2020), https://doi.org/10.1371/journal.pone.0242432.
[27] A. Azeem, S.R. Ahmed, A. Qadir, A.S. Hussainy, Predictive habitat suitability modelling of axis porcinus (Hog deer) under current and future climate change scenarios in Punjab, Pakistan, Appl. Ecol. Environ. Res. 19 (4) (2021), https://doi.org/10.15666/aeer/1904_31813201.
[28] S. Janizadeh, S. Chandra Pal, A. Saha, I. Chowdhuri, K. Ahmadi, S. Mirzaei, A.H. Mosavi, J.P. Tiefenbacher, Mapping the spatial and temporal variability of flood hazard affected by climate and land-use changes in the future, J. Environ. Manag. 298 (2021), https://doi.org/10.1016/j.jenvman.2021.113551.
[29] M. Avand, H. Moradi, M.R. lasboyee, Using machine learning models, remote sensing, and GIS to investigate the effects of changing climates and land uses on flood probability, J. Hydrol. 595 (2021), https://doi.org/10.1016/j.jhydrol.2020.125663.

[30] Q.B. Pham, S. Chandra Pal, A. Saha, I. Chowdhuri, J.A. Albanai, S. Janizadeh, K. Ahmadi, K.M. Khedher, D.T. Anh, W. Duan, Current and future projections of flood risk dynamics under seasonal precipitation regimes in the Hyrcanian Forest region, Geocarto Int. 37 (25) (2022) 9047–9070, https://doi.org/10.1080/10106049.2021.2009921.

[31] M.V. Anaraki, S. Farzin, S.F. Mousavi, H. Karami, Uncertainty analysis of climate change impacts on flood frequency by using hybrid machine learning methods, Water Resour. Manag. 35 (1) (2021), https://doi.org/10.1007/s11269-020-02719-w.

[32] N. Khan, D.A. Sachindra, S. Shahid, K. Ahmed, M.S. Shiru, N. Nawaz, Prediction of droughts over Pakistan using machine learning algorithms, Adv. Water Resour. 139 (2020), https://doi.org/10.1016/j.advwatres.2020.103562.

[33] M. Fooladi, M.H. Golmohammadi, H.R. Safavi, V.P. Singh, Fusion-based framework for meteorological drought modeling using remotely sensed datasets under climate change scenarios: resilience, vulnerability, and frequency analysis, J. Environ. Manag. 297 (2021), https://doi.org/10.1016/j.jenvman.2021.113283.

[34] B. Feizizadeh, Z. Abdollahi, B. Shokati, A GIS-based spatiotemporal impact assessment of droughts in the hyper-saline Urmia lake basin on the hydrogeochemical quality of nearby aquifers, Rem. Sens. 14 (11) (2022), https://doi.org/10.3390/rs14112516.

[35] Q.B. Pham, S. Chandra Pal, R. Chakrabortty, A. Saha, S. Janizadeh, K. Ahmadi, K.M. Khedher, D.T. Anh, J.P. Tiefenbacher, A. Bannari, Predicting landslide susceptibility based on decision tree machine learning models under climate and land use changes, Geocarto Int. 37 (25) (2022), https://doi.org/10.1080/10106049.2021.1986579.

[36] Y. Ahi, Ç. Coşkun Dilcan, D.D. Köksal, H.T. Gültaş, Reservoir evaporation forecasting based on climate change scenarios using artificial neural network model, Water Resour. Manag. 37 (6–7) (2023), https://doi.org/10.1007/s11269-022-03365-0.

[37] B. Ghazi, E. Jeihouni, Z. Kalantari, Predicting groundwater level fluctuations under climate change scenarios for Tasuj plain, Iran, Arabian J. Geosci. 14 (2) (2021), https://doi.org/10.1007/s12517-021-06508-6.

[38] S. Ghimire, Z.M. Yaseen, A.A. Farooque, R.C. Deo, J. Zhang, X. Tao, Streamflow prediction using an integrated methodology based on convolutional neural network and long short-term memory networks, Sci. Rep. 11 (1) (2021), https://doi.org/10.1038/s41598-021-96751-4.

[39] A.H. Baghanam, M. Eslahi, A. Sheikhbabaei, A.J. Seifi, Assessing the impact of climate change over the northwest of Iran: an overview of statistical downscaling methods, Theor. Appl. Climatol. 141 (3–4) (2020), https://doi.org/10.1007/s00704-020-03271-8.

[40] N.S. Loyeh, A.M. Bavani, Daily maximum runoff frequency analysis under non-stationary conditions due to climate change in the future period: case study ghareh sou basin, J. Water Clim. Change 12 (5) (2021), https://doi.org/10.2166/wcc.2021.074.

[41] A.H. Baghanam, A.J. Seifi, A. Sheikhbabaei, Y. Hassanzadeh, M. Besharat, E. Asadi, Policy-making toward integrated water resources management of Zarrine River Basin via system dynamics approach under climate change impact, Sustainability 14 (6) (2022), https://doi.org/10.3390/su14063376.

[42] K. Rahmati, P.-S. Ashofteh, R. Afzali, H.A. Loáiciga, System-dynamics approach to multireservoir energy generation under climate change, J. Hydrol. Eng. 27 (9) (2022), https://doi.org/10.1061/(asce)he.1943-5584.0002197.

[43] A. Sheikhbabaei, A. Hosseini Baghanam, M. Zarghami, S. Pouri, E. Hassanzadeh, System thinking approach toward reclamation of regional water management under changing climate conditions, Sustainability 14 (15) (2022), https://doi.org/10.3390/su14159411.

[44] S.H. Moghadam, P.S. Ashofteh, H.A. Loáiciga, Investigating the performance of data mining, lumped, and distributed models in runoff projected under climate change, J. Hydrol. 617 (2023), https://doi.org/10.1016/j.jhydrol.2022.128992.

[45] M. Niazkar, M.R. Goodarzi, A. Fatehifar, M.J. Abedi, Machine learning-based downscaling: application of multi-gene genetic programming for downscaling daily temperature at Dogonbadan, Iran, under CMIP6 scenarios, Theor. Appl. Climatol. 151 (1–2) (2023), https://doi.org/10.1007/s00704-022-04274-3.

[46] J. Rahimi, A. Khalili, J. Bazrafshan, Modeling uncertainty of statistical downscaling methods in quantifying the climate change impacts on late spring frost risk over Iran, Model. Earth Syst. Environ. 4 (1) (2018), https://doi.org/10.1007/s40808-018-0416-2.

[47] M.H. Shahani, V. Rezaverdinejad, S.A. Hosseini, N. Azad, Assessing climate change impact on river flow extreme events in different climates of Iran using hybrid application of LARS-WG6 and rainfall-runoff modeling of deep learning, Ecohydrol. Hydrobiol. 23 (2) (2023), https://doi.org/10.1016/j.ecohyd.2023.02.002.

[48] A. Adib, S. Ghafari Rad, Development of a new integrated method for generation of IDF curves based on three scenarios of climatic changes, Sci. Iran. 26 (2) (2019), https://doi.org/10.24200/sci.2017.4593.

[49] R. Modarres, M. Ghadami, S. Naderi, M. Naderi, Future extreme rainfall change projections in the north of Iran, Meteorol. Appl. 25 (1) (2018), https://doi.org/10.1002/met.1667.

[50] D.T. Nguyen, S. Ashraf, M. Le, L.Q. Trung, M. Ali, Projection of climate variables by general circulation and deep learning model for Lahore, Pakistan, Ecol. Inf. 75 (2023), https://doi.org/10.1016/j.ecoinf.2023.102077.

[51] S. Jafari, O. Bozorg-Haddad, P.S. Ashofteh, H.A. Loáiciga, Uncertainties in agricultural water supply under climate change: Aidoghmoush basin, Iran, Proc. Inst. Civ. Eng.: Water Manag. 174 (3) (2021), https://doi.org/10.1680/jwama.19.00032.

[52] M. Aghapour Sabbaghi, M. Nazari, S. Araghinejad, S. Soufizadeh, Economic impacts of climate change on water resources and agriculture in Zayandehroud river basin in Iran, Agric. Water Manag. 241 (2020), https://doi.org/10.1016/j.agwat.2020.106323.

[53] D. Arabacı, Ç. Kuşçu Şimşek, Prediction of climatic changes caused by land use changes in urban area using artificial neural networks, Theor. Appl. Climatol. 152 (1–2) (2023), https://doi.org/10.1007/s00704-023-04386-4.

[54] R.K. Singh, V.S.P. Sinha, P.K. Joshi, M. Kumar, Modelling agriculture, Forestry and other land use (AFOLU) in response to climate change scenarios for the SAARC nations, Environ. Monit. Assess. 192 (4) (2020), https://doi.org/10.1007/s10661-020-8144-2.

[55] Z. Aslan, G. Erdemir, E. Feoli, F. Giorgi, D. Okcu, Effects of climate change on soil erosion risk assessed by clustering and artificial neural network, Pure Appl. Geophys. 176 (2) (2019), https://doi.org/10.1007/s00024-018-2010-y.

[56] B. Aslam, U. Khalil, M. Saleem, A. Maqsoom, E. Khan, Effect of multiple climate change scenarios and predicted land-cover on soil erosion: a way forward for the better land management, Environ. Monit. Assess. 193 (11) (2021), https://doi.org/10.1007/s10661-021-09559-0.

[57] S.K. Hamidi, M. de Luis, C.P.A. Bourque, M. Bayat, R. Serrano-Notivoli, Projected biodiversity in the Hyrcanian Mountain Forest of Iran: an investigation based on two climate scenarios, Biodivers. Conserv. (2022), https://doi.org/10.1007/s10531-022-02470-1.

[58] M. Bayat, T. Knoke, S. Heidari, S.K. Hamidi, H. Burkhart, A. Jaafari, Modeling tree growth responses to climate change: a case study in natural deciduous mountain forests, Forests 13 (11) (2022), https://doi.org/10.3390/f13111816.

[59] A. Katip, Meteorological drought analysis using artificial neural networks for Bursa city, Turkey, Appl. Ecol. Environ. Res. 16 (3) (2018), https://doi.org/10.15666/aeer/1603_33153332.

[60] M.İ. Gürsoy, O. Orhan, S. Tekin, Creation of wildfire susceptibility maps in the Mediterranean Region (Turkey) using convolutional neural networks and multilayer perceptron techniques, For. Ecol. Manag. 538 (2023), https://doi.org/10.1016/j.foreco.2023.121006.

[61] S. Moghanlo, M. Alavinejad, V. Oskoei, H. Najafi Saleh, A.A. Mohammadi, H. Mohammadi, Z. DerakhshanNejad, Using artificial neural networks to model the impacts of climate change on dust phenomenon in the Zanjan region, north-west Iran, Urban Clim. 35 (2021), https://doi.org/10.1016/j.uclim.2020.100750.

[62] I.A. Rana, R.H. Lodhi, A. Zia, A. Jamshed, A. Nawaz, Three-step neural network approach for predicting monsoon flood preparedness and adaptation: application in urban communities of Lahore, Pakistan, Urban Clim. 45 (2022), https://doi.org/10.1016/j.uclim.2022.101266.

[63] N. Khan, S. Shahid, T. Bin Ismail, F. Behlil, Prediction of heat waves over Pakistan using support vector machine algorithm in the context of climate change, Stoch. Environ. Res. Risk Assess. 35 (7) (2021), https://doi.org/10.1007/s00477-020-01963-1.

[64] A. Salih, Z. Raisi-Estabragh, I.B. Galazzo, P. Radeva, S.E. Petersen, G. Menegaz, K. Lekadir, A perspective on explainable artificial intelligence methods: SHAP and LIME. https://doi.org/10.1002/aisy.202400304, 2023.

[65] D. Kochkov, J. Yuval, I. Langmore, P. Norgaard, J. Smith, G. Mooers, M. Klöwer, J. Lottes, S. Rasp, P. Düben, S. Hatfield, P. Battaglia, A. Sanchez-Gonzalez, M. Willson, M.P. Brenner, S. Hoyer, Neural general circulation models for weather and climate. https://doi.org/10.1038/s41586-024-07744-y, 2023.

[66] L.J. Slater, L. Arnal, M.A. Boucher, A.Y.Y. Chang, S. Moulds, C. Murphy, G. Nearing, G. Shalev, C. Shen, L. Speight, G. Villarini, R.L. Wilby, A. Wood, M. Zappa, Hybrid forecasting: blending climate predictions with AI models, Hydrol. Earth Syst. Sci. 27 (9) (2023), https://doi.org/10.5194/hess-27-1865-2023.

[67] M. Moghaddasi, M.M. Ghaleni, M. Akbari, S. Salari, Potential impacts of climate change on groundwater levels in Golpayegan Plain, Iran, Water Supply 22 (5) (2022), https://doi.org/10.2166/ws.2022.179.

[68] V. Nourani, P. Ghaneei, S.A. Kantoush, Robust clustering for assessing the spatiotemporal variability of groundwater quantity and quality, J. Hydrol. 604 (2022), https://doi.org/10.1016/j.jhydrol.2021.127272.

[69] M. Ehteram, Z. Kalantari, C.S. Ferreira, K.W. Chau, S.M.K. Emami, Prediction of future groundwater levels under representative concentration pathway scenarios using an inclusive multiple model coupled with artificial neural networks, J. Water Clim. Change 13 (10) (2022), https://doi.org/10.2166/wcc.2022.198.

[70] E. Jeihouni, M. Mohammadi, B. Ghazi, Response of the Shabestar Plain aquifer to climate-change scenarios through statistical and hybrid soft computing techniques, Groundwater Sustain. Dev. 15 (2021), https://doi.org/10.1016/j.gsd.2021.100649.

[71] N. Zeydalinejad, H.R. Nassery, A. Shakiba, F. Alijani, Prediction of the karstic spring flow rates under climate change by climatic variables based on the artificial neural network: a case study of Iran, Environ. Monit. Assess. 192 (6) (2020), https://doi.org/10.1007/s10661-020-08332-z.

[72] L. Shakarami, P.S. Ashofteh, V.P. Singh, Disaggregating the effects of climatic variability and dam construction on river flow regime, Water Resour. Manag. 36 (10) (2022), https://doi.org/10.1007/s11269-022-03235-9.

[73] F. Yazdandoost, S. Moradian, Climate change impacts on the streamflow of Zarrineh River, Iran, J. Arid Land 13 (9) (2021), https://doi.org/10.1007/s40333-021-0091-4.

[74] O. Bozorg-Haddad, P. Dehghan, B. Zolghadr-Asli, V.P. Singh, X. Chu, H.A. Loáiciga, System dynamics modeling of lake water management under climate change, Sci. Rep. 12 (1) (2022), https://doi.org/10.1038/s41598-022-09212-x.

[75] A. Modaresi Rad, J. Kreitler, J.T. Abatzoglou, K. Fallon, K.R. Roche, M. Sadegh, Anthropogenic stressors compound climate impacts on inland lake dynamics: the case of Hamun Lakes, Sci. Total Environ. 829 (2022), https://doi.org/10.1016/j.scitotenv.2022.154419.

[76] H. Hemati, A. Abrishamchi, Water allocation using game theory under climate change impact (Case study: Zarinehrood), J. Water Clim. Change 12 (3) (2021), https://doi.org/10.2166/wcc.2020.153.

[77] K. Haleem, A.U. Khan, S. Ahmad, M. Khan, F.A. Khan, W. Khan, J. Khan, Hydrological impacts of climate and land-use change on flow regime variations in upper Indus basin, J. Water Clim. Change 13 (2) (2022), https://doi.org/10.2166/wcc.2021.238.

[78] V. Nourani, N. Rouzegari, A. Molajou, A. Hosseini Baghanam, An integrated simulation-optimization framework to optimize the reservoir operation adapted to climate change scenarios, J. Hydrol. 587 (2020), https://doi.org/10.1016/j.jhydrol.2020.125018.

[79] K. Ahmed, D.A. Sachindra, S. Shahid, Z. Iqbal, N. Nawaz, N. Khan, Multi-model ensemble predictions of precipitation and temperature using machine learning algorithms, Atmos. Res. 236 (2020), https://doi.org/10.1016/j.atmosres.2019.104806.

[80] A. Nusrat, H.F. Gabriel, S. Haider, S. Ahmad, M. Shahid, S.A. Jamal, Application of machine learning techniques to delineate homogeneous climate zones in river basins of Pakistan for hydro-climatic change impact studies, Appl. Sci. 10 (19) (2020), https://doi.org/10.3390/app10196878.

[81] A. Ullah, N. Salehnia, S. Kolsoumi, A. Ahmad, T. Khaliq, Prediction of effective climate change indicators using statistical downscaling approach and impact assessment on pearl millet (Pennisetum glaucum L.) yield through Genetic Algorithm in Punjab, Pakistan, Ecol. Indicat. 90 (2018), https://doi.org/10.1016/j.ecolind.2018.03.053.

[82] W. Rafaqat, M. Iqbal, R. Kanwal, W. Song, Study of driving factors using machine learning to determine the effect of topography, climate, and fuel on wildfire in Pakistan, Rem. Sens. 14 (8) (2022), https://doi.org/10.3390/rs14081918.

[83] D. Martin-Benito, N. Pederson, N. Köse, M. Doğan, H. Bugmann, M. Mosulishvili, C. Bigler, Pervasive effects of drought on tree growth across a wide climatic gradient in the temperate forests of the Caucasus, Global Ecol. Biogeogr. 27 (11) (2018), https://doi.org/10.1111/geb.12799.

[84] F. Granata, F. Di Nunno, Forecasting evapotranspiration in different climates using ensembles of recurrent neural networks, Agric. Water Manag. 255 (2021), https://doi.org/10.1016/j.agwat.2021.107040.

[85] N. Mandal, K. Chanda, Performance of machine learning algorithms for multi-step ahead prediction of reference evapotranspiration across various agro-climatic zones and cropping seasons, J. Hydrol. 620 (2023), https://doi.org/10.1016/j.jhydrol.2023.129418.

[86] F. Sayyahi, S. Farzin, H. Karami, Forecasting daily and monthly reference evapotranspiration in the Aidoghmoush basin using multilayer perceptron coupled with water wave optimization, Complexity (2021), https://doi.org/10.1155/2021/6683759, 2021.

[87] K. Han, R. Zuo, P. Ni, Z. Xue, D. Xu, J. Wang, D. Zhang, Application of a genetic algorithm to groundwater pollution source identification, J. Hydrol. 589 (2020), https://doi.org/10.1016/j.jhydrol.2020.125343.

[88] X. Yang, Z. Zhang, A CNN-LSTM model based on a meta-learning algorithm to predict groundwater level in the middle and lower reaches of the Heihe river, China, Water (Switzerland) 14 (15) (2022), https://doi.org/10.3390/w14152377.

[89] C. Chen, H. Zhang, W. Shi, W. Zhang, Y. Xue, A novel paradigm for integrating physics-based numerical and machine learning models: a case study of eco-hydrological model, Environ. Model. Software 163 (2023), https://doi.org/10.1016/j.envsoft.2023.105669.

[90] L. Chen, B. Han, X. Wang, J. Zhao, W. Yang, Z. Yang, Machine learning methods in weather and climate applications: a survey, Appl. Sci. 13 (21) (2023), https://doi.org/10.3390/app132112019.

[91] R. Oruche, L. Egede, T. Baker, F. O'Donncha, Transfer learning to improve streamflow forecasts in data sparse regions. http://arxiv.org/abs/2112.03088, 2021.

[92] M. Talha, S.F. Rashid, Z. Iftikhar, M.T. Afzal, L. Ying, Transferable learning architecture for scalable visual quality inspection, in: 2nd IEEE International Conference on Artificial Intelligence, ICAI, 2022, https://doi.org/10.1109/ICAI55435.2022.9773637, 2022.

[93] C. Deng, X. Yin, J. Zou, M. Wang, Y. Hou, Assessment of the impact of climate change on streamflow of Ganjiang River catchment via LSTM-based models, J. Hydrol.: Reg. Stud. 52 (2024), https://doi.org/10.1016/j.ejrh.2024.101716.

[94] H. Guo, X. Zhu, J. Jeanne Huang, Z. Zhang, S. Tian, Y. Chen, An enhanced deep learning approach to assessing inland lake water quality and its response to climate and anthropogenic factors, J. Hydrol. 620 (2023), https://doi.org/10.1016/j.jhydrol.2023.129466.

[95] L. Rodríguez-López, D.B. Usta, I. Duran-Llacer, L.B. Alvarez, S. Yépez, L. Bourrel, F. Frappart, R. Urrutia, Estimation of water quality parameters through a combination of deep learning and remote sensing techniques in a Lake in Southern Chile, Rem. Sens. 15 (17) (2023), https://doi.org/10.3390/rs15174157.

[96] Z. Wen, Q. Wang, Y. Ma, P.A. Jacinthe, G. Liu, S. Li, Y. Shang, H. Tao, C. Fang, L. Lyu, B. Zhang, K. Song, Remote estimates of suspended particulate matter in global lakes using machine learning models, Int. Soil Water Conserv. Res. 12 (1) (2024), https://doi.org/10.1016/j.iswcr.2023.07.002.

[97] R. Yang, J. Hu, Z. Li, J. Mu, T. Yu, J. Xia, X. Li, A. Dasgupta, H. Xiong, Interpretable machine learning for weather and climate prediction: a survey. http://arxiv.org/abs/2403.18864, 2024.

[98] P. Muruganantham, S. Wibowo, S. Grandhi, N.H. Samrat, N. Islam, A systematic literature review on crop yield prediction with deep learning and remote sensing, Rem. Sens. 14 (9) (2022), https://doi.org/10.3390/rs14091990.

[99] K. Moller, A.P. Nejadhashemi, M. Talha, M. Chikafa, R. Eeswaran, N.V. Junior, A.J.P. Carcedo, I. Ciampitti, J.C. Bizimana, A. Diallo, P.V.V. Prasad, Unveiling the resilience of smallholder farmers in Senegal amidst extreme climate conditions, Food Energy Secur. 13 (1) (2024), https://doi.org/10.1002/fes3.523.

[100] A.X. Wang, C. Tran, N. Desai, D. Lobell, S. Ermon, Deep transfer learning for crop yield prediction with remote sensing data, in: Proceedings of the 1st ACM SIGCAS Conference on Computing and Sustainable Societies, 2018, https://doi.org/10.1145/3209811.3212707. *COMPASS 2018*.

[101] A. Joshi, B. Pradhan, S. Gite, S. Chakraborty, Remote-sensing data and deep-learning techniques in crop mapping and yield prediction: a systematic review, Rem. Sens. 15 (8) (2023), https://doi.org/10.3390/rs15082014.

[102] J. Jagannathan, C. Divya, Deep learning for the prediction and classification of land use and land cover changes using deep convolutional neural network, Ecol. Inf. 65 (2021), https://doi.org/10.1016/j.ecoinf.2021.101412.

[103] P.H. Verburg, K. Neumann, L. Nol, Challenges in using land use and land cover data for global change studies, Global Change Biol. 17 (2) (2011), https://doi.org/10.1111/j.1365-2486.2010.02307.x.

[104] S. Senanayake, B. Pradhan, A. Alamri, H.J. Park, A new application of deep neural network (LSTM) and RUSLE models in soil erosion prediction, Sci. Total Environ. 845 (2022), https://doi.org/10.1016/j.scitotenv.2022.157220.

[105] A. Mondal, D. Khare, S. Kundu, S. Mukherjee, A. Mukhopadhyay, S. Mondal, Uncertainty of soil erosion modelling using open source high resolution and aggregated DEMs, Geosci. Front. 8 (3) (2017), https://doi.org/10.1016/j.gsf.2016.03.004.

[106] C.J. Ellis, Predicting the biodiversity response to climate change: challenges and advances, Syst. Biodivers. 9 (Issue 4) (2011), https://doi.org/10.1080/14772000.2011.634448.
[107] Z.M. Hamdi, M. Brandmeier, C. Straub, Forest damage assessment using deep learning on high resolution remote sensing data, Rem. Sens. 11 (17) (2019), https://doi.org/10.3390/rs11171976.
[108] R. Bentivoglio, E. Isufi, S.N. Jonkman, R. Taormina, Deep learning methods for flood mapping: a review of existing applications and future research directions, Hydrol. Earth Syst. Sci. 26 (Issue 16) (2022), https://doi.org/10.5194/hess-26-4345-2022.
[109] A. Dikshit, B. Pradhan, Explainable AI in drought forecasting, Mach. Learn. Appl. 6 (2021), https://doi.org/10.1016/j.mlwa.2021.100192.
[110] F.A. Prodhan, J. Zhang, F. Yao, L. Shi, T.P.P. Sharma, D. Zhang, D. Cao, M. Zheng, N. Ahmed, H.P. Mohana, Deep learning for monitoring agricultural drought in south asia using remote sensing data, Rem. Sens. 13 (9) (2021), https://doi.org/10.3390/rs13091715.
[111] A.R.M.T. Islam, A. Saha, B. Ghose, S.C. Pal, I. Chowdhuri, J. Mallick, Landslide susceptibility modeling in a complex mountainous region of Sikkim Himalaya using new hybrid data mining approach, Geocarto Int. 37 (25) (2022), https://doi.org/10.1080/10106049.2021.2009920.