# Warning Systems in Cloud Computing Early Warning Systems

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Contributor: Israel Edem Agbehadji , Tafadzwanashe Mabhaudhi , Joel Botai , Muthoni Masinde

An early warning system (EWS) is an integrated system that facilitates preparedness and response mechanisms through the dissemination of early warning to reduce the impact of a natural disaster. An early warning system is an indispensable tool that helps save lives and reduce the impact of disasters on any infrastructure, such as roads, buildings, farmlands, etc. It has been estimated that USD 800 million is spent annually to develop and operationalize EWSs in developing countries that lack the requisite resources to mitigate the impact of any natural disaster.

early warning systems cloud-based early warning systems

## 1. Introduction

An early warning system (EWS) is an integrated system that facilitates preparedness and response mechanisms through the dissemination of early warning to reduce the impact of a natural disaster. An early warning system is an indispensable tool that helps save lives and reduce the impact of disasters on any infrastructure, such as roads, buildings, farmlands, etc. It has been estimated that USD 800 million is spent annually to develop and operationalize EWSs in developing countries that lack the requisite resources to mitigate the impact of any natural disaster [1]. From a global context, it is estimated that the ratio of persons with access to early warning services is one in three people, whereas the proportion is twice as high in Africa. Currently, it is estimated that 3.3 to 3.6 billion people live in situations that are highly vulnerable to climate-related events [2]. Thus, Africa might have more vulnerable people than any part of the world. Therefore, to bridge this gap, new adaptation strategies that leverage the capability of digital technologies are required to empower the majority of vulnerable people and to ensure effective risk knowledge gathering, monitoring, prediction, dissemination of warning information, and response mechanisms [3].

An early warning system helps with people's coping mechanisms during a natural disaster. However, its limited use can negatively impact coping mechanisms. Aside from this, EWSs are unable to effectively share computational resources because of platform dependency constraints and the need to protect legacy early warning systems. Consequently, this limits system integration and data acquisition that support climate events simulation models. Furthermore, even if large data are fed into climate models, as the data sets grow exponentially, their computational capability deteriorates, leading to inaccurate climate event prediction. Despite this, no single climate model addresses all the uncertainties of an early warning system [4]. Therefore, the choice of computational model has an impact on an EWS's computational performance, which can cause a delay in warning dissemination [5].

Climate change has the propensity to threaten human lives, and this calls for international organizations and researchers to intervene in finding alternative approaches that harness computational models for improved performance, thereby ensuring everyone on the planet is protected by early warning systems. There is a need for dynamic climate data-capturing techniques in order to create a uniform integrated service structure that supports early warning service management [2]. An effective warning system coordinates different stakeholders to create the required EWS value chain that could assure the provision of a standard early warning alert procedure among stakeholders. Dutta [6] suggests that information dissemination among stakeholders is still a gap in the design of EWS, and if this is addressed, it can provide efficiently reliable, timely, and accurate information to all stakeholders within the value chain of climate risk reduction and mitigation.

## 2. Fundamental Tenet of Early Warning Systems

The Early Warning System (EWS) framework comprises complex processes interlinked to provide the needed structure that supports timely information dissemination on natural disasters. Its fundamental tenet of the framework comprises a warning model including a monitoring model, a communication strategy, and an emergency plan to help in managing natural disasters [7][8]. This shows an interdisciplinary knowledge integration between scientists, researchers, and stakeholders towards creating an effective climate-related EWS model for disaster management [9]. Key stakeholders who interface with the processes include government agencies, communities, and individuals. The challenge with the fundamental tenet is the extent of coverage of a climate event and the adequacy of tools for risk gathering, which includes observation and data collection and the likely impact on people, infrastructure, etc. Climate risk is multidimensional and comprises exposure of people or assets to the hazard, vulnerability, and coping strategies of persons exposed to the hazard [10]. An example of a risk framework is INFORM [11], which is an open-source risk framework. The monitoring and prediction utilise technologies or tools to assist in processing observed climate conditions in real time to determine the possible outcome of climate-related events. Dissemination and response mechanisms help in communicating prediction outcomes to communities that are impacted by climate events. Though there are challenges associated with each process, a timely response mechanism from an established relief agency is the most challenging [12]. Unfortunately, even when warning information is issued in good time, it either may not reach many people at risk or people in the affected community may fail to adhere to warning messages [13]. Though [14] outlined factors hindering the effective operation of disaster management practices, it is imperative to establish effective service platforms that leverage technologies, such as cloud computing, in bridging the gap in disaster-related management practices.

The Sendai framework is also a disaster risk framework that provides measures to address multidimensional risk factors and prevent emerging risks. Sendai's framework outlines seven global pillars for sustainable access and availability of early warning systems, which is equally in line with the 2030 vision of increasing the availability and access of early warning systems. In spite of this, multinational organizations, such as the World Meteorological Organization (WMO) and the Global Water Partnership, have programmes and policies to support the implementation of the Sendai Framework. The challenge with the Sendai framework is the lack of consistent and systematic data collection and reporting regimes from established government agencies [15]. Resolving this challenge enhances communication and ensures that early warnings reach the final consumer or individual. Therefore, the social, technological, and organizational contexts are imperative for improving the value-addition process of EWSs. Within the social context, an EWS serves as the information delivery mechanism for people who are vulnerable. The technological context focuses on tools that help in the automation of services to build the required EWS value chain. The organizational context focuses on agencies responsible for receiving appropriate funding that helps in implementing an intervention mechanism for society. These contexts are significant in creating a value chain to ensure the timely delivery of early warnings. Scientific and managerial considerations are drivers for effective communication of early warning [16]. In view of these, scientific knowledge helps to give credence and quantitative measures on drivers for effective warning systems and also helps identify practical, managerial, or technical considerations to inform the right stakeholders of the appropriate intervention.

## 3. Existing Early Warning Systems

Existing EWSs store and process climate risk data in-house or on local servers, where data processing becomes a challenge when climate data is voluminous. Existing EWSs deployed on web-based platforms that are managed on a single server need continuous updates of their dataset; however, due to the volume of data required, its operation becomes a challenge. Therefore, it is imperative to ensure an effective integrated service automation. Thus, a web-based platform is a basic step toward operating EWSs [17]. For the purpose of this research, existing EWSs are described as warning systems developed without using a cloud computing framework. Web-based systems that offer static and limited interaction with data might have structured processes but lack dynamism in gathering risk information, monitoring, and predicting recurring or occurring natural disasters, including droughts, floods, earthquakes, etc., [18].

A drought EWS is complex because of the biophysical drivers involved in creating different drought indicators. Additionally, human experiences of drought and its impacts contribute to the complexity of creating a drought EWS, thus leading to a challenge in designing drought monitoring early warning (MEW) systems, which are key in drought preparedness [19]. Flash drought has rapid intensification without sufficient early warning, which poses a challenge in current flash drought early warning systems, and thus, typifying flash drought events to find the risk of exposure is still a challenge [20]. The challenges with on-site earthquake EWSs include predicting the location, magnitude, and structural drift to enhance seismic preparedness and safety measures [21][22][23]. For example, the extended “integrated particle filter” (IPFx) is an automated earthquake source identification system for the “Japanese earthquake early warning” (EEW) system, which sends early warnings during active seismicity [24]. Floods are the most frequent type of natural disaster, and the challenges with a flood EWS include the accurate sensing of flood to prevent damage to property and life [25], determination of the warning module’s threshold, hydraulic model development, and calibration [26]. An example of a flood-based EWS that leverages the web-application technology, server, and IoT has been proposed by [27]. A landslide EWS requires monitoring and prediction because of its internal mechanism, which requires precise mechanistic models [28]. While many early warning systems can be identified, hydro meteorological hazards remain the most prevalent that impact society both simultaneously and sequentially [29].

The underlying automated technique of an EWS is a computational algorithm that automates the data processing and modelling of the right set of metrics for any natural disaster [30]. Examples of such computational algorithms include artificial neural networks (ANNs) for detecting control risk parameters [30], recursive neural networks for drought forecasting [31], a combination of neural networks and support vector machines for drought prediction [32], the FinDer algorithm [33], etc. DroughtCast includes a machine-learning framework for forecasting drought a week or month before its occurrence [34]. Similarly, "ANYWHERE DEWS" (AD-EWS) is a hydrometeorological drought forecasting system that provides a wide range of indices on water cycle components, such as groundwater, soil moisture, etc. [35]. In spite of these algorithms, the success of early warning systems depends on end-users because they act on the warning message to reduce the impact of climate events on their lives and infrastructure [35].

The challenge with existing climate-related EWS is the inability to process a large set of climate-related data to fit different sets of climate conditions. For instance, data on the location of vulnerable people and infrastructure can be very large, such that it becomes difficult to create and process the required set of risk map metrics. Though the underlying algorithm of an EWS can lead to different processing outcomes at the same time [36], as technology advances, more effective computational platforms with several algorithms can be utilised to overcome the computational challenges of existing climate-related EWSs.

## 4. Cloud Computing-Based EWS Opportunities

Cloud computing is an information technology framework that provides a service infrastructure for different users to access large-scale and shared computing infrastructure capability over the internet. Cloud-based computing platforms also use web-based infrastructure to offer computing capabilities and robust data processing computational models. They can offer substantial access to several warning systems using their shared pool capabilities, thereby ensuring sustainable availability. Sharing cloud resources is more advantageous than expanding existing web-based platforms [37]. The advantage of cloud computing technology is access to real-time voluminous data processing and its ability to obtain a huge volume of data from different integrated systems. Again, its mechanism facilitates easy deployment, offers on-demand scalability, and ensures wide accessibility of resources to help create dynamic systems [38]. The success of EWSs can be measured by their impact on saving lives, land, and infrastructures and supporting the long-term sustainability of the EWS. Generally, people adopt different coping mechanisms for different climate-related events based on the warning information they receive. The benefit of a cloud computing platform is that it provides well-tested cloud platforms that can support pre-emptive modelling of climate events in real time. Again, cloud interoperability ensure one cloud service is connected with another to share data, thereby increasing access to early warning information.

Cloud computing, as an information technology architecture, hosts remote servers on the internet and provides virtual data storage and processing of data. Its architecture can be categorised into private, public, hybrid, and multi-cloud. The hybrid cloud combines a company's on-premises private cloud and third-party, public cloud services into a single application. The multi-cloud architecture uses several cloud vendors to distribute applications on several cloud environments. Aside from the cloud computing architecture, there are three main services that are provided: infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS). IaaS provides computation, networking, and storage resources on demand, whereas PaaS provides hardware, software, and platforms to support the development and maintenance of software or applications on an organization's computing infrastructure. SaaS is similar to IaaS and PaaS in that it offers software online that can be subscribed to by its users. Multi-cloud provides a mix of IaaS, PaaS, or SaaS resources. This architecture and its services ensure the availability of applications and data governance. Data governance defines how data is collected, stored, and used from top-down and bottom-up [39], thus creating the required framework to support information dissemination from the national (government), local (community), and user (individual) levels. Big data has become an important intangible asset to many organizations, and when measurable performance indicators are set, it creates the needed value chain for data governance [40]. In this regard, cloud computing architecture guarantees reliable data for accurate prediction of climate events in EWS [41].

Both cloud computing-based EWSs and non-cloud EWSs (i.e., existing EWSs) use the internet as a backbone. However, the difference lies in the underlying architecture, which can either be IaaS, SaaS, and PaaS or server-client (e.g., a local server). Cloud storage provides a set of servers with larger capacities to manage voluminous demands for data storage and access. However, the barriers to cloud computing adoption include organisational culture, security, and trust in adopting new technology, such as the "cloud" [42]. Amron, Ibrahim [43] ranked compatibility, top management support, and benefit as the first three factors that influence acceptance of cloud technology.

Since cloud computing allows the sharing of resources, it is easy to share location data [18], which can be used to identify vulnerable communities and people in any disaster situation. Cloud-based search engines that leverage location data in real-time facilitate risk knowledge gathering, monitoring, and warning dissemination to create a customised visualization of a map of a geographical location [18]. Planning the infrastructure of the EWS is crucial to ensure a dynamic location data gathering [44]. Some examples of cloud computing-based EWS include Geological Hazard EWS [45]. Cloud computing-based search engines employ parallel cloud computing capabilities to overcome location data computational challenges. Thus, this makes it easy to incorporate climate-driven data in spatial scales. Among the parallel cloud computing search engines or applications is Google Earth Engine, which provides real-time remote sensing [18]. Search engines are built using algorithms that are executed by the cloud servers for geological disaster prediction and modelling in Geographic Information Systems [45]. "Retrieving Environmental Analytics for Climate and Health" (REACH) is another cloud-based application that uses Google Earth Engine (GEE) to process data on land surface temperature, spectral indices, and precipitation [46]. Algorithms (e.g., machine-learning algorithms), when put on a single platform, such as hybrid cloud, provide the needed flexibility of performing different computing tasks at a greatly reduced cost. In contrast, non-cloud-based systems are unable to provide such algorithm flexibility, which impacts negatively on their performance. Artificial intelligence and cloud-based collaborative platforms provide a logical and structured approach for algorithms to collect and analyse data in order to devise the required strategy for any natural disaster management [47].

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