Review Paper:

Advancing AI Models for Drought Forecasting, Challenges and Future Directions

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Abstract
Drought, a persistent natural disaster, poses significant challenges to ecosystems, agriculture, water resources and socio-economic stability worldwide. The evolution of drought forecasting models reflects a continuous pursuit of greater accuracy and lead time, particularly highlighted by events like the 2012 US Midwest drought. Traditional models relying on empirical relationships have faced limitations in capturing the complexities of meteorological droughts, leading to the exploration of AI-driven approaches. This comprehensive review explores the landscape of drought forecasting, focusing on the integration of AI and hybrid models. The advantages of AI, such as its ability to handle nonlinear relationships and vast datasets, have revolutionized drought assessment and prediction.

Various AI techniques including Neural Networks, Support Vector Machines, Fuzzy Logic and Deep Learning, offer unprecedented accuracy and real-time monitoring capabilities. Hybrid models, combining AI with traditional statistical or dynamical approaches, show promise in enhancing predictive capabilities. The integration of Wavelet Transform with Neural Networks and other hybrid strategies has demonstrated success in capturing non-linear relationships and improving prediction accuracy. The future of AI-driven drought forecasting lies in collaborative efforts, innovative research and ethical practices. By navigating these challenges and seizing opportunities, AI models can contribute significantly to building resilience and sustainable management of water resources globally.

Keywords: Drought Forecasting, Artificial Intelligence, Machine Learning.

Introduction
Drought, an enduring and pervasive natural disaster, poses formidable challenges to ecosystems, agricultural productivity, water resources and socio-economic stability worldwide[1]. Defined by prolonged periods of deficient precipitation, droughts manifest in various forms, ranging from meteorological deficits to agricultural and hydrological distress, ultimately exerting profound impacts on human livelihoods and the environment[2,3]. The severity and unpredictability of drought events underscore the critical necessity for advanced and precise forecasting models to mitigate their deleterious effects[4]. Throughout history, humanity has grappled with the devastating repercussions of droughts, often witnessing their catastrophic toll on communities, particularly in vulnerable regions.

The history of drought prediction models reflects an ongoing quest for methods to anticipate, monitor and respond to these natural phenomena. From early rudimentary methods relying on observed climatic patterns to the advent of sophisticated statistical models, the evolution of drought forecasting has been marked by a continual pursuit of greater accuracy and lead time[5–7]. The 2012 drought in the US Midwest stands as a stark reminder of the urgent need for robust early warning systems. This event, characterized by prolonged dry spells and scorching temperatures, inflicted widespread agricultural losses, water scarcity and economic disruption[8,9]. It served as a poignant catalyst for re-evaluating existing drought prediction methodologies and exploring novel approaches to enhance forecasting precision.

Traditional drought prediction models have historically relied on empirical relationships between climatic variables and observed historical patterns[10,11]. These models, while providing valuable insights, often struggled to capture the complex interplay of factors influencing drought dynamics[12]. Meteorological droughts, characterized by prolonged deficits in precipitation, present particularly intricate challenges due to their nonlinear and multivariate nature [13]. The limitations of traditional models in accurately forecasting such events have spurred the exploration of alternative methodologies including the integration of artificial intelligence (AI) and machine learning techniques[14].

The integration of AI into the realm of drought assessment, monitoring and prediction has brought about a seismic shift in our understanding and management of this critical environmental phenomenon[15]. Leveraging advanced computing methods such as Neural Networks, Support Vector Machines (SVM), Fuzzy Logic and others, researchers and experts are now equipped with powerful tools to unravel the complex web of climatic factors that contribute to the onset and progression of droughts[16,17]. One of the most significant advantages offered by AI-driven approaches is the unprecedented level of accuracy, they provide in forecasting and monitoring drought conditions[18,19]. These technologies have the capability to analyze vast amounts of data from various sources including satellite imagery, weather stations, soil moisture sensors and more.

By processing this data through sophisticated algorithms, AI can identify patterns and correlations that may escape traditional statistical methods[20,21]. Real-time monitoring is another game-changing aspect facilitated by AI in drought management. With AI-powered systems and continuously processing incoming data streams, stakeholders can receive up-to-the-minute information on changing drought conditions [22,23]. This enables timely and informed decision-making, allowing for proactive interventions and the implementation of effective mitigation strategies.

The emergence of hybrid forecasting systems represents a further evolution in this field[24,25]. By combining the strengths of AI with traditional statistical or dynamical models, these hybrid approaches offer enhanced predictive capabilities[26]. One such example is the integration of Wavelet Transform with Neural Networks, which has demonstrated remarkable success in capturing non-linear relationships and improving prediction accuracy. Successful case studies of these hybrid models abound across the globe. In various regions facing diverse climatic challenges, these AI-enhanced systems have proven their mettle. From predicting the onset of droughts in arid regions to monitoring soil moisture levels in agricultural landscapes, these technologies are transforming how drought management is approached[27–29].

For instance, in agriculture, AI-powered systems can provide farmers with precise information on when and how much to irrigate their crops, optimizing water usage and maximizing yields [30]. In urban planning, AI-driven assessments of water availability can inform infrastructure development and water resource management strategies [31]. In essence, the fusion of AI with drought assessment and prediction represents a paradigm shift towards a more proactive, data-driven and efficient approach in managing one of the most pressing challenges posed by climate change [32]. As these technologies continue to evolve and become more accessible, their potential to mitigate the impacts of droughts and build resilience in vulnerable regions grows ever more promising.

The integration of technological advancements, particularly remote sensing data and meteorological observations, has further enriched the capabilities of drought prediction models. Remote sensing technologies such as satellite imagery and ground-based sensors, provide valuable insights into soil moisture levels, vegetation health and atmospheric conditions, facilitating more precise and comprehensive drought monitoring [2,33,34]. Despite these advancements, challenges persist in the domain of drought prediction. Climate change-induced uncertainties, limited data availability in certain regions and the complexities of modeling non-linear drought dynamics continue to pose significant hurdles [35]. However, these challenges also present opportunities for further innovation and collaboration across scientific disciplines.

This comprehensive review aims to explore the evolving landscape of drought forecasting, with a specific focus on the integration of AI and hybrid models. By synthesizing insights from recent studies, examining case studies from diverse regions and discussing the advantages and limitations of various approaches, this review seeks to provide a holistic understanding of the current state of drought prediction methodologies. Furthermore, it aims to outline future directions for research, emphasizing the need for enhanced data collection, refined modeling techniques and interdisciplinary collaborations to advance the field of drought forecasting and contribute to sustainable water and agricultural management globally.

The review will delve into the historical context of drought prediction, the role of AI in assessment, monitoring and prediction and the application of hybrid models for meteorological drought forecasting. The exploration of opportunities and challenges in this field will provide a roadmap for improving drought forecasting accuracy and lead time, crucial for sustainable water and agricultural management. This comprehensive review aims to serve as a valuable resource for researchers, policymakers and stakeholders involved in drought prediction and mitigation efforts. It synthesizes diverse perspectives, from traditional models to cutting-edge deep learning algorithms, providing a holistic understanding of the challenges, advancements and future directions in the field of drought forecasting. Through this exploration, the review seeks to contribute to the development of innovative solutions to address the pressing challenges posed by droughts and their far-reaching impacts on global ecosystems and societies.

Advancing Drought Forecasting: The Superiority of Artificial Intelligence Models

Traditionally, the field of drought forecasting has relied heavily on physically based dynamic models and statistical approaches. Physically based models, rooted in the fundamental equations governing atmospheric dynamics, have been instrumental in understanding the complex interactions between the land, atmosphere and ocean [36–38]. These models, developed over decades, utilize partial differential equations to simulate the dynamic processes influencing drought conditions. However, despite their sophistication, physically based models are not without their limitations. One of the primary challenges with physically based models is the inherent uncertainty stemming from simplified assumptions and the sensitivity to initial conditions[12].

Small variations in the initial values can lead to significant divergences in predicted outcomes, limiting the precision of drought forecasts. The work of pioneers like Henri Poincaré and Edward Lorenz highlighted the fundamental role of accurate initial states in predicting chaotic yet deterministic systems, setting the stage for the ongoing quest for improved predictability [39,40]. On the other hand, statistical models offer an alternative approach to drought forecasting by focusing on the historical patterns and relationships within drought indicators. These models leverage the temporal persistence of drought indicators such as the Standardized Precipitation Index (SPI) and Palmer Drought Severity Index (PDSI), as well as teleconnections between different types of droughts[41,42]. By analyzing these relationships, statistical models aim to predict future drought conditions based on past observations and trends.

The emergence of AI models has brought about a significant transformation in the field of drought forecasting[43]. AI including Neural Networks, Support Vector Machines and Deep Learning algorithms, has revolutionized our approach in predicting droughts by offering unparalleled capabilities in handling complex data relationships and processing vast datasets rapidly[44]. Physically based dynamical models and statistical approaches have long been the mainstays of drought forecasting. However, compared to these traditional methods, AI models demonstrate several distinct advantages. One of the most significant advantages lies in their ability to capture nonlinear relationships within drought data, a task that linear models often struggle with. By identifying intricate patterns and correlations, AI models provide a more nuanced understanding of drought dynamics[45–47].

Moreover, AI models exhibit adaptability and continuous learning, allowing them to stay updated with changing conditions and incorporate new data seamlessly. This adaptability is particularly crucial in dynamic environments where drought conditions evolve rapidly over time. Additionally, AI models excel in handling the spatial and temporal complexities inherent in drought forecasting, offering detailed insights into large geographical regions over extended periods[48–50]. When compared to physically based dynamic models and statistical approaches, AI models offer several key advantages. They can capture nonlinearities more effectively, adapt to changing conditions and learn from new data continuously. Furthermore, AI models are proficient in handling big data, providing comprehensive insights into drought conditions with improved spatial and temporal resolution[51]. Additionally, AI models offer probabilistic forecasting, presenting a range of possible outcomes along with their likelihoods, enabling decision-makers to assess the risk of various drought scenarios and plan accordingly.

Drought Forecasting using Various AI Techniques

In recent years, the integration of AI techniques has revolutionized the field of drought assessment and forecasting. Artificial Neural Network (ANN) stands as a prominent computational model inspired by biological neural networks. Widely acknowledged for its ability to capture complex relationships between inputs and outputs, ANN has emerged as a valuable tool in hydrologic forecasting[52,53]. Its architecture typically comprises of layers layers: input, hidden and output layers, each consisting of interconnected neurons[54].

In the context of drought assessment and prediction, ANN has been extensively employed. For instance, researchers have successfully utilized ANN models to predict drought onset, duration and severity[42,55].

By incorporating climatic parameters such as precipitation, temperature, wind speed and humidity as input data, ANN models have demonstrated higher accuracy compared to traditional statistical methods, particularly in arid and semi-arid regions[56–58]. Moreover, ANN's capability to handle nonlinear relationships and its flexibility in modeling complex systems make it a preferred choice in drought forecasting endeavors.

Support Vector Machine (SVM) is another powerful AI technique employed in drought forecasting. SVM operates by constructing hyperplanes in multidimensional space to separate different class labels, thereby facilitating classification tasks[59,60]. In the realm of drought prediction, SVM models have exhibited high accuracy and low error rates. Utilizing input parameters such as temperature, humidity and precipitation, SVM has outperformed other models in forecasting drought conditions, especially in semi-arid regions[61–63]. For instance, SVM models have been successfully applied in forecasting drought in provinces like North Khorasan in Iran, showcasing superior performance compared to ANN and ANFIS models [64]. By leveraging SVM's ability to handle both regression and classification tasks, researchers have achieved significant advancements in accurately predicting drought events and their impacts on water resources[61].

Extreme Learning Machine (ELM) is a feedforward neural network known for its fast-learning speed and efficient training process. In the domain of drought assessment and prediction, ELM has emerged as a promising AI technique[65,66]. By random assignment of weights and biases in hidden layers and analytically determining output weights, ELM models offer rapid computation and high generalization performance.

Researchers have successfully utilized ELM models for drought prediction in various regions. Through the integration of wavelet preprocessing techniques, ELM models have demonstrated superior accuracy in assessing drought conditions and predicting future events. The computational efficiency and effectiveness of ELM models make them invaluable tools for decision-making in drought-prone regions[67–72].

Deep Learning, characterized by complex neural network architectures, has garnered significant attention for its remarkable capabilities in drought forecasting[44]. With its ability to recognize intricate patterns and relationships in data, deep learning models have exhibited superior performance in assessing drought conditions[73]. By leveraging deep neural networks, researchers have achieved enhanced forecasting capabilities, particularly in regions prone to agricultural and ecological impacts of drought [74]. Deep learning approaches, such as Deep Belief Networks (DBN), have been utilized to predict long-term drought events with greater accuracy compared to traditional models like Multilayer Perceptron (MLP) and Support Vector Regression (SVR)[75–77].

Additionally, deep learning techniques have proven effective in monitoring meteorological and agricultural droughts using satellite data, providing valuable insights for drought management and preparedness[77]. Fuzzy Logic, renowned for its flexibility and ability to handle uncertain and imprecise data, has found extensive applications in drought analysis and forecasting[43].

By incorporating fuzzy logic with Geographic Information System (GIS) tools, researchers have developed robust frameworks for drought management and risk assessment[78–80]. Fuzzy logic-based models have demonstrated effectiveness in accurately forecasting drought events with longer lead times, thereby enabling proactive measures to mitigate drought impacts[78]. Moreover, the integration of fuzzy logic with other techniques such as wavelet analysis, has further improved the accuracy and reliability of drought forecasting models[81]. Through the utilization of fuzzy logic, researchers have made significant strides in understanding the spatial and temporal variability of drought, leading to more effective early warning systems and decision support tools[43,82,83].

Adaptive Neuro Fuzzy Inference System (ANFIS) combines the strengths of neural networks and fuzzy logic to provide accurate and reliable predictions in drought forecasting[84,85]. ANFIS models, with their adaptive learning capabilities, have been widely adopted for various drought assessment tasks. By utilizing different timescales and input parameters such as Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI), ANFIS models have demonstrated high accuracy and reliability in forecasting drought events[41]. Moreover, ANFIS models offer advantages such as improved interpretability and reduced computational complexity, making them valuable tools for decision-making in drought-prone regions.

Deep Learning for Drought Forecasting

Deep learning, a subset of machine learning, has emerged as a powerful tool in the realm of drought forecasting. Within this domain, Convolutional Neural Networks (CNNs) have proven invaluable, particularly in processing satellite images for insightful predictions[86]. These CNN models, such as VGGNet and AlexNet, are tailored with specific architectures, often comprising of convolutional layers, pooling layers and dense layers[79,80]. By utilizing techniques like carpooling and average pooling, these models can extract essential features from images while efficiently managing computational complexity [88]. Notably, studies have showcased the superiority of CNNs over other models, exhibiting better accuracies when incorporating indices such as the Normalized Difference Vegetation Index (NDVI)[89–91].

On the other hand, Recurrent Neural Networks (RNNs) find their niche in handling time series data, a crucial component in drought prediction[92]. Models like Convolutional Long Short-Term Memory Neural Networks (ConvLSTM) excel in capturing both spatial and temporal variabilities in climate data, providing a comprehensive understanding of evolving drought patterns[93,94]. Moreover, the use of Long Short-Term Memory (LSTM) models has demonstrated remarkable performance, especially when leveraging historical data alongside relevant climatic variables.

Delving deeper into neural network architecture, Deep Belief Networks (DBNs) offer a generative approach to drought analysis. These networks, constructed with layered Restricted Boltzmann Machines (RBMs), have been pivotal in precipitation forecasting, showcasing optimal performance compared to traditional machine learning approaches[95]. Furthermore, the integration of Generative Adversarial Networks (GANs) has paved the way for generating artificial data, an asset in refining drought prediction models[96]. In pursuit of even greater accuracy, researchers have ventured into hybrid models, combining the strengths of various deep learning architectures. These models such as Broad Learning (BL) models with improved signal decomposition methods and hybrid Empirical Mode Decomposition-Deep Belief Network (EMD-DBN) models, have demonstrated superior predictive capabilities[97].

Additionally, the fusion of decision tree models with Season AutoRegressive Integrated Moving Average (SARIMA) models has proven effective in classifying data into rainfall or drought categories, offering valuable insights into the Keetch-Byram Drought Index values [75]. Through these innovative applications, deep learning continues to revolutionize the field of drought forecasting, offering unparalleled precision and insight into this critical environmental challenge.

Hybrid AI Models for Meteorological Drought Prediction

Meteorological drought prediction presents a complex challenge due to the interplay of various climatic factors and their impact on water availability. In recent years, the integration of AI with traditional statistical or dynamical approaches has emerged as a promising solution. These hybrid models harness the strengths of both AI techniques and existing forecasting methods, offering improved accuracy and insights into meteorological droughts. Hybrid models, by combining the strengths of AI and traditional methods, address some of the limitations inherent in standalone approaches. They can effectively capture the non-linear relationships and intricate patterns present in meteorological data, leading to enhanced prediction accuracy. Additionally, these models are more adaptable to changing environmental conditions, providing more robust and reliable forecasts[98–101].

One notable example of a successful hybrid model for meteorological drought prediction is the combination of Wavelet Transform with Neural Networks. The Wavelet Transform is a mathematical tool used to decompose time-series data into different frequency components, allowing for the identification of patterns at different scales[102,103]. In the context of drought forecasting, the Wavelet Transform is used to preprocess meteorological data, extracting relevant features and reducing noise. These processed data are then fed into Neural Networks, which excel at learning complex patterns and relationships. The Neural Networks analyze the transformed data to predict future drought conditions based on historical patterns and trends.

Numerous case studies have demonstrated the effectiveness of hybrid AI models in meteorological drought prediction across different regions[102,104–107]. Studies have shown that hybrid models offer superior accuracy in drought prediction compared to standalone methods Pathak et al.[106] found that hybrid models, such as those combining Neural Networks, Support Vector Machines and Fuzzy Logic, demonstrate enhanced accuracy in forecasting drought conditions.

Forecasting daily river flow in tropical areas has shown great efficacy for the Enhanced Extreme Learning Machine (ELM) model modified with Complete Orthogonal Decomposition (COD) as a hybrid technique[66]. This model showed that it could produce accurate and dependable forecasts, which is crucial for managing water resources in these kinds of areas. The assessment of spatiotemporal drought patterns has been made possible using SPI and Standardized Precipitation Evapotranspiration Index (SPEI) in hybrid models[108–111]. These indices provide important information on the intensity and spread of drought occurrences. They are calculated using rainfall grid data from satellites.

The effectiveness of the Wavelet-Based Extreme Learning Machine (W-ELM) model in forecasting Australia's monthly Effective Drought Index (EDI) was assessed by Jalalkamali et al[72]. This hybrid model beats existing models like wavelet-based Least Squares Support Vector Regression (w-LSSVR) and wavelet-based Artificial Neural Networks (w-ANN) by using wavelet pre-processing. Rohith et al[112] studied the efficacy of Wavelet-Based Artificial Neural Networks (W-ANN) models using indices such as the Standardized Water Storage Index (SWSI) and the Standardized Index of Annual Precipitation (SIAP). These models were useful for estimating and evaluating drought conditions.

Researchers are increasingly turning to hybrid modeling approaches to address the growing challenges posed by droughts. These models offer a pathway to more accurate, reliable and timely predictions, aiding policymakers, water resource managers and agriculturists in implementing effective mitigation strategies[12,42,82,113]. As climate change intensifies, the development and application of hybrid models will continue to play a pivotal role in understanding and mitigating the impacts of drought events. In addition to the studies, researchers have explored various hybrid optimization modeling approaches to predict droughts in different regions. Evolutionary neuro fuzzy methods such as Adaptive Neuro Fuzzy Inference Systems (ANFIS) with Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Colony Algorithm (ACO) and Butterfly Optimization Algorithm (BOA), have been evaluated using SPI[114–120]. These approaches offer valuable insights for hydrologists, water resource planners and agriculturists working in arid and semi-arid regions. Table 1 shows the application of different AI applications applied in drought prediction and management.

Challenges in Drought Forecasting using AI Models

While AI models have shown immense promise in improving the accuracy and timeliness of drought forecasting, several challenges persist in the field. These challenges must be addressed to further enhance the effectiveness of AI-driven approaches:

a) Data Quality and Availability: Many regions, especially in developing countries, lack sufficient historical data on climatic variables. This scarcity hampers the training and validation of AI models. Inaccurate or incomplete data can lead to biased model predictions. Ensuring data accuracy and reliability is crucial for robust forecasting.

b) Model Interpretability and Transparency: Black Box nature of deep learning, Complex deep learning models often lack transparency, making it challenging to understand the reasoning behind predictions. Developing methods to explain AI model predictions is essential for building trust among stakeholders and decision-makers.

c) Incorporating Non-Climate Factors: Drought impacts are influenced by socio-economic factors such as population density, agricultural practices and infrastructure. Integrating these factors into AI models can improve forecasting accuracy. Understanding the interaction between ecosystems and drought conditions is crucial. AI models should consider ecological variables for comprehensive predictions.

d) Scalability and Operational Implementation: Ensuring that AI models can scale to cover large geographical areas and varying spatial resolutions is essential for widespread application, bridging the gap between research and operational use is critical. Implementing AI-driven tools in real-world decision-making processes requires collaboration with stakeholders.

e) Computational Resources and Infrastructure: Training complex AI models requires significant computational resources and infrastructure, which may not be readily available in all settings. Leveraging cloud computing can mitigate these challenges, but cost and accessibility remain concerns, especially for resource-constrained regions.

f) Transferability and Generalization: Ensuring that AI models trained in one region or dataset can be effectively applied to other regions with different environmental conditions, AI models should generalize well to unseen data, avoiding overfitting to specific datasets.

Table 1
Show the different AI application applied in drought predication and management

Applications	Objective	Contribution
Drought forecasting using AI methods (GRNN, LSSVM, GMDH, ANFIS-FCM)[121]	Investigate accuracy of AI methods in forecasting MSPI in Iran	Found GMDH to have best accuracy for short-term forecasting, acceptable long-term forecast up to 2-3 months ahead, better performance in mountainous arid-cold regions
Forecasting drought using MLP ANN, ANFIS, SVM, ARIMAX[122]	Compare models for SPI forecasting in Yazd, Iran	ARIMAX performed best for 9-month forecast of SPI values
Predict SPEI using AI models (MLPNN, SVR, ANFIS, EDT) in Iran[123]	Determine best input data sets and predict SPEI at synoptic stations	Identified best models (W-MLPNN, W-SVR) for different time scales, enhanced AI efficiency in longer time scales
Drought forecast using ANNs and SPI in Fars Province, Iran[124]	Develop regional drought forecast method with ANNs	Achieved 73% agreement with observed maps, spatial and temporal relationships in forecast
Forecasting SPEI using EWT, DWT, MLP, GMDH in Iran[125]	Investigate machine learning models for SPEI forecast	EWT improved performance, best results with EWT and MLP-EKF
CNN-LSTM model for SPEI drought forecasting in Turkey[126]	Develop CNN-LSTM model for meteorological drought forecast	CNN-LSTM outperformed benchmarks, accurate SPEI prediction
NDVI forecasting with ANN using SOI and NAO indices in Iran[127]	Forecast NDVI in Ahar-chay Basin with ANN	Predicted NDVI using climatic signals with high accuracy
Drought forecasting in Gorganrood, Iran using SPI[128]	Compare RMLP, RSVR and ARIMA for SPI forecasting	ICA-RMLP, ICA-RSVR outperformed ARIMA, practical for drought warning system
Comparison of ANFIS variants in SPI forecasting in Iran[129]	Investigate ANFIS-PSO, ANFIS-GA, ANFIS-ACO, ANFIS-BOA	Evolutionary methods outperformed classical ANFIS for SPI forecasting
Drought forecasting using LSTM in Australia[130]	Use LSTM to predict SPEI, compare with other ML methods	Achieved R2 > 0.99, AUC 0.82-0.83, improved drought forecasting
SHDI forecasting using hybrid optimization-ANN[131]	Forecast SHDI using hybrid models, compare with ANN	Hybrid models outperformed conventional ANN, PSO performed best
Drought estimation models using W, ANFIS, SVM, ANNs in Turkey[132]	Develop drought estimation models, compare different approaches	W-ANFIS model performed best for 6-months period
Drought forecasting using IoT, ANN, ARIMA in India[133]	Forecast drought using IoT and ANN, compare with ARIMA	Achieved high accuracy, sensitivity, specificity with IoT-ANN-ARIMA
SPEI estimation with ML models in Tibetan Plateau[134]	Use ML models (RF, XGB, CNN, LSTM) for SPEI estimation, compare scenarios	Achieved good fits with RF, XGB models for SPEI-3, SPEI-6
ANN with Effective Drought Index in Kenya[135]	Develop ANN models with EDI for drought forecasting in Kenya	Achieved accuracies up to 98%, enhancement to current solutions
AI methods for MSPI forecasting in Iran[136]	Investigate AI methods (GRNN, LSSVM, GMDH, ANFIS-FCM) for MSPI	GMDH showed best accuracy, promising results for multivariate drought forecasting
Drought Prediction with SVR and Optimization[137]	Hybridize SVR with PSO and HHO for EDI prediction in Uttarakhand State, India	SVR-HHO model outperformed SVR-PSO model in predicting EDI, providing reliable predictions for the study area

Short-term Meteorological Drought Prediction[138]	Predict short-term drought using hybrid ML models with SPI as the index	Hybrid VMD-GPR model performed best for 1-month, 3-month and 6-month time scales, outperforming standalone models
Statistical and Hybrid Models for SPI6 Forecast[139]	Investigate ESP, wavelet machine learning and hybrid models for SPI6 forecasting in China	Hybrid model combining statistical and dynamic models improved SPI6 forecast, ESP and wavelet models outperformed other statistical models
Hydrological Drought Forecasting with Optimization[140]	Forecast short-term SHDI using hybrid of optimization algorithms with ANN	PSO outperformed other optimization algorithms, hybrid model better than conventional ANN in SHDI forecasting
Fusion-based Approach for Drought Estimation[141]	Use fusion methodologies with remotely sensed data for SPI estimation in Iran	ORNESS-OWA method showed superior performance, effective in SPI estimation using remote sensing data, especially in drought-prone regions
LSTM and ARIMA Hybrid for SPEI Prediction[142]	Combine ARIMA and LSTM for SPEI prediction in Iran	Hybrid model improved short-term drought prediction, ARIMA-LSTM best for 6-month scale
Hybrid Models for SPI Prediction[143]	Combine preprocessing, permutation entropy and AI methods for SPI prediction in Iran	Hybrid models showed significantly better performance compared to single models, effective for drought modeling
Dynamical-Statistical Framework for Precipitation[144]	Use hybrid framework combining dynamical (NMME) and statistical (analog-year) models for precipitation prediction	Improved seasonal precipitation predictions in southwestern United States, balance between positive and negative anomalies
Dynamic-LSTM Model for Drought Prediction[145]	Develop dynamic-LSTM model for SPI3 prediction in China	Dynamic-LSTM model improved prediction skills, especially in specific regions and seasons, more accurate in drought onset prediction
Meteorological Drought Prediction with Heuristic[146]	Use CANFIS, MLPNN and MLR models for EDI prediction in Uttarakhand State, India	CANFIS and MLPNN models outperformed MLR for meteorological drought prediction, useful for decision-making in drought mitigation
ARIMA-LSTM Hybrid for Short-term Drought Prediction[147]	Propose ARIMA-LSTM hybrid for SPEI prediction in China	Hybrid model (ARIMA-LSTM) showed higher prediction accuracy compared to single models, especially for longer-term drought forecasting

Future Directions and Opportunities

Addressing the challenges outlined above opens exciting avenues for the future of drought forecasting using AI models. Here are some key directions and opportunities:

a) Enhanced Data Collection and Integration: Leveraging advancements in satellite imagery and Internet of Things (IoT) sensors for real-time data collection on various climatic variables. Promoting open-access data repositories to facilitate the sharing of climate, hydrological and socio-economic data for model training.

b) Hybrid Modeling Approaches: Combining the strengths of different AI models, such as CNNs, RNNs, SVMs and Fuzzy Logic, in hybrid frameworks for more robust predictions. Incorporating AI-driven insights into physically based models to improve accuracy and overcome limitations.

c) Explainable AI and Model Transparency: Developing methods to explain AI model predictions, such as feature importance, SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations). Creating user-friendly interfaces for stakeholders to interact with AI-driven tools, enhancing trust and adoption.

d) Focus on Vulnerable Regions and Communities: Developing region-specific AI models that account for the unique challenges faced by vulnerable communities. Empowering local stakeholders with the knowledge and tools to utilize AI-driven forecasts for decision-making.

e) Climate Change Adaptation: Extending AI models to predict long-term climate trends and their implications for droughts. Using AI-driven forecasts to develop adaptive strategies for climate change resilience such as drought-resistant crop varieties and water management plans.

f) Collaboration and Knowledge Sharing: Encouraging collaboration between climate scientists, data scientists, policymakers and local communities to co-create effective solutions. Establishing international partnerships for data sharing, model development and capacity building in drought-prone regions.

g) Ethical Considerations and Bias Mitigation: Developing ethical frameworks for AI-driven drought forecasting, including privacy protection and fair use of data. Implementing strategies to detect and mitigate biases in AI models, ensuring equitable and unbiased predictions.

Conclusion

In conclusion, the integration of AI models into the realm of drought forecasting represents a significant advancement in our ability to mitigate the impacts of this enduring natural disaster. The evolution from traditional, empirical methods to sophisticated AI-driven approaches reflects a continuous quest for greater accuracy, timeliness and comprehensiveness in predicting drought events. The advantages offered by AI models, such as their ability to handle nonlinear relationships, to process vast datasets and to provide real-time monitoring, have revolutionized drought assessment and prediction. Techniques like Neural Networks, Support Vector Machines (SVM), Fuzzy Logic and Deep Learning have demonstrated unprecedented accuracy in capturing the complexities of meteorological droughts.

These models enable stakeholders to make timely, informed decisions and implement proactive interventions to mitigate the impacts on ecosystems, agriculture, water resources and communities. Hybrid models, which combine the strengths of AI with traditional statistical or dynamical approaches, offer a promising pathway to enhance predictive capabilities further. The integration of Wavelet Transform with Neural Networks and other hybrid strategies has shown remarkable success in improving prediction accuracy and capturing non-linear relationships. However, challenges such as limited data availability, model interpretability, scalability and computational resources remain pertinent. Overcoming these challenges presents opportunities for enhancing data collection methods, developing explainable AI techniques and tailoring solutions for vulnerable regions.

The future of AI-driven drought forecasting holds immense promise. Collaborative efforts, innovative research and ethical practices will be crucial in harnessing the full potential of these models. By navigating these challenges and seizing opportunities for advancement, AI models can play a pivotal role in building resilience, adapting to changing climatic conditions and ensuring sustainable water and agricultural management on a global scale. The integration of AI into drought forecasting represents a paradigm shift towards a more proactive, data-driven and efficient approach in managing one of the most pressing challenges posed by climate change. Through continued research, collaboration and implementation, we can leverage the power of AI to mitigate the impacts of droughts, to protect ecosystems, to support agriculture and to safeguard the well-being of communities worldwide.

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