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# REVIEW-EFFECT OF FLASH FLOOD

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*Abstract*— **Flash flood assessment by using physiographic features, flooded areas effect can be seen quickly by satellite imagery data. Radar and microwave data is improved to an extent that it can process images even on cloudy days. Aster digital elevation model data is preferred by most of authors to extract DEM from satellite data. Individual data used in evaluation of flood flow for future safety planning and to take precautions to reduce risk damage. These criteria used for identifying areas effected by flash floods.**

*Keywords*— **Flash flood, Satellite imagery, Microwave data, Aster digital elevation model.**

## I. INTRODUCTION

Natural overflow [43] of rivers is called floods, is a devastating natural hazard endangering lives and damaging agriculture [22], roads, and cities. Flood Urban development networks are low profile in drainage [24] management. Interception reduces flow along with runoff [4]. Unwarned disasters are predominant, like floods [6] now and then. The socio-economic activity's undertaken to minimize risks. Strict movement conservation is a cause of flood in low-lying areas [25].

Urban areas give no evaporation [1-4] change of slope, and infiltration. Floods come under both natural and unnatural. The property and wellbeing of people are affected by these unwanted vast spreading floods [29]. These may be triggered by age of construction because of defaults like storage capacity, leaks, and silt conditions [14]. Silting well and stream gauges used to find flood depth [5] along river basin near livelihood.

Snow thaw, heavy rainfall causes heavy flash floods which accumulate more water in less duration with the capacity to move heavy objects. Strong winds, heavy waves in coastal areas breach coast dike called coastal floods. Overflow of rivers causes river floods. Nowadays urban and sewage floods are more frequent in zone four. If urban drainage cannot absorb heavy rainwater with a lack of natural drainage causes urban flooding. Puddles and ponds are formed in flat rural areas where terrain can't absorb water, which is called pluvial flooding.

This risk assessment indulges several other measurements. Hydrological modeling [30] using weather data is a primary key. Statistical parameters like forecasting rainfall, soil data [27], real-time slope, types of usages on land play a key role in this research. The insurance sector deals with affects through risk portfolio [18]. Organizations monitor the effects daily to alert, monitor flood Ground truth data.

Flood prevention measures are creating sponge cities to drain water naturally by employing urban farms [23], recharging groundwater, and reusing wastewater. It reduces sewer overflow runoff [8] rates and neutralizes acid effects in rainwater. Create flood plains in heavy urban flooded areas so its overflow concentration diverts to rivers or flood plains [22]. Separating storm water and sewage water helps in effective treatment planning.

Water infiltration devices, grid chambers, drainage chambers, pits, with high porous soil to allow penetration of storm water to reduce runoff alternatively increasing groundwater recharge. Pervious roads, with high organic soil fill lands, reduce runoff [35]. Dredging, flood barriers, trees, better drainage, Embankments, pits, detention tank, diversion canals, check dams to control the flow of running water.

Unpredictable floods are checked by meteorologists and are common, particullary in low-lying areas [12]. Future flood estimations are important, especially in urban zones with low drainage facilities [38] causing urban floods. Most of the deaths reflect unpreparedness in these timings. Rainfall intensities influence flood damages on public property [20].

Prioritizing resources based on strategic decision-making. Through a series of analyses, experts analyzed it is better to stick to natural indicators rather than social information to weigh hazard and vulnerability for risk assessments [25].

Various tools have been developed for vulnerability assessments. Collecting, customizing, mapping, correcting, and selecting data from various resources is an important step. Decision making by professional in the selection of tools, practical recommendations, design to involve. In the social flood vulnerability index [1] relying on public opinion by their experience is unsure, nontechnical for research.

## II. LITERATURE SURVEY

J. C. J. H. Aerts et al. 2018, used an agent-based model to integrate flood areas. Human behavior in limited terms, potent mannerism in short time interval to planning strategies is key roles. Limited to human perception did not include any practical results. This data used for preliminary research to identify risk zones.

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Lyu. H. M. et al. 2019, included four approaches they are statistical, multi-criteria, analysis with geographical information system, and scenario base. They used regionally to local, qualification to quantification with global positioning for locating position and build information method a piece of advance information giving device. Changpan station, Wuhan station flood prevention measures are designed qualitatively, first by assessing flood level. Fuzzy AHP used for identifying high flood risk levels. The major drawback in his research is neglecting backfill material or external pressures around tunnels during floods.

Miau. et al. 2020, did flood by comparing change in water table in time series using CNN, ANN, LSTM with the same benchmark while ANN had less error compared to the other two. Information of upstream and downstream with change in water line in a duration of time is taken. LSTM used for water level estimation by long-term dependence. CNN is used for accuracy and stable predictions as it recognizes similar patterns from old data. He compared all models of CNN, GRU, SEQ2SEQ, ANN (Meresa et al. 2019) , LSTM but combining GRU with CNN gave them accurate results further modeled on Gaussian distribution for anomalous detection. As a neural network does not need any pre-defined data, it can work on normal water level data, it is easy to handle. As CON-GRU is used in identifying variant object anomaly detection. Among all these methods GRU performed well, the accuracy was found using random mean square error, mean absolute error, mean absolute percentage error formulae.

Lim and lee et al. 2018, by using satellite-based knowledge got from inaccessible locations, researchers simulated flood damage in North Korea. For both, the delineation of flood inundated areas using visible Google Earth high-resolution imagery, expert-based multiple remote sensing, and geographic information approaches were chosen. The flood areas were discovered via Sentinel-1 radar images. The Geomorphon model simulates stream flows along with geomorphology. The study's individuality is reflected in this method range, which included several combinations of input parameters. Finally, the most robust model could identify flood areas, which matched the harm data in the Korean government's studies.

Liu et al. 2019, developed a flash flood risk model in China, which is prone to flooding. Flash floods, unlike normal floods, are extremely dangerous, making it difficult for people to leave their homes. A theory was established by using an artificial intelligence idea named the least squares to support vector machine classifier is using satellite-based meteorological, topographical, hydrological, and anthropological indices as input variables that affect flash floods. The least-square support vector machine with a kernel [25] had the best model output with regard to effectiveness. The curve number in the topographical factors, in particular, was perhaps most paramount to the flash risk of flooding model. In terms of effectiveness, the least square support vector with the kernel [15] generated that best model output.

Kim et al. 2019, Tropical cyclones are one of the most devastating natural calamities to human lives and damage to property. Several studies taken out to automate the process of assessing if a cyclone is forming. Using machine learning techniques, they implemented an automatic Cyclone initiation detection system and compared the solutions using metrics like heat rate, false alarm rate, Peirce ability score, and lead time. WinSAT data on sea surface wind and rainfall were used to create three machine learning-based models i.e., decision trees, random forest, fuzzy and support vector machine, and also a traditional model based on linear discriminant analysis. The models were tested utilizing data from Joint Typhoon Warning Center's best track, which included both developing and non-developing tropical disturbances. The feature sets showed that perhaps the machine learning models significantly improved than the weighted linear analysis model. Machine learning models, in particular, can spot cyclone initiation 26–30 hours until a cyclone was identified as a tropical depression, that was 5–9 hours ago then weighted linear model prediction.

Han et al. 2019, built machine learning algorithms to calculate total perceptible liquid from Himawari-8 data within sunny conditions, using the ERA-Interim total perceptible water as a reference for Northeast Asia. Cloud identification was performed using the radiative model. A critical feature in determining hydrological conditions is the total perceptible water, which is a line of gases in the atmosphere. This is also connected to catastrophe severity concerning convective potential energy. Random Forest, extreme gradient boosting, and deep neural networks all were evaluated and compared to machine learning methods. When evaluated with ERA-Interim and radiosonde observation results, the deep neural network result surpassed the other models. Total perceptible water obtained from satellite data with a 10 min period would help a disaster control system to deal with extreme floods and rains.

Washko et al. 2019, Using the extension of HEC HMS for ARCGIS software where geometrical values and flow path of river in Huroncreek watershed based on hundred-year flood data. HEC-HMS tool used to assign channel geometry before we draw a vector form of a watershed in ArcGIS. Data constructed in GIS is importable from HEC HMS. Vulnerable areas are identified and, flow is analyzed in HEC HMS. The flood depth is exported to the RAS mapper for a visual representation of flow in software. Risk measures belong to control flood risk zone areas along the river bed.

## III. CONCLUSION

It is very important to examine and predict effect of flood flow before it prevails. Even several flood assessments made, day-by-day floods are increasing due to anthropogenic activities as explained above in Literature review and tells clearly how to identify effect without being in field using models by using latest technology remote sensing and gis.

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