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Harnessing Generative AI for Educators: Case Study of Accurate Wildfire Location Mapping

Prof. Asif Ahmed, State University of New York, Polytechnic Institute

Asif Ahmed is an Assistant Professor at College of Engineering at SUNY Polytechnic Institute, Utica, New York. Dr. Ahmed is a strong advocate of STEM education, inclusion of Diversity, Equity, and Inclusion (DEI) in curriculum. Primarily trained as a Geotechnial Engineer, Dr. Ahmed's current research also focuses on engineering education. Currently, his interest is modification of the civil engineering curriculum to accomodate the infrastructure monitoring, DEI concepts to prepare students better for the workforce. He is very interested to work with the high school and community colleges to increase the STEM enrollment in campus.

SATHVIKA KATIKANENI, State University of New York, Polytechnic Institute
Ashish Gunda, State University of New York, Polytechnic Institute

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Abstract

Incorporating generative artificial intelligence (AI) into engineering education presents an innovative opportunity to enhance student learning outcomes by equipping future engineers with cutting-edge tools for disaster management and infrastructure resilience. This paper explores how generative AI can be leveraged by engineering educators to teach students advanced techniques for wildfire prediction and geospatial analysis. Focusing on the use of generative AI in the classroom, the methodology demonstrates how students can engage with platforms like Google Earth Engine to access and analyze satellite imagery and environmental datasets, such as MODIS Active Fire Detections and LANDSAT/Sentinel Burn Severity. By integrating generative AI tools (e.g., ChatGPT, Gemini), educators can guide students through the process of automating code generation for wildfire location mapping, enhancing their problem-solving skills and technical competence. The use of generative AI simplifies traditionally complex geospatial analysis tasks, allowing students to focus on interpreting data and understanding the real-world implications of their work. Through hands-on exercises, students can apply AI-driven models to identify wildfire-prone areas, gaining practical experience in disaster risk management. Moreover, the flexibility of generative AI extends to a variety of natural disasters, including floods, hurricanes, and tornadoes, allowing educators to incorporate diverse scenarios into their teaching. This approach not only deepens students' technical knowledge but also fosters critical thinking and prepares them for the evolving challenges in the engineering profession. By leveraging generative AI in the classroom, engineering educators can significantly improve students' understanding of disaster resilience, proactive planning, and the ethical use of technology in civil engineering contexts.

Introduction

The frequency of wildfires in California has markedly increased in recent years, driven by a combination of climatic and anthropogenic factors. Rising temperatures, prolonged droughts, and shifting precipitation patterns, all exacerbated by climate change, have created more favorable conditions for wildfires (Lee and Banerjee 2021, Keelay, J. et al. 2009). Additionally, increased development in fire-prone areas and accumulated vegetation due to past fire suppression efforts have further heightened the risk. As a result, the state has seen a surge in both the number and intensity of wildfires, leading to devastating impacts on communities, ecosystems, and air quality. This trend underscores the urgent need for comprehensive wildfire management strategies and climate action to mitigate future risks. In August 2020, a series of lightning strikes ignited hundreds of wildfires across California, culminating in the largest wildfire in the state's recorded history (Shumel and Heifetz 2022). This disaster occurred less than a year after Australia's "Black Summer," during which the continent experienced its largest bushfires, burning 11 million hectares (Burgess et al. 2020).

To mitigate the severity, the associated professionals need to rely on experts to produce maps of burnt areas. Google Earth Engine (GEE) is a powerful cloud-based platform that enables users to visualize and analyze vast amounts of geospatial data (Zhao et al. 2021). It combines extensive satellite imagery and geospatial datasets with advanced analytical capabilities, allowing for the creation of detailed and dynamic maps. However, coding is always difficult for civil engineers. In most of the undergraduate curriculum, computer programming is absent. That is why traditional civil engineers need to rely on experts for producing such informative maps. However, due to the emergence of generative AI languages (i.e. ChatGPT), it can now assist in generating the relevant code based on the ‘query’ or prompt’ provided (Wu et al. 2023). As such, generative AI models like ChatGPT have revolutionized the way non-coders can interact with complex platforms like Google Earth Engine (GEE). Traditionally, using GEE required proficiency in JavaScript or Python, which posed a significant barrier to entry for many users. However, with the advent of generative AI, even individuals without coding experience can now harness the powerful capabilities of GEE to analyze geospatial data and produce maps (Li and Ning 2023).

Wildfire associated danger estimation is crucial for habitat management and firefighting strategies. However, accurate prediction of size and occurrence of wildfire induced burn areas is challenging due to a variety of factors. Prediction of wildfire occurrence was previously based on empirical and statistical models. In recent years, satellite data combined with advanced image processing techniques have made global datasets with millions of wildfire observations available (Trucchia et al. 2022). These extensive datasets offer an opportunity to enhance the predictions of current machine learning models and accurately identify the most hazardous fires. Therefore, accurate maps are a valuable input for the predictions of wildfire burnt areas. Leveraging the coding assistance provided by the ChatGPT or similar language (i.e. Gemini), we undertook an initiative to generate the California wildfire maps of the last two decades by combining ChatGPT and GEE platform. Initially, we provided appropriate prompts to produce the necessary codes required in the GEE platform. Later, we generated the maps utilizing the codes. While doing so, we needed to look at several datasets which can provide us the accurate maps. At the end, we also attempted to produce such maps for flooding incidents as frequent flooding has been also an increasing disaster in the United Staes. We didn’t attempt to predict any wildfire burnt areas in this study, our focus was only on map generation from scratch. The methodology described in the paper can assist the appropriate authority for enhancing their capacity for comprehensive disaster risk management and infrastructure resilience.

Methodology

In order to work with ChatGPT, we need to provide ‘prompt’ first. ‘Prompt’ can be otherwise described as *User Input*, where the user provides input for an output. For example, if we need to generate California wildfire map for the year of 2017, we can use ‘*I need a map showing the burnt areas due to wildfire in California use for 2017’*. Based on the input, the Chat GPT platform provides the code required to put in the GEE platform. While working on it, we faced several challenges to have an accurate map because of the image source. There can be several sources from which we can obtain satellite images. Based on the accuracy of the source file, the output image quality may vary.

In this study, we have looked at three different datasets for acquiring satellite images. Below is a description of the dataset, source, and relevance to our project.

1. MODIS Active Fire Detections (MODIS, 2023)

- *Description*: Near real-time detection of fires using thermal anomalies.
- *Source*: Earth Engine Data Catalog - FIRMS (Moderate Resolution Imaging Spectroradiometer).
- *Relevance*: Provides timely information on active fire locations, aiding in monitoring and response efforts during wildfire events.

2. National Incident Feature Service (NIFS) Wildfire Perimeters (NIFC, 2023)

- *Description:* Historical perimeters of large, notable wildfires in the US.
- *Source:* Earth Engine Data Catalog - USFS_NIFS_WFIGS_CONUS.
- *Relevance:* Offers detailed outlines of burned areas, facilitating post-fire analysis and assessment of wildfire impacts on ecosystems and communities.

3. LANDSAT/Sentinel Burn Severity (LANDSAT, 2023)

- *Description:* Post-fire analysis assessing the severity of burn scars.
- *Source:* Various datasets available in the Earth Engine Catalog.
- *Relevance:* Enables the evaluation of vegetation loss and ecosystem changes caused by wildfires, aiding in understanding the long-term ecological effects of fire disturbances in California.

We used MODIS dataset for producing our maps in the study. While we were facing difficulties in obtaining the exact California maps, we also used the *Gemini* platform to generate the codes. The images we presented in this paper are based on the code produced in *Gemini* platform. We attempted to document the wildfire maps from the year 2000 to 2023, for a total of 24 years in the study. The following Figure 1 exhibits the steps to produce the California yearly wildfire maps.

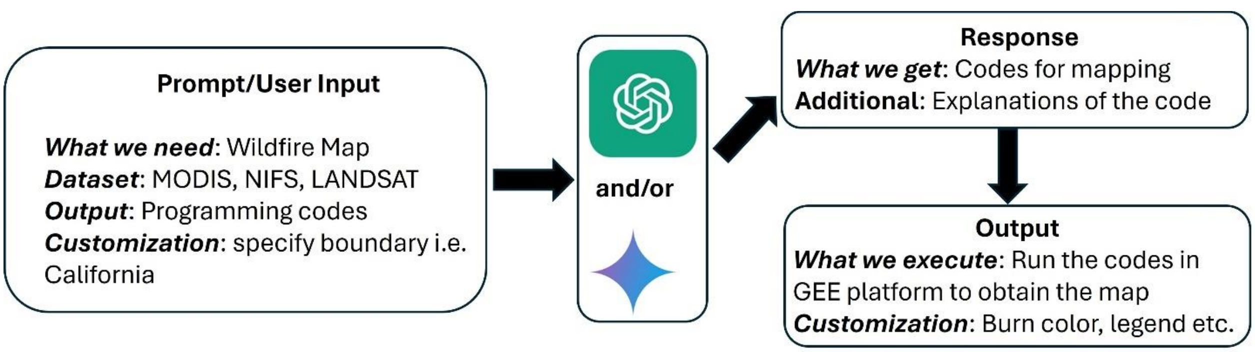


Figure 1: Steps undertaken to produce California wildfire maps

Example of a sample coding

For the convenience of the readers, the authors are showing a sample code file that was produced using Generative AI platform and later used in GEE to obtain a map.

For wildfire in California

```
// Load MODIS fire detections
var modisFires = ee.ImageCollection('FIRMS')
  // Choose a relevant date range
  .filterDate('2010-01-01', '2010-12-31');
// Get California's geometry
```

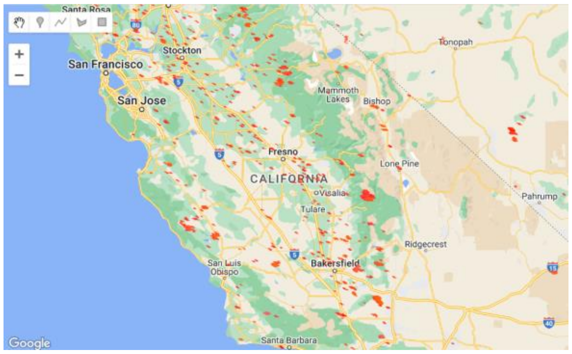
```
var california = ee.FeatureCollection('TIGER/2018/States')
  .filter(ee.Filter.eq('NAME', 'California'));
// Checking to see if CA map was selected properly
Map.addLayer(california, {}, "California Boundary")
// Filter to California
var firesCalifornia = modisFires.map(function(img){
  return img.clip(california)})
// Display on a map
Map.addLayer(firesCalifornia, {color: 'red'}, "California Fires");
```

As can be seen in the code, we used the MODIS dataset to generate the maps. In addition, we also filtered the date for the year 2010. Further, we narrowed it down to California boundary to show only burnt areas from California state. The output of the code is shown in Figure 2. The red patches in the figure are showing the burnt areas of the state in 2010. The fire spread sporadically across the states while the most concentration was found near Sacramento, the northern part of the state. As the black boundary on the image is compromising some visibility, the authors opted out from the filtering California only from the map. For the rest of the paper, the produced maps are shown without the California boundary.

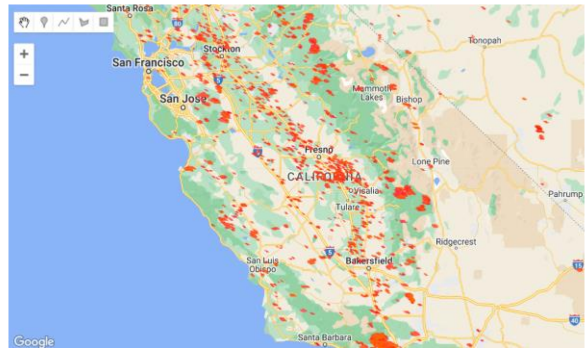
Figure 2: Burnt area of California state in the year of 2010

Results

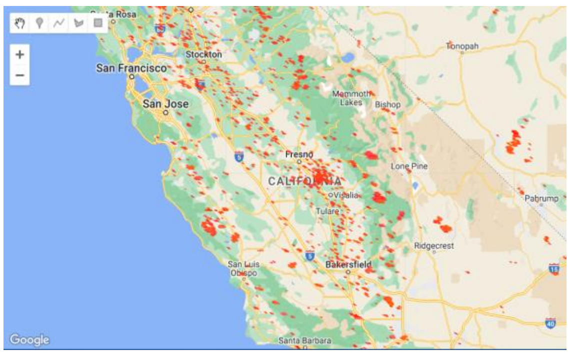
As discussed in the previous section, a total of 24 maps were produced to check the wildfire severity. To conserve space, not all of them are displayed in the paper. A total of 12 maps are shown. The first set of maps are selected from 2000-2014 when the wildfire severity isn't that high (Figure 3) whereas the next set of maps are selected from 2015-2023 (Figure 4) when the red dot areas kept increasing across the state.



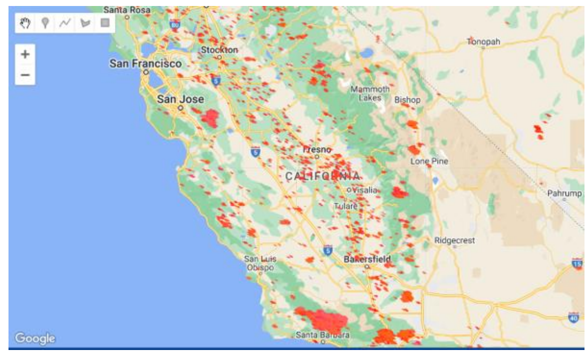
(a)



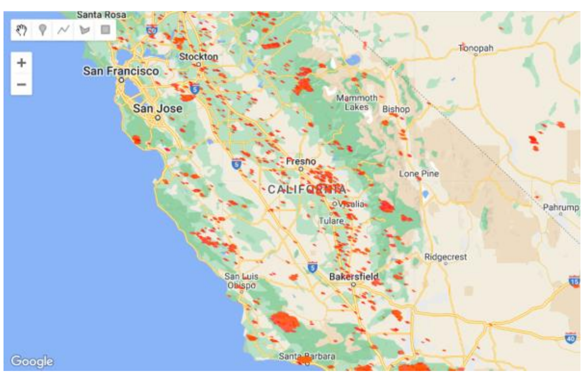
(b)



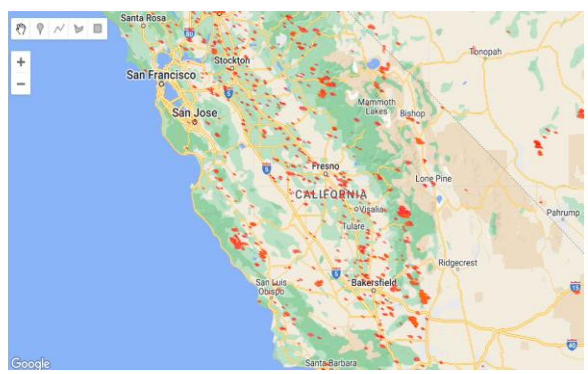
(c)



(d)



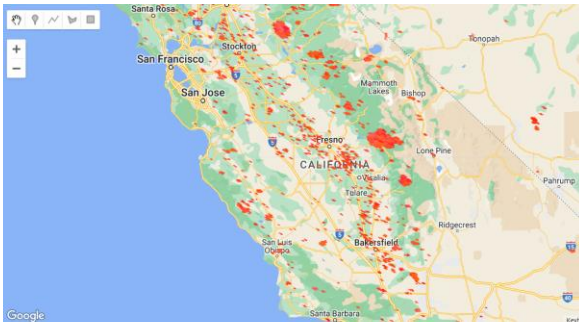
(e)



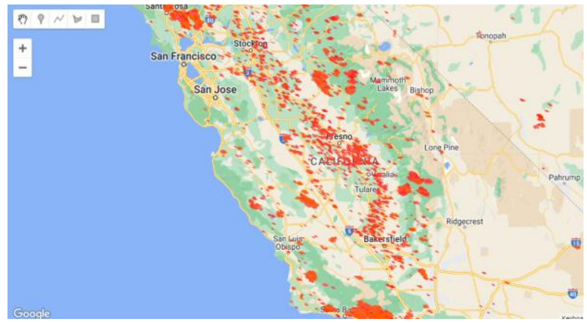
(f)

Figure 3: Map of burnt areas due to wildfire in the year of (a) 2000, (b) 2003, (c)2005, (d) 2007, (e) 2009, and (f) 2012 in the state of California, USA

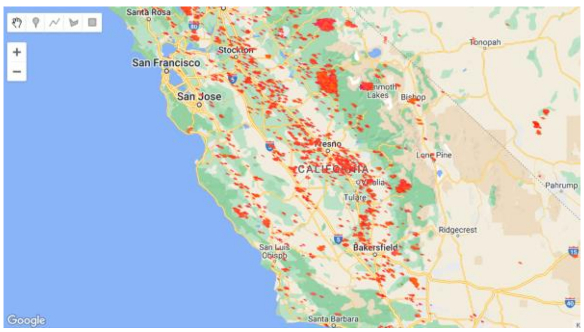
As can be seen from Figure 3, the wildfire frequency in the year 2000 is not severe. The trend of wildfire in the years 2005, 2007, 2009 and 2012 are similar. The red patches in 2003 indicate the regions that experienced burns, which are dispersed throughout the state but appear more concentrated in the northern and central parts, particularly around San Francisco and the Sierra Nevada range. This visual representation highlights the widespread nature of the wildfires during that year. In 2003, California saw significant wildfire activity, including notable incidents like the Cedar Fire, which alone burned over 273,000 acres and was the largest wildfire in California's history at the time (Keeley et al. 2004). The map underscores the extensive impact of the 2003 wildfire season on the state's landscape.



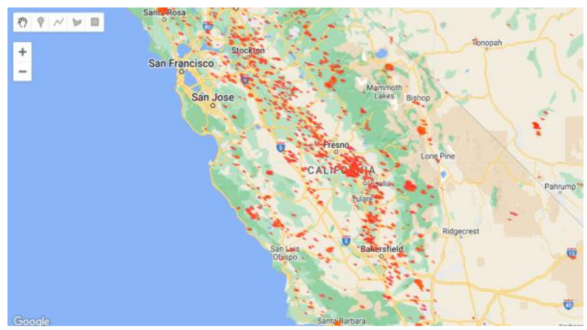
(a)



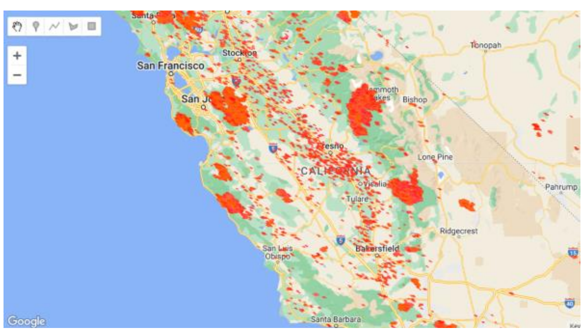
(b)



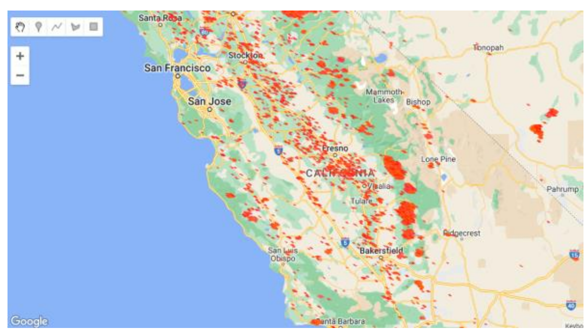
(c)



(d)



(e)



(f)

Figure 4: Map of burnt areas due to wildfire in the year of (a) 2015, (b) 2017, (c) 2018, (d) 2019, (e) 2020, and (f) 2021 in the state of California, USA

Looking at Figure 4, it can be said qualitatively that there are more wildfire events after the year 2015. The severity increased in 2017, covering mostly the areas near the forest with less burnt areas near the Pacific shoreline. In the year 2020, a wildfire breakout happened where the amount of burnt area was the highest. The 2020 California wildfires were unprecedented in both scale and impact, setting them apart from previous incidents in the region. Sparked by a rare and intense series of lightning storms in August, the fires quickly spread due to extremely dry conditions and high temperatures, exacerbated by climate change. This resulted in the largest wildfire season in California's recorded history, with over 4 million acres burned, thousands of structures destroyed, and widespread evacuations (Safford et al. 2022). Unlike previous wildfire seasons, the 2020 fires were notable for their sheer number and simultaneous occurrence, overwhelming firefighting resources and highlighting the growing influence of climate change on fire behavior and frequency. As the 2020 wildfire incident is captured on the map, it acted as a point of validation about the accuracy of our produced maps.

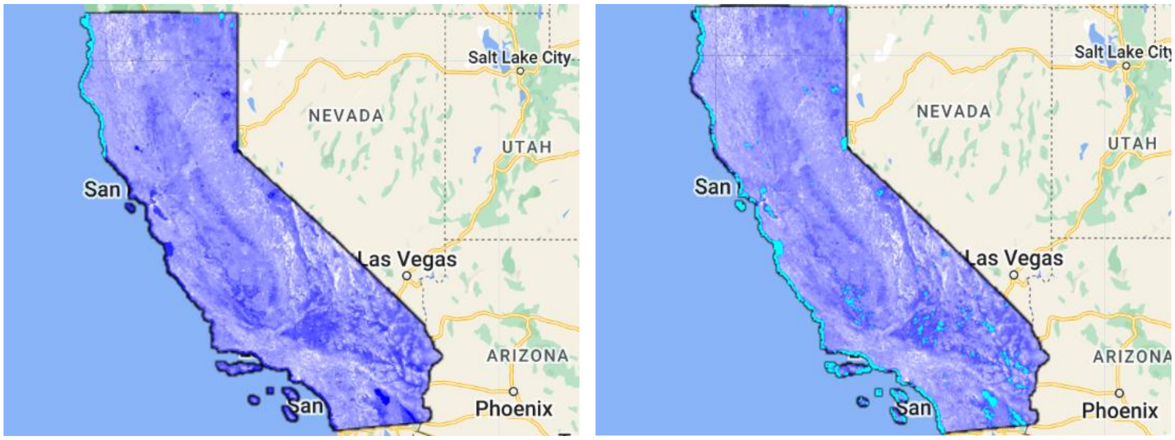
Discussion

Challenges faced during the study

When we started working on this project, we anticipated the generated code would suffice to produce the desired maps. However, it was not a straight line going from the codes to the maps. Initially, we didn't get any burnt area maps depending on the codes provided to the GEE environment. At this stage, we were using the free version (ChatGPT 3.5) after which we upgraded to the paid version. We also used the responses obtained from paid version of Gemini platform. After that, we started to have colored maps showing the burnt areas. In addition, we also struggled with using the correct dataset. As discussed in the previous section of the paper, there are several datasets available to obtain satellite images. We finally produced our maps using the MODIS dataset. During the process, we also discovered there are some paid resources to obtain satellite images, however, we stuck to the available no-cost resources for the study. The authors are not promoting any generative AI platform; our prompts (user input) were not detailed enough to generate the desired maps initially. Providing exact prompts is the key to obtaining the needed output. Another important aspect is understanding the code details. The first author of the paper is a civil engineer by training, however, the graduate students who worked on this project are from computer science backgrounds. Therefore, it was easier for the group to find any discrepancy in the code, which later assisted to modify the code accordingly.

Experimentation with flood maps

To check whether the adopted methodology works for other kinds of disasters, we attempted to produce flooding maps for the same state. Similar to the wildfire mapping, we asked ChatGPT to produce the codes for flooding maps to run in the GEE environment. We used the same MODIS dataset to produce the maps. The two maps in Figure 5 show the flooding events for 2018 (Figure 5a) and 2019 (Figure 5b) respectively. The blue color responds to the presence of water in the map whereas the cyan color adds another layer when the water amount is above a specific threshold value. As can be seen, there are less cyan areas except the Pacific shoreline in the north in 2018 whereas there are several cyan areas in the southern part of the state. As we just attempted to check whether some extent of flooding map generation is possible or not, we did not focus on the evaluation of the flooding maps.



(a) (b)

Figure 5: Flooding maps of California in (a) 2018 and (b) 2019

How Engineering Educators can implement it in the classroom

This section outlines actionable strategies for engineering educators to incorporate generative AI into their curriculum, enabling students to explore cutting-edge technologies in disaster management.

Simplifying Coding for Non-Programmers

Generative AI can alleviate one of the most significant barriers to geospatial analysis: coding proficiency. Platforms like Google Earth Engine (GEE) traditionally require expertise in JavaScript or Python, which may not be part of a civil engineering curriculum. By using AI to generate code from simple prompts, students can quickly produce wildfire prediction maps or analyze geospatial data. For example, an educator could design an assignment where students input a prompt such as, "Generate a map of wildfire-prone areas in California for 2020," and then use the AI-generated code within GEE to visualize the data.

Teaching Prompt Engineering and Data Interpretation

Effective use of generative AI requires skill in crafting precise prompts and interpreting the results. Educators can incorporate exercises on prompt engineering, challenging students to refine their inputs to obtain accurate and useful outputs. Furthermore, interpreting AI-generated outputs, such as wildfire heat maps or burn severity analyses, fosters critical thinking and enhances students' ability to evaluate data quality and model assumptions.

Exploring Multi-Scenario Applications

Wildfire prediction and geospatial analysis are just the beginning of what generative AI can offer. Educators can extend assignments to include related disaster scenarios such as flood mapping or drought analysis, allowing students to explore the versatility of these tools. For instance, a project might require students to compare wildfire patterns across different years or simulate the impact of hypothetical environmental changes on wildfire spread.

Integrating Ethical Considerations

Generative AI introduces ethical challenges, including data privacy and the risk of over-reliance on AI outputs. Educators can use these challenges as discussion points, encouraging students to consider the limitations of AI and the importance of verifying results against independent datasets. Such discussions prepare students to use AI responsibly in professional practice. Some government agencies in the USA are blocking ChatGPT in their offices due to concerns over data security, confidentiality, and compliance with regulatory standards (Serbu, J. 2024, Heilweil, R. 2024). These agencies handle sensitive information, and the use of AI-driven tools like ChatGPT, which process and generate text based on vast datasets, could pose risks if not properly managed. There are fears that interaction with such AI systems might inadvertently lead to data breaches, leaks of confidential information, or violations of data protection laws. Additionally, there may be apprehensions about the reliability and accuracy of the information generated by AI, which could impact decision-making processes within these critical government functions. Therefore, the user must act responsibly to use AI as a tool not weapon.

Building Collaborative Learning Environments

Generative AI platforms can be used in team-based projects, fostering collaboration between students from diverse disciplines such as computer science, environmental science, and civil engineering. Collaborative projects might include creating a wildfire risk assessment report that combines geospatial analyses, policy recommendations, and engineering solutions.

Providing Real-World Case Studies

Case studies, such as those focusing on California's wildfire history or Australia's "Black Summer," can contextualize AI applications in real-world scenarios. Students can use generative AI to analyze historical data, predict future wildfire risks, and propose engineering interventions, thereby gaining insights into the practical applications of AI in disaster management. In our study, we used Google Earth Engine (GEE) platform to produce the maps; however, any other third-party integrated development environment (IDE) (i.e. Google Collaborator) would also fulfill the purpose (Tao and Xu 2023). If any user is comfortable in the ArcGIS software, ChatGPT/Gemini can also leverage existing visualization packages (i.e. Python library 'Matplotlib'), ArcPy library for generating the python scripts. As an AI chatbot, ChatGPT can understand users' map requests through conversational interactions.

Future Directions

Future directions for this work could focus on enhancing the accuracy and usability of AI-generated geospatial analysis by refining prompt engineering techniques and integrating real-time data sources. Expanding the application of generative AI beyond wildfires to other climate-related disasters, such as droughts and hurricanes, could further demonstrate its versatility in disaster risk management. Additionally, incorporating machine learning models to improve predictive capabilities and integrating AI tools into decision-support systems for emergency response agencies could maximize their practical impact. From an educational perspective, developing structured curricula that teach engineering students how to effectively utilize AI-driven geospatial tools will be essential for equipping future professionals with the necessary skills to address climate challenges. Finally, addressing concerns related to AI transparency, model interpretability, and data ethics will be crucial to ensuring responsible implementation in geospatial analysis.

Conclusions

This study highlights the potential of generative AI in transforming geospatial analysis for wildfire mapping. By utilizing Google Earth Engine and leveraging AI-generated code, we documented wildfire-affected areas in California over 20 years. The application of generative AI tools not only streamline coding processes but also enables practitioners and students without extensive programming experience to contribute to disaster risk management effectively. Furthermore, the successful application of this approach to flood mapping demonstrates its adaptability to other natural disasters. Despite challenges related to prompt engineering and dataset selection, this work illustrates the practical utility of AI-driven methods in civil engineering. Future efforts should focus on integrating these tools into engineering curricula, fostering interdisciplinary collaboration, and addressing ethical concerns surrounding data privacy and AI reliability. By doing so, we can better prepare students to meet the demands of an increasingly climate-challenged world. In addition, by leveraging datasets such as MODIS Active Fire Detections, NIFS Wildfire Perimeters, and LANDSAT/Sentinel Burn Severity, stakeholders can better understand the spatial and temporal patterns of wildfires.

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