Leveraging large language models for floods mapping and advanced spatial decision support: A user-friendly approach with SATGPT

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Flood mapping plays a crucial role in disaster management, but traditional methods often suffer from limitations in speed, accessibility, and real-time data utilization. This paper introduces SATGPT, a novel tool that leverages the code-writing abilities of Large Language Models (LLMs) to automate flood mapping using Google Earth Engine (GEE). Users simply input a prompt with flood duration and location, and SATGPT utilizes LLMs to generate GEE code for either extracting data from historical databases or performing unsupervised classification for flood detection. The resulting flood maps are presented in a user-friendly interface with 3D visualization, enabling detailed analysis of flooded areas and building footprints. Additionally, a self-paced learning course was developed and launched at the UNU-INWEH Water Learning Center to share knowledge and foster wider adoption. This paper presents the architecture and workflow of SATGPT, showcases its performance through flood map examples, and discusses the advantages, limitations, and future directions of LLM-powered flood mapping tools. We believe SATGPT offers a user-friendly, efficient, and scalable approach that can democratize access to flood information and empower informed decision-making in disaster management.

Keywords – Big Earth data, data analysis, disaster risk reduction, flood mapping, geospatial, Large Language Models (LLMs), remote sensing

1. INTRODUCTION

This Large Language Models (LLMs) have revolutionized numerous aspects of modern life, demonstrating remarkable capabilities in language processing, code generation, and knowledge synthesis. Their potential extends to supporting the achievement of various Sustainable Development Goals (SDGs), offering innovative approaches to tackling complex global challenges. One promising application area is the mapping and monitoring phenomena measurable through Earth Observation (EO) data. It's estimated that around 40 of the 169 SDG targets and 30 of the 232 SDG indicators could benefit from the insights provided by the EO data analysis [1]. The use of Artificial Intelligence (AI) for EO data analysis can further improve the number of SDG indicators that can be monitored with a higher accuracy and frequency.

In this context, research is underway to develop multimodal LLMs capable of directly processing EO data. However, these models are often computationally expensive to train, develop, and maintain, making them less feasible for low-capacity, high-risk countries that urgently need technological solutions for disaster mitigation. To address this challenge, we introduce SATGPT (accessible at satgpt.net), an innovative solution that leverages the current capabilities of LLMs and integrates them with cloud computing platforms and EO data. SATGPT represents a fully functional, innovative spatial decision support system designed for rapid deployment, particularly in resource-limited contexts.

This paper presents an instance of SATGPT configured for flood mapping, as an example. It simplifies the process with a user-friendly interface requiring only a prompt specifying flood duration and location. SATGPT leverages LLMs to generate GEE code dynamically, access historical databases, or perform unsupervised classification to detect flooded areas. This innovative integration of LLMs with GEE enhances the speed, accessibility, and real-time capabilities of flood mapping, making it more accessible to non-specialists and supporting resilient disaster management practices.

Flooding poses a devastating and persistent threat throughout the Asia-Pacific region. Extreme weather events, vulnerable populations, and rapid urbanization create a dangerous confluence of risk, placing millions at risk. The economic and human costs are staggering, demanding effective disaster management strategies. According to the Asia-Pacific Disaster Report 2023, floods are the region's most frequent natural hazard, causing roughly 40% of all disaster events [2]. Between 2021 and 2022 alone, Asia-Pacific floods led to over 5 000 deaths and economic losses exceeding USD 40 billion. To mitigate this risk, accurate and timely flood mapping is crucial for preparedness, response, and long-term resilience planning.

Traditional flood mapping methods often involve time-consuming manual analysis of remote sensing imagery or complex geospatial software. These approaches possess inherent limitations: a lack of real-time data integration and the need for specialized technical expertise hinder effective disaster response. SATGPT addresses these challenges and aligns with the Asia-Pacific Plan of Action on Space Applications for Sustainable Development (2018–2030), which emphasizes the vital role of space-based technologies and geospatial information in disaster risk reduction [3]. This novel tool democratizes access to flood information by harnessing LLMs for automated flood mapping using Google Earth Engine (GEE).

Furthermore, to build the capacity to use these technologies effectively, the paper discusses the development of an online, free, and self-paced course titled "Introduction to Geospatial Data Analysis with ChatGPT and Google Earth Engine." This course introduces participants to the fundamentals of ChatGPT and the Earth Engine Code Editor platform, empowering them to process and interpret geospatial data effectively outside the SATGPT [4]. The innovative aspect of the course is developing the Geo-Prompt Engineering (GPE) concept, which focuses on using spatial, temporal, and satellite sensor-specific information in the prompt engineering process. The course aims to foster broader adoption of SATGPT and similar tools, equipping users with the knowledge and skills needed to leverage advanced technologies in disaster management.

This paper is structured to provide a comprehensive overview of SATGPT and its contribution to enhancing flood mapping and disaster management in the Asia-Pacific region. Following this introduction, we delve into a literature review that situates SATGPT within the existing body of work on flood mapping and the application of LLMs and GEE in environmental monitoring. The methodology section details the design and functionality of SATGPT, including its innovative use of LLMs for code generation and the workflow from user input to map visualization. We then present case studies and performance evaluations that demonstrate the effectiveness of SATGPT in real-world scenarios. The discussion explores the implications of these findings, highlighting the advantages, limitations, and potential future directions for LLM-powered tools in disaster management. Finally, the conclusion summarizes the key contributions of this work and its significance in advancing the field of flood mapping, underscored by the strategic alignment with the Asia-Pacific Plan of Action and the capacity-building efforts through the online course.

2. LITERATURE REVIEW

Integrating LLMs into remote sensing represents a transformative approach to analyzing EO data. This literature review is divided into two sections; the first section delves into recent advancements and applications of LLMs in the field of EO and SDGs-related applications, highlighting the different approaches adopted and the challenges to applications for SDGs. The second section focuses on the applications of LLMs, cloud computing, and big Earth data for flood mapping.

2.1 LLMs and EO data analysis

The integration of LLMs into forestry remote sensing workflows, as demonstrated by Du et al. [5] exemplifies the innovative application of these models. The Tree-GPT system, a modular LLM expert system, significantly enhances the efficiency of forestry data analysis by integrating image understanding modules with domain knowledge bases.

Further expanding the scope of LLM applications, Osco et al. [6] explored the potential of Visual ChatGPT in remote sensing. This model combines LLM capabilities with visual computation, offering novel approaches to image analysis. Despite its early stage of development, Visual ChatGPT's ability to generate textual descriptions of images and perform image segmentation marks a significant step towards automating remote sensing image processing.

Additionally, the RS-CapRet method proposed by Silva et al. [7] leverages LLMs for image captioning and text-image retrieval tasks in remote sensing. By integrating a large decoder language model with image encoders adapted for remote sensing imagery, RS-CapRet achieves state-of-the-art performance, illustrating the effectiveness of LLMs in processing and retrieving remote sensing images.

Collectively, these studies underscore the significant potential of LLMs to revolutionize remote sensing data analysis. However, the development and training of modular LLMs are recognized for their substantial resource consumption and complexity. Sachdeva et al. [8] highlights the resource-intensive nature of LLMs, emphasizing the need for data-efficient pre-training approaches to mitigate the high costs associated with their development. Similarly, Zhang et al. [9] discusses the unaffordability of fully training LLMs for personalized generation due to excessive resource consumption.

The training cost and resource intensiveness of modular LLMs significantly impede their application in advancing Sustainable Development Goals (SDGs), especially in countries with high disaster risk and low capacity. Gangavarapu [10] discusses the potential of LLMs in healthcare within low-resource nations, aligning with SDG 3, yet acknowledges the barriers posed by inadequate data, infrastructure, and funding constraints. Similarly, Sunarti et al. [11] emphasizes the integration of disaster risk reduction with SDGs, highlighting the need for capacity building and advocacy in regions where disaster management is not prioritized due to resource limitations. Day et al. [12] addresses the challenges of rapid decision-making in disaster management within the context of global megatrends like climate change and resource scarcity, pointing out the necessity for effective localization strategies that build self-sufficiency.

2.2 LLMs, cloud computing, and big Earth data for flood mapping

Flood mapping is an essential tool in disaster management, providing critical information for several SDG indicators focused on risk assessment, emergency response, and recovery planning. Traditional flood mapping techniques have evolved over time, leveraging remote sensing imagery and geospatial software to delineate flood extents. However, these methods come with their own set of advantages and limitations.

One common approach to flood mapping involves the use of Synthetic Aperture Radar (SAR) data and Landsat images alongside Geographic Information Systems (GIS). Kumar and Jayarajan [13] highlighted the effectiveness of these tools in mapping, tracking, and evaluating the distribution of floodwater in the lower reaches of the Periyar river basin, Kerala.

Despite the advantages, traditional flood mapping techniques often face challenges related to the speed of data processing and analysis. Munasinghe et al. [14] conducted an intercomparison of satellite remote sensing-based flood inundation mapping techniques, including supervised and unsupervised classification, delta-cue change detection, and the use of Normalized Difference Water Index (NDWI) and modified NDWI (MNDWI). Their findings suggest that while supervised classification yielded the highest accuracy, the process is time-consuming and requires significant expertise, highlighting a common limitation of traditional methods in terms of accessibility and real-time data integration.

Furthermore, Clemente, Yang, and Barroca [15] discussed the development of flood mapping techniques and their impact on flood assessment and management in European coastal cities. The study underscored the importance of data visualization, transfer, and communication, pointing out that graphic semiology plays a crucial role in making data usable for different stakeholders. This emphasizes another challenge of traditional flood mapping methods: the need for effective data communication and visualization techniques to support decision-making.

In the context of Nigeria, Adewoyin et al. [16] utilized geospatial techniques for flood mapping of Fadama areas, identifying regions susceptible to flooding and examining the economic and social implications. The study highlighted the lack of government intervention and the reliance on community efforts to mitigate flood risks, pointing to the broader issue of resource allocation and support for flood-prone areas.

The integration of LLMs into environmental science and disaster management represents a burgeoning field of research, offering innovative approaches to data analysis, decision support, and predictive modeling. Recent studies have begun to explore the potential of LLMs in various environmental contexts, from forestry and urban planning to environmental flow management and multimodal applications in geography and agriculture.

As discussed earlier, Du et al. [5] introduced Tree-GPT, a modular LLM expert system designed for forest remote sensing image understanding and interactive analysis. This system demonstrates the potential of LLMs to enhance the efficiency of data analysis in forestry by integrating image understanding modules, domain knowledge bases, and toolchains. However, the study also highlights a significant gap in the current capabilities of LLMs: their limited ability to extract or comprehend information from images without domain-specific adaptations, a challenge that SATGPT aims to address in the context of flood mapping.

In urban science research, Fu et al. [17] explored the opportunities and challenges presented by pre-trained LLMs, including content creation, information extraction, and disaster monitoring. Their findings underscore the effectiveness of LLMs in facilitating urban spatial form identification and sensing public sentiment, while also pointing to technical limitations and the need for domain-specific model development. SATGPT seeks to fill these gaps by providing a tailored solution for flood mapping that leverages LLMs for automated code generation and data interpretation within the specific domain of disaster management.

Stein et al. [18] and Tan et al. [19] further illustrate the broad potential and existing limitations of LLMs in environmental applications. Stein et al. call for improved models that couple watershed and ocean forcing at appropriate scales, a research need that SATGPT addresses through its integration with GEE for real-time flood mapping. Tan et al. evaluate the capabilities of GPT-4V in environmental science, agriculture, and urban planning, highlighting the challenges in fine-grained recognition and precise counting. SATGPT's approach to automated flood mapping using LLMs directly responds to these challenges by providing a specialized tool that enhances the accessibility and accuracy of flood information.

GEE has emerged as a transformative tool in the field of disaster management, offering unparalleled capabilities for rapid, large-scale analysis of environmental data. Its application in flood mapping has demonstrated significant advantages over traditional methods, providing timely, accurate, and accessible information critical for effective disaster response and planning.

Volke, Abarca-del-Río, and Warner [20] explored the use of GEE for fully automated mapping of disaster-related coastal land cover changes following the Chile 2010 earthquake and tsunami. Their study highlights GEE's strengths in cloud computing and open-source software integration for generating training samples, evaluating machine learning algorithms, and producing high-accuracy change maps. This approach significantly reduces the time and resources required for post-disaster land cover mapping, underscoring GEE's efficiency and cost-effectiveness.

Dwivedi et al. [21] developed a real-time flood mapping and monitoring web-based application using Sentinel-1 time-series data on the GEE platform for the Ganga sub-basin in Uttar Pradesh. Their approach leverages SAR data's ability to penetrate cloud cover, addressing a major limitation of optical data during floods. The study showcases GEE's potential for near-real-time flood mapping, offering a valuable resource for emergency response and risk assessment.

The integration of LLMs with Google Earth Engine (GEE) represents a novel frontier in the application of AI to environmental science and disaster management. While both LLMs and GEE have individually demonstrated significant potential in their respective fields, research on their combined use, especially in the context of flood mapping and disaster response, remains sparse. This gap presents an opportunity for innovative approaches that leverage the strengths of both technologies to enhance disaster management practices.

LLMs, with their advanced natural language processing capabilities, offer a promising avenue for automating and improving the efficiency of data analysis and decision-making processes. On the other hand, GEE's powerful cloud-based platform for Earth observation data analysis provides a comprehensive tool for environmental monitoring and disaster impact assessment. Despite the clear potential benefits of integrating these technologies, the literature reveals a lack of focused research on leveraging LLMs to interpret, analyze, and generate actionable insights from GEE's vast datasets in the context of disaster management.

This gap is precisely where SATGPT positions itself as a pioneering solution. SATGPT introduces an innovative framework that combines the code-writing abilities of LLMs with the extensive Earth observation data processing capabilities of GEE. By doing so, SATGPT addresses a critical need for more accessible, efficient, and real-time flood mapping tools. The system enables users to input natural language prompts, which are then interpreted by LLMs to generate GEE code for data extraction, analysis, and flood mapping. This process not only democratizes access to advanced flood mapping capabilities but also significantly reduces the time and expertise required to generate accurate and timely flood maps.

To date, previous work in the literature lacks specific examples of projects or studies that have successfully integrated LLMs with GEE for disaster management purposes, highlighting the innovative nature of SATGPT. The development of SATGPT thus represents a significant step forward in the field, offering a new paradigm for using AI in environmental monitoring and disaster response.

3. METHOD

This section describes: a) the workflow of SATGPT, including the user interface, LLM integration, and GEE integration; b) how user prompts are designed to extract relevant information; and c) the development and launch of the self-paced learning course focusing on prompt engineering.

3.1 SATGPT workflow

SATGPT's workflow seamlessly integrates a user-friendly interface, LLM-based code generation, and GEE's geospatial processing capabilities. The interface, developed using Mapbox GL JS, simplifies query creation by enabling users to visually select their area of interest and specify the desired flood duration (Fig. 1). Mapbox GL JS, a client-side JavaScript library, renders high-performance, interactive web maps directly in the user's browser, allowing seamless interaction with spatial layers and precise selection of areas of interest. The interface includes clear input formats, feedback mechanisms, and progress indicators to ensure a transparent user experience.

Once the user submits a query, SATGPT leverages ChatGPT, a Generative Pre-trained Transformer (GPT) model, to process the natural language prompt. ChatGPT translates the user's input into parameterized instructions, extracting key information such as location coordinates and the start and end dates of flood events. These structured prompts are tailored to GEE's scripting environment, enabling accurate code generation while adhering to syntax limitations. Error-handling mechanisms are incorporated to address potential ambiguities or misinterpretations in the prompts.

The generated code is executed on the GEE platform, which serves as the primary engine for retrieving, processing, and analyzing satellite imagery and remote sensing data. GEE's extensive data catalog, cloud computing capabilities, and algorithmic tools allow SATGPT to execute complex geospatial analyses, including flood mapping, with scalability and efficiency.

Geo-Prompt Engineering (GPE) plays a critical role in connecting ChatGPT with GEE. GPE ensures that user queries are structured effectively, aligning with the requirements of the LLM and GEE (further detailed in Section 3.3). The workflow incorporates error-handling strategies to minimize inconsistencies and provides users with reproducible, accurate results.

Fig. 2 illustrates the full UI/UX flow for SATGPT, from accessing the tool to generating interactive flood maps, downloading GEE code, and utilizing advanced visualization features such as transparency adjustment and 3D views.

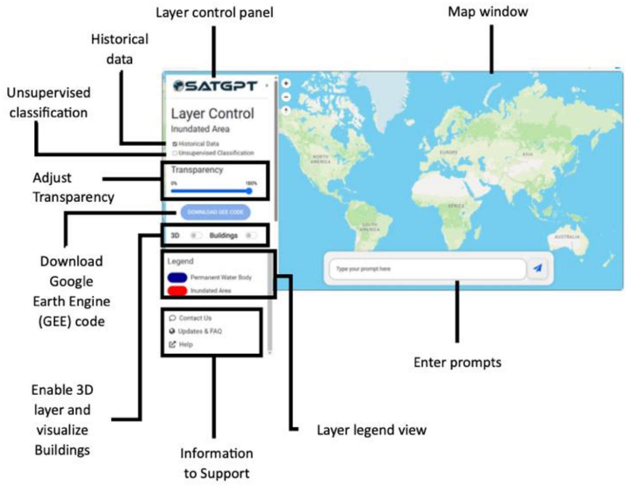

Figure 1 – SATGPT interface overview

Geo-Prompt Engineering (GPE) is crucial within the workflow that connects GEE with ChatGPT. GPE is explained in detail in Section 3.3, as part of the discussion on the online course. Natural language information from user queries is structured into instructions. This structuring includes extracting location coordinates and start/end dates of flood events. These prompts also adhere to the syntax limitations of the selected LLM, as discussed in Section 4. The LLM then leverages its coding capabilities to generate customized GEE code tailored to these defined parameters. SATGPT incorporates error-handling mechanisms to mitigate potential issues due to ambiguous prompts or misinterpretations by the LLM. The UI/UX flow for SATGPT is shown in Fig. 2.

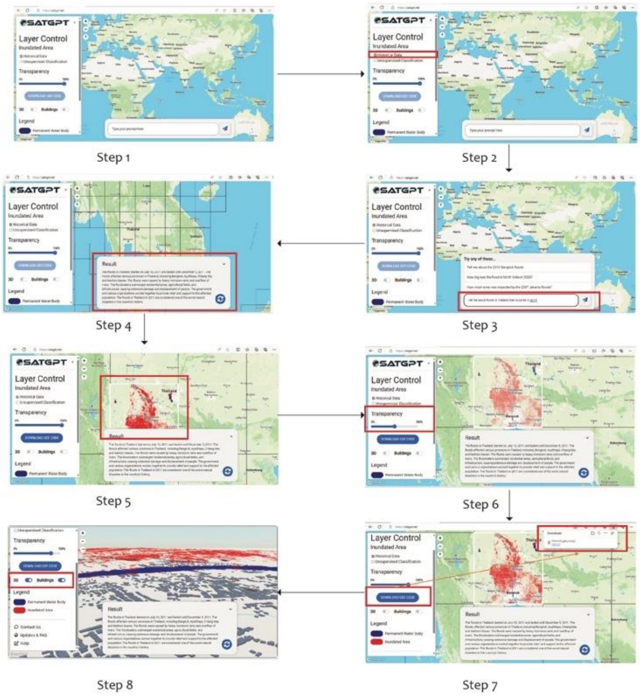

Figure 2 – UI/UX flow of SATGPT: step 1)access the tool at satgpt.net; step 2) select the operation tool to map the inundation area; step 3) enter the prompt of interest specifying an incidence of flood occurrence specific to a region and run the prompt; step 4) the prompt will run to generate the response and result with detailed information of the specific flood event; step 5) zoom and click the area of interest to see the flood map; step 6) adjust transparency according to preferences using the sliders on the option panel; step 7) click Download GEE code button to receive the JavaScript file that can be used directly in the Google Earth Engine (GEE); step 8) use the toggle button on the options panel to enable 3D view and building view.

Finally, the generated GEE code initiates execution. Here, GEE accesses its vast remote sensing databases and harnesses its cloud computation power to process the query. Datasets relevant to flood mapping are retrieved, and data extraction or unsupervised classification algorithms are applied based on the query specifications. Processed results are returned to SATGPT's interface with interactive visualizations for user assessment.

For historical data, the Joint Research Center's Yearly Water Classification History, v1.4, is used as the default dataset. This data was generated using 4 716 475 scenes from Landsat 5, 7, and 8 acquired between 16 March 1984 and 31 December 2021. Each pixel was individually classified into water / non-water using an expert system and the results were collated into a monthly history for the entire time period and two epochs (1984-1999, 2000-2021) for change detection [22]. Whereas for unsupervised classification, Weka algorithms are used with Landsat data available on GEE.

Regarding the technical stack used, SATGPT establishes a cloud-based infrastructure to support data management, remote-sensing task execution, and user interaction. Amazon S3 provides scalable storage with an initial monthly allocation of 100GB.

To support essential geospatial processing and code generation, SATGPT integrates with the ChatGPT API, Google Cloud, and Google Earth Engine API as shown in Fig. 3. The development environment utilizes the Flask web framework, providing a flexible foundation for rapid prototyping and feature implementation.

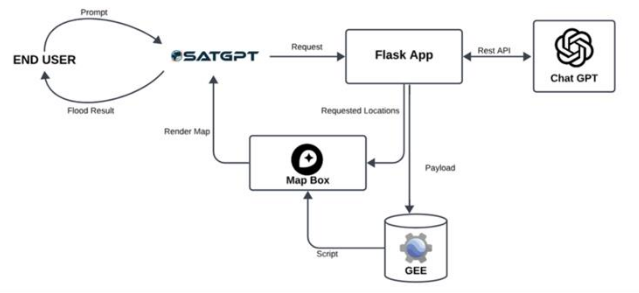

Figure 3 – Technical stack used in SATGPT

To prioritize an accessible user experience, we developed a UI/UX design emphasizing intuitive interaction and clarity. The visual interface leverages Mapbox layer functionality to ensure users maintain geospatial context through informative popups as they navigate and refine their area of interest.

3.2 User prompt design

SATGPT's success depends on its ability to translate user needs into relevant LLM prompts. To extract flood location and duration information accurately, a hybrid approach was used. This approach balances open-ended language understanding with a degree of structure for parameter-specific elements. Instead of relying solely on open-ended natural language prompts, providing guided step-by-step inputs or interactive forms could streamline prompt generation and reduce the potential for errors in LLM code generation. Additionally, offering clear examples within the interface supported users in accurately formatting their inquiries, thus improving the reliability of code generation.

3.3 Online course

To facilitate the widespread adoption of SATGPT and enhance its accessibility, a self-paced online learning course has been developed and is hosted on the United Nations University Institute on Water, Environment and Health (https://lc.unu.edu). The course provides participants with a comprehensive introduction to geospatial data analysis, focusing on the integration of **ChatGPT** with **GEE**. It is designed to equip users with the necessary skills to leverage SATGPT effectively for geospatial tasks while understanding its underlying architecture and principles.

The course requires approximately 7–10 hours to complete and is structured into a series of modules. These include an introduction to geospatial data analysis, an overview of ChatGPT's capabilities in geospatial workflows, practical exercises using GEE, and real-world case studies demonstrating SATGPT's applications in environmental monitoring, disaster management, agriculture, and urban planning. The curriculum balances theoretical concepts with hands-on practice, ensuring participants gain both foundational knowledge and practical expertise [4].

Recognizing that effectively crafting prompts is critical for successful interaction with LLMs, the course dedicates a module to mastering this skill. Learners explore best practices for prompt design in the context of geospatial tasks, ensuring that they can seamlessly communicate their needs to GEE and tailor code generation output.

GPE consists of three rules:

(a) Be specific: specify the programming language, functionality, and satellite sensor to be used.

(b) Provide context: specify the analysis domain, location, and time period. This is crucial as it adds a spatial element to the prompt.

(c) Define inputs and outputs: specify inputs and output formats to be ingested or generated.

Fig. 4 shows two prompts developed using GPE and discussed during the online course. Each step is color-coded and mapped to the prompt. GPE is a flexible process that allows users to generate a prompt based on their needs. However, it ensures that the outputs are consistent, and running the prompt repeatedly would generate the same results.

Prompt 1:
Write a JavaScript code using the Google Earth Engine API to generate a median composite image from the USGS Landsat 8 Collection 2 Tier 1 TOA Reflectance dataset (ID: ee.ImageCollection ('LANDSAT/LC08/C02/T1_TOA')) over Vietnam. Extract the shapefile of Vietnam from 'USDOS/LSIB_SIMPLE/2017' and clip the resulting composite image over the shapefile. For visualization, employ a False Color Composition of bands

Prompt 2:
Act as an urban planner tasked with assessing environmental conditions in Vietnam for 2021 using satellite imagery. Utilize the Google Earth Engine JavaScript API to calculate and visualize key indices such as NDVI (Normalized Difference Vegetation Index), NDBI (Normalized Difference Builtup Index), and MNDWI (Modified Normalized Difference Water Index).

Prompting Rules:
Rule 1: Be Specific
Rule 2: Provide Context
Rule 3: Define Inputs and Outputs

Figure 4 – Sample prompts developed using GPE

4. RESULTS

This section discusses the accuracy results for SATGPT and the reach and engagement of the online learning course.

SATGPT's accuracy was tested for the ability to map historical floods and the ability to mitigate potential issues due to ambiguous prompts. SATGPT was prompted to map eight randomly selected flood events in Asia and the Pacific; the prompts listed below and the resultant maps are shown in Fig. 5. The prompts are generated with varying levels of information; SATGPT was successfully able to extract the location and date for each flood and then generate the GEE code and show the results to the user. The average time from prompt to map was 6.73 seconds on a stable connection.

Prompts:

(a) Peninsular Malaysia, Sumatra, and Sabah suffered floods between December 2006 and January 2007; map the floods.
(b) The 2008 Indian floods affected several states in India between July 2008 and September 2008 during an unusually wet monsoon season.
(c) Map the 2020 China floods.
(d) Tell me about the 2017 Southern Thailand floods.
(e) Show me the 2020 Assam floods.
(f) 2015 Myanmar flood.
(g) In August–September 2011, there were floods in Khammouane Province in Laos; I want to know the extent of the map.
(h) Korea saw one of its worst floods ever in May 2006; what do you have to tell me about these floods?

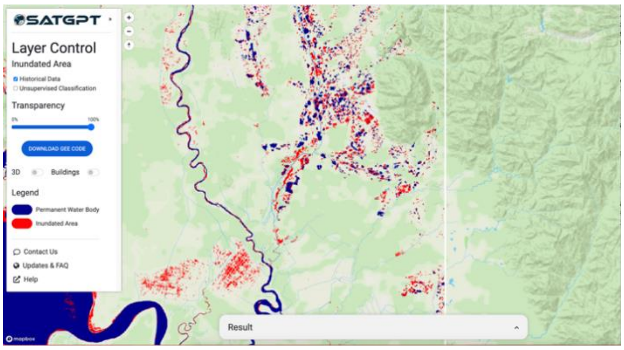

Figure 5(a) – Output of prompt a

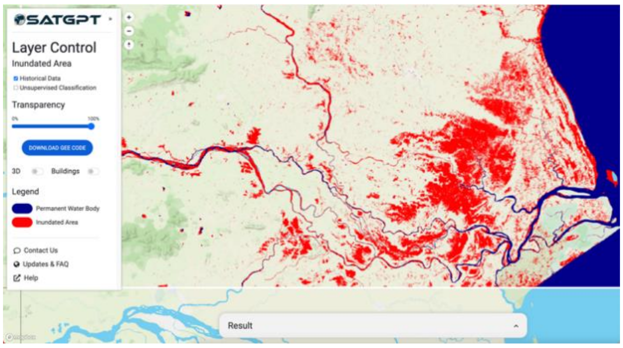

Figure 5(b) – Output of prompt b

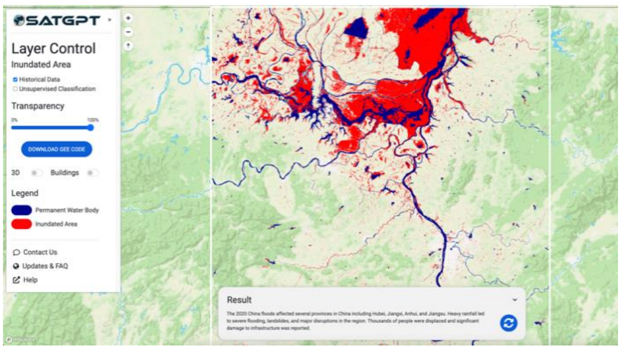

Figure 5(c) – Output of prompt c

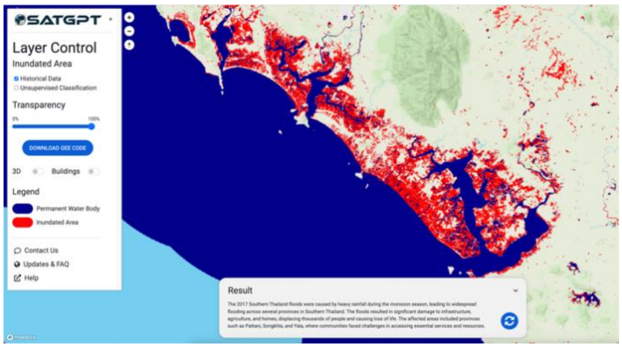

Figure 5(d) – Output of prompt d

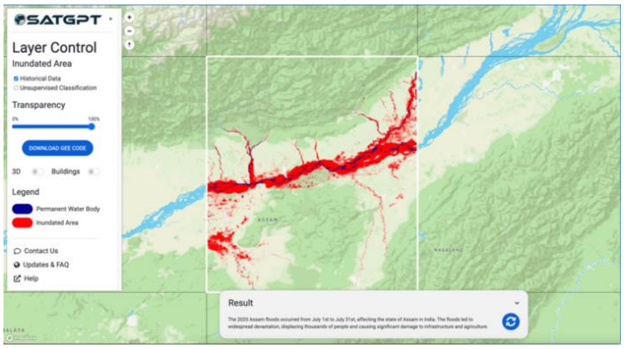

Figure 5(e) – Output of prompt e

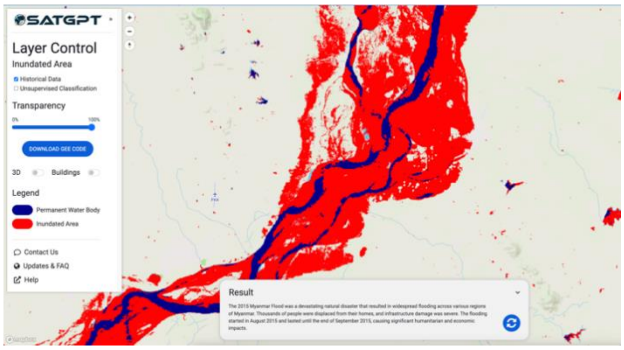

Figure 5(f) – Output of prompt f

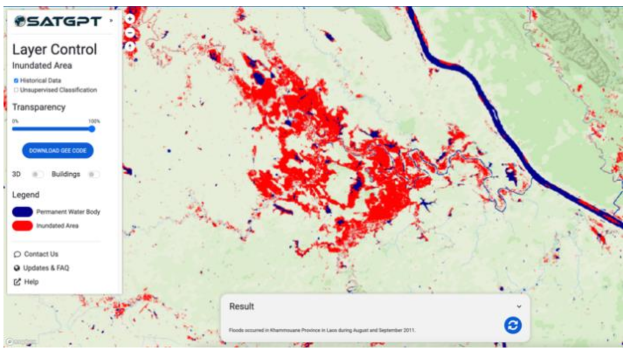

Figure 5(g) – Output of prompt g

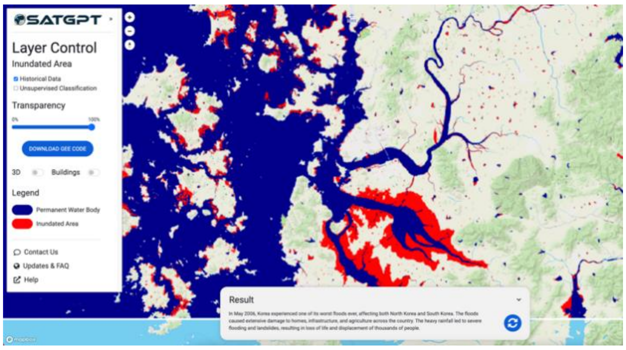

Figure 5(h) – Output of prompt h

To measure SATGPT's ability to mitigate potential issues due to ambiguous prompts, a list of 10 ambiguous prompts were used to map the 2011 flood in Bangkok, the ambiguous includes prompts with spelling mistakes and grammatical mistakes. SATGPT was able to map the 2011 floods in Bangkok correctly with all the prompts. The resultant map is shown in Fig. 6.

Prompts with spelling mistakes:

(a) "Mapp 2011 flods in Bangkok"
(b) "Map 2011 fluds in Bangcok"
(c) "Map 211 floods in Bankok"
(d) "Map 2011 foods in Bangkok"
(e) "Map 2011 floods in Bangkook"

Prompts with grammatical mistakes

(f) "Map 2011 flood in Bangkok"
(g) "Maps 2011 floods in Bangkok"
(h) "Map 2011 floods are in Bangkok"
(i) "Mapping 2011 floods was in Bangkok"
(j) "Map of 2011 floods have in Bangkok"

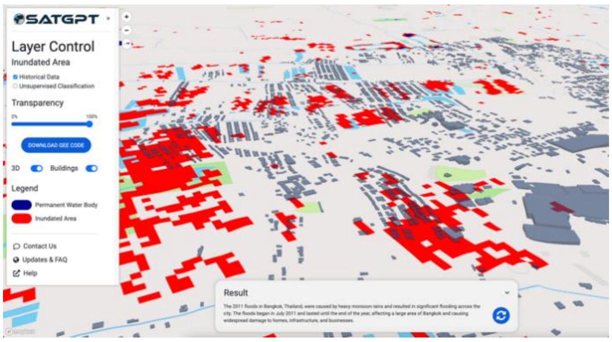

Figure 6(a) – Output of prompts with 3D view and building footprint

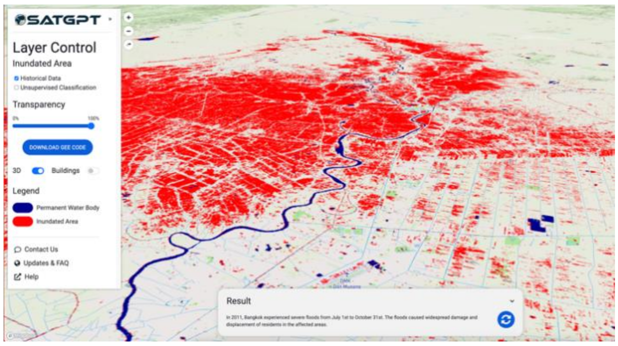

Figure 6(b) – Output of prompts with 3D view

The code generated for all the prompts in SATGPT was downloaded and tested to ensure that the same results were generated in GEE as well.

The online course has attracted 3 500 participants from 110 countries, with the majority originating from Asia and the Pacific. This region includes countries identified as highly vulnerable to climate change impacts and with limited capacity to adopt digital technologies for resilience building. Participants from these countries accounted for a significant proportion of enrollments, demonstrating the course's alignment with its target audience of users in regions with heightened disaster risk and constrained technical capacity.

The average participant age is 32, indicating interest from young professionals and graduate students. The completion rate is 19%, consistent with industry standards for self-paced online courses. Gender distribution was nearly equal (53% male, 47% female), showing inclusivity in this technical domain.

5. DISCUSSION

The development of SATGPT marks a significant milestone in the fusion of LLMs with remote sensing technologies, offering a proof-of-concept that paves the way for advanced spatial decision support systems. This integration is tailored to enhance disaster management strategies and contribute to SDGs, making sophisticated EO data analysis more accessible. By establishing a direct connection between LLMs and platforms like GEE, SATGPT empowers users to generate flood maps and perform complex geospatial analyses through simple natural language queries, thereby lowering the barriers to advanced EO data utilization, especially for users in regions with limited capacity and heightened disaster risk.

The combination of LLMs with extensive EO data and cloud computing technologies addresses key challenges in disaster management by improving the frequency and timeliness of mapping and data analysis, which are crucial for effective emergency responses and mitigation efforts. This integration also leverages cloud computing's scalability and LLM-driven automation to offer cost-effective solutions, supporting the creation of adaptable decision support systems across a range of SDG-related areas, including climate action, environmental protection, urban planning, and agricultural monitoring.

The development of SATGPT marks a significant advancement in flood mapping. It has the potential to democratize access to these sophisticated capabilities by simplifying the flood mapping process through natural language interactions. SATGPT's integration with the extensive satellite imagery and data processing capabilities of GEE offers a novel approach to enhancing global flood management strategies. This framework significantly lowers technical barriers, making it accessible to policymakers, disaster response teams, and community leaders, especially those who lack technical expertise in geospatial analysis.

Addressing potential challenges and biases is crucial for maximizing SATGPT's effectiveness. Ensuring the use of high-quality, diverse, and current training data is essential for maintaining the accuracy of outputs. As SATGPT evolves, refining its natural language processing capabilities and enhancing real-time data processing will further improve its user-friendliness and efficiency in emergency situations. Continuous updates to the training datasets and the incorporation of user feedback will also enhance the system's relevance and accuracy.

Looking ahead, SATGPT's capabilities are planned to expand into a range of new applications, including flood hotspot mapping, air pollution monitoring, and poverty mapping.

For flood hotspot mapping, SATGPT will identify regions at high risk of flooding by combining historical flood data, hydrological models, and real-time EO data to support disaster preparedness and resilience-building efforts.

For air pollution mapping, SATGPT will integrate satellite data such as Aerosol Optical Depth (AOD) from MODIS and pollutant data from Sentinel-5P. These datasets will be coupled with algorithms for pollution analysis and air quality monitoring to assess air pollution and its impacts on public health and the environment.

For poverty mapping, SATGPT will combine EO data, such as night-time lights and high-resolution imagery, with socioeconomic datasets, including population density, infrastructure, and income levels. This integration will enable the identification of impoverished regions and the evaluation of poverty alleviation programs.

Additionally, integrating sectoral data, including socioeconomic, health, and infrastructure information, will allow SATGPT to perform more comprehensive analyses across these applications. These developments aim to enhance SATGPT's utility in addressing critical challenges related to disaster management, environmental monitoring, and sustainable development.

SATGPT exemplifies the transformative impact of integrating LLMs with EO data analysis on disaster management, environmental monitoring, and advancing sustainable development. By overcoming challenges related to training data quality, interpretability, and bias, and by expanding its application scope, SATGPT and similar technologies have the potential to empower communities, build resilience, and contribute to a more sustainable future.

6. CONCLUSION

SATGPT represents a transformative approach to integrating LLMs with remote sensing data analysis, offering significant advancements in flood mapping and disaster management. Its development provides a scalable model for leveraging cutting-edge technologies to address a wide range of geospatial challenges, from flood risk assessment to broader applications such as environmental monitoring, urban planning, and climate resilience.

By addressing challenges such as biases in training data and limitations in real-time processing, and through continuous refinement of its capabilities, SATGPT can enhance disaster management practices not only in the Asia-Pacific region but also on a global scale. This approach demonstrates the potential for democratizing access to advanced geospatial tools, enabling policymakers, disaster response teams, and community leaders worldwide to make informed decisions and build resilience.

The broader implications of SATGPT's development underscore the critical role of artificial intelligence and remote sensing in advancing sustainable development, improving disaster preparedness, and fostering global collaboration to mitigate the impacts of climate change.

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