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Perspective

A transformative framework reshaping sustainable drought risk management through advanced early warning systems

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SUMMARY

In light of the increasing vulnerability to drought occurrences and the heightened impact of drought-related disasters on numerous communities, it is imperative for drought-sensitive sectors to adopt proactive measures. This involves the implementation of early warning systems to effectively mitigate potential risks. Guided by Toulmin's model of argumentation, this research proposes a framework of eight interconnected modules introducing Fourth Industrial Revolution technologies to enhance drought early warning capabilities. The framework emphasizes the Internet of Things, drones, big data analytics, and deep learning for real-time monitoring and accurate drought forecasts. Another key component is the role of natural language processing in analyzing data from unstructured sources, such as social media, and reviews, essential for improving alerts, dissemination, and interoperability. While the framework optimizes resource use in agriculture, water, and the environment, overcoming impending limitations is crucial; hence, practical implementation and amendment of policies are necessary.

INTRODUCTION

Drought early warning systems (DEWS) are an essential part of drought risk management as they connect risk-related information to a communication system to provide advance notifications for effective drought preparation and responses.[1] The emergence of DEWS can be traced back to the 1980s, a period marked by severe famines in Sudan and Ethiopia that highlighted the need to anticipate and prevent future disasters.[2] Before 1995, DEWS tended to be reactive, focusing on monitoring and response only after a drought event had already begun.[3] Common to these systems was the inclusion of drought indices that use ground-based meteorological variables and field reports; yet, this approach was later proven to be ineffective, primarily because it was subjective and not immediately available, prompting the need for improved forecasting.[4]

Over time, DEWS have evolved to incorporate a wider range of information and services, making them more accessible to end-users.[5] Since their conception, remote sensing has been an integral part of these systems, enabling the monitoring and detection of drought conditions across many regions.[6] Subsequently, advancements in computer modeling and data analysis have enabled DEWS to incorporate a wider range of factors, such as climate variability, socio-economic conditions, and land use patterns, into their forecasts.[7,8]

During the 2000s, emerging knowledge and technical tools for the assessment of risks, predictions, and warnings improved.[9] The improvements were largely the result of a greater understanding of natural hazards,[10] together with the use of the modern information and communication technologies of the Digital Age.[11] This allowed for the development of web-based DEWS[12] that could utilize internet-based communication and remote devices such as cell phones and laptop computers. Subsequently, an enormous amount of data were generated and consumed regularly across all industries, creating a foundation for the Fourth Industrial Revolution (4IR), also called Industry 4.0.[11]

Technologies of the 4IR, which were introduced around 2010, are currently making a significant impact in all areas of study, with industrial applications being redefined and technology advancing in every sector.[13] Hence, there is an increasing effort to explore the application of these technologies and how they can be utilized to bring about positive change.[14] For instance, David et al.[15] established that 4IR technologies have had an impact on the nexus of water, energy, and food, leading to the adoption of cleaner production methods and resource management strategies. In the water and sanitation sector, the use of 4IR technologies has been shown to be effective in providing stakeholders with timely, relevant information, while also reducing costs by eliminating the need to build or use physical versions of modeled resources.[16]

Recently, disaster management has been identified as an area with potential for the application of 4IR technologies.[14,17,18] This integration has garnered significant interest within the field, particularly the use of the Internet of Things (IoT) during acute disasters such as cyclones,

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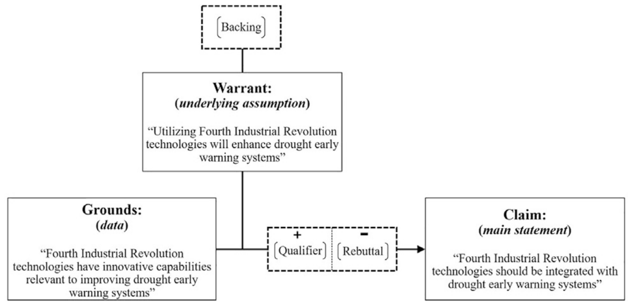

Figure 1. Framework applied to analyze and construct the argument for an integrated 4IR-based DEWS, according to Toulmin's model of argumentation[20]

earthquakes, and floods that require rapid emergency responses.[19] However, concerning drought, which tends to have a gradual onset, there is a lack of research connecting the application of these technologies to DEWS. To bridge this gap, the study explored the potential role of fourth industrial revolution-based drought early warning systems (DEWS 4.0). Through logical assessments of the technological landscape and DEWS, the study elucidated the research that will be needed for the practical implementation of this framework to enhance the overall effectiveness of DEWS in addressing related risks and vulnerabilities. Together, the findings provide a perspective of the prospects, implications, and challenges for the incorporation of 4IR-based DEWS for drought risk management.

METHODOLOGICAL APPROACH

The research followed a conceptual approach to generate theoretical perceptions by employing Toulmin's model of argumentation (Figure 1). This model offers a systematic approach to examining and constructing logical arguments based on three main components: claim, grounds, and warrant.[20] Extensive research has been conducted utilizing this model in various fields, including education,[21] policy science,[22] environment,[23] and disaster management.[18] The model suggests that a claim, which is the main proposition being presented, is warranted when it is supported by the appropriate grounds.[24] Here, the claim was that "4IR technologies should be integrated with DEWS." The grounds were established to demonstrate that these technologies have innovative capabilities relevant to improving DEWS. The warrant provided the logical reasoning and explanation for the connection between the grounds and the claim. The remaining components of the model are additional evidence that supports the warrant (backing), the degree of certainty of the claim (qualifier), and the opposing viewpoints that challenge the claim (rebuttal).[20]

To establish the grounds, a bibliometric analysis was conducted by reviewing studies that discuss existing theories and concepts related to 4IR technologies and DEWS. A rigorous process of retrieving literature through a Boolean search was applied to published journal articles, conference proceedings, books, and book chapters held in the Web of Science database in April 2024. The search used the following query: "fourth industrial revolution OR digitization OR cybersecurity OR blockchain OR virtual reality OR UAV [unmanned aerial vehicle] OR unmanned aircraft systems OR remotely piloted aircraft system OR 3D printing OR smart cities OR drones OR Industry 4.0 OR quantum computing OR robotics OR deep learning OR artificial intelligence OR IoT [Internet of Things] OR Big data OR cloud computing OR machine learning OR disruptive technologies OR 4IR OR Unmanned aerial vehicles OR micro air vehicles OR small unmanned aircraft systems OR web 3 OR cyber physical systems OR 5G (Keywords) AND drought (Title)".

The search produced 297 documents that were extracted and imported into VOSviewer v. 1.6.19 software (https://www.vosviewer.com/), which is designed for analyzing and visualizing bibliometric data.[25] The extracted data were analyzed to identify the most prominent research focusing on the co-occurrence of keywords within the scientific literature pertaining to 4IR and DEWS. For an inclusive analysis, the next step was to search for keywords leading to the identification of all relevant technologies. Both logic and inductive reasoning techniques were utilized to form the warrant, and thus elements of a DEWS 4.0 were identified on the basis of existing DEWS components, 4IR technologies, and innovative requirements. Finally, the benefits and challenges were collated to illustrate the degree of certainty and limitation of the claim.

MAPPING THE TECHNOLOGICAL REQUIREMENTS FOR DEWS 4.0

A density map of keywords within the drought research literature related to the application of 4IR technologies was constructed to facilitate an enhanced understanding of the patterns of research focus in the field (Figure 2). Keywords with a high density included machine learning, drought, prediction, remote sensing, deep learning, and artificial intelligence, whereas keywords with a low density included cloud computing, IoT, fog computing, UAV, grain yield, drought stress, and climate change. These findings highlight prominent themes as well as areas that are currently less extensively addressed in the context of 4IR technologies applied to drought research, prompting further investigation.

The selection of technologies was informed by a systematic literature review, content analysis, and comprehensive understanding of the essential requirements of a DEWS, as outlined in the literature. The identified technologies, including IoT, big data analytics (BDA), cloud

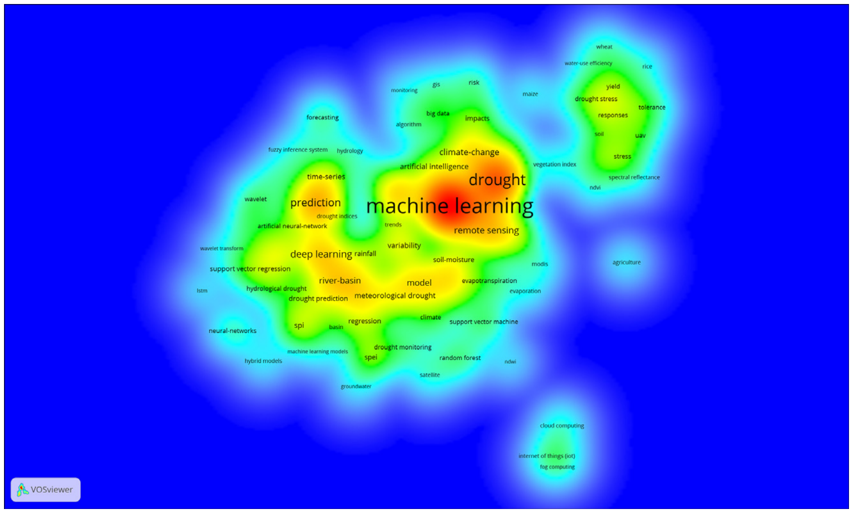

Figure 2. Density map of keywords within the drought research literature related to the application of 4IR components
Red indicates the highest density and blue the lowest.

computing, artificial intelligence (AI), robotics, nanotechnology, extended reality (XR), and blockchain, were considered integral components based on their relevance to meeting the specified requirements (Table 1).

INTERCONNECTED FRAMEWORK MODULES

As outlined by the United Nations, all four fundamental components of DEWS—knowledge of risk, monitoring and warning, dissemination, and response—must be fully embraced to ensure the system's effectiveness.[33] By considering these components and drawing from the capabilities of the applicable 4IR technologies, a conceptual framework comprising eight DEWS 4.0 modules was constructed (Figure 3). In this context, a module refers to a distinct element within a system that serves a specific function or performs a particular task. The following sections describe each of the modules to demonstrate their ability to address drought challenges and show the various technologies, processes, and intended effects to fulfill the objectives of the overall system.

Module 1: Advanced analytics

The advanced analytics module is essential for analyzing historical and real-time data to gain an understanding of drought severity,[34] patterns, trends, and potential impacts for risk and vulnerability assessments.[35] This module emphasizes the application of innovative algorithms to combine data into integrated sets and remove errors and outliers to facilitate analysis. The BDA techniques can identify patterns, correlations, and anomalies that may not be apparent through traditional data-processing methods,[36] playing a significant role within the advanced analytics module by handling the substantial computational requirements of data analysis and processing,[19] and thus enabling effective data integration, pattern recognition, and anomaly detection.

The use of AI techniques, such as machine learning and deep learning,[37] can be directly integrated into the advanced analytics module to model droughts and identify trends and anomalies. Natural language processing, a subset of AI, can process human language to extract insights from unstructured data sources such as social media feeds, news articles, and user reviews.[38] Traditionally, high-performance computing required specialized on-premises infrastructure with powerful hardware and dedicated resources.[39] Now, cloud computing can provide the high-performance computing and storage capabilities needed for processing such big data,[40] benefiting DEWS 4.0 by enabling efficient and timely data analysis.

Module 2: Digital archive

Given the vast amount of data that will be generated in the system, the digital archive module provides a comprehensive repository of historical data, including drought occurrences, impacts, and responses, facilitating a profound understanding of drought dynamics, and enabling effective mitigation strategies. The capacities of 4IR technologies, especially via the functions of AI, BDA, cloud computing, and blockchain, can benefit the gathering, compiling, and retrieval of diverse datasets related to drought. By employing AI algorithms, this module ensures that DEWS 4.0 can automatically identify and categorize data to generate comprehensive metadata on important details such as location, date, and drought severity levels. This would allow users to efficiently navigate, retrieve, and explore historical drought records, not only relying on traditional search parameters but also benefiting from the system's ability to adapt and learn over time. The adaptive learning function ensures that the archiving process remains dynamic, incorporating evolving patterns and trends in drought data, propelled by the

Table 1. Relevance of 4IR technologies necessary for developing DEWS 4.0

Technology	Relevance
i. Internet of Things	Automated exchange of data among objects through sensor networks without human intervention.[26]
ii. Big data analytics	Management of large volumes of data.[19]
iii. Cloud computing	Access to and use of resources hosted on remote servers managed by a cloud service provider.[27]
iv. Artificial intelligence	Enables intelligent systems capable of learning, reasoning, and making decisions on the basis of data and experiences.[28]
v. Robotics	Performs tasks autonomously or in collaboration with humans through intelligent mechanisms and algorithms.[29]
vi. Nanotechnology	Enables the development of innovative materials and applications at the nanoscale.[30]
vii. Extended reality	Provides users with the ability to interact with computer-generated content within a real-world context.[31]
viii. Blockchain	Ensures secure and transparent record-keeping across various applications.[32]

advanced analytics module. Moreover, the automated process eliminates the need for manual input, significantly reducing the potential for errors and ensuring a consistent and standardized dataset.

Another key aspect of this module is the use of cloud computing, which provides the necessary infrastructure for data processing and storage.[41] The flexibility of cloud technology allows fluxes in data volume, enhances accessibility of historical records, and further promotes collaborative efforts among stakeholders, by securely interacting with the data from diverse locations and devices. In such situations, a blockchain enables the security and transparency of historical records, by verifying and tracing changes in the data.[42] For instance, if multiple users, each contributing valuably to the system, need to collaborate, the cloud infrastructure would facilitate seamless sharing and retrieval of archived data, while the blockchain technology ensures that data are cryptographically secured within a decentralized registry, preventing unauthorized modifications.

Module 3: Smart data networks

The smart data networks module provides a network of interconnected sensors and devices to facilitate activities such as collecting, storing, and retrieval of drought-relevant data. These activities are accomplished by various technologies, including the IoT, robotics, nanotechnology, and cloud computing, to enhance data collection and storage. Through strategically positioned IoT sensor nodes, real-time data describing soil moisture, weather, streamflow, and groundwater level can be collected.[17] In addition, connected wearable devices equipped with environmental sensors can be used by various stakeholders to collect localized data to centralized systems such as IoT platforms, cloud computing services, or dedicated monitoring centers.[43] Moreover, nanosatellites equipped with nanosensors can capture high-resolution images to collect valuable data on vegetation health, land cover, and water resources.[30] These sensors, either used individually or integrated with IoT sensor nodes, offer sensing capabilities with improved sensitivity, selectivity, and miniaturization.[44]

To maximize data collection capabilities, UAVs, a subfield of robotics, will play a significant role. Equipped with remote sensing technologies, UAVs offer high spatial resolution and real-time data collection, enabling efficient data gathering from remote or inaccessible areas.[45] Moreover, through deep learning and cognitive computing algorithms of AI,[37] DEWS 4.0 can automatically identify specific objects within images or videos to assist decision-makers in monitoring and assessing the impact of drought events. This expansion of coverage and data type will increase the overall amount of data to be processed and transmitted for DEWS 4.0. Thus, the collected data will need to be wirelessly transmitted to a cloud-based platform for further processing and analysis. Cloud computing offers scalable and cost-effective storage and computing resources, ensuring efficient handling of the large volumes of data.[46] After the collection and processing, the use of BDA becomes crucial, allowing the system to continuously store and analyze incoming data streams from various sources.[41] This ability allows the system to provide real-time updates on drought conditions by detecting significant changes in the indicators of drought onset, severity, and end, as well as potential risks during a drought.

Module 4: Predictive modeling

The predictive modeling module uses predictive analytics techniques to develop accurate drought predictions. Predictive models are developed by using AI techniques, including machine learning and deep learning, which identify complex patterns for accurate forecasts.[47] The model development process involves using algorithms such as regression models,[48] support vector machines,[49] random forests,[50] and neural networks[51] to predict or estimate drought conditions on the basis of available data. For instance, with AI, DEWS 4.0 can analyze historical rainfall, temperature, and river flow data to predict water availability and anticipate water shortages swiftly by continuously learning from real-time data.

By processing large datasets using BDA and cloud computing, the predictive modeling module can create predictive models and forecasting algorithms that consider diverse datasets. Cloud computing provides the necessary computational power and storage capacity to handle the extensive data-processing and model-training requirements of predictive modeling. This integration of real-time model analysis and cloud computing capabilities ensures that DEWS 4.0 can respond swiftly to changing environmental conditions and provide accurate and dependable predictions.

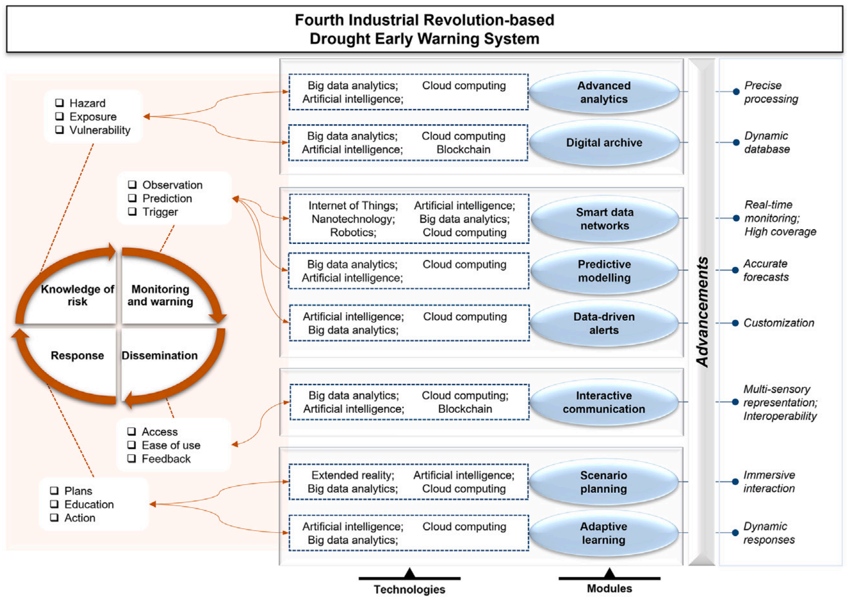

Figure 3. Conceptual framework of DEWS 4.0 outlining relationships among modules and their contributing technologies with respect to the four main components of DEWS

Module 5: Data-driven alerts

The data-driven alerts module allows for the generation of customized drought warning alerts. Although the module is founded on the functionalities of drought forecasting and monitoring, at its core, it uses the capabilities of 4IR to enhance the accuracy, speed, and personalization of these alerts. Integrating innovative technologies such as AI, BDA, and cloud computing, ensures that stakeholders receive real-time, tailored alerts that can be used for effective drought response and mitigation efforts. The application of AI techniques such as machine learning allows the system to continuously process real-time data from various sources and identify early indicators of drought onset, severity, and end, as well as potential risks during a drought, which can then be used to generate alerts.

To enhance the alert generation process, cognitive computing techniques can be used to process unstructured data sources. By incorporating this technology, DEWS 4.0 can automatically analyze real-time data and extract information relevant to drought management. To further personalize recommendations, the module integrates machine learning algorithms to categorize users into different segments based on their characteristics and historical interactions with the system. This deep understanding of the social and environmental impacts of drought enriches the customized alerts with valuable human context and sentiment analysis.[52] However, the large volumes of real-time data generated will require robust BDA techniques to efficiently process, analyze, and obtain significant information. Here, cloud computing will play a key role in providing the necessary computational power and storage capacity[53] to ensure the timely delivery of real-time alerts and eliminate delays in responses to evolving drought conditions.

Module 6: Interactive communication

The interactive communication module is another critical component within DEWS 4.0, utilizing the capabilities of the 4IR to modernize the presentation and understanding of drought information. Through innovative technologies, it extends beyond visuals, as it can employ a combination of audio, and tactile visual elements to create multi-sensory representations such as interactive maps and voice-activated query systems to enhance the user experience by maximizing the impact of wide-ranging representations. By utilizing BDA, this module can effectively transform complex data into informative visuals such as dynamic maps, charts, and graphs that display real-time and predictive drought information.[54] Going beyond visuals, AI offers the module advanced image recognition and natural language processing capabilities, allowing the system to categorize and interpret images, extract information from textual data, and structure it in a way that can be conveyed through speech.

The use of cognitive computing also provides language-translation capabilities, ensuring that DEWS 4.0 can automatically translate text or speech from one language to another.[55] This facilitates the processing of multilingual data, providing real-time translations that allow users to make informed decisions regardless of language barriers. The module's use of an application programming interface, in conjunction with cloud-based systems and other technologies, acts as a link for data sharing and collaboration between stakeholders, enabling them to acquire and incorporate drought information into their own platforms or software systems. Thus, a blockchain can serve as a trusted platform for data sharing, making collaboration more efficient by verifying the authenticity of the shared data.[42] Furthermore, blockchain-based smart contracts can be used to govern data-sharing agreements.

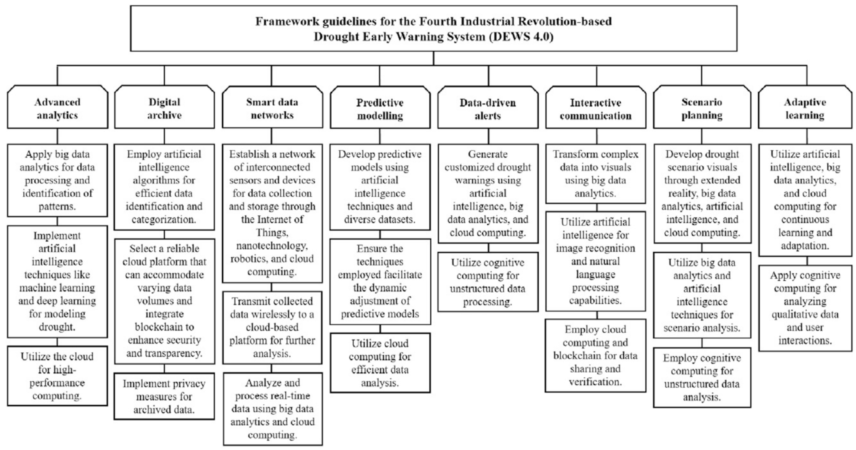

Figure 4. DEWS 4.0 framework guidelines for application

Module 7: Scenario planning

The scenario planning module visualizes drought-related data to allow stakeholders to simulate drought scenarios, interact with the data, and assess the impact of different measures on responses and preparedness. It connects a range of innovative technologies, including XR, BDA, AI, and cloud computing. XR, comprising virtual reality and augmented reality, is a key 4IR technology that offers interactive visualizations in 3D and contextual environments.[56] By examining different scenarios, decision-makers can identify the most vulnerable areas, assess resource allocation needs, and implement timely interventions to mitigate the effects of drought on their regions.

The module further benefits from the use of BDA and AI techniques to process complex datasets and identify patterns within data, enhancing the accuracy and relevance of the generated scenarios.[41] The system's cloud-based infrastructure ensures continuous collaboration, while an application programming interface facilitates data exchange between systems, enhancing the interoperability of the scenario planning module with the other modules and systems. Through cognitive computing, the system can efficiently process large volumes of unstructured data, saving time for decision makers who need up-to-date information.

Module 8: Adaptive learning

The adaptive learning module uses advanced algorithms to enable DEWS 4.0 to continually enhance its performance and accuracy through self-adjustment and self-optimization. This innovative approach allows the system to adapt its strategies and responses dynamically, increasing its efficiency in mitigating the impacts of drought. It further ensures that stakeholders receive training that suits their specific requirements. Key 4IR technologies that directly contribute to the success of the adaptive learning module include AI, BDA, and cloud computing. The integration of AI and BDA techniques allows the module to learn from historical data for continuous improvement. For example, after every drought, the module gathers data on user responses, and the algorithms identify the most successful and efficient strategies for each region, creating a knowledge base of best practices.

Although adaptive learning is common in the field of education,[57] it has significant potential applications in DEWS 4.0 for enhancing the learning and response capabilities of stakeholders. AI plays a crucial role in this process, as it allows the module to personalize training programs for end-users, decision makers, and other stakeholders involved in drought responses. Furthermore, cloud capabilities ensure that stakeholders can receive training regardless of their location.[58] The application of cognitive computing allows for the analysis of qualitative data, such as surveys or impact feedback forms, to identify recurring themes related to specific drought response measures, which may also be crowdsourced. This technology enhances the module's ability to understand and learn from stakeholders' interactions.

APPLYING THE DEWS 4.0 FRAMEWORK AND FUTURE DIRECTIONS

The DEWS 4.0 framework is aimed at significantly improving how drought is managed within drought-sensitive sectors in any region, thus revolutionizing the field of DEWS during the 4IR era. When compared to previous industrial revolutions, the 4IR provides important technological improvements such as speed, accuracy, and automation.[15] The framework guidelines offer practical applications for implementing DEWS 4.0 in the real-world context of drought prediction, monitoring, and response (Figure 4). However, the actual outcomes of DEWS 4.0 will vary depending on the implementation and integration of the system within existing governance structures, policies, and socio-economic contexts.

The study assessed the proposed framework's potential applications across diverse sectors by considering various cases (Figure 5). For instance, by using machine learning techniques, such as gradient boosting and outlier detection techniques to predict soil water requirements, Campos et al.[59] identified significant savings (56.4%–90%) in irrigation water requirements, displaying the technologies' impact on

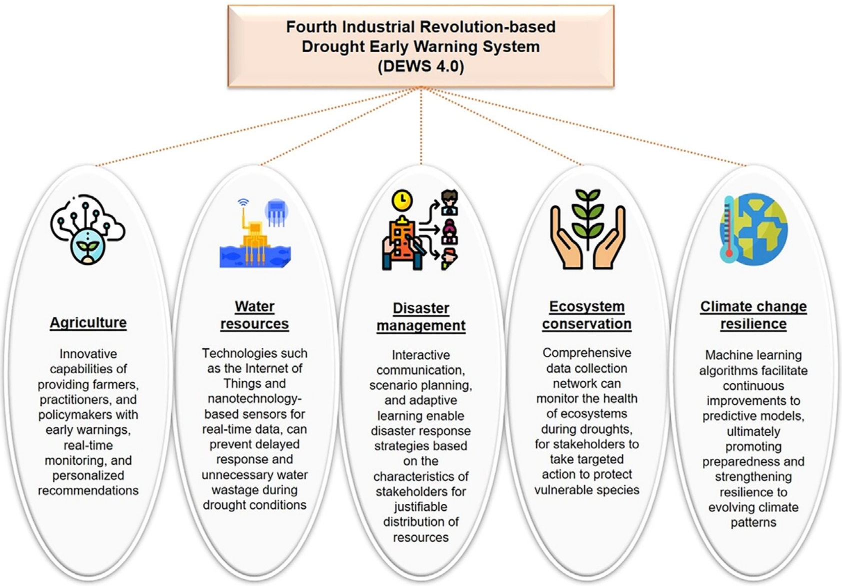

Figure 5. Applications of DEWS 4.0 in various sectors

accurately optimizing water usage for agricultural practices. In Florida, Gong et al.[60] demonstrated the use of real-time data and advanced modeling techniques to predict groundwater levels one, two, or three months in advance, while a smart flood early warning system in Malaysia forecasted flood conditions within 9 h of the flood's occurrence to facilitate proactive management strategies.[14] This demonstrates the potential to enhance disaster management interventions and further protect ecosystems by applying the efficient processing methods proposed in this framework. For climate change resilience,[61] demonstrated the transformative potential of AI in revolutionizing weather forecasting, climate monitoring, and prediction.

During the shift from traditional DEWS to DEWS 4.0, there will likely be challenges to overcome such as potential pressures on computational resources and the need for faster data processing and reducing operational costs (Table 2). Another possible limitation lies in the inconsistencies of internet connectivity due to unequal infrastructure development and socioeconomic factors. Even in regions where the network is considered reliable, receiving alerts through multiple channels can overwhelm users with a lot of messages. Thus, ensuring equitable scalability during droughts remains a critical challenge that DEWS 4.0 must address. Furthermore, cybersecurity measures must form an integral component of policies to protect sensitive information.[11] Policy frameworks should advocate for a balanced approach, wherein technological advancements blend with human-driven responses. Such a holistic approach would lay the foundation for a more resilient, responsive, and sustainable system.

Table 2. Potential benefits and challenges of implementing DEWS 4.0

Module	Benefits	Challenges
Advanced analytics	Advanced analysis with reduced human error.	Need for skilled data scientists.
Digital archive	Dynamic techniques for collecting, storing and accessing historical data.	Complexities in ensuring the integrity and preservation of long-term data.
Smart data networks	Enhanced sensor integration and automation for early drought detection.	Equipment maintenance and network discrepancies.
Predictive modeling	Improved forecasting accuracy.	Increased operational costs.
Data-driven alerts	Consistent and tailored alerts.	Complexities in processing and understanding crucial information.
Interactive communication	Interoperability and practical access to information.	Inconsistencies in internet connectivity, digital literacy, and technology fatigue.
Scenario planning	Accurate and timely interventions to mitigate drought effects.	High initial costs and limited technical expertise, potentially delaying module use.
Adaptive learning	Targeted response allocation and enhanced capacity building.	May overlook emerging strategies owing to the use of historical information.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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