sustainability

MDPI

Review

A General Overview of the Risk-Reduction Strategies for Floods and Droughts

Tsun-Hua Yang [1] and **Wen-Cheng Liu** [2,*]

[1] Department of Civil Engineering, National Chiao Tung University, Hsinchu 30010, Taiwan; tshyang@nctu.edu.tw
[2] Department of Civil and Disaster Prevention Engineering, National United University, Miaoli 36063, Taiwan
* Correspondence: Correspondence: wcliu@nuu.edu.tw

Received: 28 February 2020; Accepted: 25 March 2020; Published: 29 March 2020

Abstract: Water is a limited resource but essential to sustaining life and supporting economic development. Only 2.5% of all the water on Earth is freshwater and can be used to meet basic human needs such as a clean supply of water for drinking, cooking, and bathing. Water scarcity is the result of an imbalance between supply and demand. Efficient water resource management is definitely of interest to research and is a practical topic. At the same time, water-related disasters such as floods and droughts cause the loss of life and property. Disasters increase the difficulty of effective water resource management. An increase in climate extremes can also increase the risk of floods and droughts. This overview covers 150 peer-reviewed journal publications from the last twenty years focusing on risk-reduction strategies for floods and droughts. First, a definition and classification of flood and drought was introduced. Second, studies and techniques associated with risk reduction were grouped into three themes and discussed: prediction and warning; monitoring; and impact assessment, response, and management. As a result, many studies were solely focused on, and achieve excellence in, their own themes. Special attention was needed to find in these studies what can convert the adverse impacts such as flood water to positive outcomes such as drought relief. Multidisciplinary cooperation is necessary to achieve sustainability and to adapt to climate change. Finally, advanced techniques such as artificial intelligence (AI) and the internet of things (IoT) were foreseen to have a tremendous impact on future disaster risk reduction.

Keywords: water management; disaster; sustainability; climate change; resilience

1. Introduction

The United Nations (UN) proposed 17 sustainable development goals (SDGs) in 2015, which promote economic, environmental, and social advancements to achieve a better and more sustainable future for all. The SDGs are interconnected, and none of them is less important than the others. It is a call for action by all countries who recognize that the achievement of the goals by the target date of 2030 must go hand in hand with strategies to solve and address different social and economic issues, while tackling climate change and working to preserve our living environment [1]. Water resources are essential and significantly interconnected to the content of the SDGs. For example, Goal 6 demonstrates that clean, accessible water for all is an essential part of the world if humans want to live sustainably. However, water scarcity is still an issue. Only 2.5% of all the water on Earth is freshwater, and the remainder is saltwater. Of this freshwater, two-thirds is snow and ice, and one-third is below ground. Therefore, only 0.3% of all the freshwater on Earth is available as surface water for use. The UN mentioned that more than 2 billion people are living with the risk of reduced access to freshwater resources, and at least one in four people is likely to be affected by chronic or recurring shortages of freshwater by 2050. Water scarcity is the result of an imbalance between supply and demand. Over 1.7 billion people are currently living in river basins where water use exceeds supply [1]. Therefore, efficient water resource management reduces the risk of water scarcity that affects the global population and helps sustain life on Earth. Goal 13 calls on all nations to take action on climate change. The consequences of climate change, such as sea-level rise and frequent extreme weather events, affect lives, costing people, communities, and countries dearly today. For example, the El Niño/Southern Oscillation (ENSO) is the dominant climate phenomenon affecting extreme weather conditions worldwide. Cai et al. [2] showed that ENSO-related catastrophic weather events are likely to occur more frequently because of a slowdown in the Walker circulation. However, the results of the study are still waiting for further testing when new models, observations, and insights become available. The increase in catastrophic events, such as floods and droughts, is significant for achieving SDGs because it generates multiple impacts, including loss of life, damage to property, destruction of crops, and outbreaks of waterborne diseases. Water-related disasters such as floods and droughts are the most frequent calamities worldwide [3]. These disasters cause significant loss of life and property. For example, the 2011 Thailand flood caused over hundreds of deaths and the economic damage was estimated to be 40 billion USD [4]. The impact of the 2002 South Dakota, USA drought on crops and livestock production was estimated to be from 1.4 billion to 1.8 billion USD [5]. Climate extremes increase the risk of floods and droughts. However, the consequences of natural disasters such as floods and wildfires are not necessarily negative. For example, floods in natural systems maintain key ecosystem functions and biodiversity by linking the river with the land surrounding it, recharging groundwater systems, filling wetlands, increasing the connectivity between aquatic habitats, and moving both sediment and nutrients around the landscape and into the marine environment [6]. Therefore, innovative water hazard preparedness and management can secure the resilience of communities and even turn adverse impacts (e.g., excess water) into positive outcomes (e.g., drought relief).

This literature overview aims to provide a systematic summary focused on the advanced technologies that have been developed to mitigate and prevent damage from droughts and floods. The overview employs three databases and does not limit itself to specific journals, or publishers, but mainly focuses on research after 2000. The study selected three research databases that are commonly used in literature reviews: Scopus, Google Scholar, and Web of Science. In line with other systematic literature reviews in the field, the keywords flood, drought, water management, disaster, sustainability, climate change, and resilience were used as search criteria. The search was conducted in January 2020, when a combination of the keywords was used to retrieve over 150 related journal publications. Among them, 92 publications were on the flood issue and 53 publications were on the drought issue. The remains of the publications were on the integrated studies for floods and drought. It is expected that professionals and experts in water resources have an obligation to plan and manage water resource systems so that they will fully contribute to an improved quality of life for all people, now and in the future. This paper is organized as follows. Section 2 presents the classification of natural disasters and focuses on floods and droughts. Section 3 shows the literature review metrics adopted and proposes an overall synthesis of the results. Section 4 provides examples of a systematic disaster risk reduction strategies for floods and droughts. Finally, Section 5 includes some concluding remarks.

2. Definition and Classification of Flood and Drought

Natural disasters are divided into six disaster groups: biological, geophysical, meteorological, hydrological, climatological, and extraterrestrial [7]. Floods are in the hydrological group. There are three disaster subtypes in this group: general (river) floods, flash floods, and storm surges or coastal floods. Drought is in the climatological group, and there are no disaster subtypes. A classification and associated definition of floods and droughts based on a variety of studies are discussed below and shown in Table 1. It serves as a foundation for further discussion in other sections in this literature review.

2.1. Flood

This literature overview classifies floods into three categories: (1) pluvial flooding, (2) fluvial flooding, and (3) coastal flooding. The categories are similar to those in study [7], but this literature review uses fluvial flooding instead of general flooding to describe river floods. The details are described below.

(1) Pluvial flooding occurs in rural areas, when the rate of precipitation falling on an area exceeds the infiltration rate into the ground, and in urbanized areas, when the floodwater exceeds the capacity of the built storm drain systems. Pluvial flooding is defined as flooding that results from rainfall-generated overland flow and ponding before the runoff enters any watercourse, drainage system or storm drain, or cannot enter it because the network is full to capacity [8]. Some studies [8–13] differentiate "surface water flooding" from "pluvial flooding", and the former term is usually adopted to describe the source of flooding being surface water during heavy rainfall in urban areas. More broadly, "surface water flooding" includes pluvial flooding, sewer flooding, flooding from small open-channel and culverted urban watercourses, and overland flows from groundwater springs [8]. The discussion of differences in these two terms is beyond the scope of this review and will not be addressed hereafter. It appears that the frequency of pluvial flooding caused by extreme rainfall events is leading to increased impacts in terms of the threat to life and damage. The frequency is possibly increased further as a result of climate change [9,10]. The term "flash flooding" attracts much attention because of its unpredictability and disaster-causing characteristics [13,14]. Flash flooding may also be associated with high-intensity rainfall and cause flooding within 6 hours [14]. Therefore, the details of "flash flooding" are provided in the section on "fluvial flooding".

(2) Fluvial flooding, similar to pluvial flooding, usually occurs when an excessive amount of rainfall exceeds the capacity of a river. In some areas, such as North America, fluvial flooding can also be caused by heavy snowmelt and ice jams [15,16]. There are two main types of riverine flooding: One is "overbank flooding", which is the most common, and occurs when water rises to overflow the edges of a river. Second, "flash flooding" is characterized by an intense, high-velocity torrent of water that occurs in a river within 6 hours or less. The causes of flash floods can be high-intensity rainfall or the sudden breakage of a dam or levee. Flash floods along with debris are very dangerous and destructive not only because of the force of the water but also because of the short warning and response times in comparison with that of normal floods [17]. Flash floods can also occur in mountainous areas due to steep topographic and geological conditions. These conditions may intensify flash-flood damage, but most damage is still found in flat lowlands where population and property are often concentrated [18]. Studies have shown that fluvial flooding is an essential natural process for river and floodplain ecosystems [19,20]. Maintaining the proper functioning of river ecosystems from floods while minimizing damage is definitely a research topic of interest.

(3) Coastal flooding in low-lying areas is usually caused by wind waves and elevated water levels [21]. They are usually generated by large waves, storm surge, high tides, and mean sea-level anomalies. In some areas, such as deltas and estuaries, precipitation and river flow may also contribute to coastal flooding [21]. Many studies have predicted that with climate change, there will be an increase in the intensity and frequency of tropical cyclones and sea-level rise [22–24]. As a result, coastal flooding from storm surges will become more frequent with sea-level rise [24]. Furthermore, densely populated regions affected by coastal flooding from tropical cyclones have experienced a rate of sea-level rise near or greater than the global average [23]. It is expected that the population will continue to grow along coastal areas in the future. The frequency of coastal flooding will increase as a result of accelerated sea-level rise and frequent tropical cyclones [22]. Unfortunately, most coastal populations are still not prepared for an increase in the frequency of extreme coastal flooding or a significant rise in sea level [23].

2.2. Drought

A precise definition of drought is not clear because of different hydrometeorological conditions, geographical locations, or even stochastic water demands in different regions around the world [25]. For example, the World Meteorological Organization (WMO) [26] and UN [27] identified drought as a condition of deficiency in precipitation. It can be identified as a condition in which crops fail due to the lack of moisture in the soil [28]. It can also be defined as a condition in terms of low annual daily streamflow [29]. Droughts are typically classified into four categories: (1) meteorological drought, (2) hydrological drought, (3) agricultural drought, and (4) socio-economic drought [25,30,31]. The details are described below. It is noted that groundwater drought is not included in this literature overview because only limited research has been done on the occurrence and propagation of droughts in groundwater. Some studies considered groundwater drought as a new type of drought [25,32]. However, groundwater drought is difficult to quantify due to a lack of comprehensive groundwater observations at regional and global scales [32]. Therefore, groundwater drought may be treated as a new type of drought when more data are available [25]. The details of the four types of drought are described below.

(1) Meteorological drought is defined as precipitation deficits over a region for a period of time. It is considered drought when precipitation is below the average values [33]. The time frame to determine drought can be monthly or seasonal precipitation [34,35]. A previous study has shown that meteorological drought is highly related to sea surface temperature (SST) as well as temperature anomalies. However, the level of deficit required to define a meteorological drought is not yet clear [35].

(2) Hydrological drought is related to a period with surface and subsurface water resource (drought in rivers, lakes, and groundwater) shortfalls on adequate water supplies for established water uses (e.g., sources of drinking water or support for aquatic animals and ecosystems) of a given water resource management system [25]. Therefore, the assessment of hydrological drought is crucial for water resource management. Instead of precipitation data used for meteorological drought, streamflow data have been widely applied for hydrologic drought analysis [36,37]. Hydrological droughts can cover extensive areas and can last for months to years [38]. Major differences between meteorological and hydrological droughts are related to the features of climate and catchment [37].

(3) Agricultural drought refers to a period with declining soil moisture and consequent crop failure without any reference to surface water resources [25,39]. Drought starts with meteorological drought and persistent dry conditions and then induces agricultural, hydrological, and agricultural droughts [35]. A decline in soil moisture depends on several factors, such as soil properties, climate, weather, topography, and land cover [40]. For example, when evaporation is greater than precipitation, a depletion of soil water and crop wilting occur to trigger agricultural droughts. Food production is in jeopardy and agricultural droughts cause socio-economic impacts.

(4) Socio-economic drought is associated with the failure of available water resources to meet water demands, thus associating droughts with the supply of and demand for an economic good [25,31]. Socio-economic drought occurs when the demand for an economic good exceeds supply as a result of a weather-related shortfall in water supply [25]. Therefore, the first three drought categories address ways to measure drought as a physical phenomenon. Among the four types of drought, socio-economic drought has a direct impact on human production and daily life [41].

Table 1. Classification of floods and droughts.

Disaster Classification	Definition	Reference
Flood		
Pluvial	The rate of precipitation falling on an area exceeds the infiltration rate into the ground.	[8–14]
Fluvial	The excessive amount of rainfall exceeds the capacity of a river.	[15–20]
Coastal	Flood in low-lying areas is usually caused by wind waves and elevated water level.	[21–24]
Drought		
Meteorological	Precipitation deficits occur over a region for a period of time.	[33–35]
Hydrological	Surface and subsurface water resources are not enough to meet water supplies of a given water resources management system.	[36–38]
Agricultural	Declining soil moisture and consequent crop failure are without any reference to surface water resources.	[35,39,40]
Socio-economic	The demand for an economic good exceeds supply of a weather-related shortfall in water supply.	[41]

3. Recent Research on Disaster Reduction

Measures taken to prevent or mitigate the impacts of floods and droughts can be identified as structural and nonstructural measures. Common structural measures, such as retention ponds, dams, river improvement, urban drainage systems, and levees or dikes, are used to store floodwater, decrease peak stage, and retain floodwater to mitigate the impact of floods [42–44]. Nonstructural measures include early flood warning, hydrological taxes, flood emergency planning and response, and environmental education [44,45]. Structural measures are engineering constructions that aim to reduce or remove the volume of floods. Some studies argue that structural measures are fundamental to solving most flood problems, but in addition to being costly, they do not by themselves effectively and sustainably resolve the most complex problems [45,46]. Nonstructural measures are applied to prevent and reduce damage through actions, legislation, standards, and programs [45,47]. One study showed that flood impacts are more efficiently reduced with structural strategies compared to nonstructural strategies [48]. Nevertheless, the benefits based on the avoided damages from these measures must be compared to their costs. Therefore, a cost-benefit analysis must be carried out for further evaluation [48]. Measures to mitigate drought impacts are classified into three categories: (1) water-supply measures, (2) water-demand measures, and (3) impact minimization measures [49]. The first two measures tackle water-scarcity issues, and the third measure minimizes the social, economic, and environmental impacts of drought on human society. Structural measures can increase new water storage, such as the construction of new reservoirs, and improve existing water system efficiency, such as leak detection. Nonstructural measures are the development of drought warning systems to identify early warning signals of drought and the taking of response measures and policy-related actions that can be taken to reduce the impact on society. For example, Texas in 2011 suffered from drought and the government used an insurance program to pay out $10.8 billion for agriculture compensation [50]. Other actions, such as the reduction of water usage for industrial sectors and incentives for low flow fixtures, can also be taken according to the drought stage and existing conditions.

This overview focuses on nonstructural measures that are more proactive and easier to apply and understand from the public point of view. Meanwhile, nonstructural measures are also relatively cost effective, require a short time to implement, and supplement structural measures well. Many published papers were reviewed following the major themes and subtopics in the years from 2000 to 2020. A typical disaster-reduction cycle consists of prevention, preparedness, and emergency response as well as recovery and rehabilitation. In terms of research themes corresponding to the cycle, this review identified three major themes: prediction and warning; monitoring; and impact assessment, response, and management (Figure 1). The three categories are interconnected. In other words, the initiated item can be any of them. For example, flood disaster mitigation can start with the establishment of a monitoring network and then provide prediction and warning information to decision makers for taking necessary response measures. A systematic overview of these three categories is provided here, and Table 2 shows the number of published papers according to different themes from 2000 to 2020. The details of each theme are discussed below.

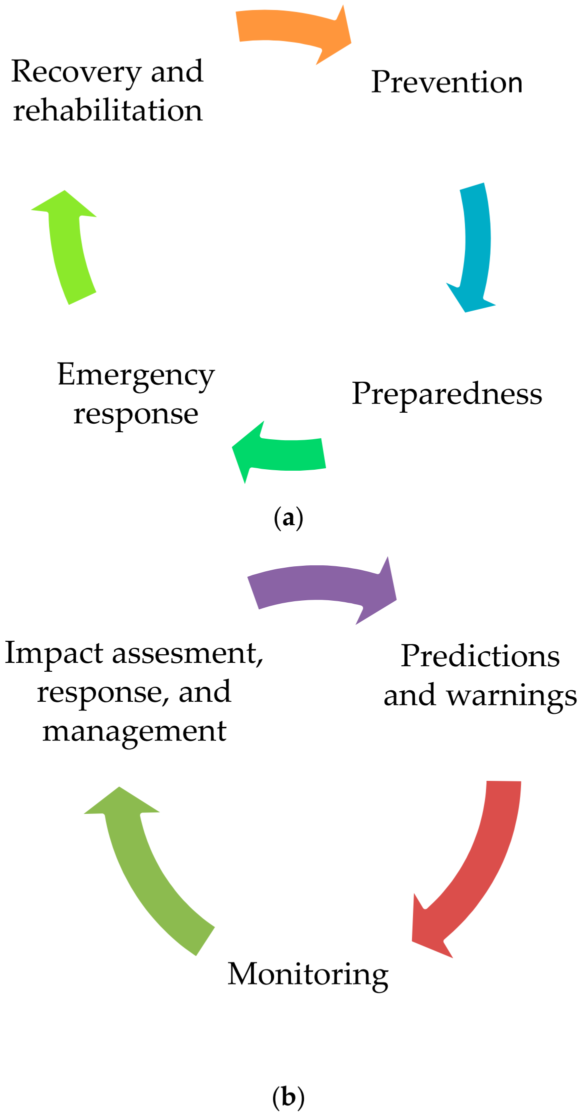

Figure 1. (**a**) Disaster reduction cycle; (**b**) research themes corresponding to the cycle.

3.1. Prediction and Warning

3.1.1. Flood

Prediction and warning are proactive approaches to disaster management. The most common information used for the prediction and warning for floods are flood levels and peak discharges. Along with an emergency response strategy, this approach can be implemented before and during the events to evacuate residents or to prevent the failure of structural measures, such as levees or reservoirs. The impact of disasters can be decreased due to precautionary measures. Studies have shown that the development of an early warning system is the most cost-effective measure because it saves lives and property [51,52]. There are various approaches to simulate flooding when rainfall information is given, and the most common approaches are divided into three groups: data-driven-based methods, physics-based models, and other alternatives [53]. The latter considers mass conservation and moment equations to better describe flow behaviors and provide high spatial details in terms of flood forecasts. For example, one-dimensional modeling in the hydrodynamic model usually assumes that flow discharge and water level along the flow direction are parameters of interest. The most well-known model is the HEC-RAS model, which was developed and is continuously maintained by the US Army Corps of Engineers [54]. It is a commercial free software, and many studies have applied it for various purposes, not only limited to flood modeling but including sediment transport simulation and dam break, etc. (e.g., [55–57]). The newer version of HEC-RAS even extends its capabilities to two-dimensional inundation modeling [58]. Regarding two-dimensional models, Saint-Venant equations are the most applicable assumptions in two-dimensional flood modeling. Most well-known models, such as HEC-RAS, CCHE2D, MIKE21, and SOBEK, are designed to provide more details regarding fluid motion, such as flow velocities in the longitudinal and transverse directions (e.g., [59–61]). Some studies considered lumped and distributed hydrological models, such as SWAT, AnnAGNPS, WEPP, or APEX, to provide peak flow at watershed scale [62–64]. The usefulness of lumped hydrological models for forecasting may be limited by their coarse resolution, the need for long-term historical data for calibration, and an inapplicability to poorly gauged catchments [14]. When the data is limited or there are no gauging stations at the study area, for example precipitation data is missing or there is not enough, numerical models can be applied to generate future data of flow used in models such as HEC-RAS for flood forecasting [65–68]. However, research on data scarcity or ungauged basins is another fast-growing topic but beyond the scope of this overview. The topic itself deserves another systematic review. Computational cost and data requirements are significant in solving the detailed governing equations. During emergency response, efficiency and numerical stability become very important for further applications in flood prediction and warning. As a result, a variety of alternatives have been developed to improve the computing efficiency. Despite active research in the field, rapid and accurate flood modeling at high spatiotemporal resolutions remains a significant challenge in hydrologic and hydraulic studies. The data-driven-based model, also referred to as the black-box model, is one of the models to attract the most attention. The model itself may not include the abovementioned governing equations but instead involves mathematical equations from the analysis of time series data. The analysis can then be used to provide flood predictions and warnings e.g., [69,70]. The quantity and quality of data have a significant impact on the performance. Its performance also deteriorates when the forecast lead time is extended [71]. Other than the abovementioned categories, simple physics- (or conceptual models), threshold-, or index-based models have also recently been discussed by many studies (e.g., [18,72–74]). Both simple physics- and index-based models can provide rapid flood hazard assessments in different spatial and temporal solutions. Therefore, the requirements of emergencies in terms of efficiency and reliability are easily met. However, due to their simplicity in assumptions, they should not be considered as an alternative to the complex hydrometeorological models but can be immediate tools for purely nontechnical decision makers in the case of early warnings and flash floods [75]. As a conclusion, the trend of prediction and modeling from traditional physics-based flood models moves to simple physics-based flood models to meet the needs of operational purpose. Because of rapid development in data science, the artificial intelligent or data-driven models are getting most researchers' attention if observation data is provided. Among all models, Adaptive Neuro Fuzzy Inference System (ANFIS), Support Vector Machine (SVM), and Artificial Neural Network (ANN) are most commonly used [69–71].

3.1.2. Drought

Short-term or immediate measures are of great benefit to reduce flood damage. Drought, unlike floods, is usually a long-term effect. The slow progression and inception of drought can be advantageous. Decision makers can foresee these events in advance and therefore take corresponding responses [76]. Therefore, long-term but not short-term advance prediction and warning are most important for early preparedness to reduce the impact of drought. As addressed in the previous section, drought can be classified into four categories. Among these, meteorological drought can precede and lead to the three other categories [77]. Because of this prerequisite and the fact that drought involves a long-term variation in climate, prediction and warning are usually focused on meteorological drought. The two most common approaches to provide early drought information are dynamic modeling and statistical modeling. The latter approach includes regression analysis and stochastic, probabilistic, and artificial intelligence-based modeling [78,79]. Dynamic modeling can provide real-time results. Given accurate real-time environmental monitoring information, such as rainfall, streamflow, and temperature, and remote sensing data, such as broader earth weather or the water content of the soil, drought monitoring and prediction systems can be established [80–82]. The results from dynamic modeling can provide predictions and warnings for meteorological drought. Along with hydrological modeling and socio-economic methods, three other types of drought can also be evaluated [83]. Dynamic modeling usually involves large-scale observations in larger areas, and its complexity, such as the model structure itself and the requirement of computational resources, makes dynamic drought modeling difficult to adopt by individuals. Monitoring information such as remote sensing data serves as input, and its accuracy, therefore, has a significant impact on the performance of dynamic modeling. In contrast, statistical modeling is relatively simpler than dynamic modeling. Many drought indices have been derived for assessing the effect of a drought and defining drought parameters, such as the intensity severity and spatial extent [79]. Among them, as rainfall is the primary source for water resources, the standardized precipitation index (SPI) is the index most adopted by different countries [84]. Many studies have applied the SPI as a drought-quantifying factor to predict drought conditions at various time scales (up to 24 months lead time) with reasonable accuracy [69,85–87]. Different statistical models have their advantages and disadvantages. For example, the regression model is the simplest and most direct model. Its linearity assumption may limit its application for longer lead time forecasting. Probabilistic models show good performance but need larger computational resources in comparison with that of other statistical models [78]. Similar to flood forecasting, drought forecasting traditionally was done based on dynamic modeling or observation-based indexing. The trend of recent research is moving to the application of artificial intelligence [79,84,88,89]. As with most applied modeling in flood forecasting, ANN, ANFIS, and SVM are also the most mentioned models for drought forecasting [78,90,91]. The SVM model seems to outperform other artificial intelligence models, especially for long-term forecasting [86,90]. This ca be explained by SVMs seeking to minimize the generalization error while other models seek to minimize the training error. Its advantage is to avoid overfitting and local minima [78]. Regardless of what data-driven models are used to provide predictions or warnings, long-term and accurate monitoring information is important to serve as inputs and has significant impacts on forecast performance.

3.2. Monitoring

Monitoring data that are ground or remote sensing based, such as rainfall, weather, crop conditions, soil moisture, stream stage, and flow, serve as water availability inputs in early warning systems for prediction [18,92–94]. The temporal length and spatial coverage of the data can also help the understanding of extreme events in detail [17,34]. The reliability and credibility of data determine the performance of prediction [95]. The spatial coverage of information such as rainfall observation data is always an issue because gauging stations are never dense enough to characterize events [88]. Other than being inputs to the models, information from ground-based gauges is also used as ground truth to calibrate and validate the model performance. Ground-based monitoring systems can only offer limited coverage in terms of spatial extent. Remote sensing-based observations such as satellite and radar can complement data collected by ground systems. Satellites can observe soil and vegetation moisture or provide images to estimate the SPI to understand drought conditions [96–98]. A technique called data assimilation integrates remote sensing-based data and improves the performance of large-scale models for extreme forecasting, such as weather prediction models (WRFs) [99–101]. Along with artificial intelligence, satellite observations can then provide precipitation estimations [102]. Recent studies have applied satellite images for flood detection or flood mapping [103,104]. This approach is particularly helpful for those areas or countries without adequate ground-based observations [105,106]. The improvement in radar observation techniques in dual-polarization radar instead of single-polarization radar provides more accurate rainfall estimation [107]. Quality assurance (QA) and quality control (QC) for the data are essential for subsequent applications. The common approach is to adaptively correct remote sensing-based data with ground-based observations [108,109]. Recent studies have used data-driven or data-mining techniques to identify possible data bias or extremes and further correct them simultaneously to meet the needs of disaster response [110–112]. Finally, because of rapid progress in the internet of things (IoT), sensors and associated components are becoming cheaper than ever before. The deployment of large-scale and economically efficient sensory networks is expected, and the quantity and quality of the monitoring can be increased and improved accordingly [113,114]. New techniques, such as the application of commercial microwave links for rainfall observations, the analysis of pictures from cameras, or the crowdsourcing of personal weather stations, are rapidly developing to extend the horizon of monitoring for sustainability [115–118]. Other than the monitoring task itself, gauging stations according to their locations (e.g., upstream of a watershed) can be used to for flood forecasts at a downstream area [119,120]. The early warning systems based on upstream gauging stations can provide predictions within a watershed but only with a limited lead time. If the time of concentration of the watershed is short (i.e., less than a few hours), then the time window of disaster response is also narrow. Efficient numerical models such as HEC-RAS, rapid flood evaluation models, or data-driven models are commonly applied to meet the requirement of a short response time [119,121]. In conclusion, much research has put a lot of effort into remote sensing monitoring technologies such as Synthetic Aperture Radar (SAR) flood detection [122]. Its 24-hour, all-weather monitoring capability can improve the accuracy of inundation area detection. In addition, it is hard to build a dense monitoring network due to high cost of monitoring devices. It is expected that much research will pay attention to low-cost devices and use them to provide accurate and high-frequency monitoring data.

3.3. Impact Assessment, Response, and Management

3.3.1. Flood

Impact assessment, in terms of different disaster types, is carried out on the basis of the persistence of stressed conditions, population, and critical infrastructure and, finally, its effect on social and economic losses. The response means the measures during and after events to mitigate the impacts of disasters. Management includes planning for water management through policymaking, better water and crop management, and increased public awareness and education. Impact assessment is a tool to support decision making. It not only provides flood risk assessment but also directly translates the risk into the expected socio-economic impacts [123]. Along with flood or drought warning and prediction models, the integration of different information and tools, such as geographic information systems (GISs), satellite images, consensus data, the locations of critical structures, and socio-economic impact assessment tools, is necessary [123,124]. Impact assessment can be classified according to its evaluation time into pre- or during-disaster assessment. Pre-disaster impact assessments consider climate change [22,125] and planning- or preparedness-related applications [126,127]. During-disaster impact assessment is usually directly associated with immediate response [128–130]. A comprehensive and well-established monitoring network is necessary for during-disaster or so-called near real-time impact assessment. Given real-time observations along with detailed socio-economic investigation data, the efficiency of predictions is another important issue. The computer models or evaluation approaches must adopt the input information (such as real-time observations) and provide assessments in a timely manner to meet the need of emergency response. As mentioned before, drought usually develops slowly and has a prolonged impact. Floods usually have a clear and sudden start and end, but drought does not. However, drought can be unexpectedly ended by extreme precipitation [131]. Therefore, long-term instead of short-term impact assessment (here, short-term means a few hours to a few days) is usually more important for drought. The assessment scale varies from a city to a national scale according to the problems. Responses are consistent with being pre-disaster or during disasters accordingly. In terms of flood reduction, Hegger et al. [132] distinguish five types of flood management strategies: (1) flood defense through structural measures; (2) risk prevention by considering proactive spatial planning to avoid high-risk areas; (3) risk mitigation by the flood-adapted design and use of buildings; (4) the preparedness for response, e.g., using flood warnings and evacuation plans; and (5) recovery considering risk transfer mechanisms such as flood insurance to compensate for flood losses. These five management strategies cover structural (e.g., dams and dikes) and nonstructural measures (e.g., land use planning and insurance programs).

3.3.2. Drought

Drought, as mentioned before, is a slow-developing process; therefore, the general public usually does not feel the response in comparison to mitigation measures for floods. Short-term measures would include providing early-warning information, increased emphasis on water conservation (demand reduction), increased water supplies through other backup resources such as groundwater, and water reutilization and recycling. A short-term strategy like water recycling can immediately reduce the need of a water supply and the installation of a water recycling system can be done in a timely and cost-effective manner. However, a comprehensive plan and long-term measures are key to solving the drought issue fundamentally. Long-term measures include the construction of reservoirs, joint operation of water supplies (interconnecting water supplies between neighboring communities or nations), and drought preparedness planning to build greater institutional capacity and awareness building and education [133]. A comprehensive plan includes long-term measures to meet the long-term water demand along with short-term measures to provide a buffer to respond to the uncertainty of the future. Among all the measures, demand reduction is always the most common and efficient measure to take. It is considered that the water consumption of agriculture is always the highest. Therefore, many studies have focused on agricultural drought responses [134–136].

Table 2. Research themes and associated studies related to flood and drought mitigation.

Research Theme	Disaster Type	
Prediction and Warning	**Flood** Physics-based models [53–61] Data-driven models [69–71] Other alternatives: rainfall threshold/index-based models [72–74]	
	Drought Statistic models [78,79] Dynamic models [80–82] Monitoring information and index-based monitoring [85–87] Data-driven models [88–91]	
Monitoring	Traditional observation approach [92,94] Remote sensing techniques [96–98] Advanced monitoring network [115–118]	
Impact Assessment, Response, and Management	Climate change or planning-related assessment [125–127] Immediate disaster evaluation and response [128–130]	General measures to mitigate the drought impact [127] Specific measures for agriculture drought [134–136]

3.3.3. Other Associated Studies

It has been confirmed that the state has the primary responsibility to protect people and property from hazards. However, it has also been indicated that strengthening community-level capacities to reduce disaster risk is especially needed, considering that appropriate disaster-reduction measures enable communities and individuals to significantly reduce their vulnerabilities to hazards [137]. The traditional paradigm for emergency response is a "top-down" approach: an executive decision maker or other top person makes the decisions for emergency response. The community-based approach, a so called "bottom-up" approach, is the opposite approach, in which everything is initiated locally and designed to respond to a disaster immediately. Recent studies have shown the efficiency of community-based emergency plans [138,139]. The first priority of disaster response is to protect people. However, the interference of economic activities and the associated loss receives attention. Post-disaster impact, such as interruption to the supply chain of industries, is also significant as floods can occur in high-tech industry parks. To maintain a resilient business or a sustainable society, the concept of a business continuity plan (BCP) has been generally applied and studied [140,141]. In conclusion, many response and management strategies rely on historical records or past experiences. However, there are more and more unprecedented extreme events, which mean no one thought they would happen. The paradigm of disaster management must shift from prevention to management or mitigation in order to achieve the goal of sustainability. The concept of BCP is a very good practice for business sectors to adapt to climate extremes and return to regular trade in a timely manner [142].

4. Integration of Structural and Nonstructural Measures for Disaster Mitigation

Tables 3 and 4 show examples of risk reduction for floods and droughts, respectively. The tables provide a systematic strategy for the risk reduction of floods and droughts. Furthermore, an integration of structural and nonstructural measures is considered. The monitoring is an important role for the risk reduction of floods and drought. There is no big difference in terms of monitoring for both floods and droughts. Establishing a comprehensive monitoring network is essential for detailed observation. It provides the condition of status quo and serves as a reference for future forecasts. Prediction and warning can be done by using the monitoring information as input. At this stage, numerical models, a nonstructural measure, are applied to provide results, such as river stage forecasts for floods and SPI for droughts. Government and public entities can evaluate possible impacts, such as flood affected area and drought duration, using the abovementioned forecasts. The socio-economic impact is obtained, and decision makers can take precautionary measures as a response. The "response" is the biggest difference between floods and droughts. Due to the characteristic of drought, it is almost impossible to prevent drought from happening. Therefore, the main idea in response to droughts is to decrease the socio-economic impact. Structural measures for drought are mainly used to increase water resources. When a drought occurs, decision makers can only take nonstructural measures, such as lower water pressure, water supply reduction, and compensation, against the drought loss. Differently from droughts, the first idea in the response to floods is prevention and the second is mitigation. Therefore, structural measures such as levees and emergency bypasses are built to prevent flooding. However, people realize that the disaster cannot be prevented due to climate change and unprecedented extreme weather events. Nonstructural measures are applied to mitigate the impact of flooding and adopt to climate change. A combination of structural and nonstructural measures is the way forward to maximize the disaster loss reduction. While structural measures are mostly initiated by governments, the nonstructural measures mentioned above are more effectively supported and engaged in by the general public.

Table 3. Example of the integration of structural and nonstructural risk-reduction strategies for floods.

Strategy	Measure		Disaster Type
	Structure	**Nonstructural**	**Flood**
Monitoring	Establishment of monitoring network (gauging stations, satellite, etc.)		Precipitation, river stage, soil moisture, and, etc.
Prediction and warning	n/a	Numerical models	River stage or urban inundation forecasting
Impact assessment	n/a	Numerical models	Evaluation of flood-affected area and population
Response and management	Reservoir, levee, emergency diversion channel, temporary flood wall, water pump, etc.	Evacuation, land-use planning, flood insurance, flood-adopted design and use of buildings, etc.	Prevention of flooding and decrease the damage to life and property

Table 4. Example of the integration of structural and nonstructural risk-reduction strategies for droughts.

Strategy	Measure		Disaster type
	Structure	**Nonstructural**	**Drought**
Monitoring	Establishment of monitoring network (gauging stations, satellite, etc.)		Precipitation, river stage, soil moisture, etc.
Prediction and warning	n/a	Numerical models	Standardized precipitation index
Impact assessment	n/a	Numerical models	Estimation of drought duration and severity
Response and management	Reservoir, maintenance of water conveyance system, wastewater recycling, etc.	Low water pressure, water supply reduction, compensation to stop farming, etc.	Decrease the socioeconomic impact of drought

5. Conclusions

The occurrence frequency of floods and droughts is increasing due to climate change [143,144]. This overview provides definitions of floods and droughts and discusses the related research for disaster reduction. However, the research outcomes regarding disaster reduction are too numerous to be covered. There is always the possibility that relevant contributions or other advanced research studies have not been covered in the overview. Moreover, the overview only includes articles published in English. Therefore, articles published in other languages are not included. In conclusion, an integrated view of the research area is provided, including three research themes corresponding to the disaster-reduction cycle. Because of rapid advances in technology, the application of artificial intelligence and the internet of things in disaster reduction are also discussed in this paper. The abovementioned components and their interrelationships provide a cohesive overview of the literature on the special issue of "sustainable water resource management for disaster risk reduction". The findings of this review further indicate that further research is required to enhance the environmental and social sustainability of disaster risk reduction. The results of this review show areas lacking research or needing further development, especially through multidisciplinary research and cooperation. The detailed conclusions are provided as follows:

5.1. Implications for Flood and Drought Researchers

The results of this review help to identify the current status and studies of floods and drought in the literature. This work provides a foundation for further examination of the topic and theory development by pointing out needs for future research from various disciplines. An important contribution to this work is the definition of flood and drought classification. The core contribution is classified into three research themes (prediction and warning, monitoring, and impact assessment and response) based on the disaster-reduction cycle: preparedness, response, recovery, and prevention. This contribution is important because it helps researchers position their research better in the flood- and drought-related disaster-reduction domain. Furthermore, this work provides thoughts for future research of interest, particularly highlighting the need for sustainable development and urbanization aspects.

5.2. Future Research of Interest

This systematic review provides an overview of three research themes related to floods and drought and the associated disaster reduction. All the research works achieve significant contributions to each theme. However, multidisciplinary research and cooperation across fields are necessary to accommodate the urgent need for disaster reduction. For example, an improvement in drought and flood monitoring can be achieved by considering hybrid ground-based observation and remote sensing techniques [145]. The integration of physics-based and artificial intelligence-based models is also another research topic worth investigating. Finally, only a few studies have focused on converting a negative impact (e.g., flooding) into a positive impact (e.g., extra water resource). Disasters such as floods or drought not only occur frequently but also occur alternatively. This occurrence creates an enormous challenge for scientists and engineers to build up a resilient living environment adopted for future climate change scenarios. Rapid urbanization and population growth in countries such as China, India, and others has changed the environment and worsened the impact of disasters. Therefore, integrated urban flood/drought policymaking with sustainable urbanization policymaking to best contribute to minimizing flood and drought risks in cities is necessary [146]. Some sustainable technologies or concepts, such as low-impact development (LID), green roofs, or sponge cities, may be considered to achieve sustainable goals [147,148].

Special attention is initially paid to those research outcomes that convert negative impacts into positive impacts. For example, rapid urbanization and population growth are considered as a double-edged sword [146]. The progress exposes the population to a higher risk of disaster, but the resulting socioeconomic development creates a better living environment. However, it is a good opportunity for a city to build up the capacity to alleviate flood and drought risks by increasing investment in sustainable urban structure, developing risk warning and management systems, and reducing disaster risk through land-use planning. Another example— that of shifting drought water storage from reservoirs to underground aquifers—has made substantially more storage capacity available for winter flood management in California [149]. This requires a comprehensive and integrated reoperation of many flood and water supply system elements [15]. As a conclusion, sustainable disaster-reduction strategies should represent the ability or potential of a system to respond successfully to climate variability and change, including adjustments in both behavior and in resources and technologies responding to both floods and droughts. However, existing studies or measures still remain within in this category and there is a lack of multidisciplinary cooperation to meet the needs of future challenges.

Author Contributions: Conceptualization, T.-H.Y. and W.-C.L.; writing—original draft preparation, T.-H.Y.; writing—review and editing, W.-C.L.; supervision, W.-C.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Ministry of Science and Technology, Taiwan, grant numbers MOST 108-2625-M-239-002 and MOST 108-2625-M-009-004.

Acknowledgments: The authors acknowledge the Ministry of Science and Technology, Taiwan, for their financial support, and the three anonymous reviewers whose comments have greatly improved this manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. United Nations. Sustainable development goals. Available online: https://www.un.org/sustainabledevelopment/sustainable-development-goals/ (accessed on 26 December 2019).
2. Cai, W.; Santoso, A.; Wang, G.; Yeh, S.W.; An, S.I.; Cobb, K.M.; Collins, M.; Guilyardu, E.; Jin, F.F.; Kug, S.J.; et al. ENSO and greenhouse warming. *Nature Clim. Change* **2015**, *5*, 849–859. [CrossRef]
3. Center for Research on Epidemiology of Disasters (CRED). *Natural Disasters*; Center for Research on Epidemiology of Disasters: Brussels, Belgium, 2018.
4. Mahul, O. Toward a regional approach for disaster risk finance in Asia. In Proceedings of the ICRM Symposium, Singapore, 3–4 August 2017.

5. Ding, Y.; Hayes, M.J.; Widhalm, M. Measuring economic impacts of drought: A review and discussion. *Disaster Prevent. Manag. An. Int. J.* **2011**, *20*, 13. [CrossRef]
6. Queensland Government, Office of the Queensland Chief Scientist. Floods have Significant Consequences for the Environment. Available online: https://www.chiefscientist.qld.gov.au/publications/understanding-floods/flood-consequences (accessed on 26 December 2019).
7. Below, R.; Wirtz, A.; Guha-Sapor, D. *Disaster Category Classification and Peril Terminology for Operational Purposes*; Centre for Research on the Epidemiology of Disasters: Brussels, Belgium, 2009.
8. Falconer, R.H.; Cobby, D.; Smyth, P.; Astle, G.; Dent, J.; Golding, B. Pluvial flooding: New approaches in flood warning, mapping and risk management. *J. Flood Risk Manag.* **2009**, *2*, 198–208. [CrossRef]
9. Hurford, A.P.; Priest, S.J.; Parker, D.J.; Lumbroso, D.M. The effectiveness of extreme rainfall alerts in predicting surface water flooding in England and Wales. *Int. J. Climatol.* **2012**, *32*, 1768–1774. [CrossRef]
10. Kaźmierczak, A.; Cavan, G. Surface water flooding risk to urban communities: Analysis of vulnerability, hazard and exposure. *Landsc. Urban. Plan.* **2011**, *103*, 185–197. [CrossRef]
11. Houston, D.; Werrity, A.; Bassett, D.; Geddes, A.; Hoolachan, A.; McMillan, M. *Pluvial (rain-related) Flooding in Urban Areas: The Invisible Hazard*; Joseph Rowntree Foundation: London, UK, 2011.
12. Apreda, C. Climate change, urban vulnerability and adaptation strategies to pluvial flooding. *UPLanD-J. Urban. Plan. Landsc. Environ. Design* **2016**, *1*, 233.
13. Montz, B.E.; Gruntfest, E. Flash flood mitigation: Recommendations for research and applications. *Global Environ. Change B Environ. Hazards* **2002**, *4*, 15–22. [CrossRef]
14. Hapuarachchi, H.A.P.; Wang, Q.J.; Pagano, T.C. A review of advances in flash flood forecasting. *Hydrol. Process.* **2011**, *25*, 2771–2784. [CrossRef]
15. Lund, J.R. Flood management in California. *Water* **2012**, *4*, 157–169. [CrossRef]
16. Changnon, S.A. Assessment of flood losses in the United States. *J. Contemp. Water Res. Edu.* **2008**, *138*, 38–44. [CrossRef]
17. Archer, D.R.; Fowler, H.J. Characterising flash flood response to intense rainfall and impacts using historical information and gauged data in Britain. *J. Flood Risk Manag.* **2018**, *11*, S121–S133. [CrossRef]
18. Liu, C.; Guo, L.; Ye, L.; Zhang, S.; Zhao, Y.; Song, T. A review of advances in China's flash flood early-warning system. *Nat. Hazard.* **2018**, *92*, 619–634. [CrossRef]
19. Acreman, M.C.; Riddington, R.; Booker, D.J. Hydrological impacts of floodplain restoration: A case study of the River Cherwell, UK. *Hydrol. Earth Syst. Sci. Disc.* **2003**, *7*, 75–85. [CrossRef]
20. Acreman, M.; Arthington, A.H.; Colloff, M.J.; Couch, C.; Crossman, N.D.; Dyer, F.; Overton, I.; Pollino, C.A.; Stewarson, M.; Young, W. Environmental flows for natural, hybrid, and novel riverine ecosystems in a changing world. *Front. Ecol. Environ.* **2014**, *12*, 466–473. [CrossRef]
21. Wolf, J. Coastal flooding: Impacts of coupled wave–surge–tide models. *Nat. Hazard.* **2009**, *49*, 241–260. [CrossRef]
22. Heberger, M.; Cooley, H.; Herrera, P.; Gleick, P.H.; Moore, E. Potential impacts of increased coastal flooding in California due to sea-level rise. *Clim. Change* **2011**, *109*, 229–249. [CrossRef]
23. Woodruff, J.D.; Irish, J.L.; Camargo, S.J. Coastal flooding by tropical cyclones and sea-level rise. *Nature* **2013**, *504*, 44. [CrossRef]
24. Dawson, R.J.; Dickson, M.E.; Nicholls, R.J.; Hall, J.W.; Walkden, M.J.; Stansby, P.K.; Mokrech, M.; Richards, J.; Zhou, J.; Milligan, J.; et al. Integrated analysis of risks of coastal flooding and cliff erosion under scenarios of long term change. *Clim. Change* **2009**, *95*, 249–288. [CrossRef]
25. Mishra, A.K.; Singh, V.P. A review of drought concepts. *J. Hydrol.* **2010**, *391*, 202–216. [CrossRef]
26. World Meteorological Organization (WMO). *Report on Drought and Countries Affected by Drought During 1974–1985*; WMO: Geneva, Switzerland, 1986; p. 118.
27. UN Secretariat General. *United Nations Convention to Combat Drought and Desertification in Countries Experiencing Serious Droughts and Desertification, Particularly in Africa*; UN Secretariat General: Paris, France, 1994.
28. FAO. *Report of FAO-CRIDA Expert Group Consultation on Farming System and Best Practices for Drought-Prone Areas of Asia and the Pacific Region. Food and Agricultural Organization of United Nations*; Central Research Institute for Dryland Agriculture: Hyderabad, India, 2002.
29. Gumbel, E.J. Statistical forecast of droughts. *Bull. Int. Assoc. Sci. Hydrol.* **1963**, *8*, 5–23. [CrossRef]
30. Wilhite, D.A.; Glantz, M.H. Understanding the Drought Phenomenon: The Role of Definitions. *Water Int.* **1985**, *10*, 111–120. [CrossRef]

31. American Meteorological Society (AMS). Statement on meteorological drought. *Bull. Am. Meteorol. Soc.* **2004**, *85*, 771–773.
32. Kumar, R.; Musuuza, J.L.; Loon, A.F.V.; Teuling, A.J.; Barthel, R.; Broek, T.J.; Mai, J.; Samaniego, L.; Attinger, S. Multiscale evaluation of the Standardized Precipitation Index as a groundwater drought indicator. *Hydrol. Earth Syst. Sci.* **2016**, *20*, 1117–1131. [CrossRef]
33. Gibbs, W.J. Drought, its definition, delineation and effects. In *Drought: Lectures Presented at the 26th Session of the WMO*; Report No. 5; WMO: Geneva, Switzerland, 1975; pp. 3–30.
34. Haslinger, K.; Blöschl, G. Space-time patterns of meteorological drought events in the European Greater Alpine Region over the past 210 years. *Water Resour. Res.* **2017**, *53*, 9807–9823. [CrossRef]
35. Schubert, S.D.; Stewart, R.E.; Wang, H.; Barlow, M.; Berbery, E.H.; Cai, W.; Hoerling, M.P.; Kanikicharta, K.K.; Koster, R.D.; Lyon, B.; et al. Global meteorological drought: A synthesis of current understanding with a focus on SST drivers of precipitation deficits. *J. Clim.* **2016**, *29*, 3989–4019. [CrossRef]
36. Van Loon, A.F. Hydrological drought explained. *WIRES Water* **2015**, *2*, 359–392. [CrossRef]
37. Hasan, H.H.; Razali, M.; Fatin, S.; Muhammad, N.S.; Ahmad, A. Research trends of hydrological drought: A systematic review. *Water* **2019**, *11*, 2252. [CrossRef]
38. Sheffield, J.; Wood, E.F. *Drought: Past and Future Scenarios*; Earthscan Ltd.: London, UK, 2011.
39. Allah, A.A.D.; Hashim, N.B.M.; Awang, A.B. Discovering trends of agricultural drought in Tihama Plain, Yemen: A preliminary assessment. *Indonesian J. Geogr.* **2017**, *49*, 17.
40. Liu, Y.; Pan, Z.; Zhuang, Q.; Miralles, D.G.; Teuling, A.J.; Zhang, T.; An, P.; Dong, Z.; Zhang, J.; He, D.; et al. Agriculture intensifies soil moisture decline in Northern China. *Sci. Rep.* **2015**, *5*, 11261. [CrossRef]
41. Guo, Y.; Huang, S.; Huang, Q.; Wang, H.; Fang, W.; Yang, Y.; Wang, L. Assessing socioeconomic drought based on an improved Multivariate Standardized Reliability and Resilience Index. *J. Hydrol.* **2019**, *568*, 904–918. [CrossRef]
42. Chan, N.W.; Ghani, A.A.; Samat, N.; Hasan, N.N.N.; Tan, M.L. Integrating structural and non-structural flood management measures for greater effectiveness in flood loss reduction in the Kelantan River Basin, Malaysia. In *Proceedings of the AICCE'19, AICCE 2019, Lecture Notes in Civil Engineering*; Mohamed, N.F., Ed.; Springer: Berlin/Heidelberg, Germany, 2020; p. 53.
43. Kundzewicz, Z.W.; Hegger, D.L.T.; Matczak, P.; Driessen, P.P.J. Opinion: Flood-risk reduction: Structural measures and diverse strategies. *Proc. Nat. Academ. Sci USA* **2018**, *115*, 12321–12325. [CrossRef]
44. Li, C.; Cheng, X.; Li, N.; Du, X.; Yu, Q.; Kan, G. A framework for flood risk analysis and benefit assessment of flood control measures in urban areas. *Int. J. Environ. Res. Publ. Health* **2016**, *13*, 787. [CrossRef]
45. Albuquerque, M.B.; de Araújo, A.A.; Martinez, C.E.N.M.; Mauad, F.F.; Okawa, C.M.P. Sustainable Urban Drainage: A brief review of the compensatory techniques of structural and non-structural measures. *Revista Eletrônica em Gestão, Educação e Tecnologia Ambiental* **2019**, *23*, 35.
46. Enomoto, C.F. Método para elaboração de mapas de inundação: Estudo de caso na bacia do rio Palmital. Ph.D. Thesis, Setor de Tecnologia/Universidade Federal do Paraná, Curitiba, Brazil, 2004.
47. Kawatoko, I.E.S. Estabelecimento de cenários de medidas estruturais e não estruturais para gestão das águas urbanas em escala de lote. Ph.D. Thesis, Escola de Engenharia de São Carlos/USP, São Carlos, Brazil, 2012.
48. Velasco, M.; Russo, B.; Cabello, À.; Termes, M.; Sunyer, D.; Malgrat, P. Assessment of the effectiveness of structural and nonstructural measures to cope with global change impacts in Barcelona. *J. Flood Risk Manag.* **2018**, *11*, S55–S68. [CrossRef]
49. Rossi, G. Drought mitigation measures: A comprehensive framework. In *Drought and Drought Mitigation in Europe. Advances in Natural and Technological Hazards Research*; Vogt, J.V., Somma, F., Eds.; Springer: Dordrecht, The Netherlands, 2000; p. 14.
50. Klomp, J.; Hoogezand, B. Natural disasters and agricultural protection: A panel data analysis. *World Develop.* **2018**, *104*, 404–417. [CrossRef]
51. Rogers, D.; Tsirkunov, V. Costs and Benefits of Early warning Systems. Available online: https://www.preventionweb.net/english/hyogo/gar/2011/en/bgdocs/Rogers_&_Tsirkunov_2011.pdf (accessed on 20 January 2020).
52. Sättele, M.; Bründl, M.; Straub, D. Reliability and effectiveness of early warning systems for natural hazards: Concept and application to debris flow warning. *Reliab. Eng. Syst. Saf.* **2015**, *142*, 192–202. [CrossRef]
53. Teng, J.; Jakeman, A.J.; Vaze, J.; Croke, B.F.; Dutta, D.; Kim, S. Flood inundation modelling: A review of methods, recent advances and uncertainty analysis. *Environ. Model. Softw.* **2017**, *90*, 201–216. [CrossRef]

54. U.S. Army. *HEC RAS River Analysis System. User's Manual, Version 5*; US Army Corps of Engineers: Sacramento, CA, USA, 2016.
55. Rojas, O.; Mardones, M.; Rojas, C.; Martínez, C.; Flores, L. Urban growth and flood disasters in the coastal river basin of south-central Chile (1943–2011). *Sustainability* **2017**, *9*, 195. [CrossRef]
56. Gibson, S.; Sánchez, A.; Piper, S.; Brunner, G. New One-dimensional sediment features in HEC-RAS 5.0 and 5.1. In Proceedings of the World Environmental and Water Resources Congress, Sacramento, CA, USA, 21–25 May 2017; pp. 192–206.
57. Kilania, S.; Chahar, B.R. A dam break analysis using HEC-RAS. In *World Environmental and Water Resources Congress, Hydraulics, Waterways, and Water Distribution Systems Analysis*; American Society of Civil Engineers: Reston, VA, USA, 2019; pp. 382–389.
58. Quirogaa, V.M.; Kurea, S.; Udoa, K.; Manoa, A. Application of 2D numerical simulation for the analysis of the February 2014 Bolivian Amazonia flood: Application of the new HEC-RAS version 5. *Ribagua* **2016**, *3*, 25–33. [CrossRef]
59. DHI. MIKE. *21-2D Modelling of Coast and Sea*; DHI Water & Environment Pty Ltd.: Hørsholm, Denmark, 2012.
60. Shih, S.S.; Kuo, P.H.; Lai, J.S. A nonstructural flood prevention measure for mitigating urban inundation impacts along with river flooding effects. *J. Environ. Manag.* **2019**, *251*, 109553. [CrossRef]
61. Doong, D.J.; Lo, W.; Vojinovic, Z.; Lee, W.L.; Lee, S.P. Development of a new generation of flood inundation maps-A case study of the coastal city of Tainan, Taiwan. *Water* **2016**, *8*, 521. [CrossRef]
62. Shukla, M. (Ed.) . *Soil hydrology, Land use and Agriculture: Measurement and Modelling*; Cabi: Wallingford, UK, 2011.
63. Sith, R.; Nadaoka, K. Comparison of SWAT and GSSHA for high time resolution prediction of stream flow and sediment concentration in a small agricultural watershed. *Hydrology* **2017**, *4*, 27. [CrossRef]
64. Sommerlot, A.R.; Nejadhashemi, A.P.; Woznicki, S.A.; Giri, S.; Prohaska, M.D. Evaluating the capabilities of watershed-scale models in estimating sediment yield at field-scale. *J. Environ. Manag.* **2013**, *127*, 228–236. [CrossRef] [PubMed]
65. De Girolamo, A.M.; Lo Porto, A.; Pappagallo, G.; Tzoraki, O.; Gallart, F. The hydrological status concept: Application at a temporary River (Candelaro, Italy). *River Res. Appl.* **2015**, *31*, 892–903. [CrossRef]
66. Abdelwahab, O.M.M.; Bingner, R.L.; Milillo, F.; Gentile, F. Effectiveness of alternative management scenarios on the sediment load in a Mediterranean agricultural watershed. *J. Agric. Eng.* **2014**, *45*, 125–136. [CrossRef]
67. Mtibaa, S.; Hotta, N.; Irie, M. Analysis of the efficacy and cost-effectiveness of best management practices for controlling sediment yield: A case study of the Joumine watershed, Tunisia. *Sci. Total Environ.* **2018**, *616–617*, 1–16. [CrossRef]
68. Ricci, G.F.; Jeong, J.; De Girolamo, A.M.; Gentile, F. Effectiveness and feasibility of different management practices to reduce soil erosion in an agricultural watershed. *Land Use Policy* **2020**, *90*, 104306. [CrossRef]
69. Lin, G.F.; Lin, H.Y.; Chou, Y.C. Development of a real-time regional-inundation forecasting model for the inundation warning system. *J. Hydroinform.* **2013**, *15*, 1391–1407. [CrossRef]
70. Pan, T.Y.; Lin, H.T.; Liao, H.Y. A data-driven probabilistic rainfall-inundation model for flash-flood warnings. *Water* **2019**, *11*, 2534. [CrossRef]
71. Badrzadeh, H.; Sarukkalige, R.; Jayawardena, A.W. Hourly runoff forecasting for flood risk management: Application of various computational intelligence models. *J. Hydrol.* **2015**, *529*, 1633–1643. [CrossRef]
72. Lhomme, J.; Sayers, P.B.; Gouldby, B.P.; Samuels, P.G.; Wills, M.; Mulet-Marti, J. Recent development and application of a rapid flood spreading method. In Proceedings of the Conference FLOODrisk 2008, Flood Risk Management: Research and Practice, Oxford, UK, 30 September–2 October 2009.
73. Yang, T.H.; Chen, Y.C.; Chang, Y.C.; Yang, S.C.; Ho, J.Y. Comparison of different grid cell ordering approaches in a simplified inundation model. *Water* **2015**, *7*, 438–454. [CrossRef]
74. Yang, T.H.; Hwang, G.D.; Tsai, C.C.; Ho, J.Y. Using rainfall thresholds and ensemble precipitation forecasts to issue and improve urban inundation alerts. *Hydrol. Earth Syst. Sci.* **2016**, *20*, 4731–4745. [CrossRef]
75. Martina, M.L.V.; Todini, E.; Libralon, A. A Bayesian decision approach to rainfall thresholds based flood warning. *Hydrol. Earth Syst. Sci.* **2006**, *10*, 316–324. [CrossRef]
76. Anshuka, A.; van Ogtrop, F.F.; Vervoort, R.W. Drought forecasting through statistical models using standardised precipitation index: A systematic review and meta-regression analysis. *Nat. Hazard.* **2019**, *97*, 955–977. [CrossRef]

77. Yeh, H.F.; Hsu, H.L. Stochastic model for drought forecasting in the Southern Taiwan Basin. *Water* **2019**, *11*, 2041. [CrossRef]
78. Fung, K.F.; Huang, Y.F.; Koo, C.H.; Soh, Y.W. Drought forecasting: A review of modelling approaches 2007–2017. *J. Water Clim. Change* **2019**, 236. [CrossRef]
79. Mishra, A.K.; Singh, V.P. Drought modeling–A review. *J. Hydrol.* **2011**, *403*, 157–175. [CrossRef]
80. Luo, L.; Wood, E.F. Monitoring and predicting the 2007 US drought. *Geophys. Res. Lett.* **2007**, *34*, L22702. [CrossRef]
81. Bae, D.H.; Son, K.H.; Ahn, J.B.; Hong, J.Y.; Kim, G.S.; Chung, J.S.; Jung, U.S.; Kim, J.K. Development of real-time drought monitoring and prediction system on Korea & East Asia region. *Atmosphere* **2012**, *22*, 267–277.
82. Li, Y.; Yuan, X.; Zhang, H.; Wang, R.; Wang, C.; Meng, X.; Zhang, Z.; Wang, S.; Yang, Y.; Han, B.; et al. Mechanisms and early warning of drought disasters: Experimental drought meteorology research over China. *Bull. Am. Meteorol. Soc.* **2019**, *100*, 673–687. [CrossRef]
83. Forni, L.G.; Medellín-Azuara, J.; Tansey, M.; Young, C.; Purkey, D.; Howitt, R. Integrating complex economic and hydrologic planning models: An application for drought under climate change analysis. *Water Resour. Economics* **2016**, *16*, 15–27. [CrossRef]
84. Svoboda, M.; Fuchs, B. *Handbook of Drought Indicators and Indices*; WMO-No. 1173; World Meteorological Organization: Geneva, Switzerland, 2016.
85. Bahrami, M.; Bazrkar, S.; Zarei, A.R. Modeling, prediction and trend assessment of drought in Iran using standardized precipitation index. *J. Water Clim. Change* **2019**, *10*, 181–196. [CrossRef]
86. Choubin, B.; Malekian, A.; Golshan, M. Application of several data-driven techniques to predict a standardized precipitation index. *Atmósfera* **2016**, *29*, 121–128. [CrossRef]
87. McKinnon, K.A.; Rhines, A.; Tingley, M.P.; Huybers, P. Long-lead predictions of eastern United States hot days from Pacific sea surface temperatures. *Nat. Geosci.* **2016**, *9*, 389–394. [CrossRef]
88. Adamowski, J.; Belayneh, A. *Drought Forecasting. Exploring Natural Hazards: A Case Study Approach, 207*; Taylor & Francis Group: Abingdon, UK, 2018.
89. Kousari, M.R.; Hosseini, M.E.; Ahani, H.; Hakimelahi, H. Introducing an operational method to forecast long-term regional drought based on the application of artificial intelligence capabilities. *Theor. Appl. Climatol.* **2017**, *127*, 361–380. [CrossRef]
90. Mokhtarzad, M.; Eskandari, F.; Vanjani, N.J.; Arabasadi, A. Drought forecasting by ANN, ANFIS, and SVM and comparison of the models. *Environ. Earth Sci.* **2017**, *76*, 729. [CrossRef]
91. Maca, P.; Pech, P. Forecasting SPEI and SPI drought indices using the integrated artificial neural networks. *Comput. Intell. Neurosci.* **2016**, *3*, 1–17. [CrossRef]
92. Gourley, J.J.; Flamig, Z.L.; Vergara, H.; Kirstetter, P.E.; Clark III, R.A.; Argyle, E.; Arthur, A.; Martinaitis, S.; Terti, G.; Erlingis, J.M.; et al. The FLASH Project: Improving the tools for flash flood monitoring and prediction across the United States. *Bull. Am. Meteorol.l Soc.* **2017**, *98*, 361–372. [CrossRef]
93. López-Trujillo, D. *Real Time Flood Alert System (RTFAS) for Puerto Rico*; US Department of Interior, US Geological Survey: Washington, DC, USA, 2010.
94. Ceppi, A.; Ravazzani, G.; Corbari, C.; Salerno, R.; Meucci, S.; Mancini, M. Real-time drought forecasting system for irrigation management. *Procedia Environ. Sci.* **2014**, *19*, 776–784. [CrossRef]
95. Hossain, F. Towards formulation of a space-borne system for early warning of floods: Can cost-effectiveness outweigh prediction uncertainty? *Nat. Hazard.* **2006**, *37*, 263–276. [CrossRef]
96. Wei, L.; Jiang, S.; Ren, L.; Yuan, F.; Zhang, L. Performance of Two Long-Term Satellite-Based and GPCC 8.0 Precipitation Products for Drought Monitoring over the Yellow River Basin in China. *Sustainability* **2019**, *11*, 4969. [CrossRef]
97. Wang, L.; Qu, J.J. NMDI: A normalized multi-band drought index for monitoring soil and vegetation moisture with satellite remote sensing. *Geophys. Res. Lett.* **2007**, *34*. [CrossRef]
98. Hazaymeh, K.; Hassan, Q.K. Remote sensing of agricultural drought monitoring: A state of art review. *Aims Environ. Sci.* **2016**, *3*, 604. [CrossRef]
99. Ahmadalipour, A.; Moradkhani, H.; Yan, H.; Zarekarizi, M. Remote sensing of drought: Vegetation, soil moisture, and data assimilation. In *Remote Sensing of Hydrological Extremes*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 121–149.

100. Dance, S.L.; Ballard, S.P.; Bannister, R.N.; Clark, P.; Cloke, H.L.; Darlington, T.; Flack, D.L.A.; Gray, S.L.; Hawkness-Smith, L.; Husnoo, N.; et al. Improvements in forecasting intense rainfall: Results from the FRANC (Forecasting Rainfall exploiting new data Assimilation techniques and Novel observations of Convection) project. *Atmosphere* **2019**, *10*, 125. [CrossRef]
101. Van Wesemael, A.; Landuyt, L.; Lievens, H.; Verhoest, N.E. Improving flood inundation forecasts through the assimilation of in situ floodplain water level measurements based on alternative observation network configurations. *Adv. Water Resour.* **2019**, *130*, 229–243. [CrossRef]
102. Chao, L.; Zhang, K.; Li, Z.; Zhu, Y.; Wang, J.; Yu, Z. Geographically weighted regression based methods for merging satellite and gauge precipitation. *J. Hydrol.* **2018**, *558*, 275–289. [CrossRef]
103. Clement, M.A.; Kilsby, C.G.; Moore, P. Multi-temporal synthetic aperture radar flood mapping using change detection. *J. Flood Risk Manag.* **2018**, *11*, 152–168. [CrossRef]
104. Munasinghe, D.; Cohen, S.; Huang, Y.F.; Tsang, Y.P.; Zhang, J.; Fang, Z. Intercomparison of Satellite Remote Sensing-Based Flood Inundation Mapping Techniques. *J. Am. Water Resour. Assoc.* **2018**, *54*, 834–846. [CrossRef]
105. Uddin, K.; Matin, M.A.; Meyer, F.J. Operational flood mapping using multi-temporal sentinel-1 SAR images: A case study from Bangladesh. *Remote Sens.* **2019**, *11*, 1581. [CrossRef]
106. Bozza, A.; Durand, A.; Confortola, G.; Soncini, A.; Allenbach, B.; Bocchiola, D. Potential of remote sensing and open street data for flood mapping in poorly gauged areas: A case study in Gonaives, Haiti. *Appl. Geomatics* **2016**, *8*, 117–131. [CrossRef]
107. Chen, H.; Chandrasekar, V.; Bechini, R. An improved dual-polarization radar rainfall algorithm (DROPS2. 0): Application in NASA IFloodS field campaign. *J. Hydrometeor.* **2017**, *18*, 917–937. [CrossRef]
108. Yang, Z.; Hsu, K.; Sorooshian, S.; Xu, X.; Braithwaite, D.; Verbist, K.M. Bias adjustment of satellite-based precipitation estimation using gauge observations: A case study in Chile. *J. Geophysi. Res. Atmos.* **2016**, *121*, 3790–3806. [CrossRef]
109. Kimani, M.W.; Hoedjes, J.C.; Su, Z. An assessment of satellite-derived rainfall products relative to ground observations over East Africa. *Remote Sens.* **2017**, *9*, 430. [CrossRef]
110. Teegavarapu, R.S.; Aly, A.; Pathak, C.S.; Ahlquist, J.; Fuelberg, H.; Hood, J. Infilling missing precipitation records using variants of spatial interpolation and data-driven methods: Use of optimal weighting parameters and nearest neighbour-based corrections. *Int. J. Climatol.* **2018**, *38*, 776–793. [CrossRef]
111. Hunziker, S.; Gubler, S.; Calle, J.; Moreno, I.; Andrade, M.; Velarde, F.; Ticona, L.; CarroscO, G.; Castellon, Y.; Croci-Maspoli, M.; et al. Identifying, attributing, and overcoming common data quality issues of manned station observations. *Int. J. Climatol.* **2017**, *37*, 4131–4145. [CrossRef]
112. Ha, J.H.; Kim, Y.H.; Im, H.H.; Kim, N.Y.; Sim, S.; Yoon, Y. Error correction of meteorological data obtained with mini-AWSs based on machine learning. *Adv. Meteorol.* **2018**, 1–8. [CrossRef]
113. Ghapar, A.A.; Yussof, S.; Bakar, A.A. Internet of Things (IoT) architecture for flood data management. *Int. J. Future Gene. Commun. Network.* **2018**, *11*, 55–62. [CrossRef]
114. Bande, S.; Shete, V.V. Smart flood disaster prediction system using IoT & neural networks. In Proceedings of the International Conference on Smart Technologies for Smart Nation (SmartTechCon), Bangalore, India, 17–19 August 2017; pp. 189–194.
115. Chwala, C.; Kunstmann, H. Commercial microwave link networks for rainfall observation: Assessment of the current status and future challenges. *WIRES Water* **2019**, *6*, 1337. [CrossRef]
116. Mishra, B.K.; Thakker, D.; Mazumdar, S.; Simpson, S.; Neagu, D. Using deep learning for IoT-enabled camera: A use case of flood monitoring. In Proceedings of the 10th International Conference on Dependable Systems, Services and Technologies (DESSERT), Leeds, UK, 5–7 June 2019; pp. 235–240.
117. Tauro, F.; Olivieri, G.; Petroselli, A.; Porfiri, M.; Grimaldi, S. Flow monitoring with a camera: A case study on a flood event in the Tiber River. *Environ. Monitor. Assess.* **2016**, *188*, 118. [CrossRef]
118. De Vos, L.W.; Leijnse, H.; Overeem, A.; Uijlenhoet, R. Quality Control for Crowdsourced Personal Weather Stations to Enable Operational Rainfall Monitoring. *Geophys. Res. Lette.* **2019**, *46*, 8820–8829. [CrossRef]
119. Engel, F.L.; Choi, N. Flood warning toolset for the Medina River in Bandera County, Texas: U.S. Geological Survey Fact. Sheet, 2019–3043. Available online: https://doi.org/10.3133/fs20193043. (accessed on 20 January 2020).
120. Ghimire, E. Evaluation of one-dimensional and two-dimensional HEC-RAS models for flood travel time prediction and damage assessment using HAZUS-MH: A case study of Grand River, Ohio. (Electronic Thesis or Dissertation. 2019. Available online: https://etd.ohiolink.edu/ (accessed on 20 January 2020).

121. Sosa, J.; Sampson, C.; Smith, A.; Neal, J.; Bates, P. A toolbox to quickly prepare flood inundation models for LISFLOOD-FP simulations. *Environm. Model. Softw.* **2020**, *123*, 104561. [CrossRef]
122. Grimaldi, S.; Xu, J.; Li, Y.; Pauwels, V.R.; Walker, J.P. Flood mapping under vegetation using single SAR acquisitions. *Remote Sens. Environ.* **2020**, *237*, 111582. [CrossRef]
123. Ritter, J.; Berenguer, M.; Corral, C.; Park, S.; Sempere-Torres, D. ReAFFIRM: Real-time assessment of flash flood impacts–a regional high-resolution method. *Environ. Int.* **2020**, *136*, 105375. [CrossRef] [PubMed]
124. Sutanto, S.J.; van der Weert, M.; Wanders, N.; Blauhut, V.; Van Lanen, H.A. Moving from drought hazard to impact forecasts. *Nat. Commun.* **2019**, *10*, 1–7. [CrossRef] [PubMed]
125. De Silva, M.M.G.T.; Kawasaki, A. Socioeconomic vulnerability to disaster risk: A case study of flood and drought impact in a rural Sri Lankan community. *Ecol. Econ.* **2018**, *152*, 131–140. [CrossRef]
126. Raikes, J.; Smith, T.F.; Jacobson, C.; Baldwin, C. Pre-disaster planning and preparedness for floods and droughts: A systematic review. *Int. J. Disast. Risk Red.* **2019**, *38*, 101207. [CrossRef]
127. Wilhite, D.; Easterling, W.; Wood, D.A.; Rasmusson, E. *Planning for Drought: Toward a Reduction of Societal Vulnerability*; Routledge: Abingdon, UK, 2019.
128. Olyazadeh, R.; Aye, Z.C.; Jaboyedoff, M.; Derron, M.H. Prototype of an open-source web-GIS platform for rapid disaster impact assessment. *Spat. Inform. Res.* **2016**, *24*, 203–210. [CrossRef]
129. Ahamed, A.; Bolten, J.; Doyle, C.; Fayne, J. Near real-time flood monitoring and impact assessment systems. In *Remote Sensing of Hydrological Extremes*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 105–118.
130. Oddo, P.C.; Ahamed, A.; Bolten, J.D. Socioeconomic impact evaluation for near real-time flood detection in the lower Mekong river basin. *Hydrol.* **2018**, *5*, 23. [CrossRef]
131. West, H.; Quinn, N.; Horswell, M. Remote sensing for drought monitoring & impact assessment: Progress, past challenges and future opportunities. *Remote Sens. Environ.* **2019**, *232*, 111291.
132. Hegger, D.L.; Driessen, P.P.; Dieperink, C.; Wiering, M.; Raadgever, G.T.; van Rijswick, H.F. Assessing stability and dynamics in flood risk governance. *Water Resour. Manag.* **2014**, *28*, 4127–4142. [CrossRef]
133. Wilhite, D.A. *National Drought Management Policy Guidelines: A Template for Action*; Integrated Drought Management Programme (IDMP) Tools and Guidelines Series; World Meteorological Organization: Geneva, Switzerland, 2015; p. 1.
134. Łabędzki, L. Actions and measures for mitigation drought and water scarcity in agriculture. *J. Water Land Develop.* **2016**, *29*, 3–10. [CrossRef]
135. Müller, A.; Mora, V.; Rojas, E.; Díaz, J.; Fuentes, O.; Giron, E.; Gaytan, A.; van Etten, J. Emergency drills for agricultural drought response: A case study in Guatemala. *Disasters* **2019**, *43*, 410–430. [CrossRef] [PubMed]
136. Li, X.; Yang, Y.; Poon, J.; Liu, Y.; Liu, H. Anti-drought measures and their effectiveness: A study of farmers' actions and government support in China. *Ecol. Indic.* **2018**, *87*, 285–295. [CrossRef]
137. Hyogo Declaration. In Proceedings of the World Conference on Disaster Reduction: International strategy for disaster reduction, Hyogo, Japan, 18–22 January 2005.
138. Yamada, F.; Kakimoto, R.; Yamamoto, M.; Fujimi, T.; Tanaka, N. Implementation of community flood risk communication in Kumamoto, Japan. *J. Aav. Transport.* **2011**, *45*, 117–128. [CrossRef]
139. Shaw, R. Critical issues of community based flood mitigation: Examples from Bangladesh and Vietnam. *Sci. Cult.* **2006**, *72*, 6.
140. Wallace, M.; Webber, L. *The Disaster Recovery Handbook: A Step-By-Step Plan to Ensure Business Continuity and Protect Vital Operations, Facilities, and Assets*; Amacom: New York, NY, USA, 2017.
141. Hatton, T.; Grimshaw, E.; Vargo, J.; Seville, E. Lessons from disaster: Creating a business continuity plan that really works. *J. Bus. Contin. Emer. Plan.* **2016**, *10*, 84–92.
142. Yang, T.H.; Yang, S.C.; Kao, H.M.; Wu, M.C.; Hsu, H.M. Cyber-physical-system-based smart water system to prevent flood hazards. *Smart Water* **2018**, *3*, 1. [CrossRef]
143. Lehner, B.; Döll, P.; Alcamo, J.; Henrichs, T.; Kaspar, F. Estimating the impact of global change on flood and drought risks in Europe: A continental, integrated analysis. *Clim. Change* **2006**, *75*, 273–299. [CrossRef]
144. Marengo, J.A.; Tomasella, J.; Nobre, C.A. Climate change and water resources. In *Waters of Brazil*; Springer: Cham, Switzerland, 2017; pp. 171–186.
145. Casagli, N.; Frodella, W.; Morelli, S.; Tofani, V.; Ciampalini, A.; Intrieri, E.; Raspini, F.; Rossi, G.; Tanteri, L.; Lu, P. Spaceborne, UAV and ground-based remote sensing techniques for landslide mapping, monitoring and early warning. *Geoenviron. Disast.* **2017**, *4*, 9. [CrossRef]

146. Cai, J.; Kummu, M.; Niva, V.; Guillaume, J.H.; Varis, O. Exposure and resilience of China's cities to floods and droughts: A double-edged sword. *Int. J. Water Resour. Develop.* **2018**, *34*, 547–565. [CrossRef]
147. Zhao, H.; Zou, C.; Zhao, J.; Li, X. Role of low-impact development in generation and control of urban diffuse pollution in a pilot sponge city: A paired-catchment study. *Water* **2018**, *10*, 852. [CrossRef]
148. Jia, H.; Wang, Z.; Zhen, X.; Clar, M.; Shaw, L.Y. China's sponge city construction: A discussion on technical approaches. *Front. Environ. Sci. Eng.* **2017**, *11*, 18. [CrossRef]
149. Tanaka, S.K.; Zhu, T.; Lund, J.R.; Howitt, R.E.; Jenkins, M.W.; Pulido, M.A.; Tauber, M.; Ritzema, R.S.; Ferreira, I.C. Climate warming and water management adaptation for California. *Clim. Change* **2006**, *76*, 361–387. [CrossRef]