A Comparative Study of Flood Monitoring Techniques Using the UN-SPIDER Recommendations and a Generative AI-Based Model (SATGPT): A Case Study in Ayutthaya, Thailand

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Abstract

This study presents a dual-track workflow for systematic flood mapping and analysis in Ayutthaya Province, Thailand, a critical region frequently subjected to severe flooding from monsoonal rainfall and the overflow of the Chao Phraya River. The research detected and analyzed multiple flood events that occurred over a significant five-year period, from 2016 to 2020. The objective was to compare the flood extent derived from the UN-SPIDER recommendations using SAR imagery with that obtained from the generative AI-based model known as SATGP. The first technique utilized a physics-based change detection method applied to Sentinel-1 Synthetic Aperture Radar (SAR) imagery, executed entirely on the Google Earth Engine (GEE) cloud computing platform. To ensure high delineation accuracy for inundated areas, the methodology incorporated rigorous post-processing filters. These steps included: applying a harmonized ratio threshold of 1.25 to the post-flood/pre-flood image ratio; masking out permanent water bodies using the JRC Global Surface Water dataset; and excluding areas with a slope greater than five percent via a Digital Elevation Model (DEM) to minimize topographic errors. The second technique explored an innovative AI-assisted retrieval approach, employing SATGPT. This cutting-edge geospatial decision-support tool leverages generative artificial intelligence to efficiently translate complex natural-language prompts into executable geospatial analyses and final raster outputs. Comparative analysis confirmed that both methods successfully generated detailed flood maps, yet they displayed distinct spatial patterns. The GEE/SAR product typically mapped medium-to-large, spatially continuous patches primarily concentrated within the province's principal flood risk zones. In contrast, the SATGPT-derived maps showed higher fragmentation with dense, fine-scale patches that closely followed the intricate network of canals and field-bunds, resulting in greater pixel-level coverage but less spatial continuity. Spatially, recurrent flood hotspots were consistently identified in the western low-relief floodplain and along the province's northern corridor. This study validates the complementary value of this dual-track methodology, where the GEE/SAR output provides an authoritative baseline for event delineation, while the SATGPT product offers utility for rapid triage, visualization, and actionable stakeholder briefings.

Keywords: Ayutthaya, Flood Monitoring, SAR, SATGPT, UN-SPIDER Recommendation

1. Introduction

Flooding in Phra Nakhon Si Ayutthaya Province remains a recurring and destructive hazard that severely affects communities, agriculture, industry [1], and even UNESCO World Heritage sites. Effective monitoring and timely mapping of flood events are therefore critical for disaster management and mitigation planning. Traditional optical satellite imagery, though widely used for flood detection, is often limited by cloud cover and adverse weather conditions during flood events [2]. In contrast, Sentinel-1 Synthetic Aperture Radar (SAR) provides an effective alternative due to its ability to penetrate clouds, operate under all weather and lighting conditions, and deliver frequent, high-resolution observations [3]. When combined with cloud-based platforms such as Google Earth Engine (GEE), this technology enables rapid data processing and near-real-time flood mapping [4].

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Such advancements in Earth observation technologies significantly enhance the ability to generate reliable flood extent information vital for emergency response, resource allocation, and long-term resilience planning[5].

Despite these technological capabilities, effective utilization of SAR data still demands technical expertise in image processing, coding, and geospatial analysis. Conventional workflows in GEE, for instance, require users to write scripts for filtering images, applying thresholding algorithms, and masking non-flood areas, tasks that can be time-consuming and technically challenging [6]. This creates barriers for many local planners and disaster management practitioners who may lack specialized training or access to advanced analytical tools. Consequently, there is a growing need for approaches that can simplify and accelerate satellite-based flood mapping, making the results more accessible and actionable for decision-makers [7]. Recent advances in artificial intelligence (AI), particularly generative AI and large language models (LLMs), have opened new opportunities for geospatial data analysis and decision support [8]. These systems can interpret natural language queries and automate analytical workflows, bridging the gap between complex satellite data processing and end-users who require spatial insights but are not remote sensing experts [9].

In this context, the present study aims to demonstrate and compare two approaches for flood mapping in Ayutthaya Province: a traditional Sentinel-1 SAR analysis using Google Earth Engine, and an AI-assisted method using the SATGPT generative AI tool. Specifically, the objectives are to:

1. Develop a satellite-based flood mapping workflow for Ayutthaya Province using multi-temporal Sentinel-1 SAR data (2016–2020) within the Google Earth Engine environment.
2. Apply the SATGPT generative AI tool to automatically retrieve and generate flood maps or raster data outputs for the same period and area, using natural language queries.

The study focuses on Ayutthaya Province in central Thailand, which covers approximately 2,556.6 square kilometers [10]. The temporal coverage spans five years (2016–2020), during which flood inundation patterns were analyzed. The methodology encompasses two major components: (1) remote sensing analysis using Sentinel-1 SAR data on Google Earth Engine, and (2) AI-assisted flood mapping through SATGPT. It should be noted that Sentinel-1 data are available on Google Earth Engine from October 14, 2014, to the present, while the SATGPT database currently provides flood information only up to 2021.

This research highlights how integrating Earth observation technologies with emerging AI systems can enhance flood mapping efficiency and accessibility, providing a foundation for more inclusive and timely disaster management practices in flood-prone regions such as Ayutthaya.

2. Materials and Methods

2.1 Study Area

Phra Nakhon Si Ayutthaya Province is located in the Central Plains of Thailand, approximately 85 km north of Bangkok. The region lies within a vast, low-lying alluvial plain with slope of approximately 0.00003 [11] characterized by soft, spongy soil and minimal elevation variation. The province is situated at the confluence of several major rivers the Chao Phraya, Pa Sak, and Noi Rivers (Figure 1) forming a natural island around the historic city center, which is recognized as a UNESCO World Heritage Site [12].

Ayutthaya's geographical and hydrological setting makes it highly prone to seasonal flooding, particularly during the southwest monsoon period from July to October. Several districts, including Sena, Bang Ban, Phak Hai, and Bang Sai, function as designated flood retention zones ("monkey cheeks") under Thailand's national flood management strategy, designed to mitigate flood impacts downstream in Bangkok [13]. Flooding is further intensified by upstream water discharges from the Chao Phraya Dam in Chai Nat, limited local drainage capacity, rapid urban and industrial development, and increasingly erratic rainfall patterns associated with climate change.

The province's recurring and severe flood events, combined with its mix of agricultural lands, industrial zones, and cultural heritage sites [14], make Ayutthaya an important case study for flood detection and risk management. The frequent inundations provide ideal conditions for the application of Synthetic Aperture Radar (SAR) imagery, particularly from the Sentinel-1 satellite. SAR's ability to penetrate cloud cover and capture data in all weather and lighting conditions is especially valuable during the monsoon season [15]. Moreover, floodwaters are easily distinguishable in SAR imagery because smooth water surfaces strongly reflect radar signals away from the sensor, appearing as dark areas. The province's diverse land use patterns also provide a complex environment to evaluate the performance of SAR-based flood mapping algorithms.

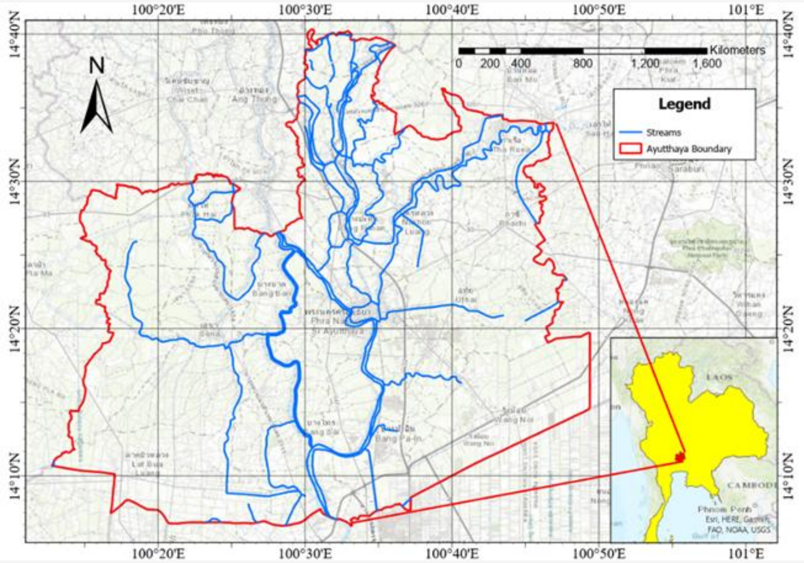

Figure 1: Phra Nakhon Si Ayutthaya Province in Central Thailand

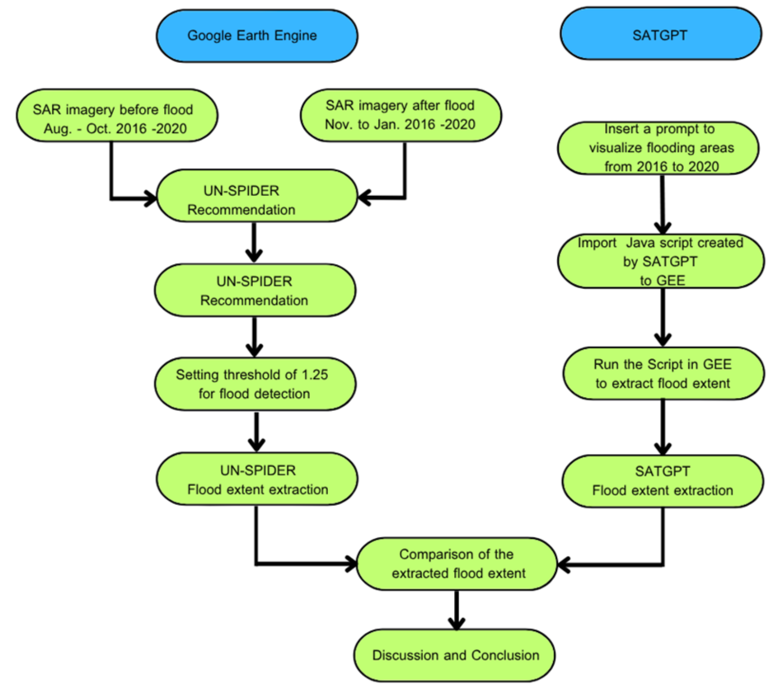

Figure 2: Comparative of flood monitoring using UN-SPIDER recommendations and SATGPT methodological workflow

2.2 Methodology

This study compared flood monitoring techniques using Synthetic Aperture Radar (SAR) imagery from Sentinel-1, processed through Google Earth Engine (GEE) with the SATGPT artificial intelligence platform for geospatial analysis. The methodology is summarized in Figure 2. The analytical techniques employed in this study include the UN-SPIDER recommendations and the generative AI-based platform, SATGPT. A detailed description of these techniques is provided in Table 1. Google Earth Engine was used for processing Sentinel-1 SAR imagery. The Google Earth Engine can be accessed at https://code.earthengine.google.com/, while SATGPT is available at https://satgpt.net/. A comparison of the two analytical approaches is summarized in Table 2.

Table 1: Data processing platforms

No.	Platform	Description
1	Google Earth Engine (GEE)	Cloud-based geospatial platform supporting analysis of Sentinel-1 GRD data through server-side processing. Provides tools for SAR change detection, masking, and slope filtering.
2	SATGPT web applicataion	Integrates large language models with cloud-based processing (GEE) to translate natural-language prompts into geospatial flood analyses and hotspot maps.

Table 2: Comparative characteristics of GEE/SAR and SATGPT

Aspect	GEE/SAR	SATGPT
Data source	Sentinel-1 SAR	JRC, GSW, ESA WorldCover, GPW, and OpenLandMap
Temporal coverage	Continuous (2014-present)	1984 - 2021
Spatial resolution (m)	10	10 – 1,000
Analytical approach	SAR change detection (UN-SPIDER recommendations)	AI-driven query-based processing

2.2.1 Sentinel-1 Satellite Imagery

The Sentinel-1 mission, operated by the European Space Agency (ESA) under the Copernicus program, provides crucial data for flood detection and monitoring. The constellation consists of two satellites, Sentinel-1A and Sentinel-1B, both equipped with Synthetic Aperture Radar (SAR) sensors [15]. SAR imagery is accessible via Copernicus Open Access Hub at https://browser.dataspace.copernicus.eu/. Unlike optical satellite sensors, SAR can capture imagery regardless of weather conditions or daylight, allowing reliable monitoring even in regions with frequent cloud cover or nighttime flooding. Sentinel-1 satellites offer a high revisit frequency, typically every 6 to 12 days depending on the location, facilitating near-real-time observation of flood events and their development. This capability is critical for timely flood detection and post-event damage assessment [16].

The value of Sentinel-1 lies in its ability to provide both pre-flood and post-flood imagery, enabling a clear assessment of flood impact and severity. By analyzing differences between images captured before and after a flood, affected areas can be accurately delineated [17]. Variations in radar backscatter caused by standing water or changes in surface conditions serve as indicators of flood extent, supporting the generation of precise flood maps.

2.2.2 UN-SPIDER recommendation

The United Nations Platform for Space-based Information for Disaster Management and Emergency Response (UN-SPIDER) was established by the United Nations Office for Outer Space Affairs (UNOOSA) to strengthen the application of space-based technologies in disaster management, emergency operations, and risk reduction [18]. Its overarching mission is to facilitate the effective use of satellite-derived data and tools to support decision-making before, during, and after disasters. UN-SPIDER serves as a global hub for knowledge exchange and collaboration among space agencies, governmental bodies, humanitarian organizations, and disaster management professionals. By promoting the integration of space technology into operational practices, the platform bridges the gap between technical capabilities and on-the-ground disaster management needs.

A major component of UN-SPIDER’s efforts involves formulating practical guidelines and best practices for utilizing satellite data in disaster situations [19]. In the context of flood mapping and post-disaster evaluation, the platform provides specific recommendations for employing Earth observation data, particularly Synthetic Aperture Radar (SAR) imagery from Sentinel-1 satellites. These guidelines emphasize the effective use of satellite imagery to delineate inundated zones, estimate the extent of flooding, and assess the associated impacts on infrastructure, agricultural land, and affected communities [20].

UN-SPIDER advocates for the use of radar-based sensors, such as Sentinel-1, because they can acquire reliable data regardless of weather conditions or cloud coverage. SAR imagery is particularly advantageous for flood monitoring since radar signals can penetrate cloud cover and detect standing water, allowing for accurate distinction between flooded and dry surfaces. The recommended methodology involves comparing satellite images captured before and after the flood event to determine its spatial extent and severity across urban and rural environments [21].

For comprehensive damage assessment, UN-SPIDER advises integrating satellite-based flood maps with complementary data sources, including ground surveys and information from other satellite missions. This multi-source approach enhances the precision of damage estimation across key sectors such as infrastructure, agriculture, and natural resources. The ultimate objective is to provide disaster managers with reliable and timely information to guide response actions, optimize resource deployment, and support recovery planning. Following these established guidelines enables agencies to make evidence-based decisions that improve both immediate disaster response and long-term resilience to future flooding events [22]. The UN-SPIDER guidelines adopted in this study are detailed in [23].

2.2.3 Google earth engine

Google Earth Engine (GEE) is a cloud-based geospatial platform that offers access to extensive satellite datasets, environmental measurements, and topographic information. It is widely used for environmental monitoring, including flood mapping [24]. GEE provides powerful computational capabilities and advanced geospatial algorithms, allowing users to efficiently process large volumes of satellite data. For flood monitoring, it enables the analysis of high-resolution imagery from sources such as Sentinel-1 and Landsat, supporting rapid detection and evaluation of flood events.

A significant advantage of GEE is its ability to handle and integrate massive datasets from multiple sources, while offering tools for time-series analysis. This allows users to compare pre- and post-flood imagery to detect landscape changes caused by flooding [25] and [26]. For instance, radar data from Sentinel-1, accessible through GEE, can reveal areas of water accumulation and surface changes [27], even under dense cloud cover, which is often challenging for optical sensors.

GEE also supports automated classification and change detection, which is particularly valuable for flood mapping [28] and [29]. Using machine learning and spectral analysis, it can distinguish between water and land and classify various land cover types without manual interpretation [30]. Time-series capabilities further enable the monitoring of flood progression, allowing near-real-time tracking of events as they unfold. Overall, Google Earth Engine is an essential tool for modern flood monitoring, combining large-scale data access, advanced processing capabilities, and real-time analytical tools to support disaster management and decision-making. Flood extent was mapped using a change detection approach between pre-flood and post-flood Sentinel-1 SAR images, following UN-SPIDER guidelines [23]. The provincial boundary of Ayutthaya was imported into Google Earth Engine (GEE) as the study area. Pre-flood (January–March) and post-flood (August–November) mosaics were generated for 2016–2020 using VH polarization and consistent orbit directions.

Flooded pixels were identified by computing pixel-wise backscatter ratios (post-/pre-flood) and applying a threshold of 1.25, validated by [3][23] and [31]. Permanent water bodies were masked using the JRC Global Surface Water dataset (water presence >10 months/year). Terrain with slopes >5% was excluded using a 3-arc-second DEM from WWF HydroSHEDS, and isolated pixel clusters (<8 pixels) were removed to reduce speckle noise [23]. The processed rasters were projected to calculate inundated areas in hectares, and flood polygons were aggregated and visualized in GEE. This workflow produced annual flood maps for 2016 - 2020, providing spatially explicit information on flood extent.

2.2.4 SATGPT

SATGPT (Satellite GPT) is a cloud-based geospatial decision-support system developed by UN ESCAP that integrates a large language model (LLM) with Earth Observation (EO) data processing [32]. It enables users to query satellite imagery in natural language and generates both descriptive insights and corresponding map layers, supporting applications such as flood mapping, disaster management, and urban planning. ATGPT uses a transformer-based LLM to interpret user queries and dynamically generate Google Earth Engine (GEE) scripts [33]. The LLM handles query reasoning and code generation, while GEE performs large-scale EO data processing. This setup allows rapid mapping and analysis by combining natural-language understanding with cloud-based image computation, following a retrieval-augmented generation paradigm.

The SATGPT platform retrieves flood information through a structured workflow that converts natural language queries into geospatially explicit flood maps. The user interface of SATGPT is presented in Figure 3. According to the workflow in Figure 4, users begin by opening the SATGPT web application and waiting for the basemap and Layer Control panel to load. The desired analytical mode is then selected: Single Inundation Event for discrete flood episodes (e.g., the Ayutthaya flood of October–November 2011) or Inundation Hotspot for multi-year flood frequency analysis, with the Hotspot Duration slider specifying a 5–25year temporal window.

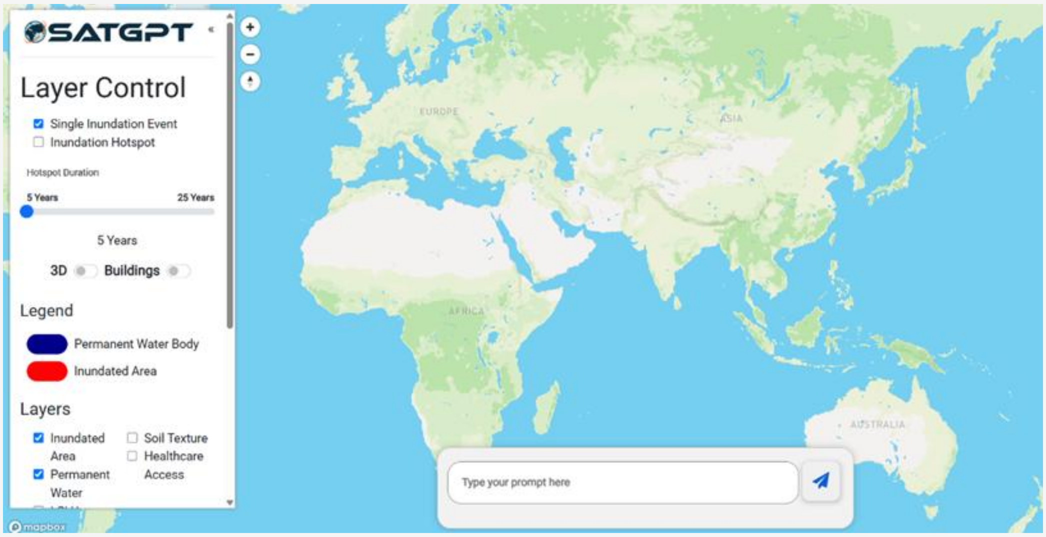

Figure 3: SATGPT user interface

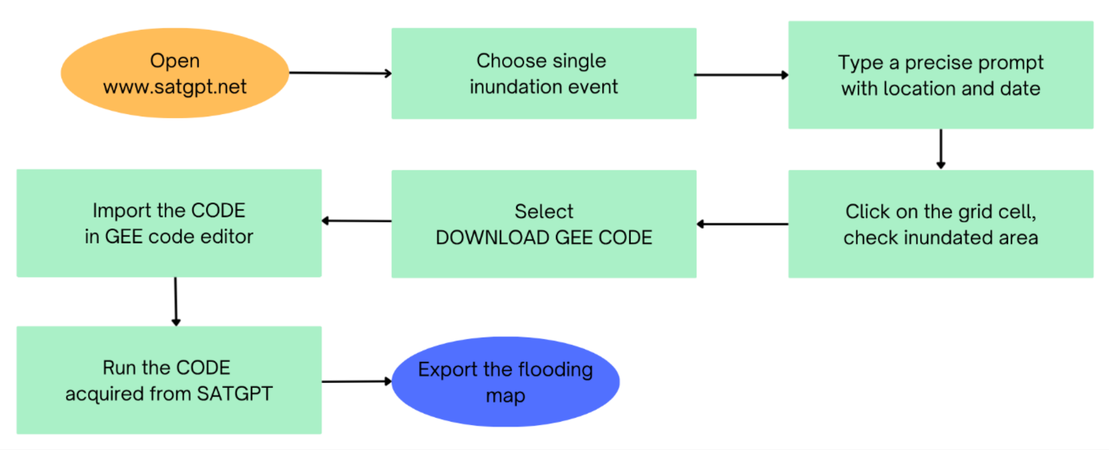

Figure 4: SATGPT flood mapping workflow

A precise query specifying the study area and time period is entered in the chat input field (e.g., "Map the inundated extent of the 2016 flood in Ayutthaya Province, Thailand"). Submitting the prompt generates a Result panel summarizing the analysis. Users adjust the map view to locate the study area, enable the Inundated Area layer (red) to visualize flooding, and optionally activate the Permanent Water layer (blue) to distinguish perennial water bodies. Layer transparency and 3D visualization options can be adjusted to enhance interpretability. If no output appears, adjustments may include refining the temporal window, checking adjacent grid cells, or ensuring that the Inundated Area layer is enabled. The DOWNLOAD GEE CODE option allows users to obtain the underlying Google Earth Engine (GEE) JavaScript script for reproducibility and further customization. This script can be pasted into the GEE Code Editor (https://code.earthengine.google.com), where the Area of Interest (AOI) is defined, and the script is executed to render the flood layers, enabling verification of the generated inundation patterns.

3. Results

3.1 Flood Extent from GEE/SAR

The flood extent was delineated using a change detection approach that computes the ratio between post-flood and pre-flood Sentinel-1 SAR images. To identify inundated areas, a threshold value of 1.25, as recommended by UN-SPIDER was applied to distinguish flooded from non-flooded regions. Pixels with values greater than 1.25 were classified as flooded, whereas those below this threshold were categorized as non-flooded [31]. This process generated a binary raster layer representing the spatial distribution of inundation. Flooded areas derived from Sentinel-1 SAR imagery revealed substantial interannual variability.

Figure 5 presents representative GEE outputs for Ayutthaya from 2016 to 2020, showing the progressive delineation of inundated zones. According to the results shown in Figure 5, the interannual comparison of flood extents from 2016 to 2020 are as follows:

2016 (Figure 5(a)): Inundation was limited and spatially fragmented. Numerous small flood patches were observed, primarily concentrated in the western and southwestern lowlands, with only isolated clusters elsewhere. The high degree of patchiness and weak spatial connectivity suggest localized ponding and short-lived overbank flows rather than a province-wide flood event.

2017 (Figure 5(b)): This year exhibited the most extensive and spatially continuous flooding in the series. Broad inundation covered much of the central floodplain and extended along the northern distributary network, indicating widespread overbanking and strong hydraulic connectivity. Patch coalescence was high, and fragmentation was minimal, consistent with sustained high water stages in the Chao Phraya–Lop Buri river system.

2018 (Figure 5(c)): Flooding remained widespread but was reduced relative to 2017. The western floodplain persisted as a major inundation hotspot, while northern channels remained active but exhibited greater fragmentation and edge complexity. Overall, the areal extent and connectivity were intermediate between the high-flood year (2017) and the low-flood years.

2019 (Figure 5(d)): Flooding became more localized, with pronounced clusters in the western floodplain and smaller pockets in the northern sector. The central and eastern regions showed limited inundation. Patch sizes were smaller, edge density increased, and continuous flood corridors were rare characteristics typical of moderate or late-season events.

2020 (Figure 5(e)): Inundation was modest and discontinuous, concentrated mainly in the western sector and along select northern channels. The eastern and southeastern regions exhibited minimal flooding. Compared with 2019, flood patterns were similarly constrained but exhibited greater fragmentation in the central portion of the province.

Across the five-year period, recurrent inundation was consistently observed in the western low-relief floodplain downstream of the main confluence zone and along sections of the northern distributary and irrigation network. These zones exhibit high flood persistence, occurring in more than three of the five years, which reflects underlying geomorphic and hydraulic controls.

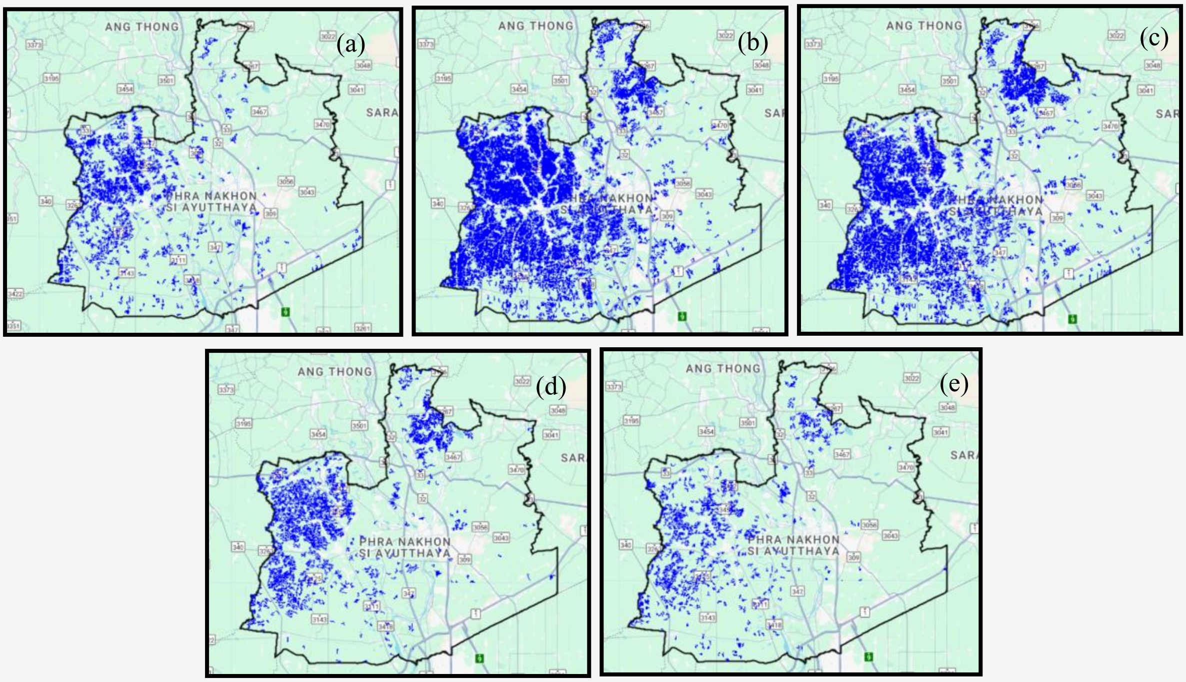

Figure 5: Spatial distribution of floods derived from GEE/SAR
(a) 2016, (b) 2017, (c) 2018, (d) 2019, and (e) 2020

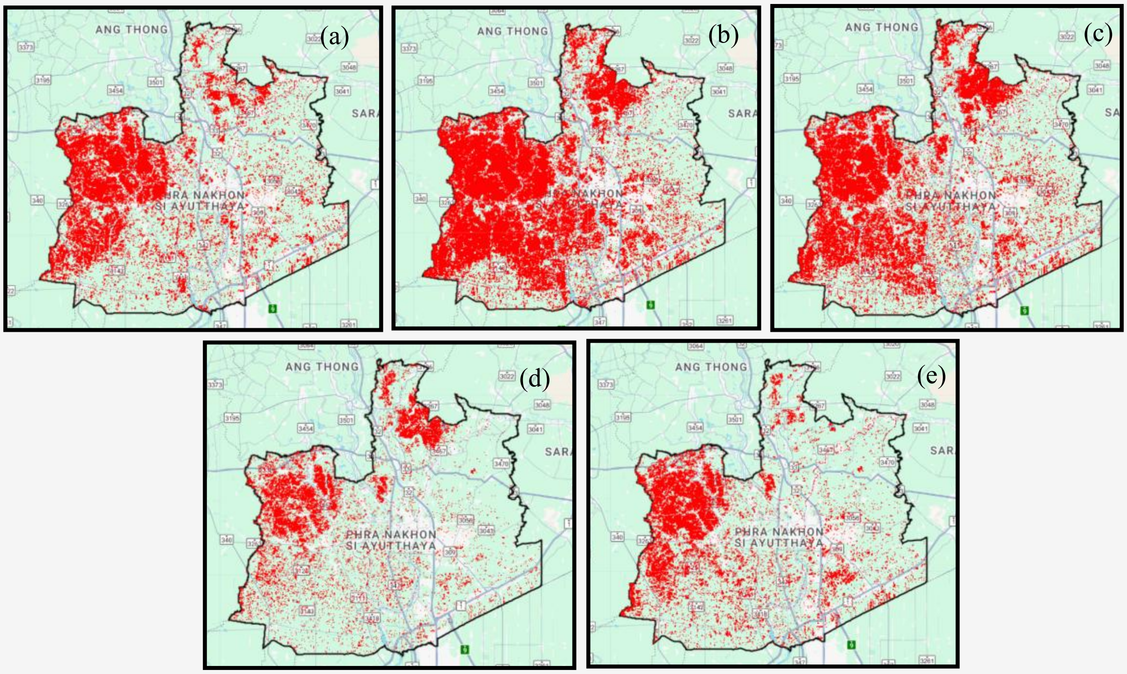

Figure 6: Spatial distribution of floods derived from SATGPT (a) 2016, (b) 2017, (c) 2018, (d) 2019, and (e) 2020

Factors such as gentle topographic gradients, high flood storage capacity, and the presence of floodways and canal networks contribute to repeated water retention and routing. In contrast, the eastern and southeastern provinces show low recurrence, corresponding to slightly higher elevations and more efficient surface drainage.

3.2 Flood Extent from SATGPT

SATGPT produced parallel flood maps for 2016–2020 (Figure 6). Outputs included composite layers of flood extents, land cover (ESA WorldCover), population density (GPWv4), and soil texture (OpenLandMap). The SATGPT results showed generally broader pixel-level coverage than the GEE/SAR maps but with more fragmented patterns. According to the results shown in Figure 6, the interannual comparison of flood extents from 2016 to 2020 are as follows:

2016 (Figure 6(a)): Inundation was moderate and spatially fragmented. Flooded clusters were concentrated in the western and southwestern lowlands, with additional scattered patches along central canal corridors and isolated pockets in the north. Overall connectivity was limited, and polygon sizes were small, consistent with localized ponding and short-lived overbank flows rather than a province-wide event.

2017 (Figure 6(b)): This year recorded the most extensive and spatially connected flooding within the series. Flood coverage expanded across the central floodplain and extended along northern distributary channels, forming broad, coalescent inundation corridors with minimal fragmentation. This pattern indicates sustained high water stages in the Chao Phraya-Lop Buri river system and extensive floodplain storage.

2018 (Figure 6(c)): Although flood extent remained substantial, it was reduced relative to 2017. The western floodplain persisted as the dominant hotspot, while northern channels remained active but displayed greater fragmentation and edge complexity. Overall areal coverage and connectivity were intermediate between the extensive inundation of 2017 and the more localized floods of subsequent years.

2019 (Figure 6(d)): Flooding became more localized, with distinct clusters observed in the western sector and smaller pockets in the north. The central and eastern areas exhibited sparse and discontinuous inundation. Patch sizes were small, and linear connectivity was weak typical of moderate or late-season flooding events.

2020 (Figure 6(e)): Flooding was moderate and discontinuous. Inundation was again concentrated in the western region, with scattered patches across the central plain and along select northern channels. Compared with 2019, the flood extent expanded slightly into the central floodplain, though overall connectivity remained lower than in 2017–2018.

Across the five-year observation period, recurrent inundation was consistently detected in the western low-relief floodplain and along sections of the northern distributary and irrigation network. These zones, which experienced flooding in three or more years, reflect strong geomorphic and hydraulic controls, including minimal surface gradients, high floodplain storage capacity, and the influence of floodways and canalized flow paths. In contrast, the eastern and southeastern sectors of the province exhibited persistently low flood recurrence, likely due to slightly higher elevations and more efficient drainage systems.

3.3 Comparison of Inundation Area between GEE/SAR and SATGPT

When considering the spatial distribution of inundation, a clear contrast is evident between the two mapping approaches. The UN-SPIDER maps (Figure 5) generally depict medium- to large-sized flood patches that are spatially continuous and concentrated in primary high-risk zones, particularly within the western lowlands and along the northern corridor, while the central and eastern sectors appear relatively sparse. In contrast, the SATGPT maps (Figure 6) exhibit higher fragmentation, characterized by a “salt-and-pepper” texture of numerous small patches distributed widely across the province and closely aligned with canal and field-bund networks. Consequently, the SATGPT outputs display higher pixel density and broader spatial coverage, though with lower spatial continuity. During the severe flood years (2017–2018), both methods delineate extensive inundation footprints, but the SATGPT maps reveal denser fine-scale networks. Conversely, in years of reduced flooding (2019–2020), the UN-SPIDER maps contract to the principal hotspot areas, whereas the SATGPT results continue to show dispersed small patches extending into the central and eastern sectors of the province.

4. Discussion

The comparative analysis between the UN-SPIDER-recommended Sentinel-1 SAR methodology and the SATGPT generative AI-based model provides valuable insights into the evolution of flood monitoring systems and their relative strengths, weaknesses, and application contexts. The study demonstrates how traditional radar-based techniques and emerging AI-driven models can jointly enhance the accuracy, accessibility, and interpretability of flood information for both scientific and operational purposes.

From a technical standpoint, the SAR-based workflow implemented in Google Earth Engine (GEE) exhibited strong consistency with hydrological principles and the established UN-SPIDER framework. The change-detection approach based on the post-flood to pre-flood backscatter ratio (threshold = 1.25) effectively delineated medium- to large-scale inundations with minimal noise [3]. The spatial continuity and reduced fragmentation of these flood polygons align with the physical nature of large overbanking events and the hydraulic behavior of Ayutthaya’s low-lying floodplain. The GEE/SAR method’s ability to minimize false positives by masking permanent water bodies and excluding areas with slopes above 5% further underscores its reliability in identifying true flood signatures [31]. These results confirm that radar-based workflows remain a critical foundation for quantitative flood mapping, particularly where repeatable, time-series analyses are required for long-term hazard monitoring and model calibration.

Conversely, SATGPT demonstrated a paradigm shift toward democratized, user-centric geospatial analytics. Its capability to translate natural-language prompts into executable geospatial analyses represents an important milestone in reducing the technical entry barrier for flood monitoring. Non-expert users, such as local planners, civil protection officers, and community organizations can now obtain rapid inundation maps without coding skills or prior experience with cloud computing platforms [32] and [33]. The SATGPT results, however, revealed a distinct pattern: while the extent of detected flooding was often broader in spatial coverage than the GEE/SAR outputs, the mapped areas were characterized by greater fragmentation, higher pixel-level granularity, and frequent detection along canal networks and agricultural field boundaries. This indicates that the AI-driven model may be capturing residual soil moisture, irrigation flooding, or sub-pixel wetness variations that the radar thresholding approach treats as non-flood conditions.

These spatial discrepancies are not merely technical differences but reflect a deeper conceptual distinction between physics-based and data-driven paradigms. The GEE/SAR workflow is rooted in physical scattering principles, emphasizing radiometric consistency and hydrological realism. SATGPT, by contrast, operates on pattern recognition across multiple open datasets (ESA WorldCover, OpenLandMap, GPWv4, and JRC Global Surface Water) and machine-learned relationships between landscape features and inundation likelihood. The generative AI model's broader pixel coverage may therefore be more sensitive to environmental nuances but also more prone to overestimation. Despite this, its value lies in its agility rapid production of flood visualizations and integration of socioeconomic layers such as population density, allowing quick situational assessments for humanitarian or emergency response.

The interannual comparison (2016–2020) revealed that both methods consistently identified recurrent flood hotspots in the western and northern portions of Ayutthaya Province, particularly along low-relief floodplains and distributary networks. The concurrence of results in the high-flood years (2017–2018) validates the robustness of both systems. In contrast, differences in moderate-flood years (2019–2020) expose their distinct sensitivities: the SAR-based product captured only hydrologically connected flood zones, whereas SATGPT detected a dispersed pattern of smaller inundations, potentially influenced by irrigation management, small reservoirs, or field-scale drainage. This divergence underscores the potential of combining both systems in a hybrid workflow where GEE/SAR establishes a reliable flood baseline and SATGPT complements it by capturing fine-scale and rapid-response details.

Another important implication of this study concerns the operational and institutional integration of these technologies. National disaster management agencies often rely on expert-driven workflows (e.g., UN-SPIDER guidelines), which are scientifically robust but resource-intensive. Meanwhile, the increasing sophistication of AI-assisted platforms such as SATGPT can serve as a decision-support tool for rapid reconnaissance, preliminary briefings, and public awareness. The co-existence of both systems can therefore foster multi-tiered flood intelligence: radar-based analytics for accuracy and AI-driven visualization for accessibility. Furthermore, the success of SATGPT in reproducing general flood patterns suggests the growing potential of generative AI models as front-end interfaces for cloud-based geospatial systems, an innovation that may redefine how disaster information is produced and shared globally.

Overall, this comparative study emphasizes that technological innovation in flood monitoring should not merely aim for automation but also for inclusivity, interpretability, and transparency. The integration of generative AI with conventional Earth Observation techniques represents a promising pathway toward achieving these goals, provided that the limitations of each system are acknowledged and systematically addressed through calibration, validation, and human-in-the-loop design.

5. Conclusion

This study evaluated two contrasting yet complementary flood monitoring techniques: the physics-based Sentinel-1 SAR change detection approach following UN-SPIDER recommendations and the generative AI-based SATGPT system. Both were applied to Ayutthaya Province, Thailand, across five years (2016–2020). The findings confirm that both approaches effectively detected major inundation events, delineated flood-prone zones, and identified consistent hotspots in the province's western floodplain and northern canal networks. The GEE/SAR approach proved highly accurate, producing spatially continuous and hydrologically coherent flood maps. Its systematic thresholding, terrain filtering, and masking procedures made it suitable for quantitative assessments and scientific analyses. However, it required technical expertise and significant computational effort, limiting its direct use by non-specialists. The SATGPT system, in contrast, offered a highly accessible, fast, and intuitive means of flood visualization. Its natural-language-driven interface eliminated the need for coding and enabled users to generate flood maps in seconds. Despite its occasional over-fragmentation and broader pixel coverage, SATGPT effectively complemented the SAR-based approach by capturing micro-scale inundations and providing multi-layered contextual information, including population and land cover. The synthesis of both techniques forms a compelling case for hybrid flood monitoring frameworks, where GEE/SAR products supply authoritative spatial references and SATGPT serves as an AI-based extension for rapid mapping and stakeholder communication. Together, they embody the convergence of Earth Observation science and artificial intelligence in supporting disaster risk reduction and climate resilience.

6. Limitations

Although this study demonstrates the potential of integrating UN-SPIDER's SAR-based methodology and the SATGPT generative AI model for flood monitoring, several limitations should be acknowledged. First, the SATGPT platform depends on multiple open-source datasets such as ESA WorldCover, JRC Global Surface Water, and OpenLandMap that differ in spatial resolution, update frequency, and temporal consistency. These discrepancies may introduce uncertainty and lead to spatial mismatches in the derived flood maps. Second, while the GEE/SAR workflow adheres to robust physical principles, it remains sensitive to radar noise in urbanized or vegetated areas, where double-bounce and volume scattering can obscure accurate water detection.

Additionally, both approaches were constrained by the lack of ground validation data, such as in-situ flood depths or duration measurements, limiting the capacity to quantitatively assess accuracy and reliability. Another constraint is the opaque nature of SATGPT's generative algorithms, which operate as a "black box" with limited interpretability of the decision-making process. Finally, the temporal coverage of Sentinel-1 imagery, though frequent, may not fully capture short-lived flash floods or localized inundations occurring between acquisition intervals.

7. Future Work Recommendations

Future research should focus on enhancing the robustness, transparency, and operational readiness of hybrid flood monitoring systems that integrate physics-based and AI-driven methods. A key priority is the fusion of multiple data sources including optical imagery (Sentinel-2, MODIS), high-resolution UAV data, and near-real-time rainfall and hydrological records to improve temporal continuity and classification precision. Efforts should also be directed toward developing explainable AI techniques that clarify how generative models such as SATGPT derive their outputs, thereby improving model transparency and trust among users. The creation of localized training datasets tailored to regional geomorphological and land-use conditions would further enhance AI adaptability and accuracy. Moreover, incorporating ground-truth observations through participatory mapping and field validation campaigns will be essential for calibrating and verifying model results. Ultimately, operationalizing these integrated approaches within multi-agency disaster early warning systems can strengthen the timeliness, inclusivity, and effectiveness of flood risk management at both local and national levels.

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