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# Exploring The Potential Of Latest Fused Techniques For Floodplain Inundation Mapping And Flood Risk Assessment

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***Abstract***
*The costs attributed to floodplain in urban areas are high and should be anticipated by experts to avoid these incidences. As cities grow, there is a constant pressure to develop land. Floodplains, unfortunately, are often seen as cheap and readily available space. This puts buildings and infrastructure directly in the path of floodwaters. When floods hit urban areas, the damage can be immense. Homes, businesses, and critical infrastructure can all be submerged, costing billions of dollars in repairs. Additionally, there are human costs: displacement, injuries, and even fatalities. Therefore, remote sensing (RS) tools offer valuable methodology to foresee the Floodplain Inundation areas in urban cities and can be utilized in mapping the risky areas that exposed to severe floods. Thereby is now imperative to investigate the possibilities of RS for flood mapping and how to develop an urban flood risk assessment using techniques based on RS. This research aims to find out the latest works in Floodplain Inundation Mapping and Flood Risk Assessment using RS tools. The review emphasized the importance of integrating more than tools to overcome the drawbacks and increase the accuracy of the flood monitoring that leads the decision-makers make a proper commitment to avoid the costs related to floods. The current research supports the precise tools to enhance devices' ability to absorb or predict the upcoming events in the future.*

***Keywords***
*Remote sensing, Flood Inundation, Risk Assessment, Digital Elevation Models, Hydraulic Modelling.*

## 1. INTRODUCTION

A warming atmosphere exhibits a heightened capacity for moisture retention, with an increase of approximately 7% per degree Celsius. This translates to more intense precipitation events during storms, overwhelming the infiltration capacity of the ground and leading to accelerated surface runoff and elevated flood risks [1]. Moreover, global warming is also accelerating through increased sea levels due to thermal expansion of seas, and melting of glaciers. This has a direct implication for coastal floodplains, where rising base levels compound flood impacts from storm surges [2]. Further, varying patterns of snowmelt as a result of warming temperatures make a further contribution to spring floods because of release of the snowmelt into the river beyond the carrying capacity [3]. Furthermore, reduced winter snowpack retention capacity also reduces river flows during summer low flows, while raising flood risk during later periods of the season when storms occur [4]. It is necessary to understand that all these climate driven changes are interrelated and mutually reinforcing. For instance, increased frequency of drought raises of drier soils, and therefore increased flood potential from excessive rainfalls [5]. An understanding of these multifaceted relations is crucial towards designing useful management strategies of flood plains in view of climate change. In the context of a shifting climate that is experiencing enhanced flood hazard [6], The potential of accurate mapping of floodplain inundation becomes seen as a key enabling factor towards proper assessment of flood risks and the development of suitable measures for management of the danger [7]. These maps give a spatial view of the areas vulnerable to flood under which scenario, this information plays an essential role in decision making for the stakeholders and policy makers. Floodplain inundation mapping is vital for refining flood hazard evaluations [8, 9], for optimal deployment of mitigation measures [10–13], in support of better land-use planning [14, 15], for better scheduling of emergency response [6], and, moreover, inundation maps benefit communities by raising their awareness of potential flood risks [16]. Azizian and Brocca [17] attempted to understand what kind of remotely sensed digital elevation model (DEM) was optimal for making flood inundation maps where data was limited. The paper looks at different remotely sensed DEMs of different altimeters ALOS, SRTM 90m and 30m, and ASTER 30m. Azizian and Brocca also established that, in constructing the geometric model and conducting the hydraulic simulation, DEM of SRTM 30 m was more effective than DEM of ASTER 30 m and DEM of SRTM 90 m when the two were compared for both the rivers. Unnithan et al. [18] developed a new technique In flood inundation mapping based on GNSS-R signals incorporated with topography data. It outlines a framework of how such data sources can be fused to enhance the fidelity and speed of the flood identification procedures and can be of interest in diverse disciplines that deal with environmental assessment and emergency preparedness. The author in [18] clearly highlighted that the integration of GNSS-R signals with topographical information for the flood inundation mapping has numerous strength and advantages such as real time, high spatial resolution, complementarity and added advantage of cost effective, However, this type of flood mapping also has some drawbacks, which includes limitation of GNSS-R signals may be restricted in the area with less satellite visibility or possible affected by the vegetation cover or man-made structures When using GNSS-R signals that provide information on soil moisture and dynamics of surface water, it is possible to obtain distorted results of flood inundation mapping due to several factors like signal attenuation, atmospheric conditions, and signal reflection with non-water objects. Munawar et al. [19] concentrated on the application of RS technologies to predict floods, with emphasis on pre-disaster stage. The authors also point out that prevention and feedback control as the key factors in the management of flood. The study categorizes three main RS techniques used for flood prediction, including multispectral imagery which Provides information about water bodies and land cover changes. While Radar offers high-resolution images for flood detection, even in bad weather conditions, Light Detection and Ranging (LiDAR) creates detailed elevation models useful for flood inundation mapping. The authors in [19] argued that recent advancements in Artificial Intelligence (AI) and image processing are improving flood risk mapping and prediction based on RS data.

The purpose of this research is to stress the necessity of fused RS data for the whole sight to achieve the optimum results of the accuracies to identify the flood inundation level. Drawing information from literature, the study describes numerous strategies for data collection to obtain a reliable estimate of flood threat in different parts of the world using different models. Further, the work elaborates the current forecast and future prospect of Floodplain Inundation Mapping accurately.

## 2. Floodplain Inundation Mapping Techniques

Hence, the floodplain inundation mapping is important for flood hazard analysis, flood management, planning, and evacuation operations [20]. While there are several methodologies for geospatial analysis which includes Hydraulic Modeling (HM), RS and DEMs, each is capable of different things [21-23]. It is agreed that comparative analysis of these techniques is highly important to consider the best method for a given region. This helps in achieving the most suitable data collection and analysis in regard to the specialty of the region under study.

### 2.1 Comparative Analysis

#### 2.1.1. Accuracy

In essence, precise floodplain mapping of inundation areas is relevant to public safety, save lives, avoid expenditures, and deliver sufficient enough approach to floods. [24,25]. RS accuracy depends on may factors, such as imagery resolution, spectral index selection, and cloud cover. RS accuracy goes down in a complex terrain or with obscured areas due to clouds [26]. While DEMs offer high accurate elevations, DEMs lack dynamic water flow information, leading to overestimation in flat areas and underestimation in complex topography, resulting in potentially misleading flood extent predictions [27]. Moreover, HM present the highest potential accuracy by simulating water flow dynamics based on detailed data [28].

#### 2.1.2. Data Requirements:

Data requirements are the foundation for accurate floodplain inundation mapping. Date requirements for RS rely on satellite imagery covering the floodplain, ideally acquired during and after flood events [29]. Historical data can aid in understanding flood patterns and calibrating algorithms. DEM data can further improve flood extent delineation. Primarily utilizes DEMs, with higher resolution data (e.g., LiDAR) leading to more accurate results [30]. DEM accuracy is critical, as errors translate directly into inaccurate flood extent predictions [31]. While HM requires the most extensive data set, including detailed topographic data (DEMs, LiDAR), historical river flow data, and channel geometry information **[32,33]**. Additionally, specialized software is necessary to run hydraulic simulations.

**2.1.3. Computational Requirements**

Computational requirements play a crucial role in floodplain inundation mapping for several reasons, such as model complexity, spatial resolution, Temporal Scale, calibration and validation, and finally Optimization and Efficiency **[34]**. In RS, processing satellite imagery can be computationally demanding. Higher resolution data and complex classification algorithms necessitate significant processing power **[35]**. Whilst DEM analysis requires relatively lower computational resources compared to RS. Analysis typically involves spatial overlay with other data or basic hydraulic modelling. HM Demands the highest computational resources. Complex models with finer resolution and longer simulation periods for flood scenarios significantly increase processing power requirements.

**2.1.4. Lead Time**

Adequate lead time is vital for floodplain inundation mapping. It allows for the development of effective mitigation strategies, facilitates community preparedness, supports efficient emergency response, integrates public input, and ensures high-quality data collection and processing. RS offers the fastest turnaround time, especially if readily available satellite imagery is used. However, cloud cover can introduce processing delays if waiting for cloud-free images **[36]**, on the other hand, lead time in DEM analysis depends on DEM availability and analysis complexity **[37]**. Existing DEMs allow for quick analysis, while obtaining new LiDAR data can add significant lead time. HM has the longest lead time due to data collection requirements (topographic and hydrologic data) and the time-consuming processes of model setup and calibration **[38]**.

The best technique depends on the project's goals and limitations. RS offers a rapid response with moderate accuracy, while DEM analysis provides a static, highly accurate representation of flood potential. HM delivers the highest potential accuracy but requires extensive resources and lead time. Selecting the most suitable technique demands careful consideration of accuracy requirements, data availability, computational limitations, and desired lead time.

**2.2 Data Fusion Techniques**

Data fusion combines information from multiple sources to create a more comprehensive and accurate picture than any single source could provide **[39-41]**. Muñoz et al. **[19]** explore a novel method to flood inundation mapping that highlights the strengths of deep learning and data fusion techniques. The authors propose a framework that utilizes deep learning, specifically Convolutional Neural Networks (CNNs), to analyse various data sources relevant to flood inundation. The data fusion approach includes high resolution of DEMs to provide detailed terrain information of flood maps at moderate (30 m) spatial resolution, RS data that covers satellite imagery or LiDAR data that can reveal land cover, water presence, and other surface characteristics, and HM data incorporated to find out the simulation of flood behaviour. The data fusion potentially leading to more accurate flood inundation maps compared to traditional methods, in addition, by fusing data from various sources, the model can better capture the intricate interactions between different flood types that occur in compound flooding events. While using natural language processing technology (BERT model), Zhang et al. **[42]** introduce GeoSemantic2vec algorithm to determine the semantic information within point of interest (POI). The mentioned algorithm extracts semantic information and clusters from various functional locations of the city by spatially sampling the study area to investigate relationship between people and the environment, and the complex impact of urban flooding. Zhang et al. claimed that the proposed algorithm improves the identification accuracy of socio-economic information of floods locations of using contexts of social media texts. Coarse waterlogging probability assessment framework designed by Xu and Ma **[43]** to enhance RS images that usually limited to the revisit cycle and cloud cover. Therefore, Xu and Ma incorporated social media data to overview the real weather, namely clouds. The proposed framework contains Coarse Waterlogging Probability (CWP) Map and Fine Waterlogging Probability (FWP) Map. The coarse waterlogging model analyzed historical data, DEM and landsats images to find out the most vulnerable locations to floods. While social media data was extracted to filter the noise information in RS data. The authors in **[43]** argued that the proposed framework has a high accuracy to floodplain inundation.Accordingly, data fused techniques have significant across various fields through enhancing

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accuracy and reliability, improving feature extraction, increasing the dynamic of flood inundation predictions, and addressing the data scarcity. By unlocking the potential of multiple data sources, data fusion methods play a critical role in improving decision-making, optimizing resource allocation, and achieving better results in various fields. **Table 1** reveals the research development in the data fused techniques to avoid the inundation flood Risk to the communities.

**Table 1** Literature reviews of different fusion techniques utilized to improve the flood inundation detection.

| Techniques Fused | Purpose of Study | Ref. |
|---|---|---|
| Image Fusion & Object-Based Image Analysis (OBIA) | Improve flood inundation detection in vegetated areas by combining high-resolution spatial data with spectral information. | [44] |
| LiDAR DEM & HM (e.g., HEC-RAS) | Generate accurate flood inundation maps with detailed water depth information by incorporating terrain elevation data into hydraulic simulations. | [45] |
| RS Data & HM | Develop flood inundation maps over large areas by integrating remotely sensed water extent data with hydrologic models. | [46] |
| Machine Learning & Flood Inundation Maps | Automate flood inundation mapping from remote sensing data using machine learning algorithms for faster and more efficient results. | [47] |
| InSAR (Interferometric Synthetic Aperture Radar) & HM | Monitor real-time flood extent and water depth changes by combining the sensitivity of InSAR to water surface variations with hydrodynamic models. | [48] |
| Multispectral & Hyperspectral RS Data | Leverage the complementary information from different spectral bands for improved flood inundation detection, especially for discriminating water from other surface types. | [49] |
| DEMs & Social Media Data | Integrate crowd-sourced flood reports from social media with DEM data to enhance real-time flood inundation mapping and damage assessment. | [50] |
| Flood Inundation Maps & Numerical Weather Prediction (NWP) Models | Incorporate weather forecasts from NWP models into flood inundation maps to predict future flood extent and severity. | [51] |
| LiDAR DEMs & UAV (Unmanned Aerial Vehicle) Imagery | Combine high-resolution topographic data from LiDAR with detailed flood extent information captured by UAVs for improved flood mapping, particularly in complex terrain. | [52] |
| GNSS (Global Navigation Satellite System) Data & HM | Utilize real-time water level measurements from GNSS stations to calibrate and validate flood inundation models for improved accuracy. | [53] |
| Machine Learning & HM | Integrate machine learning algorithms with hydrodynamic models to improve flood inundation simulations, particularly for complex flood scenarios. | [54] |
| Flood Inundation Maps & Cost-Benefit Analysis | Overlay flood inundation maps with cost data to identify areas with high potential economic losses from floods, aiding in flood risk management and mitigation strategies. | [55] |
| Statistical Downscaling & Remote Sensing Data | Combine statistical downscaling techniques with remotely sensed precipitation data to improve the spatial | [56] |

| | | |
|---|---|---|
| | and temporal resolution of flood inundation simulations. | |
| Citizen Science Data & Flood Modeling | Integrate flood observations reported by citizens through mobile applications or online platforms with flood modeling frameworks to enhance real-time flood monitoring and response. | [57] |
| Flood Susceptibility Maps & Land Use/Land Cover Data | Overlay flood susceptibility maps generated from historical flood data and flood modeling with land-use/land-cover data to identify areas vulnerable to future flood events based on environmental factors. | [58] |

The following line chart illustrates the number of research articles published in Scopus between 1980 and 2024 for floodplain inundation using fused techniques **[59]**. The Figure reveals that advancements in technology in the late twentieth century play a crucial role in embedding the different data in monitoring the floods. The line chart outlines that the number of articles published is increasing overtime to reach 13529 articles published in 2023, compared to 12488 articles published in 2022.

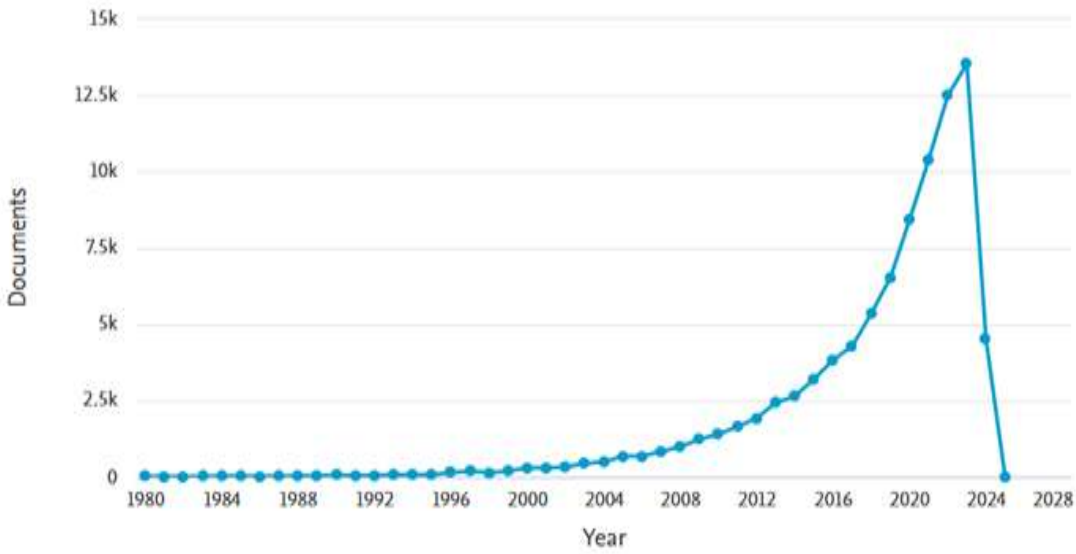


**Figure 1.** Shows the number of articles published for embedding different techniques in floodplain inundation according to scopus data **[59]**.

### 3. Flood Risk Assessment with Remote Sensing Data

RS data is a powerful tool for flood risk assessment, enabling proactive measures to mitigate flood risks and save lives. By incorporating this data into Geographic Information Systems (GIS), scientists and engineers can develop flood risk maps and models. Mojaddadia et al. **[60]** use a technique called ensemble machine learning, which combines multiple algorithms for better accuracy, to analyze various factors influencing floods, as shown in **Figure 2**. Thirteen factors, obtained from multi-sensor remote sensing data. The selected flood parameters were weighted using frequency ratio (FR) approach. Followed by modelling using support vector machine (SVM) to optimize all factors. The approach was tested on a river catchment in Malaysia and showed promising results with an accuracy of nearly 90%. This method offers a data-driven way to assess flood risks, which can be valuable for flood preparedness and mitigation strategies using the GIS-based ensemble method of FR and SVM.

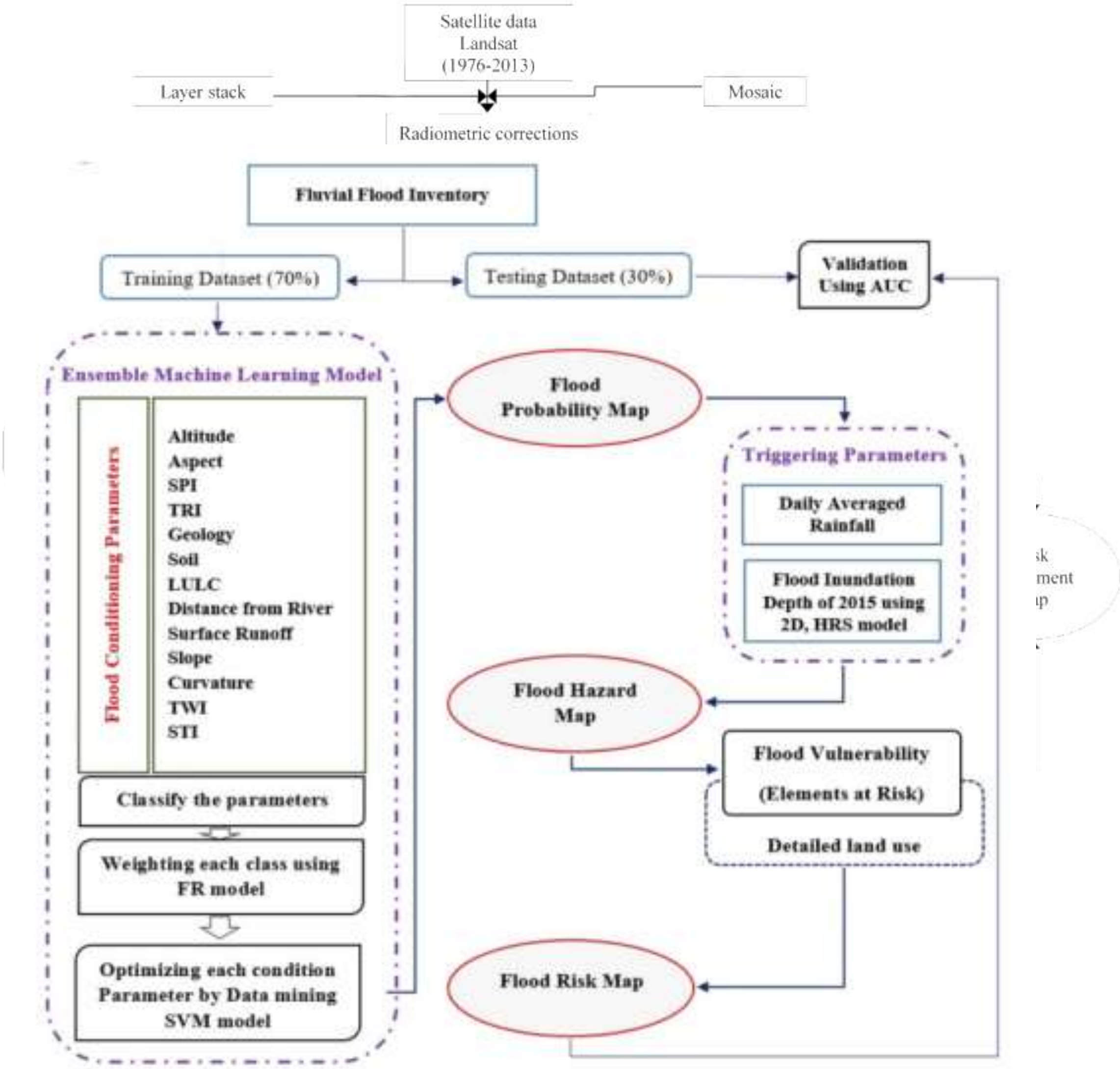


**Figure 2.** Different phases of flowchart in integration of GIS and remote sensing data for Flook risk assessment **[60].**

While Bhatt et al. **[61]** assess the flood hazards and risks in the Chamoli District of Uttarakhand, India using satellite remote sensing and GIS technique. Furthermore, the authors tried to determine the flood frequency and flood prone using DEM analysis. By combining hazard and vulnerability information, the paper likely produces flood risk maps that quantify the likelihood and potential consequences of flood events across the study area. The proposed approach appeared in **Figure 3** provides valuable information for identifying flood-prone areas, Disaster preparedness planning, and Floodplain management. The authors in **[61]** argue that these maps can aid decision-makers in understanding the spatial distribution of risk and allocating resources for preparedness and response efforts.

**Figure 2.** illustration of Flood risk assessment methodology using RS and GIS **[61].**

Farhadi and Najafzadeh **[63]** utilized random forest technique in interactive python and Google Earth Engine to spatially predict Flood Risk Mapping (**Figure 4**). The authors in **[62]** used 8 distinct types of landsats along with shuttle radar topography mssion (SRTM) of DEM to evaluate 11 risks indices, namely elevation, slope, slope aspect, land use, normalized difference vegetation index (NDVI), normalized difference water index (NDWI), topographic wetness index, river distance, waterway and river density, soil texture, and maximum one-day precipitation. Briefly, 8 satellite images were used to find four vulnerable indices of flood (NDVI, NDWI, soil texture, land use) while SRTM DEM model employed to generate six indices of flood risks, including slope, slope aspect, elevation, river distance, waterway and river density and topographic wetness index. Followed by 11 generated indices are laid into random forest model to mapping flood risks.

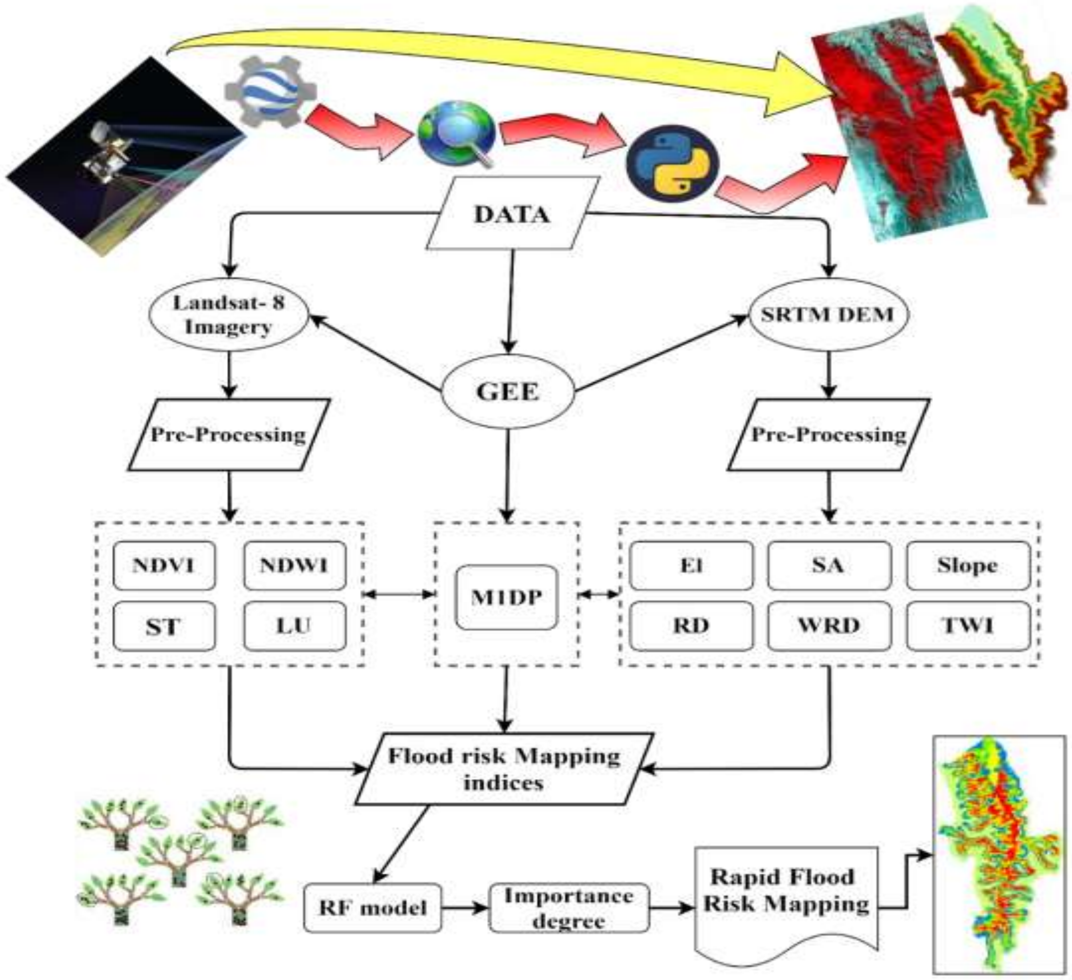


**Figure 4.** Show the designed model of flood risk mapping made by Farhadi and Najafzadeh [62]

## 4. Challenges and Future Directions

Even though remote sensing is a valuable resource for mapping flooded areas, it faces several limitations, such as uncertainty in data, satellite revisit times, real-time limitations, and urban flood mapping in which the buildings and dense vegetation can obscure flooded areas in urban environments [63]. Therefore, numerous mitigation measures surfaced to lessen the impacts of those challenges, including multispectral and hyperspectral data, data fusion, probabilistic flood maps, constellations of small satellites, predictive Modelling, Cloud-based processing platforms, high-resolution imagery, and incorporation of urban drainage data [64,65]. Addressing these challenges in remote sensing through mitigation strategies will drastically increase its accuracy in flood inundation mapping. This reflects to improved flood preparedness, quicker responses, and ultimately, saving lives and property when floods strike. Future directions of remote sensing in predicting the flood forecasting and modelling real-time simulations encompass developed machine learning algorithms to automate tasks like flood detection and water level estimation from remote sensing data, crowdsourcing data from social media and mobile phone reports during floods can provide valuable information for real-time monitoring, especially in remote areas, and techniques that integrate real-time remote sensing data with flood models will enable real-time flood forecasting, leading to improved flood warnings.

## CONCLUSION

To conclude, the research outlines the integration of unusual information, such as cost-benefit analysis and citizen science data in mapping the floodplain inundation. The importance of using various data to reveal the essence of overlay information to make a precise flood risk assessment. The review identifies distinctive fused data techniques to raise the accuracy of remote sensing data in floodplain inundation mapping and flood risk assessment. Obviously, there are several challenges to stand with accurate data due to climate change and latest weathering data, however, additional advancements in technical tools, namely, RS, HM, and TEM are required to maintain the latest reports in floodplain management.

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