





# A Survey of Remote Sensing and Geographic Information System Applications for Flash Floods

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**Abstract:** Flash floods are among the most dangerous natural disasters. As climate change and urbanization advance, an increasing number of people are at risk of flash floods. The application of remote sensing and geographic information system (GIS) technologies in the study of flash floods has increased significantly over the last 20 years. In this paper, more than 200 articles published in the last 20 years are summarized and analyzed. First, a visualization analysis of the literature is performed, including a keyword co-occurrence analysis, time zone chart analysis, keyword burst analysis, and literature co-citation analysis. Then, the application of remote sensing and GIS technologies to flash flood disasters is analyzed in terms of aspects such as flash flood forecasting, flash flood disaster impact assessments, flash flood susceptibility analyses, flash flood risk assessments, and the identification of flash flood disaster risk areas. Finally, the current research status is summarized, and the orientation of future research is also discussed.

**Keywords:** remote sensing; geographic information system; flash floods; visual analysis



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## 1. Introduction

A flash flood is a rapid response to a severe thunderstorm that occurs in a short period of time (usually only a few minutes) [1]. Rapid snowmelt and sudden releases of impounded water may also cause flash floods [2]. In recent years, increasingly severe flash floods have occurred due to increased rainfall caused by climate change [3–5]. Moreover, the risk of flash floods increases with an increase in the impervious area in a given catchment area. Urbanization and reductions in rural land areas have led to declines in drainage capacity and increased numbers of flash floods [6]. As population structures change and the degree of urbanization increases, more people will be exposed to flash floods [7–9]. Many countries have carried out research on flash floods, such as China [10], the United States [11], Saudi Arabia [1], Egypt [12], and Italy [13].

The current research on flash floods mainly involves flash flood forecasting [14–21], flash flood disaster impact assessments [22–25], identifications of flash flood hazard areas [26–35], flash flood susceptibility assessments [36–39], and flash flood risk assessments [40–45]. Therefore, the motivation for our study is to comprehensively review the major areas related to the application of remote sensing and GIS technologies to flash flood disasters. Based on the analysis, the literature is classified, the study trends and hot spots of the current study on the application of remote sensing and GIS to flash floods in the last 20 years are summarized, and the main scientific progress in the literature is also summarized. Finally, the whole paper is summarized, commented on, and prospected.

## 2. Data and Methods

### 2.1. Retrieval Strategy

Articles with flash floods and remote sensing as research topics that were published from 2000 to October 2020 were retrieved, these articles were included in the Web of Science (WOS) Core Collection. A total of 248 articles were retrieved.

### 2.2. Literature Visual Analysis

CiteSpace is software developed by Chaomei Chen with an information visualization function based on the Java environment. Through keywords, authors, institutions, etc., one can perform visual analysis and generate various knowledge graphs, which can be used to show current research hotspots and trends to help people better understand research in a certain field. To date, many people have used CiteSpace for data mining and visual analysis [46–48]. In this paper, a total of 248 articles were included to generate citation analysis reports (such as node size, keyword co-occurrence, time zone view, etc.) by CiteSpace 5.6. R4(64-bit).

- (1) First, we conducted a keyword co-occurrence analysis as follows: using the remove duplicates (WOS) function of CiteSpace to remove duplicates, we merged words with similar meanings and deleted meaningless words to generate a word cloud image (keyword co-occurrence network map). The size of the word indicates the frequency of the keyword, the larger the size of the keyword is, the more frequently the keyword appears.
- (2) Second, we generated a time zone map of keywords appearing in 248 articles, revealing the dynamic evolution of research hotspots.
- (3) Third, we conducted a co-citation analysis of references so that we could obtain landmark articles in the 248 articles, and could analyze the changes in research trends. If two articles (A and B) appear in the reference list of the third cited article (C) at the same time, the two documents constitute a cited relationship. If two articles (A and B) refer to the same article (C), there is a coupling relationship between the two articles (A and B).
- (4) Fourth, we generated a keyword burst map to find hot words that, in the field of flash flood research, use remote sensing. We define a keyword with sudden changes in frequency within a certain period of time as a burst word, which represents the hotspot of research in that stage.

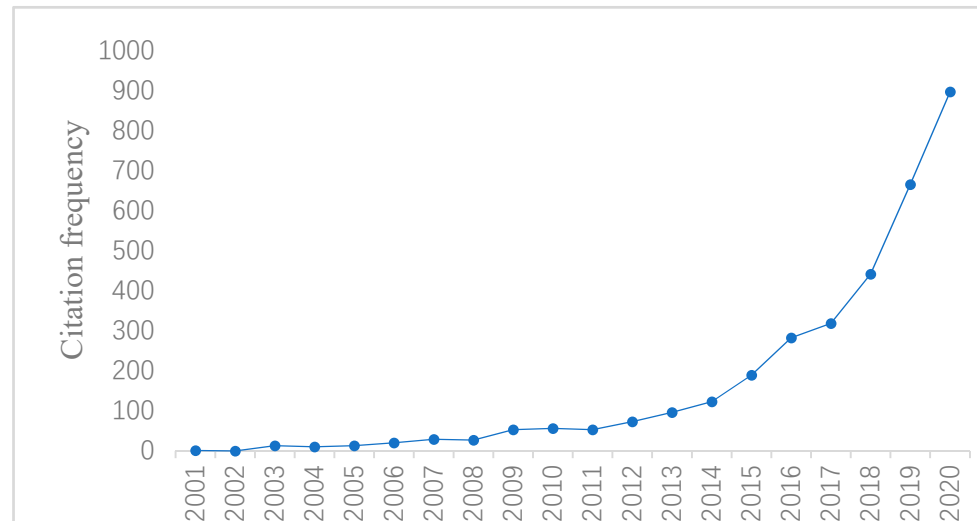
### 2.3. Explanation of Visual Map Icons in Maps

- (1) Tree ring history: this represents the citation history of an article, and the overall size of the annual ring reflects the number of times the paper has been cited. The color of the citation ring indicates the corresponding citation time. The thickness of an annual ring is proportional to the number of citations in the corresponding time zone.
- (2) Node circles: in the author's coauthored network and the institutional coauthored network, the size of the node circle represents the number of publications.
- (3) In the keyword co-occurrence network, the size of the node circle represents the frequency of keywords.
- (4) Connections between nodes: the connection between nodes indicates that they have a common copyright or have appeared at the same time, and the color of the connection indicates the time of the first cooperation or the first common appearance.
- (5) Node colors: in the keyword co-occurrence network, the colors of nodes indicate different years, the color in the center of the node represents the time when the keyword first appeared, and the thickness of the circle represents the frequency of the keyword in the corresponding year. The higher the frequency, the more often it appears.
- (6) Cluster#: in this paper, the clusters are based on the generated map, the keywords in the toolbar are clicked to cluster, and the clusters are marked by the keywords. The names of the clusters are #0, #1, #2...

### 3. Results

#### 3.1. Citation Frequency of Remote Sensing and GIS Applied to Flash Flood

From 2000 to 2020, the citation frequency of articles on remote sensing used in flash floods increased year by year. Therefore, interest in research hotspots related to flash floods using remote sensing is increasing year by year (Figure 1).



**Figure 1.** Trends in the citation frequency of the 248 included articles from 2000 to 2020.

Representative examples of highly cited articles: the 5 most cited articles from 248 articles are selected, listed in Table 1. These articles mainly involve rainfall estimation, methods of determining flood occurrence, and estimating the risk of flash floods.

The first three of these five highly cited articles are review articles. They are about radar rainfall estimation, flash flood warning systems, and flash flood forecasting modeling technology, which are all around the key issues of flash floods. The last two articles both researched a specific watershed in Egypt and used models to predict locations that are vulnerable to flash floods. The difference lies in the different models used by the two. The research of Youssef et al. [49] was conducted in a GIS environment. The amount of data is greater, the research scope is wider, and the parameters used are greater. The research of Foody et al. [50] has less data and fewer parameters, so the results obtained are less and simpler compared to Youssef's research.

The most cited articles are usually landmarks, they are groundbreaking or forward-looking. The study performed by Krajewski et al. [51] proposed some suggestions, including the establishment of long-term monitoring and verification stations to provide detailed information about precipitation, and believed that radar rain products have great development potential in flash flood forecasting. In recent years, radar has been widely used in precipitation estimation [7,51,52], confirming the prediction of Krajewski et al. [51] One of the scientific advances proposed by Borga et al. [53] is integrating multiple early warning methods, which has not been achieved until now. Whether the flash flood forecasting methods proposed in each research area can be realized in other areas still needs further discussion and verification [54]. For areas with similar topography, climate, soil, geology, land use, land cover, etc., it seems possible to use the same method for risk assessment [41]. Since cities have large impervious areas and a large population, once flash floods occur, they will cause many economic losses and casualties. Therefore, special attention should be given to flash flood forecasts in urban areas by Hapuarachchi et al. [7].

**Table 1.** Hot spot analysis of highly cited articles, classified from 248 articles using remote sensing to study flash floods.

Author	Cite Frequency	Title	Research Contents
Youssef, AM et al. [49]	177	Flash flood risk estimation along the St. Katherine road, southern Sinai, Egypt using GIS based morphometry and satellite imagery	The biggest influencing factors of flash flood disasters and key sensitive zones was discussed, and a detailed map of the most dangerous sub-basin was drawn.
Giles M. Foody et al. [50]	89	Predicting locations sensitive to flash flooding in an arid environment	The hydrological model was used to predict the location of sites that are particularly vulnerable to the threat of flooding, and peak flow was proven.
W.F. Krajewski et al. [51]	344	Radar hydrology: rainfall estimation	The problems of radar rainfall product development and the framework of rainfall estimation based on reflectivity were discussed, and the theoretical and practical requirements of radar rainfall maps and new radar technology were verified.
Marco Borga et al. [53]	192	Hydrogeomorphic response to extreme rainfall in headwater systems: flash floods and debris flows	The latest research on flash floods and debris flows was comprehensively summarized, and the progress in three areas that will produce important results were proposed.
H. A. P. Hapuarachchi et al. [7]	178	A review of advances in flash flood forecasting	The new modeling techniques and data used in flash flood forecasting from 2000 to 2010 were introduced.

In Youssef's research [49], GIS software was used to process remote sensing data, as well as to address terrain and field data to assess the risk of flash floods. Morphometrics were used to estimate the risk level of flash floods in the research basin. In subsequent research, there were a large number of articles that referred to the method in this article for the evaluation of flash flood hazards [1,41,55,56].

The research of Foody was published in 2004 [50]. The study used hydrological models to predict locations that are particularly vulnerable to flash floods under limited data conditions. This result has promoted the development of related fields and has guiding significance for subsequent research on the use of hydrological models to forecast flash floods [25,57–60].

### 3.2. Keyword Co-Occurrence

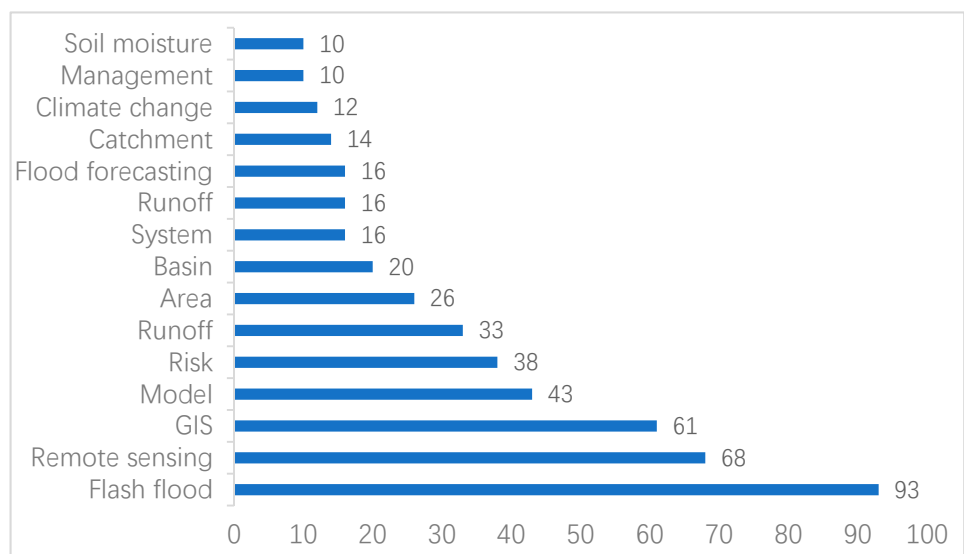
CiteSpace software was used to analyze the 248 selected articles, the software's own remove duplicates (WOS) function was used to remove duplicates; one was selected for time slicing, the keyword node type was used, and pathfinder and pruning sliced were selected for the pruning option to improve the network readability networks. After merging words with the same meaning and deleting meaningless words, keywords with a frequency of more than five times are retained, and a keyword co-occurrence map was generated, as shown in Figure 2. The list of the frequency of keywords that appear more than 10 times is shown in Figure 3.

In Figure 2, the larger the word, the more frequently it appears. In Figure 2, it can be seen that, in addition to remote sensing and flash floods, the size of GIS, model, rainfall, risk, and other words is larger. The GIS is a method discovered by Correia et al. [61] that can be used to integrate and investigate information about flood disasters and is widely used to reproduce the research results of different cases. This is not surprising. As the tool most frequently used in the research of flash floods using remote sensing data is GIS, GIS can provide powerful tools for risk assessment and can integrate a variety of remote sensing data in the GIS environment. To forecast flash floods and evaluate the risk

value of flash flood disasters, a variety of models are generated and frequently used. It is worth noting that, because the digital elevation model (DEM) can be used for hydrological analysis such as rainfall analysis, inundation analysis, and water system network analysis, the DEM is the most important factor in the hydrological model used to draw the flash flood disaster index of the study area [62]. The susceptibility of hydraulic modeling results was influenced by DEM accuracy [63]. DEM is often used in the study of flash floods [64].

evolution vulnerability sentinel-1  
 river hydrology city morphometric analysis  
 runoff basin egypt flood forecasting  
 model gis area system  
 simulation dem risk flash flood soil moisture uncertainty  
 rainfall remote sensing  
 catchment climate change  
 management scale landslide resolution  
 classification cloudburst radar impact

**Figure 2.** The keyword co-occurrence map.



**Figure 3.** Keywords with more than 10 occurrences in 248 articles.

The most commonly used remote sensing data are Sentinel-1 and radar. People are paying more attention to flash floods in Egypt. Risk appears more frequently, indicating that there are more articles on the evaluation of the risk value of flash floods, indicating that more people are concerned about where flash floods may occur in order to take preventive measures in advance.

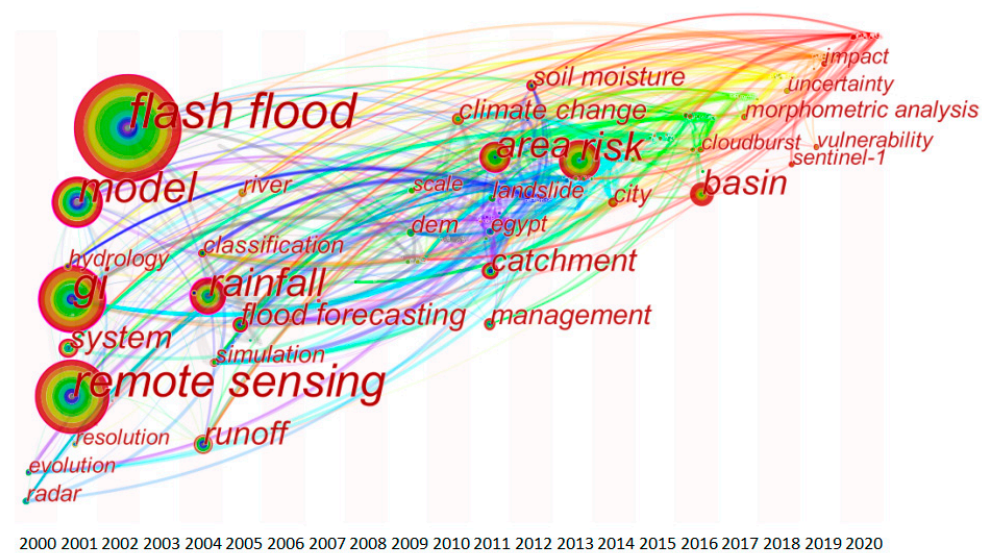
### 3.3. A Time Zone Map of Keywords

To further explore the dynamic evolution of flash flood research hotspots using remote sensing from 2000 to 2020, and to understand the key points of international research in different periods based on the generated keyword co-occurrence map, we use CiteSpace software and select “Time Zone View” in “Layout” to generate a keyword time zone map, as shown in Figure 4. (Selected keywords that appear more than five times are displayed in the figure).



The abscissa corresponding to the keyword in the figure indicates the year when it first appeared. The node colors of red, orange, yellow, green, blue, and purple are 2000 to 2020. The color of the line between the nodes indicates the year when the two keywords first appeared at the same time. Similar to the color of the node, the line colors of red, orange, yellow, green, blue, and purple correspond to the years 2000 to 2020.

From Figure 4, we can see that, in the study of flash floods using remote sensing, radar data have been used in the study of flash floods in 2000 or even before 2000, and since 2018, Sentinel-1 has been frequently used in research, the cumulative number of Sentinel-1 appearing in the article has reached six times in just three years. The images collected by Sentinel-1 can be used to obtain high-resolution images, regardless of weather conditions, so that they can be used to monitor floods. The synthetic aperture radar (SAR) data were collected from the Sentinel-1 sensor. Using SAR images, it can be used to distinguish water from other objects. Therefore, Sentinel-1 has often been used in the research of flash floods in recent years [65–68].



**Figure 4.** A time zone map of keywords.

The appearance of keywords in the picture can be roughly divided into five stages. The first stage was from 2000 to 2005. Keywords such as GIS, model, rainfall, runoff, etc. that appeared in this stage are still hotspots of current research. GIS as a research tool is effective and reliable. Research using models is also a common method. Among the factors that cause flash floods, rainfall is the most common cause of flash floods and has been studied the most. Soil erosion caused by flash floods has always been a concern. The second stage is from 2006 to 2009. During this stage, few new research hotspots appeared, and the research hotspots were mainly focused on the previous stage. The third stage is from 2010 to 2013. In this stage, climate change, risk, catchment, Egypt, etc. have become new research hotspots. People are beginning to pay attention to the increasing frequency of flash floods due to the frequent occurrence of extreme weather such as climate change and heavy rains [69,70]. Egypt is a typical area suffering from severe flash floods [71–74], this result is the same as Figure 2, but since 2010, the use of remote sensing to study flash floods has become popular. The fourth stage is from 2014 to 2015. There are few hot words in this stage, and the research hotspots are still based on previous research hotspots. In the fifth stage, from 2016 to 2019, research on basins increased, and the use of morphometric analysis and Sentinel-1 greatly promoted research on flash floods [65–68,75–77].

### 3.4. A Map of Burst Keywords from 248 Articles

Figure 5 lists the five keywords with the highest emergence intensity. From the figure, we can see that there was no keyword emergence before 2011, which means that before 2011, there were no issues that received more attention in the research on flash floods using remote sensing data. Egypt has the longest burst time. The increase in research on Egypt from 2011 to 2015 shows that there were more flash flood disasters in Egypt, and many places were affected by flash floods. The keyword with the strongest burst intensity is basin. The emergence time is 2017, and the stop time is 2020. This shows that since 2017, people's attention to the basin has increased. The burst time closest to the current burst keyword is uncertainty. The existing hydrological forecast chain is affected by many uncertain factors [78]. In recent years, with the continuous development of remote sensing technology, the pursuit of nearly real-time accurate simulation is about to become a global standard to ensure improved flash flood forecast and warning systems and ensure that models can be used in more areas and reduce the uncertainty of the model's output value. N. S. Bartsotas, Rouya Hdeib, and Hossein Mojaddadi Rizeei reduced the error of satellite precipitation estimation by optimizing algorithms and calibrating models [79–81].

### Top 5 Keywords with the Strongest Citation Bursts

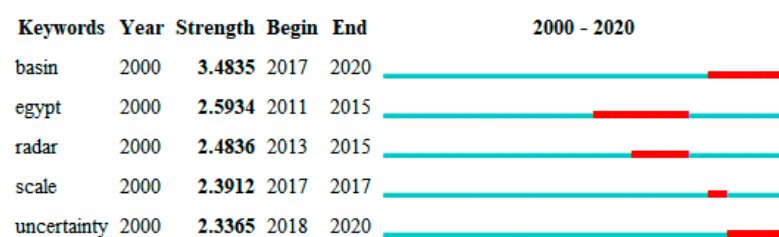


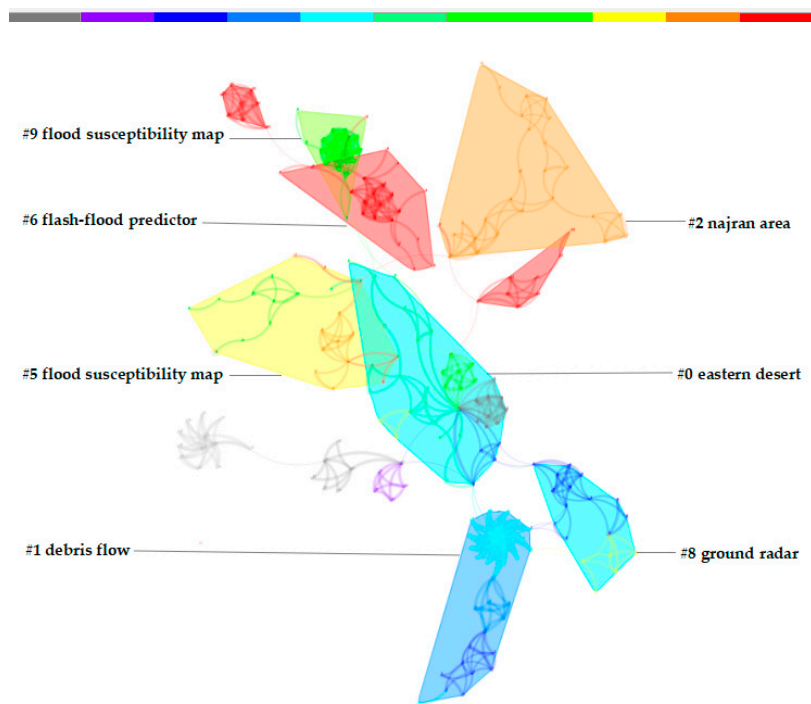
Figure 5. Keywords with the strongest citation bursts in 248 articles.

### 3.5. Co-cited Results of Cited References

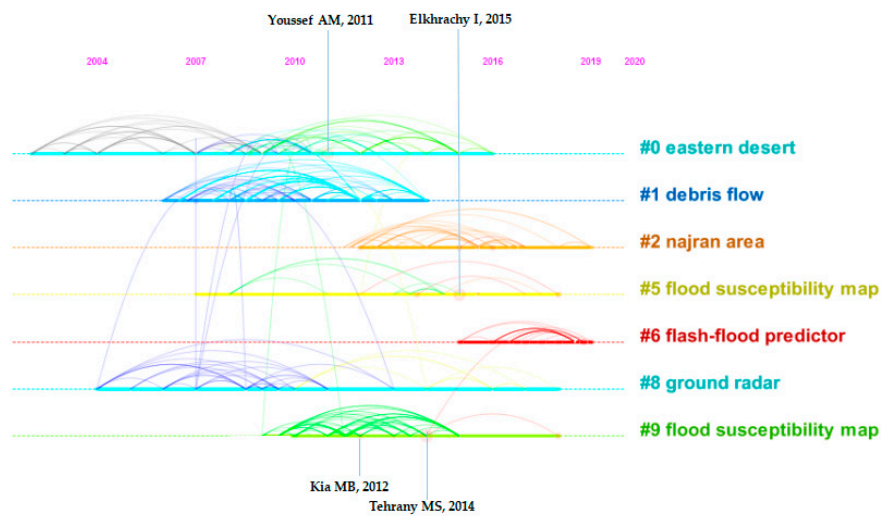
Clustering analysis of the cited references of 248 articles published from 2000 to 2020, the results can be divided into 8 clusters, using A (Abstract) to extract nominal terms to name the clusters. The results are shown in Figure 6: #0 eastern desert, #1 debris flow, #2 Najran area, #5 flood susceptibility map, #6 flash-flood predictor, #8 ground radar, and #9 flood susceptibility map.

The color of each cluster block represents the year when the co-citation relationship first appeared in each cluster. The colors of cluster blocks range from gray to purple, blue, green, yellow, and red, representing the years from 2000 to 2020. The color of each cluster block indicates the year when the co-citation relationship first appeared in each cluster. The connecting line between the nodes indicates the path of the reference. The connecting lines between the nodes indicate the path being cited, and the color of each line indicates the time when it was first cited. A few references are highly co-cited, so here, we set a threshold to show them.

The timeline map reveals changes in reference co-citations over time. According to the generated cluster diagram (Figure 6), a timeline map of cited references can be generated by the layout function. The Y-axis is defined as the cluster name defined by A (Abstract), and the X-axis is defined as the year of publication. The timeline chart shows the time span and research progress of the development and evolution of the eight clusters, as shown in Figure 7.



**Figure 6.** Reference co-citation network for the 248 included articles (clustered according to index terms).



**Figure 7.** Timeline view of the citation trends identified in the 248 included articles.

In the timeline view, the references of the same cluster are placed on the same horizontal line. In the timeline view, the number of references in each cluster can be clearly seen. More references in the cluster representing the cluster are more important. The cluster labelling on the right shows the research hotspot category associated with each reference.

The circle in the figure represents the circle of the citation directory tree, the color at the center of the circle represents the year of the reference publication (the color corresponds to the year at the top of the view in the figure), and the size of the circle represents the frequency of citations. The cluster label name on the right indicates the research hotspot category related to the references in the cluster. Gray represents the earlier publication year, and red represents the most recent publication year. The longer color line segment indicates that the citation has a large time span, and its research hotspot is the subject that people have paid attention to for a long time. The red color at the outermost layer of the



node's annual ring indicates that the citation frequency has increased rapidly or continues to increase rapidly.

Figure 7 shows four highly cited landmark articles, which are authoritative studies in the corresponding clusters. Research on the eastern desert took a long time, and a landmark article appeared in this cluster: Youssef et al. [49], which has been introduced before.

Elkhrachy et al. [1] were co-cited 14 times (Figure 8a,b), which is the most co-cited article among 248 articles. Tehrany et al. [80] were co-cited 10 times (Figure 8c,d), which is the second most co-cited article among 248 articles. Masoud Bakhtyari Kia et al. were co-cited six times (Figure 8e,f), and they are very representative articles in the field of flood susceptibility maps. Elkhrachy et al. [1] provided an accurate assessment by using SPOT and SRTM DEMs data. The analytical hierarchical process (AHP) was used to determine the relative impact weight of flash flood causative factors to obtain the composite flood hazard index (FHI). Finally, all the used data were integrated into ArcMap to generate the final flood disaster map of the study area. In previous studies, researchers have proposed many methods to perform flood susceptibility mapping, but these methods have certain shortcomings. To find a more accurate method, Tehrany et al. [80] proposed a new integration method that combines weights-of-evidence (WoE) and the support vector machine (SVM) model, not only solving the shortcomings of WoE but also enhancing the performance of SVM. The results are compared with the results obtained by using WoE and SVM alone, and the results obtained through integration are more ideal. Kia et al. [64] used artificial neural network (ANN) technology, which is one of the machine learning methods, to develop a flood model using various flood causative factors (including slope, flow accumulation, rainfall, soil, elevation, geology, and land use) to model and simulate flood-prone areas in the southern part of peninsular Malaysia. The ANN is more robust than other statistical and deterministic methods and has high computational efficiency. However, when using ANN modeling, there may be disadvantages such as errors caused by the length of the dataset.

Figure 8a,c,e are the pennant diagrams of Elkhrachy et al. [1], Tehrany et al. [80], and Kia et al. [64], respectively, which can be used to view the information for the references directly connected to a node. These figures show the distribution of articles that have a citation relationship with these articles. The closer the position of the reference article is to the bottom, the more times it has been cited. Figure 8b,d,f show the time trends, respectively, and show the number of times that Elkhrachy et al. [1], Tehrany et al. [80], and Kia et al. [64] were co-cited.

Combining Figures 7 and 8, we can see that Elkhrachy et al. [1], Tehrany et al. [80], and Kia et al. [64] were cited twice in 2016, and then, in 2019–2020, the number of citations increased suddenly, indicating that in 2016 and from 2019 to 2020, the research on flood susceptibility maps was relatively concentrated.



#### 4.1. Flash Flood Forecasting

Since a flash flood may occur suddenly and the time to reach the peak is short, the accuracy of any early warning of flash floods depends largely on the accuracy of precipitation monitoring and prediction [14,64].

Accurate and timely measurement of the temporal and spatial distribution of rainfall is the starting point for flash flood forecasting [64]. Due to the wide coverage of satellites, satellite data are regarded as an important data source for areas with sparse and uneven distributions of measurement stations. Satellite data have been widely used in meteorological research, and the ability to estimate rainfall directly affects the ability to observe flash flood time. Table 2 lists six representative studies on the evaluation of satellite precipitation products in recent years. These studies combined multiple precipitation products and evaluated them with multiple statistical indicators, abundant precipitation products, and relatively rich types of research areas covered.

**Table 2.** For evaluating satellite precipitation products.

Study	Product Name	Study Area
Haonan Chen et al. [17]	Quantitative precipitation estimation (QPE), National Weather Service (NWS) single-polarization rainfall product, NWS dual-polarization rainfall products	America
N. S. Bartsotas et al. [79]	GSMaP (v.7), Climate Prediction Center morphing method (CMORPH)	Ethiopia and Italy
Mohamed Salem Nashwan et al. [81]	Global Satellite Mapping of Precipitation (GSMaP (v. 6)), Tropical applications of meteorology using satellite data and ground-based observations (TAMSAT (v. 3)), Precipitation estimation from remotely sensed information using artificial neural networks-cloud classification system (PERSIANN-CCS)	Egypt
Mengye Chen et al. [82]	Multi-radar multi-sensor system (MRMS), Global Precipitation Measurement Mission (GPM), National Centers for Environmental Prediction (NCEP)	America
Vincenzo Levizzani et al. [83]	Advanced microwave humidity sounder-unit B (AMSU-B) onboard the National Oceanic Microwave Humidity Sounder (MHS) on board the EUMETSAT Metop-A satellite and Atmospheric Administration (NOAA) polar satellites	The Island of Madeira
Ali Behrangi et al. [84]	Rain estimation using forward adjusted-advection of microwave estimates (REFAME), REFAMEgeo, PERSIANN, PERSIANN-CCS	America

The performance of precipitation products was evaluated for arid areas, mountain areas, and urban areas [17,79,81]. Satellite precipitation products can accurately detect and estimate extreme precipitation events. There are some uncertainties in the results obtained by using satellite precipitation products [82,83]. On the one hand, the algorithm can be optimized, and the inherent deviations in the precipitation calculation can be corrected to reduce the uncertainty. On the other hand, the integration of high-resolution and multisource precipitation analysis can be considered to compensate for the deficiency of a single precipitation product [85].

#### 4.2. Impact of Flash Flood Assessment

The analysis of the disaster area after the occurrence of flash floods can better provide suggestions for regional development, flood prevention, and disaster reduction [33,86]. Table 3 lists four representative studies about the impact of flash flood assessment, which describe the impact of flash floods in terms of vegetation, agricultural products, topographic changes, and land cover.

**Table 3.** For impact of flash floods.

Study	Analytical Method	Factors
Mohammed Sadek et al. [22]	Sentinel-1 and Sentinel-2 satellite data, geolocated terrestrial photos and GIS technology, and hydrologic and hydraulic modeling were integrated to evaluate the impact of flash floods.	Catchment slope, relief ratio, drainage density, basin ruggedness number, land cover types
Bilal Ahmad Munir et al. [23]	The hydrological engineering center river analysis system (HEC-RAS) 2D hydraulic modeling was used to analyses the impact of flash floods in downstream Piedmont plains. Personal computer storm water management model PCSWMM (hydrologic) and HEC-RAS 5.x (hydraulic) models were integrated to monitor the flash flood.	Rainfall, peak events discharge, land use, land cover, soil, curve number, runoff, water surface elevation, sub-catchment width, slope, water depth, dry time, lag time, storm duration
Takahiro Sayama et al. [24]	The backpack-mounted mobile mapping system (MMS) was used to investigate and estimate landform changes.	Ground elevation, inundation depths, ground height, inundation level, latitude, sediment, rainfall
Joan Estrany et al. [33]	The meteorological, hydrological, geomorphological, damage, and risk data analyses were integrated to damage assessment based on field-based remote sensing and modeling.	Rainfall, runoff, slope, land use/cover, soil type

It can be concluded from Table 3 that hydrologic and hydraulic modeling are commonly used methods to study the effects of flash floods. Modern remote sensing technology can already use spaceborne imageries, airborne imageries, and unmanned aerial vehicle (UAV) systems to quickly and accurately map during or after a flood event. Free satellite data (Sentinel-2 images) were used to determine the impact of flash floods on Ras Ghareb city and the Wadi El-Natryn region in Egypt [22,40]. Landsat-8 and MODIS data were used to describe the impact of flash floods on rice [87,88], Landsat TM data were used to map the extent of coastal floodplain flooding [89], and multispectral Ikonos data were applied to a land use/land cover classification [90], all of which are useful for assessing the impact of flash floods. The combination of UAV data and field surveys can be used as observational data in conjunction with hydraulic models, which greatly promotes the understanding of the mechanism of flash floods [91]. Different from other studies, the backpack type MMS has been proven to be used for post-flood surveys and can ideally reproduce the flooding situation in mountainous areas [24].

#### 4.3. Identification of Flash Flood Hazard Areas

Typically, due to the remote location of the flash flood area and the harsh weather, it is difficult to arrive at the scene to analyze the behavior of mountain torrents. In GIS environments, the most commonly used method involves drawing hazard maps of flash floods using hydrological and hydrodynamic models [30–33]. Table 4 lists five articles that use hydrological models or hydraulic models to map flash flood hazards.

**Table 4.** For identification of flash flood hazard areas.

Study	Analytical Method	Factors
Aneesha Satya Bandi et al. [30]	The multiple-criteria decision-making tools were used to generate the composite flood hazard index (FHI).	Runoff, type of soil, slope percentage, surface roughness, flow accumulation, distance to main channel in the stream network, land use
Jehan Mashaly et al. [34]	The hydrological model and the fused ASTER multispectral and ALOS-PALSAR synthetic aperture radar (SAR) data were combined to predict flash flood hazard.	Surface topology variables, land use, land cover data, soil texture properties, curve number, lithology, ground surface type
Hossein Mojaddadi Rizeei et al. [35]	A 2D high-resolution sub-grid model was performed to simulate FF probability and hazard. GIS and physics-based random forest (RF) models optimized by particle swarm optimization algorithm (PSO-RF) were used to model pluvial flash flood (PFF) hazard.	Curvature, SPI, TRI, TWI, DSM, surface slope, surface runoff, maximum precipitation intensity, LULC
Mohamed Saber et al. [58]	A physics-based distributed hydrological model for flash floods simulation was proposed.	Rainfall, land use, soil types, topography, storage amount, inflow, outflow, curve number, depth of rainfall, depth of runoff, excess rainfall
Eman Ghoneim et al. [92]	The hydrological response of the study basin to a rainfall event was explored, and the hydrological model approach was used to predict flash flood hazard in the research area.	Soil texture, curve number, channel slope, longest flow path, lag time for each sub-watershed, rainfall

Hydrological models can be used to predict the spatial ranges, depths, and speeds of flash flood disasters to determine the areas with high flash flood risks [34]. Two-dimensional hydrodynamic models are considered to be the most promising model for accurate flash flood mapping [35], but such models usually require large amounts of input data. The AHP and soil conservation service curve number (CN) methods are commonly used methods for drawing flash flood hazard maps. The AHP is used to assign grades and weights and is usually used to assign weights to the causes of mountain torrents in the study of flash flood hazards [1,53,93]. The SCS model is commonly used in distributed hydrological models and research in arid and semiarid regions, which is a method developed by the U.S. Department of Agriculture (USDA) to estimate runoff and peak discharge [94]. According to specific circumstances, the hazard factors of flash floods selected by researchers are not exactly the same, but many hazard factors are recognized as necessary.

#### 4.4. Flash Flood Susceptibility Assessment

Identifying areas susceptible to flash floods is one of the most effective measures to reduce losses caused by floods and achieve flood management [95,96]. For large-scale flash flood susceptibility analysis, machine learning methods, bivariate statistics, and multicriteria decision-making methods are mainly used [97]. The machine learning method is considered to be the most advanced and first considered method [36]. Table 5 lists four representative studies that use machine learning methods, bivariate statistics, and multicriteria decision-making methods to map susceptibility to flash floods.



**Table 5.** For susceptibility mapping of flash flood.

Study	Analytical Method	Factors
Romulus Costache et al. [36]	The K-nearest neighbor (kNN) and K-star (KS) stand-alone models and kNN–AHP and KS–AHP ensemble models were used to define and calculate FFPI (flash flood potential index) in flash flood susceptibility mapping.	Slope, angle, TPI, TWI, curve number, lithology, profile curvature, plan curvature, convergence index, modified Fourier index
Viet-Nghia Nguyen et al. [37]	The chi-square automatic interaction detector (CHAID) random subspace, optimized by biogeography-based optimization (the CHAID-RS-BBO model) was proposed for the spatial prediction of flash floods.	Land use, land cover, soil type, lithology, river density, rainfall, topographic wetness index (TWI), elevation, slope, curvature, aspect
Khosravi, Khabat et al. [39].	Three multi-standard decision analysis techniques (vlse kriterijuska optimizacija i komoromisno resenje (VIKOR), technique for order preference by similarity to ideal solution (TOPSIS), and simple additive weighting (SAW)), and two machine learning methods (naïve Bayes trees (NBT) and naïve Bayes (NB) were tested for their ability to model flash flood susceptibility.	NDVI, lithology, land use, distance from river, curvature, altitude, stream transport index (STI), (TWI), SPI, soil type, slope, rainfall
Quang-Thanh Bui et al. [98]	A hybrid model for susceptibility mapping that combines swarm intelligence algorithms and deep learning neural networks was proposed.	Aspect, slope, curvature, TWI, stream power index (SPI), distance to river, river density, NDVI, NDBI, rainfall

From Table 5, the conclusion that the flash flood susceptibility mapping technologies rely on various adjustment factors representing the physical characteristics of the study area can be obtained. The choice of conditional factors depends on the scale of the studied area because it is more difficult to obtain data of the same scale or the same resolution. Therefore, if the study area is larger, the number of factors selected may be smaller, which seems reasonable. Researchers should select factors for research based on actual conditions. Of course, using more extensive data and impact factors can more accurately define the flash flood susceptibility of the study area [99,100]. Land use, slope, rainfall, TWI, and distance to the river are the most commonly considered factors. Logistic regression, bivariate statistical analysis, and AHP are the most commonly used methods to calculate factor weights. The combination of AHP and GIS can also define the flash flood susceptibility zones. The machine learning method is considered to be the most advanced and first considered method [101]. The effect of the mixed model is better than that of the single model, as proven by a large number of examples. The K-nearest neighbor (kNN) and K-star (KS) stand-alone models and kNN–AHP and KS–AHP ensemble models were used to define and calculate the FFPI (flash flood potential index) in flash flood susceptibility mapping. The Bayesian belief network (BBN) model was combined with an extreme learning machine (ELM) and back propagation (BP) structure to develop a new ensemble learning model for predicting flash flood susceptibility [102]. This fact has also been emphasized by Wang et al. [3].

#### 4.5. Flash Flood Risk Assessment

The risk proposed by the United Nations refers to the expected loss of people's lives, property, and economic activities caused by a specific natural disaster in a certain area and a given time period [103]. Therefore, the flash flood risk analysis is obtained by combining hazard analysis and vulnerability analysis. Different from flash flood susceptibility analysis and flash flood disaster analysis, some flash flood risk analyses considered the factors of city and climate change [41–43]. The different geomorphic processes and hydraulic behaviors of the watershed are controlled by its morphometric characteristics [49]. Therefore, morphometric analyses are frequently used in flash flood risk analysis [31,44,45]. Table 6 summarizes the representative literature on flash flood risk assessment in terms of analytical methods and factors.

**Table 6.** For flash flood risk assessment.

Study	Analytical Method	Factors
Ahmed M. Youssef et al. [43]	The flash flood risk map was generated using GIS based morphometry and satellite data.	Area, total stream number, total stream length, elongation ratio, circulation ratio, shape factor, slope degree, length of over land flow, ruggedness degree, relief ratio, drainage density, drainage frequency, total drainage number
Shuvasish Karmokar et al. [41]	The flash flood risk map was achieved by the susceptibility map obtained by analyzing three satellite images in a GIS environment and using morphometric parameters to assign the relative susceptibility of flash floods.	Topography, climatological, soil, geological, hydrology, land use and land cover, digitized drainage network, rainfall, geomorphological map
Ram Nagesh Prasad et al. [104]	The flash flood risk map was generated by using the weighted sum analysis (WSA) model results and Snyder synthetic hydrological parameters.	Basin perimeter, basin length, stream order, stream length, area, drainage density, stream frequency, elongation ratio, circularity ratio, form factor, shape, basin relief, relief ratio
Sara Abuzied et al. [45]	The Soil Conservation Service (SCS) rainfall-runoff model was used to estimate the hydrological response of the catchments, and all risk factors were spatially integrated; the morphometric and SCS analyses were integrated to create the risk map.	Basin dimensions, basin shape, basin surface, drainage network

## 5. Discussion

In the past 20 years, the application of remote sensing and GIS technology in flash flood research has made great progress, mainly reflected in the increasingly abundant multisource remote sensing data sources, GIS strong spatial analysis ability, and coupling ability with hydrological and hydrodynamic models. However, the uncertainty of the data and model is still a huge challenge for future research. How to obtain real-time or quasi-real-time accurate simulations and reduce the uncertainty of data input (such as precipitation, land use, evaluation unit division, etc.) and model output is the goal of future research. To date, in many areas, through remote sensing data sources, GIS, and hydrological coupling models, a large number of studies and analyses have been carried out on flash flood susceptibility analysis, flash flood disaster impact assessment, and flash flood hazard identification. Most of the experimental results show that the established or improved model is effective for the experimental area, but as to whether the model can be applied in other areas, the universality of the model needs further verification.

For flash flood forecasting, with the development of meteorological satellite technology and radar-based rainfall forecast technology, more accurate and real-time precipitation data can be used in flash flood forecasting, and after precipitation data from multiple sources are acquired, the precipitation data can be corrected via the correction model.

For the impact of flash flood disaster assessment, with the development of data association analysis and multimodel coupling technology, the impact of flash floods on the regional ecology and environment can be rapidly and quantitatively assessed.

For flash flood susceptibility assessment, at present, most of the susceptibility zoning maps belong to static mapping and cannot show the inundation depth and advance speed. Future studies should combine machine learning with the hydrodynamic model to complete the dynamic susceptibility mapping of flash flood disasters. Then, a 2D model will be researched and developed to obtain the inundation depth and advance speed.

For flash flood risk assessment and hazard area identification, mapping flash flood disaster maps and flash flood risk maps relies on various adjustment factors that represent the physical characteristics of the study area. Due to the influence of data precision, data volume, size of the study area, and the authors' subjective choices, there are some

differences among the adjustment factors selected in these papers, and the weights of the adjustment factors are not always the same. Even in regions with similar geological conditions, whether the adjustment factors selected in other areas can be used and their weights need to be further discussed and verified. It is hoped that there will be a set of systematic rules in the future so that adjustment factors and corresponding weights can be selected for regions with different sizes and different physical characteristics, according to their conditions, to obtain better results.

## 6. Conclusions

In this study, the related literature on remote sensing and GIS applied in the field of flash flood disasters was systematically analyzed. Then, a visualization analysis of the literature was adopted to perform keyword co-occurrence analysis, time zone chart analysis, keyword burst analysis, and literature co-citation analysis. Finally, several main subfields of the application of remote sensing and GIS in flash floods were summarized, including flash flood forecasting, the impact of flash flood assessment, flash flood susceptibility assessment, flash flood risk assessment, and the identification of flash flood hazard areas, which makes our study different from the previous review of remote sensing and geographical information application to natural disasters. The main conclusions are as follows: (1) through the analysis of the time zone map, the appearance of keywords can be roughly divided into five stages. (2) Analyzing the burst of keywords in 248 articles, we found that current research focuses on reducing uncertainty, and reducing the uncertainty of flash flood forecasting is the basis for real-time accurate simulation. (3) Through the co-cited analysis of 248 articles, 7 clusters were obtained. Among them, there were three highly co-cited articles from 2012 to 2015, which are landmark studies. Therefore, from this review, various applications of remote sensing and GIS in the field of flash floods and specific opportunities and challenges in different fields can be found.

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