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Chapter

Challenges and Technical Advances in Flood Early Warning Systems (FEWSs)

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Abstract

Flood early warning systems (FEWSs)—one of the most common flood-impact mitigation measures—are currently in operation globally. The UN Office for Disaster Risk Reduction (UNDRR) strongly advocates for an increase in their availability to reach the targets of the Sendai Framework for Disaster Risk Reduction and Sustainable Development Goals (SDGs). Comprehensive FEWS consists of four components, which includes (1) risk knowledge, (2) monitoring and forecasting, (3) warning, dissemination, and communication, and (4) response capabilities. Operational FEWSs have varying levels of complexity, depending on available data, adopted technology, and know-how. There are apparent differences in sophistication between FEWSs in developed countries that have the financial capabilities, technological infrastructure, and human resources and developing countries where FEWSs tend to be less advanced. Fortunately, recent advances in remote sensing, artificial intelligence (AI), information technologies, and social media are leading to significant changes in the mechanisms of FEWSs and provide the opportunity for all FEWSs to gain additional capability. These technologies are an opportunity for developing countries to overcome the technical limitations that FEWSs have faced so far. This chapter aims to discuss the challenges in FEWSs in brief and exposes technological advances and their benefits in flood forecasting and disaster mitigation.

Keywords: artificial intelligence, big data, floods, flood early warning, Internet of Things, hydrological models, remote sensing, social media

1. Introduction

Since the year 2000 through to the end of 2018, a total of 5338 water-related disasters (WRD) are reported and led to over 326,000 fatalities and economic losses of more than USD 1.7 trillion globally. Floods accounted for about 54% of all WRD. Asia appears to be the hardest-hit continent, with 41% of all flood disaster events, followed by Africa (23%), the Americas (21%), Europe (13%), and Oceania (3%). Of the deaths caused by all WRD from 2001 to 2018, some 93,470 were due to floods. During the same period, floods alone were responsible for economic losses of nearly USD 500 billion globally—about one-third of the total financial damages caused by all WRD [1, 2]. To mitigate these disastrous flood impacts, flood early warning systems (FEWSs), among other flood risk mitigation measures, are operational in many parts of the world. The UN Office for Disaster Risk Reduction (UNDRR) recognizes the importance of FEWSs to mitigate flood disaster impacts and thus has set forth Target 7 in the Sendai Framework to explicitly focus on "substantially increasing the availability of and access to multi-hazard early warning systems and disaster risk information and assessments to people [3]." Among the early warning systems, FEWSs are the most common systems since floods are widespread around the globe. Comprehensive early warning systems comprise of four closely interrelated components including (i) disaster risk knowledge; (ii) detection, monitoring, analysis, and forecasting of hazards; (iii) warning dissemination and communication; and (iv) preparedness to respond [3]. Risk assessment forms the foundation of a FEWSs, and disaster risk knowledge refers to the awareness about both the hazards and vulnerabilities present in a particular area. It can be acquired through a risk assessment that may include hazard and vulnerability mapping based on the spatial repartition of the population, infrastructure, and economic activities in the area of interest. Detection and monitoring involve a continuous collection of hydroclimatic data so that watershed states that are precursors of indicators of an unfolding disaster are identified in time to trigger the response. Analysis refers to the processing of the collected data to generate products that not only can support monitoring and detection but can also provide hints about the possible evolution of the disaster. Forecasting refers to an estimation of the state of the watershed and impacted people and assets. It involves the acquisition or generation of a weather forecast, which is post-processed and used to force hydrologic models to obtain future river discharges. The river discharge may be used as an input to predict river stage and floodplain extent using either empirical relationships or hydraulic/hydrodynamic models. For locations of interest in the area monitored by the FEWS, pre-set flood warning thresholds are identified based on the river system configuration and land occupancy. If the pre-set threshold is likely to be exceeded shortly, a flood warning is issued. The warning is then disseminated through an operational telecommunication system from Flood Forecast Centers (FFCs) to local/national governmental authorities and communities at flood risk for prompt actions such as evacuating to safe grounds prespecified by the authorities.

FEWSs range from simple, i.e., technologically basic involving manual data collection and transfer and qualitative forecasts performed based on observations, to complex, i.e., technologically advanced involving telemetric data collection and transfer and modeling-based flood forecasting systems. The level of technological complexity in an operational FEWS varies significantly among different nations as well as different river basins, depending on several factors. These factors include access to comprehensive, timely, relevant, and reliable hydroclimatic information about the area covered by the FEWS, the availability of technically skilled personnel and computational capabilities to process the information, and finally, the ability to communicate the information to relevant stakeholders efficiently. The objective of this chapter is to highlight how advances in data sciences, remote sensing, and smart sensors have the potential of revolutionizing the components of FEWS. The authors recognize that FEWSs are evolving rapidly. Some FEWSs, especially in the developed world, are using either all or part of the emerging technologies. There is, however, inertia in technology adoption, and a majority of systems are in the developing world still using "traditional technologies" such as networks of hydrometric and climatic gauges, sometimes combined with lumped or semi-distributed hydrologic models. These systems are referred to as "Traditional FEWSs" in this chapter. The next section discusses the challenges that are typically encountered by "traditional FEWS," and the following section highlights new technologies and how they can help overcome these challenges.

2. Challenges of traditional FEWSs

2.1 Challenges related to disaster risk knowledge

Flood risk knowledge can be acquired either by looking at historical flood records that occurred in the area, the survey of people and assets exposed to floods, the use of predictive modeling, expert knowledge, or any combination of the above. It also requires the knowledge of the likelihood of flood events and their impacts. The use of historical flood records is often limited by the availability of a long series of hydrologic data. Understanding vulnerabilities involves expensive mapping and surveys that need to be kept up to date with dynamic urban growth. Predictive modeling consists of the collection of spatial data sets such as topography, land use, soil, and exposure. It also requires the availability of skilled staff to run simulations and analyze the results. As a result of these challenges, risk knowledge is incomplete in most areas covered by FEWSs.

2.2 Challenges related to monitoring and detection

To accurately predict the evolution of floodwater levels, FEWS operators need to have a good knowledge of the current and past values of key hydroclimatic parameters in the watershed upstream of the location of interest, as well as their plausible evolution in the near future. Commonly monitored variables include water levels, discharges, snowpack, precipitations, and temperatures. The current and past values of these parameters are available through a monitoring system, traditionally composed of a network of ground stations that may be complemented by occasional field surveys. The ground stations usually measure the variables of interest at a particular point, giving the FEWS operators only partial information about the state of the watershed, especially if the monitoring network has inadequate spatial coverage. About 75% of the flood forecasters surveyed in Perera et al. [1] indicated that their river basins are equipped with insufficient gauging stations for rainfall, water level, and streamflow observations. A total of 50% of the FCCs that responded revealed that their measuring equipment, gauges, and data transferring instruments have deficient technology. Data transmissions from the stations to the forecasting centers are another issue, as a significant number of stations in the developing world rely on human observers, impeding the accuracy and timely transmission of the data. As a result, most of the developing countries encounter challenges in capturing the amount, distribution, and variation of critical variables such as precipitation and streamflow during extremes. Meteorological radars and remote-sensed rainfall have the potential of improving watershed monitoring by providing spatial, real-time, or near real-time information. Still, the data they provide are of lower quality than gauging data, and these technologies are too recent to have long time series that can be used for robust hydrological model simulation.

2.3 Challenges related to data analysis

Ideally, the collected hydroclimatic data are stored in a database and processed in real time by hydrologic/hydraulic models. Not all countries have a centralized database that is fed continually up to date. The data are sometimes temporarily in spreadsheets to undergo quality control before being fed in the central database days or months later. One of the significant challenges faced by operational systems is the lack of technical expertise and human resources. Trained personnel with flood forecasting expertise and adequate forecast group staffing are required by the FFCs to issue timely warnings effectively. However, 74% of the flood forecasting personnel confirm that their centers do not have the experts and staff capable of integrating data, performing forecasts, and disseminating information [1]. This can be partially attributed to the low number of specialized experts in the employment sectors and higher workload for rescue and post-disaster activities during major flood events [4]. In developing countries, the lack of investments in personnel and the absence of dedicated permanent staff is a significant limitation to the proper operation of FEWSs. Overall, Perera et al.'s [1] survey responses suggest that forecasters primarily possess technical know-how but lack knowledge of flood vulnerability assessment, warning communication, and downstream response capabilities, including evacuation preparedness.

2.4 Challenges related to forecasting

The knowledge evolution of climatic variables in the near future, especially precipitation, is an essential input for flood forecasting. Besides ground and satellite actual measurements of the land and atmosphere, meteorologists use sophisticated computer models to forecast the weather in the near future. Numerical weather predictions (NWP) focuses on taking current observations of weather and processing these data with computer models to forecast the future state of the weather. Knowing the current state of the land, ocean, and atmosphere, which influences modeling initialization at local, regional, and global scales, poses a great challenge for quantitative precipitation forecasting [5]. Also, in developed countries, forecasters have access to fine resolution modeling with ensemble predictions to capture the variability and uncertainty in the forecasts [6, 7]. National weather operational centers in developed countries provide global forecasts from their global NWP systems such as the global forecasting system [8] that could be used by developing countries. Still, those outputs are at a very low spatial resolution. These forecasts need to be downscaled by national services to a higher spatial resolution.

Nevertheless, several countries struggle to generate their high-resolution forecasts as the required expertise and resources are not present. Even when forecasts are downscaled, they may suffer from residual bias or from the inherent lack of skills of the weather forecasts, which may lead to the non-detection of upcoming extreme floods or false alarms. Even the weather forecasts are skilled; their forecasts will be affected by the quality of the data assimilation scheme used to determine the initial conditions of the hydrological/hydraulic models. It is also affected by the configuration of hydrologic/hydraulic models such as model structure, simplifications of physical processes, and quality of calibration that can affect the performance of the models used for flood forecasting. Nearly half of the flood forecasters surveyed by Perera et al. [1] mentioned that the models they use for producing early warnings are not accurate or advanced enough for the purpose. Consequently, forecast hit rates varied for different modeling systems and river basins in different climatic regions.

2.5 Challenges related to warning dissemination and communication

Perera et al. [1] found that warnings, even when issued and disseminated with enough lead time, do not necessarily reach all the people-at-risk. Flood warning dissemination is an essential step in FEWSs, usually a "top-down approach," which an FCC issues warning and communicates them to the national authorities to disseminate it to the relevant destinations. For a flood warning to be effective, it needs to reach the right stakeholders in the correct format at the right time. Unfortunately, it is doubtful whether the warning reaches all the highly vulnerable communities [9], particularly those in remote and/or coastal areas and illiterate and/or impoverished people, such as women, children, and elderly in developing and least developed countries. The reason is that warning messages are generally broadcasted on national or local media (television, radio, or website), and such vulnerable groups lack access to basic amenities required to receive these warnings [10]. These include power outages, lack of access to TV and radio, limitations in the broadcasting coverage of TV and radio, limited mobile network coverage, limited robustness of mobile and media broadcasts during hazardous flood events, and limited knowledge of using the emergency website for flood warnings and updates. The alternative modes of communication, such as sirens and loudspeakers, are used to reach low-income vulnerable people to alleviate the limited media coverage. However, this may result in a delayed response by that time, which consequently increases the risk of victimized to the oncoming flood.

Additionally, even when the warning reaches a particular community, many fail to heed the warning due to a lack of knowledge in understating the warning [11, 12]. Also, when a flood warning is delivered, it is often incomplete due to the lack of standardized terminology, protocols, and standards for issuing the warnings. This leads to inadequate, irrelevant, or missing information in the warnings [9, 13]. A flood warning needs to be tailored to the local communities' interests, needs, and values to trigger a responsive action. This involves the use of local language and content that targets the understanding of the recipient and contains an appropriately tailored course of action. An interactive and practical warning communication chain is essential to a successful FEWS since multiple stakeholders are involved at all levels and across sectors.

2.6 Challenges related to preparedness and response

As for the preparedness component of FEWSs, the identified challenges include lack of public interest, lack of risk awareness in early warnings, limited and irregular drills and training seminars, general contingency planning instead of specific and tailored to the community, lack of political commitment and will, financial and technical resource constraints, lack of participation of communities in the decision-making process, and lack of inter-agency planning and coordination particularly among transboundary river basins, among others.

Flood is a fast on-set disaster; hence, timely response from the vulnerable communities is vital to minimize life and property losses. Despite that, impediments are affecting the target communities to respond such as risk perceptions, inefficient communication chain, lack of resources to respond, limited knowledge of evacuation routes, inadequate infrastructure and other facilitation for evacuees, risk of losing livelihood, properties, and livestock, the culture of neglect, lack of trust in early warning systems, and suchlike. Affected residents often lack sufficient resources such as reliable modes of transportation, logistic support including life jackets, ropes, boat, helmet, and stretcher, knowledge of feasible escape route options, and safe shelters to respond to the warnings [14, 15].

Nationally developed contingency plans are common in many countries [16]. However, they are not customized to better adapt to the localized target communities and integrate into emergency response plans due to a lack of participatory approaches in the planning and development of warning response measures [9]. The problem is complemented by fewer than necessary updates of contingency plans owing to the technical and financial resource constraints. A timely response is essential for protecting lives, household properties, and livestock to safer locations once the warning is issued. However, strong ties to the inherited lands, risk of losing cultivated areas, livelihood, and properties impede the ability of a community to respond to early warnings.

3. Potential uses of emerging technologies in FEWSs

A FEWS is essentially a system that collects environmental data and NWP, processes it to generate risk-related information, and transfers these products to end-users through various channels. Its core functions include data acquisition, processing, visualization, and transmission. Progresses in data collection systems such as remote sensing, hydrological/hydraulic modeling, numerical weather forecasting (NWF) as well as information and computing technologies (ICT), are likely to affect the way FEWSs function.

3.1 Progress in artificial intelligence and machine learning

Artificial intelligence (AI) is a rapidly growing field that aims at building systems that can mimic human intelligence and then function intelligently and independently. AI can use various deep learning and machine learning-based algorithms to understand data in any of the spatiotemporal forms [17]. This ability to interpret data, learn from data, and utilize data to accomplish objectives is being used extensively in the next generation of FEWSs [18]. AI can be an alternative to classical hydrologic and hydraulic models and/or can be used for prediction and forecast. As an example, Google, in its *Social Good* initiative, uses AI to forecast floods accurately, which is then used as part of the regional FEWS [19]. As part of the system, the hydraulic models are optimized to run on the tensor processing units. This allows the hydraulic model to run using neural networks rather than a differential equation solver, and this allows the models to be executed with 85× times faster. The Internet of Things (IoT), also known as machine-to-machine (M2M) communication technology [20], is the notion of connecting one device to another through the Internet infrastructure, more specifically, an IoT platform. IoT is the next logical step to monitor floods in the connected world [21]. IoT is being used in the new generation of water level gauges to increase the data collection density and also to fulfill the training data requirements of AI algorithms [22]. One of these AI-enabled IoT is also known as smart sensors. Sensors are becoming less expensive, more reliable, and can serve as real-time data collectors [21]. Numerous studies were reported in recent literature elaborating on the optimization of various elements of FEWSs using smart sensors. These optimizations include water level recorder, rainfall, river flow, temperature, real-time wind direction, soil moisture data, and external influences like wind speed [23–25].

3.2 Progress in remote sensing

The information required for risk assessment is often spatial, and its collection requires considerable resources. The availability of remotely sensed products is steadily increasing with the availability of products such as satellite-derived topography, vegetation, snow cover, precipitation, and soil moisture. While not as precise as information from ground stations, satellite-derived information is in use to overcome limited data availability and has the advantage of being spatially distributed with global coverage. As the rainfall data are the primary input for FEWSs, microwave and thermal remote sensing provide an indirect assessment of rainfall by assessing scattering and emission characteristics, cloud cover, type, cloud top temperature, etc. The rainfall estimated by satellite is freely available at several institutions which can be used by the developing countries to overcome the scarcity in their ground measurements. Examples include products from the Global Precipitation Measurement mission (GPM) [26]. Retrieval techniques make near-real-time availability of satellite-derived rainfall products, for example, NASA's Integrated Multi-satellitE Retrievals for GPM (IMERG) [27], JAXA's Global Satellite Mapping of Precipitation (GSMaP) [28], Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) [29], and NOAA's the Climate Prediction Center (CPC) MORPHing method (CMORPH) [30]. Particularly, JAXA is providing GSMaP real-time products with 0-hour latency that is very useful for flood monitoring forecasting applications. GSMaP Realtime (GSMaP_NOW) has been provided within Asia-Pacific region (GEO-Himawari) since November 2015, and it has been extended to whole globe since June 2019. The JAXA Realtime Rainfall Watch website [28] equipped with graphical user interface (GUI) allows easy access to monitor and obtain current and past precipitation amount and distribution in real time, and the website is updated every 30 minutes. Similarly, NASA also provides the IMERG data product for every half an hour but with a 6-hour latency from the time of data acquisition [27]. Rainfall amounts estimated by satellite are usually bias corrected and merged with available ground records to improve their accuracy. The resulting rainfall products can be used for enhancing forecasting, early warning, preparedness, and mitigation activities [31, 32]. Recent advances in remote sensing techniques by using microwave satellite observations have also enabled the estimation of surface soil moisture (~10 cm depth) [33], thus generating global soil moisture data usable in flood forecasting [34].

For rapid flood and damage mapping at global scale, space charters such as the International Charter Space and Major Disasters [35], Global Monitoring for Environment and Security [36], and Sentinel Asia [37] provide emergency response services to access their satellite data in the event of natural disasters (e.g., flood) for registered users who can collect satellite imagery for free of charge. The maps are derived mainly from data acquired from synthetic aperture radar (SAR). SAR is independent of day-and-night visibility and weather conditions (e.g., persistent rain or cloud cover) during extreme events. To asses floods and their damages from SAR, data acquired before and during/after an extreme event are compared to detect flooded area and their extents.

3.3 Progress in hydrological/hydraulic modeling

Hydrological models have become essential tools for generating information on water-related disasters (e.g., flood peak, inundation depths, and inundation extents) to support decision-making strategies. Advances in hydrological modeling are driven by the availability of spatially distributed ground and satellite data, improved understanding of hydrological processes, and advancements in computer resources. These have boosted the development of several distributed hydrological models (DHMs) [38–44]. DHMs, which integrated the capabilities of simulating catchment-scale rainfall runoff inundation processes, are capable of providing additional information (e.g., inundation extents, flooding depths, and the direction of flow paths). They are considered to be very informative and practical tools for developing a proactive FEWS and mapping flood hazards to provide crucial flood-related information for flood risk management and damage assessment. Recent developments in 2D and 3D models have made them in the standard of practice due to their versatility in producing flood-related information. However, the increased complexity of 2D and 3D models requires high-quality data and expertise in processing and visualization to produce accurate results. Examples of DHMs include MIKE SHE [45], LISFLOOD [46], and Rainfall-Runoff-Inundation (RRI) [47], and Water and Energy Budget-based Rainfall-Runoff-Inundation Model (WEB-RRI) [48]. Accurate topographic data are in demand for 2D and 3D flood modeling and to simulate correct flood depths and inundations. An airborne survey using LIDAR or synthetic aperture radar (SAR) is finding increasing applications in flood forecasting since it yields high vertical accuracy [49]. Apart from the DHMs, data-driven models also have high potential to be operational in FCCs. Bayesian models and hybrid adaptive neural-based fuzzy inference systems (ANFIS) combined by ANN, and fuzzy theories are recent developments in data-driven models includes [49]. Visualization and geographic information system (GIS) software benefits the modern-day FEWSs by producing user-friendly and descriptive flood maps and flood propagation areas likely to be submerged [46]. More training and capacity building workshops need to be conducted to provide opportunities for the flood forecaster to understand and apply appropriate models for their particular catchments.

3.4 Progress in numerical weather prediction

Over the past 50 years, the advancements in science and technology, the proliferation of environmental observations, and improved scientific understanding of the land, atmosphere, and oceanic processes and their modeling radically transformed weather forecasting into an effective, global, and regional environmental prediction capability. Besides the remarkable developments, capturing and communicating the uncertainty in forecasting had always been a greater challenge for forecasters, who have to live with the possibility of uncertainties (i.e., misses and false alert). There are two main challenges faced by forecasters: (a) reduce uncertainty and (b) quantify the uncertainty. The increasing availability of ground and satellite observations and advancement of operational data assimilation (DA) methods and systems such as four-dimensional variational DA (4DVar), hybrid 4DVar with a local ensemble transform Kalman filter (LETKF), and hybrid data assimilation to improve the knowledge of the initial state of the atmosphere are keeping on narrowing down the range of uncertainties in the quantitative precipitation forecasting [50]. The ensemble forecasting has become a standard tool for quantifying the uncertainty in the forecast, recently. In this approach, instead of making a single forecast of precipitation, a set (or ensemble) of forecasts is produced with aims to indicate the most anticipated events, the range of possible future precipitation rates, and uncertainty information [51, 52]. As the multiple ensemble rainfall predictions can provide a better skill score than deterministic forecasts, the ensemble forecasting has become a standard in weather forecasting applications in the developed world. It is slowly being adopted in hydrological forecasting. Global ensemble prediction systems are now run by all major NWP centers [53] and available in their data portal. These data can be downloaded and downscaled at a national or local scale using mesoscale weather prediction models to produce ensemble quantitative rainfall forecast to generate ensemble flood forecasts.

3.5 Progress in big data and cloud computing

Evidence generated by data is crucial for early warning and planning of flood disaster mitigation strategies. We live in an era of big data where the massive amount of data is collected from various sources. Big data refers to data sets with particular sizes and types that traditional relational databases are unable to capture, manage, and process the data [54]. The increasing prevalence of digital and mobile devices has increased the interconnectedness of society [55], as well as the rise of AI and IoT, which has contributed to newer and more complex forms of data available for FEWSs. For instance, big data can come from satellite-based sensors, UAVs, video/audio streams, networks, log files, transactional applications, web, and social media monitoring the water bodies and flows at various spatiotemporal resolutions [54]. The big data for FEWSs can be acknowledged through properties called the 5 Vs; volume, velocity, variety, veracity, and value. The volume of data might range from tens of terabytes of data to hundreds of petabytes and may be of unknown value. The velocity refers to the rate at which data are received in real time, and variety is attributed to the new semi- and unstructured data types such as text, audio, and video that need further processing to derive information. However, two more Vs have risen in case of FEWSs, which are value and veracity, respectively, which refer to the potential capital that may be exploited and the insight and knowledge that will be gained from it to manage the floods [56]. Through big data acquisition of Twitter logs, Deltares and Floodtags were able to map floods in the real time during February 2015 floods in Jakarta, Indonesia, and subsequently provide early warnings. The organizations were able to develop a method of utilizing data from social media posts into information where approximately 900 tweets were posted during the flooding peak.

Through Twitter, census data, and hydrodynamic corrected digital elevation maps (DEM), real-time flood maps of Jakarta were created and provided adequate comparison when compared to photographs after Earth Engine Data Catalog [57]. SERVIR-Mekong, through its virtual rain gauge service, provides near real-time rainfall and stream height data from publicly available satellite measurements by the creation of a virtual network of rain gauges and stream gauges at points widely distributed over the entire Lower Mekong Region. This service is also used by the Mekong River Commission as part of their regional flood forecasting service [58]. The Google Earth Engine (GEE) cloud-based platform provides open access to 40 years of historical imagery and scientific analysis ready dataset (ARD), which has a size of 10 PB [57]. The access to ARD has transformed how remote sensing is processed for FEWSs. Chen and Han [59] developed a Flood Prevention and Emergency Response System (FPERS) based on GEE. In the preflood stage of the FPERS, a huge amount of geospatial data is integrated into the system and categorized as typhoon forecast and archive, disaster prevention and warning, disaster events, and analysis, or basic data and layers. This enabled the right data to be referred to at the right time during the flood prevention and emergency response [60].

In addition to GEE, various national-level big data repositories are being used as a data source for FEWSs. Australia has set up its own big data infrastructure called Australian Geoscience Data Cube (AGDC), which aims to realize the full potential of Earth observation data holding for Australia [61]. The Swiss Data Cube (SDC) has been set up in collaboration with various national and international agencies to support the Swiss government in environmental monitoring and reporting, as well as enable Swiss scientific institutions to fully benefit from EO data for research and innovation [62]. Other worth mentioning big data repositories include Africa Regional Data Cube (ARDC), launched in May 2018, and Mexican Geospatial Data Cube, which is under development. The Japanese Ministry of Education, Culture, Sports, Science, and Technology (MEXT) supported the development of the Data Integration and Analysis System (DIAS) as part of the Earth Observation and Ocean Exploration System. DIAS is a demonstrative data system that effectively and efficiently integrates global and local observation data and information. It has led to research breakthroughs in understanding, forecasting, and adapting to global environmental changes, particularly concerning changes in the water cycle and the effects on water management systems and societies across the globe [63].

3.6 Social media and social networking apps

Volunteered geographic information (VGI), a component of citizen science, is user-generated information that is crowdsourced, and it relies on collaborative and specific web platforms and/or mobile phone applications [64]. In terms of

FEWSs, VGI is citizen-generated data from various information sources: (i) social media, (ii) crowdsensing, and (iii) collaborative mapping [65]. Social media, as the name suggests, involves information sharing through platforms such as Twitter, Facebook, and Flickr. Crowdsensing is referred to as citizen observatories, where citizens on the web use different applications to register and share observations. Collaborative mapping is the mapping of geographic features to generate Internet-based interactive maps.

One such effort of incorporating VGI to complement official sources of information (such as static and mobile environmental sensors) and support FEWSs is A Geospatial Open collaboRative Architecture—AGORA [66]. It is a conceptual architecture that uses information from VGI and traditional information sources into three layers: acquisition, integration, and application. Currently, it aims to improve flood disaster resilience in Brazil and works in close collaboration with the National Center for Monitoring and Early Warning of Natural Disasters (CEMADEN), Brazil [67].

Social network analysis (SNA) is a broad general term that is used for representing connections among people and using graph analytic techniques to explore characteristics of that network [68]. Recently, there has been a surge in the application of SNA in flood disaster risk management [69].

Restrepo-Estrada et al. [70] developed a methodology to use geosocial media messages such as Twitter data as a proxy variable for rainfall estimates using transformation function to force hydrologic models and predict streamflow. This is particularly important for ungauged or poorly gauged sites to cover the spatial and temporal variability of ever-changing river basins. They have developed a historical and real-time global flood detecting database using 88 million tweets with 90% accuracy in reporting flood events. While the data from existing flood re-insurance sectors are not always freely accessible, Bruijn et al. [71] have made real-time data publicly available at www.globalfloodmonitor.org.

Tkachenko et al. [72] used Yahoo! Flickr tags to learn its forecasting potential for floods without the use of complementary environmental sensors using a buffer period of 5 days before flood peak and different neutral and risk signaling semantic elements. They found that alternative social sensors such as Yahoo! Flickr can be used as a potential flood disaster predictor, especially in the areas where environmental sensors are absent. The study results are impressive. However, much research is needed in the area to be used as a sole potential indicator of flood disasters in ungauged sites.

It is expected that in the future, there will be a shift toward a much broader concept of "extreme citizen science" rather than volunteered participatory monitoring merely as "citizen sensors" [73]. This will lead to involving citizens in all stages of the project life cycle, such as flood data analysis and its interpretation rather than only data collection.

3.7 Other upcoming technologies

There are some upcoming technologies such as 5G networks and Blockchain technology that are likely to affect all systems that have a telecommunication component, hence FEWSs. 5G, also known as fifth-generation mobile network, is an emerging technology; it improved on many features from the previous 4G network, such as the increase in the speed of transfer rate, connections, and efficiency of frequency and the decrease in latency time [74]. The low latency time is essential for activities that require real-time updates for FEWSs. 5G will also allow FEWS experts to increase coverage and network capacity of smart data collection devices by enabling the assimilation of heterogeneous networks that possess various wireless access technologies, coverage area sizes, and topologies. Blockchain is an emerging data structure that is a collection of records or an open, public infrastructure environment of transactions or digital events that has been conducted between agencies and/or individuals [75]. Blockchain allows for increased trust in the system as the mechanisms are transparent and resistant to alterations, which is critical for the data to be used in FEWSs. In the future, it is expected that more and more data from smart sensors to be used in FEWSs will be stored on the blockchains; this will ensure the ownership of the data producers and accuracy of FEWSs.

4. Conclusion

FEWSs are recognized as a crucial tool to estimate the flood disaster risks and to mitigate the impacts of floods. As their core functions include data acquisition, processing, visualization, and transmission, they are expected to collect necessary data from various platforms such as ground, satellite, and NWP models and integrate them to produce superior products with lesser biases, use hydrological/hydrodynamic models to covert those data into useful risk-related products such as water levels and inundation distributions, and transfer these products to end-users through various communication channels.

This chapter discusses various identified challenges in operational FEWSs worldwide. It highlights the recent progress in data collection and integration, numerical weather forecasting, hydrological/hydraulic modeling, as well as computing and information technologies that have great potential to enhance the performance of FEWSs. These scientific, technical, and technological advancements allow the integration, generation, and exploitation of large repositories of environmental and hydroclimatic information to produce valuable information for reducing flood-related risks and damages to reach the policymakers and public to collect information about flood occurrence, exposure, and vulnerabilities. These advancements are becoming available worldwide, and they can be utilized effectively to diminish the gaps between developing and developed countries in terms of FEWSs capabilities. Especially in forecast dissemination and access to nonconventional data sources such as satellite imagery, volunteered geographic information and social network analysis are possible venues where such technologies can address immediately. More and more, those technologies are becoming open-source platforms and tools which can be used by economically less privileged countries freely. However, more capacity development and training programs have to become frequent to grab the skills needed to utilize these technologies in such countries.

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Conflict of interest

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