A Conversational Intelligent Assistant for Enhanced Operational Support in Floodplain Management with Multimodal Data

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Abstract

Floodplain management is crucial for mitigating flood risks and enhancing community resilience, yet floodplain managers often face significant challenges, including the complexity of data analysis, regulatory compliance, and effective communication with diverse stakeholders. This study introduces Floodplain Manager AI, an innovative artificial intelligence (AI) based virtual assistant designed to support floodplain managers in their decision-making processes and operations. Utilizing advanced large language models and semantic search techniques, the AI Assistant provides accurate, location-specific guidance tailored to the unique regulatory environments of different states. It is capable of interpreting Federal Emergency Management Agency (FEMA) flood maps through multimodal capabilities, allowing users to understand complex visual data and its implications for flood risk assessment. The AI Assistant also simplifies access to comprehensive floodplain management resources, enabling users to quickly find relevant information and streamline their workflows. Experimental evaluations demonstrated substantial improvements in accuracy and relevance of the AI Assistant's response, underscoring its effectiveness in addressing the specific needs of floodplain managers. By facilitating informed decision-making and promoting proactive measures, Floodplain Manager AI aims to enhance flood risk mitigation operations and support sustainable community development in the context of increasing flood events driven by climate change. Ultimately, this research highlights the transformative potential of AI technologies in improving floodplain management practices and fostering community resilience.

Keywords: Floodplain Management, AI Assistant, Large Language Models, Flood Maps, Decision Support, Community Resilience

1. Introduction

Flooding is one of the most prevalent and devastating natural disasters worldwide, affecting millions of people and causing significant economic losses each year (Merz et al., 2021). The impacts of flooding extend beyond immediate physical damage to include long-term effects on communities, economies, and ecosystems (Crawford et al., 2022). Effective floodplain management is essential to mitigate these risks, enhance community resilience, and ensure sustainable development (Auliagisni et al., 2022). Floodplain management involves the careful planning and regulation of land use in areas prone to flooding, aiming to reduce flood risks to people and property while preserving the natural functions of floodplains (Jakubínský et al., 2021). Floodplain managers play a critical role in this process. They are responsible for implementing policies, regulations, and strategies that balance development needs with safety and environmental considerations (FEMA et al., 2022). Their duties encompass risk assessment, regulatory compliance, community education, and coordination among various stakeholders, including government agencies, developers, and the public (Yildirim et al., 2022).

Despite the importance of their role, floodplain managers face numerous challenges in their efforts to effectively manage flood risks; One significant challenge is the management of complex and extensive datasets (Alabbad et al., 2023). Flood risk assessment requires analyzing vast amounts of data, such as hydrological and meteorological records, topographical information, land use patterns, and historical flood events (Diaconu et al., 2021). Processing and interpreting this data demand advanced analytical tools and expertise (Mishra et al., 2022). Regulatory compliance adds another layer of complexity; Floodplain managers must navigate a myriad of federal, state, and local regulations that govern land use, building codes, and environmental protection in flood-prone areas (Heyden et al., 2022). These regulations can vary significantly between jurisdictions and are often subject to updates and changes. Ensuring adherence to all relevant regulations is critical to maintain eligibility for programs like the National Flood Insurance Program (NFIP), which provides federally backed flood insurance to property owners (Frazier et al., 2020).

Effective communication is also a crucial aspect of floodplain management; Managers must convey complex technical information and risk assessments to a diverse audience, including policymakers, developers, community leaders, and the public (Mould et al., 2020). Clear and timely communication is essential for fostering awareness, encouraging proactive measures, and facilitating coordinated responses during flood events (El Naggar et al 2024). However, communicating technical information in an accessible and understandable manner can be challenging (Mould et al., 2020). Decision-making under uncertainty is an inherent part of floodplain management (Towe et al., 2020).

Floods are influenced by numerous factors, including weather patterns, climate change, land development, and environmental conditions (Merz et al., 2021). The unpredictable nature of these factors introduces uncertainties in flood risk assessments and the effectiveness of mitigation strategies (Koc et al., 2021). Floodplain managers must make critical decisions based on incomplete or evolving information, balancing potential risks and benefits (FEMA et al., 2022). The increasing frequency and severity of flood events due to climate change further exacerbates these challenges. Changes in precipitation patterns, sea-level rise, and more frequent extreme weather events have altered flood risk profiles in many regions (Swain et al., 2020). This necessitates continuous updating of risk assessments and the development of innovative strategies to enhance resilience (FEMA et al., 2022).

Advancements in artificial intelligence (AI) offer promising opportunities to address some of these challenges (Gonzales-Inca et al., 2022). AI technologies, particularly large language models (LLMs) such as GPT-4, have demonstrated remarkable capabilities in processing and interpreting vast amounts of data, understanding natural language, and generating coherent and contextually appropriate responses (Thirunavukarasu et al., 2023). These models can analyze complex datasets, extract relevant information, and assist in interpreting regulatory documents and technical reports (Zhao et al., 2024). By leveraging these technologies, it is possible to develop intelligent tools that can assist floodplain managers in accessing information, interpreting data, and making informed decisions. AI-driven systems can enhance early warning systems by improving the accuracy of flood predictions through the analysis of real-time data from various sources (Nova et al., 2023). They can also facilitate effective communication by providing platforms for disseminating information and engaging with stakeholders (Yesilkoy et al., 2024).

This study presents the development of Floodplain Manager AI, an AI Assistant specifically designed to support floodplain managers in their daily tasks. The AI Assistant utilizes advanced AI technologies, including large language models and semantic search techniques, to provide expert knowledge, location-specific information, and assistance in navigating floodplain management processes. By integrating comprehensive data from reliable sources, such as federal and state floodplain management agencies, regulatory documents, and technical guidelines, the AI Assistant aims to enhance the efficiency and effectiveness of floodplain management practices.

The objectives of this study are to develop an AI-based tool that addresses the key challenges faced by floodplain managers and to evaluate its effectiveness in enhancing floodplain management practices. Specifically, the study aims to: (a) develop an LLM-based AI Assistant capable of understanding and responding to a wide range of floodplain management-related queries, including technical questions, regulatory clarifications, and procedural guidance; (b) integrate comprehensive and up-to-date floodplain management resources into the AI Assistant, ensuring that the information provided is accurate, relevant, and tailored to specific locations and regulatory contexts; and (c) evaluate the accuracy and relevance of the AI Assistant's responses through experimental testing and analysis, comparing its performance with existing tools and assessing its potential impact on floodplain management practices. By achieving these objectives, the study seeks to demonstrate the potential of AI technologies in supporting floodplain management and contributing to improved flood risk mitigation strategies. The development of Floodplain Manager AI represents a significant advancement in leveraging AI for environmental management, providing a valuable tool for professionals in the field.

In the remainder of this article, the study provides a detailed background on floodplain management challenges and related work, describes the methodology employed in developing the AI Assistant, presents the system architecture, and discusses the results of experimental evaluations. The study concludes with a discussion of the findings, potential improvements, and implications for future research and practice.

2. Background and Related Work

Floodplain management is essential for reducing the impacts of flooding on communities and the environment (Kiedrzyńska et al., 2015). It involves implementing strategies and policies that minimize flood risks while promoting sustainable development and preserving natural floodplain functions (Katyal et al., 2011). Floodplain managers are crucial in balancing development needs with risk reduction and environmental conservation (Erős et al., 2019). However, they face significant challenges, including managing complex and extensive datasets such as hydrological records, topographical maps, and historical flood data (Li et al., 2022; McMillan et al., 2007). Effective analysis and interpretation of this data are vital for accurate flood risk assessments and the development of mitigation strategies, necessitating advanced analytical tools and expertise (Lechowska et al., 2018).

Regulatory compliance further complicates floodplain management (Burby et al., 1994). Managers must navigate a multitude of federal, state, and local regulations governing land use, building codes, and environmental protection in flood-prone areas (Johnson et al., 2011). In the United States, the National Flood Insurance Program (NFIP), administered by FEMA, requires communities to adhere to specific regulations to participate and provide federally backed flood insurance to property owners (FEMA et al., 2022). Understanding and applying these legal requirements accurately is essential for compliance and effective floodplain management (Knowles et al., 2014).

Communication is another critical aspect, as floodplain managers must convey complex technical information and risk assessments to diverse stakeholders, including policymakers, developers, community leaders, and the public (Feldman et al., 2016). Clear and timely communication is necessary to inform decision-making, encourage proactive measures, and ensure coordinated responses during flood events (Vávra et al., 2017; Andráško et al., 2021). Additionally, decision-making under uncertainty poses inherent challenges, as flood risks are influenced by unpredictable factors such as weather patterns, climate change, land development, and environmental conditions, managers must make informed decisions based on incomplete or evolving information, balancing potential risks and benefits (Kundzewicz et al., 2014).

Climate change has intensified these challenges by altering precipitation patterns, causing sea-level rise, and increasing the frequency of extreme weather events, thereby changing flood risk profiles in many regions. Adapting to these changes requires continuous updates to risk assessments and the development of innovative resilience strategies (IPCC et al., 2021). Addressing data complexity, ensuring regulatory compliance, facilitating effective communication, and making informed decisions under uncertainty are thus critical components of effective floodplain management.

Previous research has explored the application of AI in developing tools and systems to support flood management (Sajja et al., 2024). Wang (2021) investigated the use of AI technologies, including machine learning and deep learning, to enhance flood observation using unconventional data sources. The study highlighted the potential of integrating data from surveillance cameras, social media, and crowdsourced information to improve real-time flood monitoring and situational awareness. Sermet and Demir (2022) introduced Geospatial VR, a virtual reality framework for collaborative environmental simulations. The system utilizes intelligent voice recognition and emotional state detection to create immersive training scenarios, enabling emergency responders and community members to engage in realistic simulations, thereby improving preparedness and response capabilities.

Another study by Sermet and Demir (2018) proposed an intelligent disaster preparedness system that leverages flood ontologies and natural language processing (NLP). This system facilitates knowledge discovery and communication by interpreting user queries and providing relevant information about flood risks, mitigation strategies, and emergency procedures. Additionally, Demir & Galelli (2022) discussed the integration of conversational AI with digital twins and metaverse systems in hydrology and water resources management. Digital twins, which are virtual representations of physical systems, can simulate real-world processes, and when combined with AI, they allow stakeholders to interact with virtual models of water systems, enhancing understanding, education, and operational decision-making.

These prior works demonstrate the diverse applications of AI in flood management, ranging from real-time monitoring and virtual training to intelligent information systems and interactive simulations. They underscore the potential of AI to enhance various aspects of flood management, including data analysis, communication, education (Sajja et al., 2023), and operational efficiency. However, many of these systems focus on specific functions or target audiences, such as emergency responders or the public, highlighting a gap in tools tailored specifically to floodplain managers. There remains a need for solutions that integrate comprehensive resources and provide specialized assistance in areas such as regulatory compliance, planning, and technical analysis and AI offers transformative potential to address these gaps (Pursnani et al., 2024).

AI technologies, including machine learning and deep learning, can improve risk assessment, early warning systems, emergency response, and recovery efforts by processing large volumes of data from sources like weather sensors, satellite imagery, and social media feeds to detect patterns and predict flood occurrences (Yuan et al., 2020; Mosavi et al., 2018). AI-driven early warning systems continuously learn from new data, adapting to changing environmental conditions to enhance the accuracy and timeliness of flood predictions (Wang et al., 2021). In emergency response, AI applications such as robotics and drones facilitate search and rescue operations, damage assessment, and the delivery of supplies to inaccessible areas by analyzing aerial imagery to identify affected regions and infrastructure damage (Vögler et al., 2017).

NLP, a subset of AI, enables the development of chatbots and virtual assistants that interact with individuals, providing real-time information, answering queries, and disseminating alerts across multiple communication platforms (Sermet & Demir, 2021). AI also supports decision-making through data-driven insights and recommendations, evaluating various scenarios to suggest optimal strategies for disaster mitigation and response (Liu et al., 2017). However, implementing AI in disaster management presents challenges, including data quality and availability, model interpretability, ethical considerations, and the need for domain-specific expertise. Ensuring that AI tools are transparent, reliable, and aligned with practitioners' needs is essential for their successful integration (Hamon et al., 2022).

Effective data organization is crucial in floodplain management, and ontologies play a significant role in this process. Ontology formally represents knowledge within the domain, defining key concepts such as flood events, hazard assessments, mitigation measures, regulatory requirements, and stakeholders (Sermet & Demir, 2019). This structured framework facilitates efficient information retrieval, sharing, and analysis by enabling semantic enrichment of data, where information is annotated with metadata describing its meaning and context. Semantic search capabilities allow users to query data based on concepts and relationships rather than simple keyword matches, enhancing the relevance and accuracy of information retrieval (Pursnani et al., 2023). Moreover, ontologies support data integration by providing a shared vocabulary and structure, which is particularly valuable when combining data from diverse sources like hydrological models, GIS, regulatory databases, and historical records (Bhatt et al., 2016). This consistency reduces misunderstandings and errors in analysis. Additionally, ontologies enable reasoning and inference, allowing logic-based engines to derive new knowledge from existing data, identify inconsistencies, and suggest relationships that may not be explicitly stated, thereby supporting more informed decision-making processes (Fonseca et al., 2003).

LLMs have significantly advanced NLP capabilities. Trained on vast and diverse textual datasets, these models can generate human-like text, understand complex language structures, and perform tasks like translation, summarization, question answering, and content generation (Brown et al., 2020). In floodplain management, LLMs can process and interpret extensive textual data, including regulatory documents, technical reports, and educational materials, assisting managers by summarizing documents, extracting relevant information, and answering queries related to regulations, planning guidelines, and best practices; This capability streamlines access to information and saves valuable time (Taromideh et al., 2022)

Embeddings, which represent words or phrases as numerical vectors capturing semantic relationships, enhance LLMs' understanding of context and meaning. Semantic search leverages these embeddings to improve information retrieval by considering the intent and context of queries, retrieving conceptually related documents even without exact keyword matches (Fernández et al., 2011). This is evidently useful in floodplain management, where terminology can vary across documents and regions. Additionally, multimodal models like GPT-4 can handle diverse data types, including text and images, enabling the interpretation and analysis of visual data such as flood maps, diagrams, and photographs (Li et al., 2023). This integration enhances decision support, knowledge management, and communication by providing intelligent assistance in interpreting complex information and generating contextually appropriate responses (Narne et al., 2024).

2.1. Gaps in Current Research

Despite the advancements in AI applications for flood management, several gaps persist that limit the effectiveness of existing tools for floodplain managers. The integration of comprehensive floodplain management resources into AI systems is often lacking (Sermet & Demir, 2020). Many tools do not incorporate the full breadth of information needed by floodplain managers, such as detailed regulatory requirements, technical guidelines, state-specific policies, and historical data. This limits the ability of the tools to provide precise and contextually relevant assistance (Munawar et al., 2021a).

There is a lack of focus on providing location-specific guidance. Floodplain management practices and regulations can vary significantly between different states, regions, and municipalities (Ahmad 2006). Generic AI tools may not account for these variations, resulting in advice or information that is not applicable or even misleading in a particular context. User friendliness and accessibility are critical considerations that are sometimes overlooked. Floodplain managers may not have advanced technical expertise in AI technologies. Tools with complex interfaces or requiring specialized knowledge to operate can hinder adoption and reduce their practical utility (Martelo et al., 2024).

Furthermore, continuous learning and adaptability are essential features for AI systems in floodplain management (Hopgood et al., 2021). Regulations, environmental conditions, and best practices evolve over time. AI tools need mechanisms to update their knowledge base, incorporate new data, and adapt to changing user needs. Many existing systems do not have robust updating processes, leading to outdated information and reduced effectiveness. There is a need for AI tools that can handle the complexities of floodplain management, including interpreting legal documents, analyzing technical data, and supporting decision-making under uncertainty (Kanal et al., 2014). Current tools may lack the depth of expertise or the capability to understand nuanced scenarios, limiting their usefulness for professional floodplain managers (Khosravi et al., 2018).

Addressing these gaps requires the development of AI systems that are specifically designed for floodplain management, leveraging advanced technologies such as large language models and multimodal processing (Munawar et., al 2021b). Such systems should integrate comprehensive and up-to-date resources, provide location-specific assistance, offer intuitive interfaces, and support continuous learning (Ocak et al., 2023). By doing so, AI tools can become valuable assets for floodplain managers, enhancing their ability to manage flood risks effectively (Sajja et al., 2024)

3. Methodology

The methodology for developing the Floodplain Manager AI involved a systematic approach encompassing several key stages: integration of essential packages, data collection and curation, formation of the training dataset, incorporation of embeddings, AI model implementation and fine-tuning, system architecture design, and evaluation through experimental testing. This section details each of these stages, incorporating relevant aspects from the system architecture into the methodology.

3.1. Development of Floodplain Manager AI Agent

3.1.1. Integration of Essential Components

The initial phase involved setting up the development environment and integrating the necessary software components required to build the AI Assistant. Essential components included the OpenAI API, which provided access to advanced AI models such as GPT-3.5 Turbo and GPT-4. Data processing libraries like Pandas and NumPy facilitated data manipulation and analysis, enabling efficient handling of large datasets. Natural Language Processing (NLP) tools such as NLTK and spaCy supported various text processing tasks, including tokenization, lemmatization, and part-of-speech tagging, which were vital for understanding and interpreting user queries. Document generation tools, including the python-docx library, allowed for the programmatic creation and formatting of Word documents, which was useful for documenting interactions and generating reports. These packages established the foundational infrastructure necessary for subsequent stages, facilitating efficient interaction between the AI models and the data sources, and enabling the integration of various functionalities into the system.

3.1.2. Data Collection and Curation

A comprehensive dataset is essential for training and fine-tuning the AI models to specialize in floodplain management. The data collection process involved gathering and curating information from reputable sources. Primary sources included the "Introduction to Floodplain Management" study guide provided by the National Flood Insurance Program (NFIP, 2024), state-based floodplain management resources, and guidelines from the Federal Emergency Management Agency (FEMA).

An automated tool was developed to extract content from the NFIP study guide, parsing through the document and segmenting it into manageable sections suitable for training purposes. The extracted content underwent a data processing phase, which involved cleaning and preprocessing to ensure consistency and relevance. Irrelevant information was removed, formatting issues were corrected, and terminology was standardized to align with common floodplain management language. Figure 1 illustrates the automated data collection and processing workflow employed during this stage.

To fine-tune the AI models effectively, a training dataset was created using the processed data. Each segmented portion of the study guide was transformed into a conversational format, simulating interactions between a user and an assistant. This approach leveraged the inherent capabilities of language models in handling dialogue-based contexts. For each conversation, a system message was included to set the context and role of the AI Assistant, instructing it to specialize in floodplain management topics. The dataset was structured as a series of message pairs, consisting of a user prompt and the AI Assistant's response. Each response aimed to contain approximately 1,000 tokens to provide detailed and informative answers. An example of the dataset format is presented in Table 1.

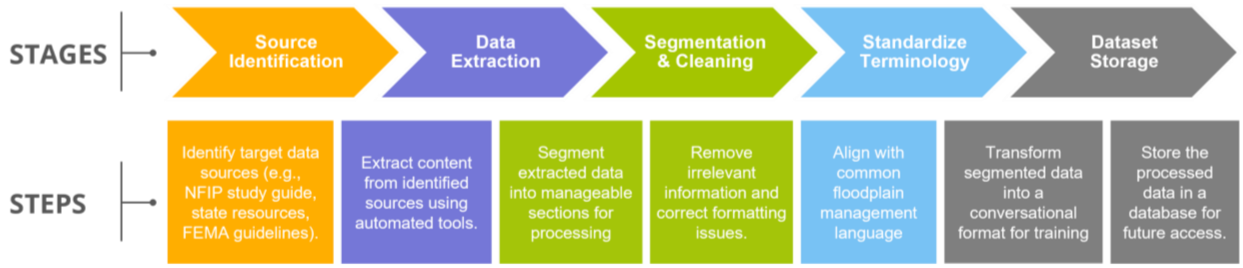

Figure 1: Automated data collection and processing workflow

Table 1: Example of Conversation Structure in Training Dataset

Role	**Content**
System	*"You are a knowledgeable assistant who specializes in the topic of floodplains."*
User	*"What is a floodplain?"*
Assistant	*"A floodplain is flat or nearly flat land adjacent to a stream or river that experiences occasional or periodic flooding. It includes the floodway..."*

3.1.3. Incorporation of Embeddings and AI Model Implementation

To enhance the AI models' understanding and retrieval capabilities, embeddings were incorporated into the system for specific models. Embeddings represent words or phrases as numerical vectors in a high-dimensional space, capturing semantic relationships between them (Mikolov et al., 2013). The ChromaDB library was utilized to store and manage these embeddings, facilitating efficient retrieval of relevant information based on user queries. With embeddings, the system was able to perform semantic search, retrieving documents and data that were conceptually related to the user's query, even if exact keywords were not matched. This approach improved the accuracy and relevance of the responses provided by the AI Assistant. Figure 2 illustrates the integration of embeddings in the system architecture.

For the implementation and fine-tuning of AI models, GPT-3.5 Turbo and GPT-4 provided by OpenAI were utilized. Fine-tuning these models was crucial to ensure that the AI Assistant could provide accurate and contextually relevant responses specific to floodplain management. The models were fine-tuned using the prepared training dataset, which involved adjusting the models' parameters to specialize in floodplain management topics. During the fine-tuning process, a new system message was introduced to embody the role of a community floodplain manager. This message outlined the responsibilities and knowledge base expected from a professional in the field, enhancing the models' ability to generate responses aligned with real-world expertise.

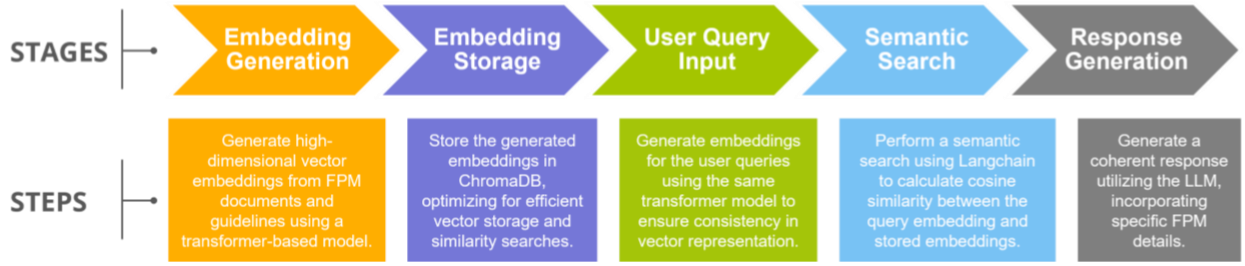

Figure 2: Integration of embeddings for enhanced information retrieval

Both fine-tuned and default versions of GPT-3.5 Turbo and GPT-4 models were tested, with and without the incorporation of embeddings, to evaluate their performance. The models were integrated into the system's backend, enabling them to process user queries and generate responses accordingly. In addition to these models, newer AI models such as GPT-4o and GPT-o1 were also evaluated. These models were tested in their default configurations without any fine-tuning or incorporation of embeddings. Assessing these models in their unaltered state provided insights into their baseline capabilities and advancements in handling specialized floodplain management queries without additional customization.

3.1.4. System Architecture Design

The system architecture was designed to facilitate seamless interaction between the user and the AI Assistant, integrating various components to handle different functionalities. The front-end interface was developed using ReactJS to provide a user-friendly chat interface where users could enter queries and receive responses in real-time. The back-end server was implemented using Flask, which handled API requests from the front-end, processed queries, and interacted with the AI models. Intent recognition and response generation capabilities were incorporated to analyze user inputs and determine the appropriate course of action. The system utilized the AI models to generate responses based on the recognized intent. For queries requiring visual interpretation, such as flood map analysis, the system leveraged GPT-4's multimodal capabilities to process and interpret images. Curated data and embeddings were stored in a database managed by ChromaDB, facilitating efficient retrieval and context-aware responses. The system is also integrated with external resources, such as FEMA databases, to access up-to-date information and provide accurate responses. Figure 3 depicts the integrated system architecture within the context of the proposed vision.

3.2. Evaluation and Experimental Setup

An evaluation was conducted to assess the effectiveness of the system across several dimensions, including its accuracy in responding to floodplain management questions, ability to provide location-specific guidance, and proficiency in interpreting FEMA flood maps. The evaluation encompassed both quantitative and qualitative analyses to provide a comprehensive understanding of the system's performance. A dataset comprising 67 comprehensive questions was compiled from the Association of State Floodplain Managers (ASFPM), covering a broad spectrum of floodplain management topics such as regulations, technical concepts, certification processes, building codes, permit applications, and legal interpretations. Correct answers were established for each question to serve as a benchmark for evaluating the models' responses.

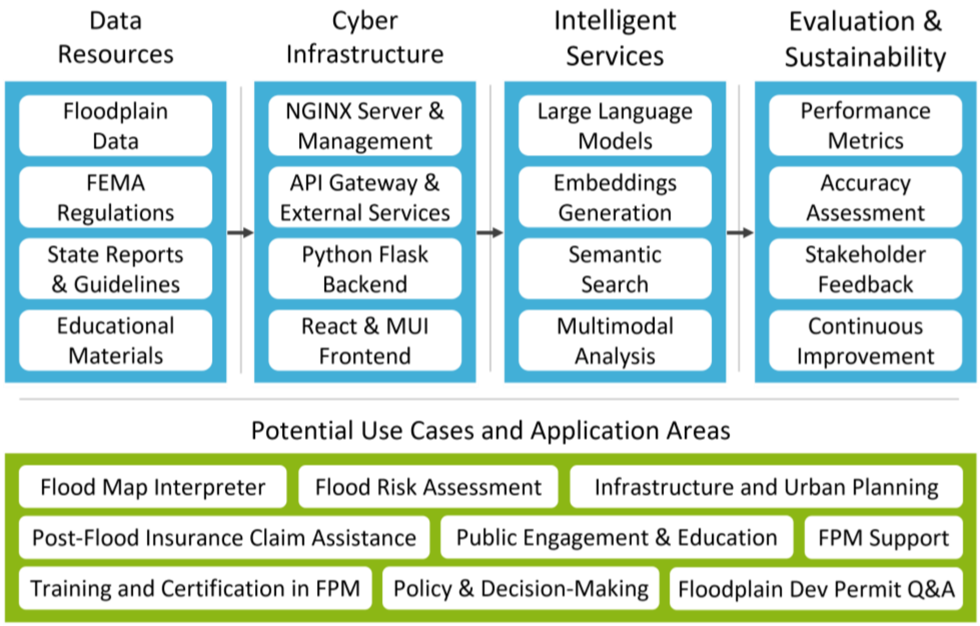

Figure 3: System architecture and components of the Floodplain Manager AI Agent

Various AI models were evaluated in this study, categorized based on their configurations. The base models included GPT-3.5 Turbo 16k and GPT-4, which were tested in their default states without any modifications. The fine-tuned versions comprised fine-tuned GPT-3.5 Turbo 16k and fine-tuned GPT-3.5 Turbo 16k with embeddings. In terms of embedding integration, models such as GPT-3.5 Turbo 16k with embeddings and GPT-4 with embeddings were also included in the evaluation. Additionally, the newer models GPT-4o-mini, GPT-4o, GPT-o1-preview, and GPT-o1-mini were tested without any fine-tuning or the incorporation of embeddings, providing insights into their baseline capabilities in handling specialized floodplain management queries without additional customization. This grouping of models allowed for a thorough examination of the impact of fine-tuning and embeddings on performance in addressing floodplain management tasks.

The primary metric used for quantitative assessment was the accuracy of the models' responses, measured as the percentage of correct answers provided. This metric facilitated a comparative analysis of the models and allowed for the evaluation of the impact of fine-tuning and the use of embeddings on model performance. Each question was presented to the models in a standardized format, including any necessary context or additional information. The models' responses were collected and evaluated against the established correct answers to determine their accuracy. Additionally, qualitative analysis was performed to assess the relevance and clarity of the responses, providing insights into the practical utility of the models in supporting floodplain management tasks.

To evaluate the models' capability to provide location-specific guidance, test scenarios requiring state-specific information, such as building codes or permit requirements, were crafted. The models' responses were assessed based on their accuracy and relevance concerning current state regulations and official guidelines. This evaluation examined the models' ability to tailor responses according to regional regulations and practices, which is essential given the variability of floodplain management policies across different jurisdictions.

The effectiveness of the models in interpreting FEMA flood maps was also evaluated. Models capable of processing visual inputs were provided with flood maps along with corresponding queries. Their interpretations were assessed for accuracy in identifying flood zones, risk levels, base flood elevations, and relevant features depicted on the maps. The integration of visual data with textual responses was examined to determine the comprehensiveness and utility of the assistance provided. This aspect of the evaluation was crucial for understanding the models' proficiency in handling multimodal inputs, which are common in floodplain management tasks. This comprehensive evaluation aimed to assess both the quantitative performance of the models and the qualitative aspects of their assistance capabilities.

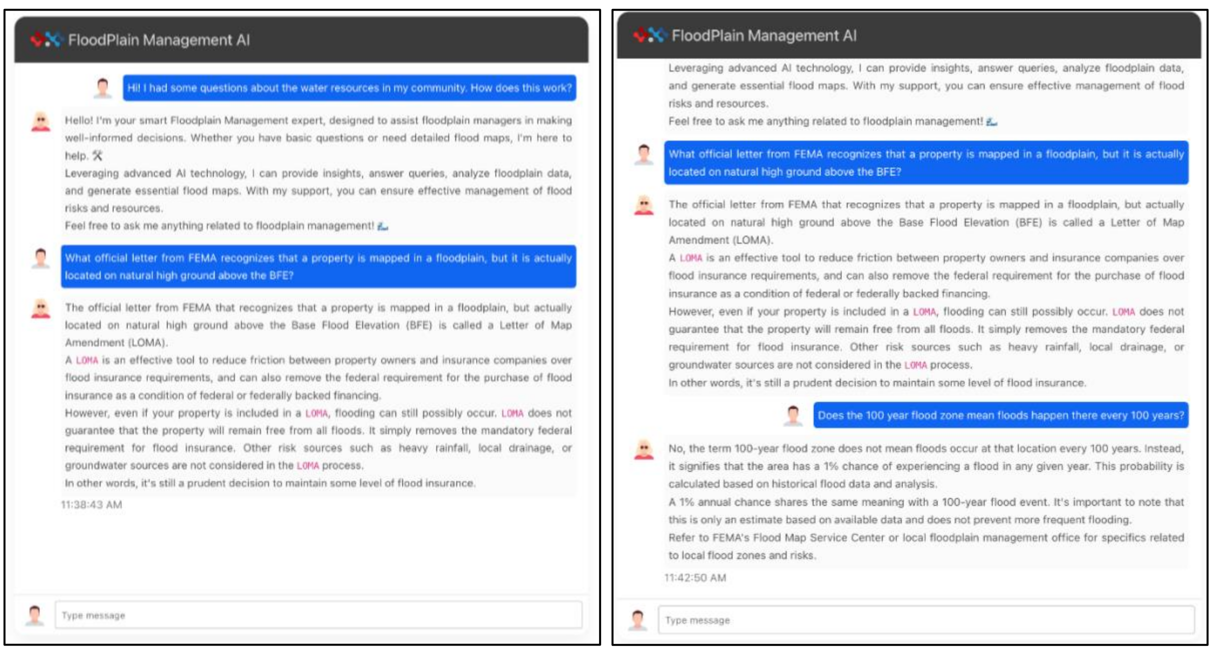

Figure 4: Generic knowledge assistance interface with sample questions and answers

4. Results

This section presents the detailed results of the experiments conducted to evaluate the performance of the Floodplain Manager AI (Figure 4). The evaluation focuses on the AI

Assistant's ability to accurately answer floodplain management-related questions, provide location-specific guidance, and interpret FEMA flood maps using multimodal capabilities. The outcomes demonstrate the effectiveness of the AI models, the impact of fine-tuning and embeddings, and the integration of advanced AI technologies in enhancing floodplain management practices.

4.1. Evaluation of AI Models

The primary evaluation involved assessing the effectiveness of different AI models in accurately responding to floodplain management questions. A dataset comprising 67 comprehensive questions was compiled, covering a wide range of topics including regulatory compliance, technical concepts, certification processes, building codes, permit applications, and legal interpretations. Each model was tasked with interpreting and responding to these questions accurately. The accuracy values achieved by each model are presented in Figure 5.

Analysis of the results indicates an enhancement in model performance achieved through fine-tuning and the incorporation of embeddings. The base GPT-3.5 Turbo 16k model exhibited an accuracy of 71.64%, which improved to 80.60% after fine-tuning. Incorporating embeddings further increased the accuracy, with the GPT-3.5 Turbo 16k model achieving 88.06% when embeddings were added. Similarly, the GPT-4 model showed an accuracy of 86.57% in its default form, which increased to 88.06% with embeddings.

Notably, the GPT-4o and GPT-o1-preview models achieved exceptional accuracies of 97.01% and 100%, respectively, without the use of embeddings. These models demonstrate a superior ability to comprehend and accurately respond to complex floodplain management queries, likely due to their advanced architecture and larger training datasets. The GPT-o1-preview model, achieving 100% accuracy, shows its potential as a highly reliable tool for professionals seeking precise information. However, the Fine-Tuned GPT-3.5 Turbo 16k with embeddings had a slightly lower accuracy (79.10%) compared to the fine-tuned model without embeddings (80.60%). This suggests that combining fine-tuning with embeddings may not always result in performance improvements and could introduce overfitting or conflicts within the model.

4.2. Evaluation of Location-Specific Assistance

The system's ability to provide accurate, location-specific guidance was evaluated qualitatively by testing its performance with queries requiring knowledge of state-specific regulations and practices. Scenarios were crafted where users posed questions necessitating detailed, location-based information. Examples of such queries included building elevation requirements for new constructions in floodplains in Florida, procedures for applying for floodplain development permits in Texas, and floodproofing requirements for non-residential buildings in Illinois.

The system demonstrated a strong capability to deliver precise and contextually appropriate information tailored to the user's specified location (Figure 6). The responses included specific regulatory references, detailed procedural guidance, and contact information for relevant state agencies. For instance, when asked about building elevation requirements in Florida, the AI Assistant referred to the Florida Building Code and explained the minimum elevation standards, including considerations for coastal high-hazard areas and flood-resistant construction practices. In another example, when queried about floodproofing requirements in Illinois, the AI Assistant detailed the standards set forth in the Illinois Administrative Code Title 17, Part 3700, explaining the criteria for dry floodproofing non-residential buildings in Special Flood Hazard Areas.

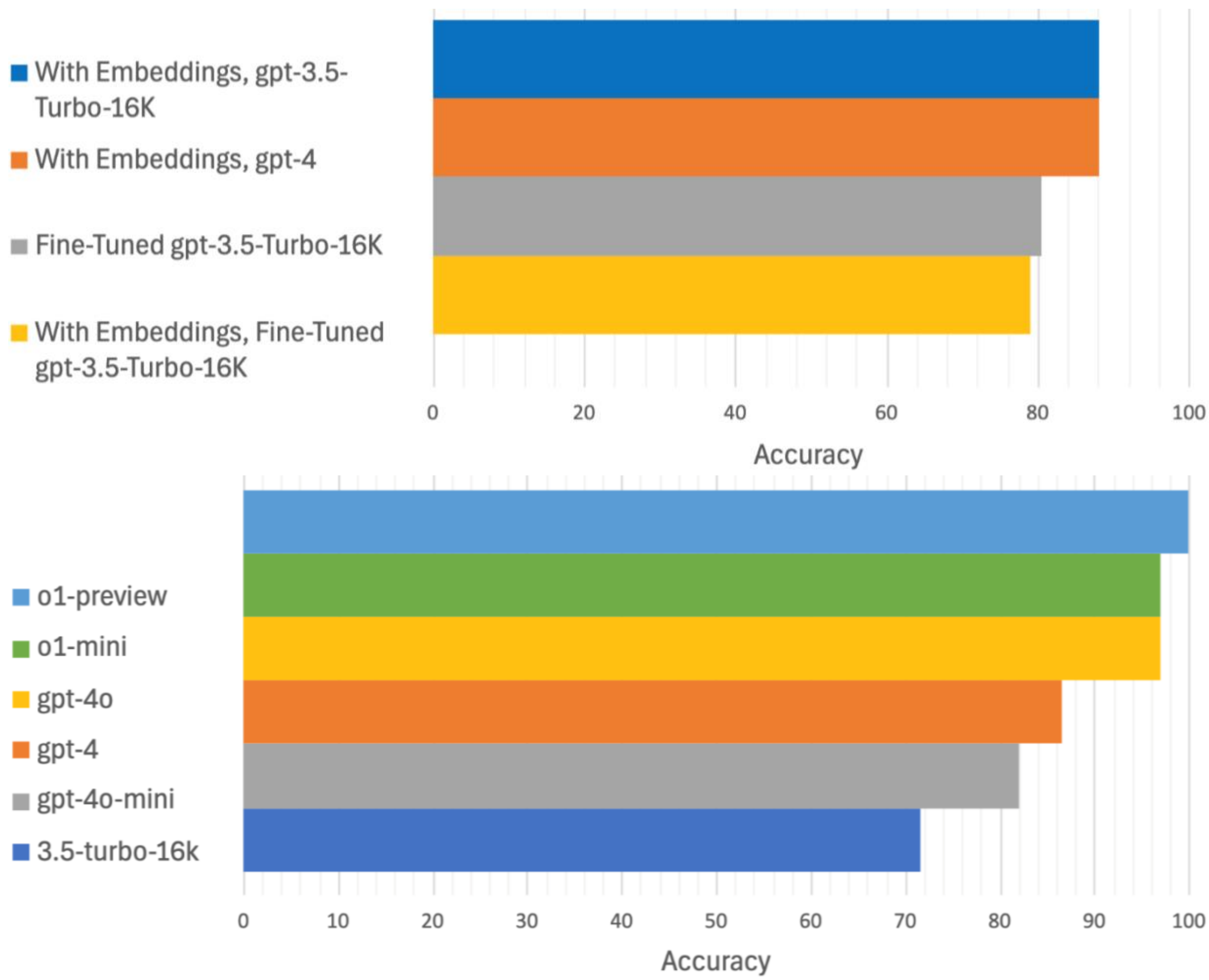

Figure 5: Experiment results: (top) Fine-tuned vs. embedding-based models; and (bottom) baseline model performance comparison

The qualitative assessment indicates that the AI Assistant effectively leverages a comprehensive database of state-specific floodplain management resources to provide accurate and relevant guidance. This location-informed assistance is critical, as floodplain management regulations can vary significantly between states due to different geographical features and flood risks. With tailored information, it enhances its utility for professionals who require precise guidance that complies with regional regulations.

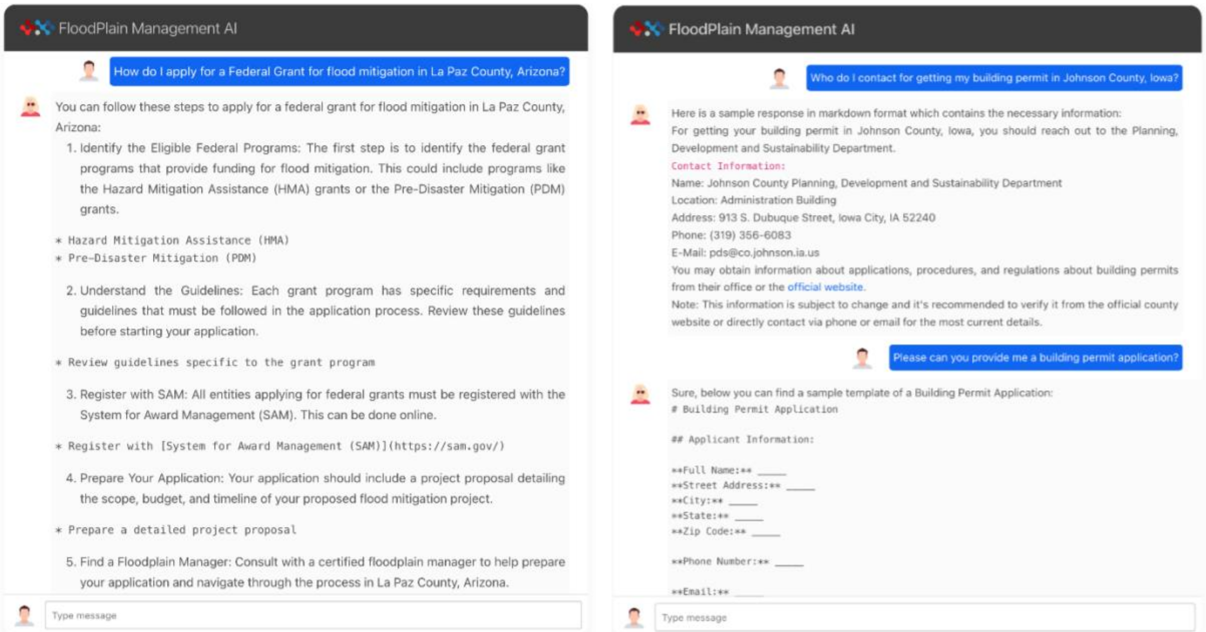

Figure 6: Location-specific assistance for La Paz County, Arizona and Johnson County, Iowa

4.3. Evaluation of Flood Map Interpretation

The Floodplain Manager AI's capability to interpret FEMA flood maps using GPT-4's multimodal vision feature was assessed qualitatively to evaluate its effectiveness in analyzing visual data and providing meaningful insights. The system retrieved FEMA flood maps on-demand and provided them as visual inputs alongside queries that required the AI Assistant to interpret specific details, such as determining whether a property is in a high-risk flood zone, identifying the base flood elevation at a specific location, and explaining the different flood zones indicated on the map (Figure 7).

The AI Assistant demonstrated proficiency in interpreting flood maps and effectively communicated the information to the users. It accurately identified specific flood zones, determined base flood elevations, and explained various symbols, lines, and notations found on flood maps, helping users understand their implications. For example, (Figure 7) when presented with a flood map and asked whether a property was in a high-risk flood zone, “Can you show me a FEMA flood map for my property on 300 Walnut St in Des Moines, Iowa?”, the AI Assistant analyzed the map and accurately identified that the property was within Zone AE, a Special Flood Hazard Area. It explained the associated risks and recommended considering flood insurance and adherence to building regulations.

In another scenario, (Figure 8) when asked to interpret the flood zones on a map, “Can you get me a flood map for 320 S Riverside Drive, Iowa City, IA and explain what is happening? What type of building permits would this type of construction require?” the AI Assistant provided detailed explanations of each zone, including the level of flood risk, regulatory requirements, and implications for property owners. This included distinctions between zones such as Zone X (areas of minimal flood hazard), Zone AE (areas with a 1% annual chance of flooding and established base flood elevations), and Zone VE (coastal areas with additional hazards due to storm-induced waves).

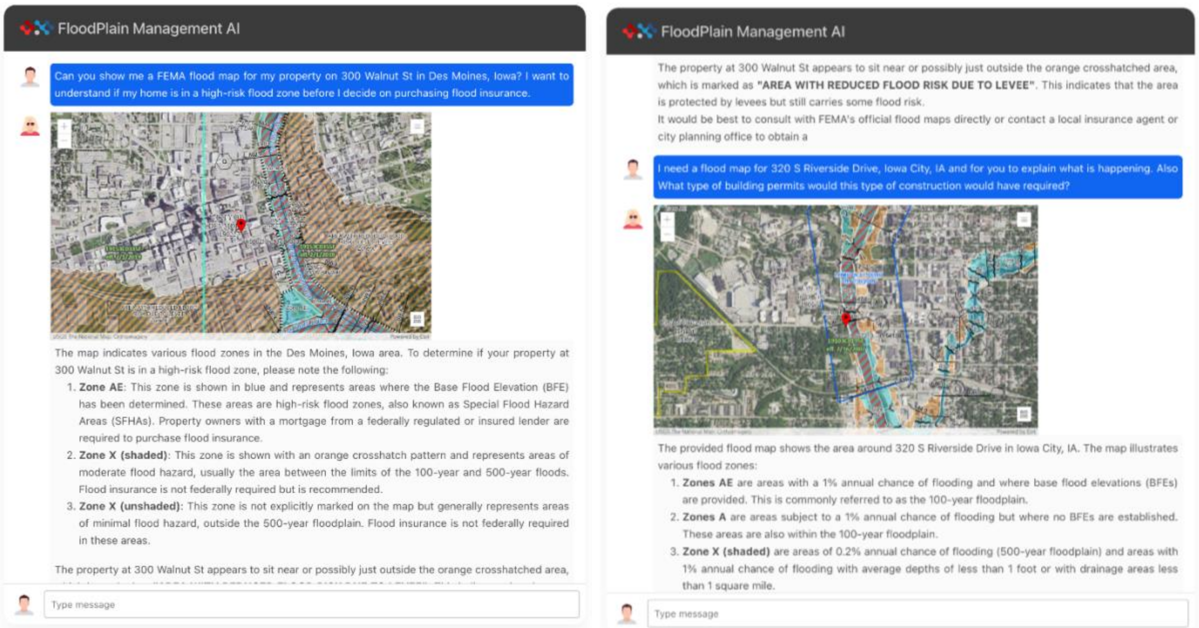

Figure 7: Multimodal FEMA flood zone classification for 300 Walnut St, Des Moines, Iowa

The qualitative evaluation suggests that the AI Assistant effectively utilizes GPT-4's multimodal capabilities to interpret complex visual data and translate it into understandable information for users. This capability enhances the tool's value by allowing it to assist with tasks that involve both textual and visual elements. By providing accurate interpretations of flood maps, the system can assist floodplain managers and property owners in assessing flood risks and making informed decisions regarding development, insurance, and compliance with regulations.

5. Discussions

The development and evaluation of the Floodplain Manager AI have demonstrated significant potential for enhancing floodplain management practices through the integration of advanced AI technologies. This project was presented at the 12th International Congress on Environmental Modelling and Software (iEMS), where valuable feedback was elicited from a diverse group of domain experts and professionals in the field. The discussions that followed highlighted several key insights regarding the system's effectiveness, usability, and areas for improvement. This section discusses the implications of the findings, the advantages and limitations, and potential areas for improvement and future work.

The integration of Floodplain Manager AI into floodplain management practices offers several significant implications. Firstly, the AI Assistant enhances the efficiency of information retrieval by rapidly providing accurate and relevant information. This reduces the time and effort required by floodplain managers to search through extensive regulatory documents and technical materials, allowing them to focus more on decision-making and strategic planning. Secondly, the provision of location-specific guidance addresses a critical challenge in navigating varying regulations across different jurisdictions. By delivering tailored information that reflects local policies and requirements, the AI Assistant supports compliance efforts and aids in the development of regionally appropriate mitigation strategies.

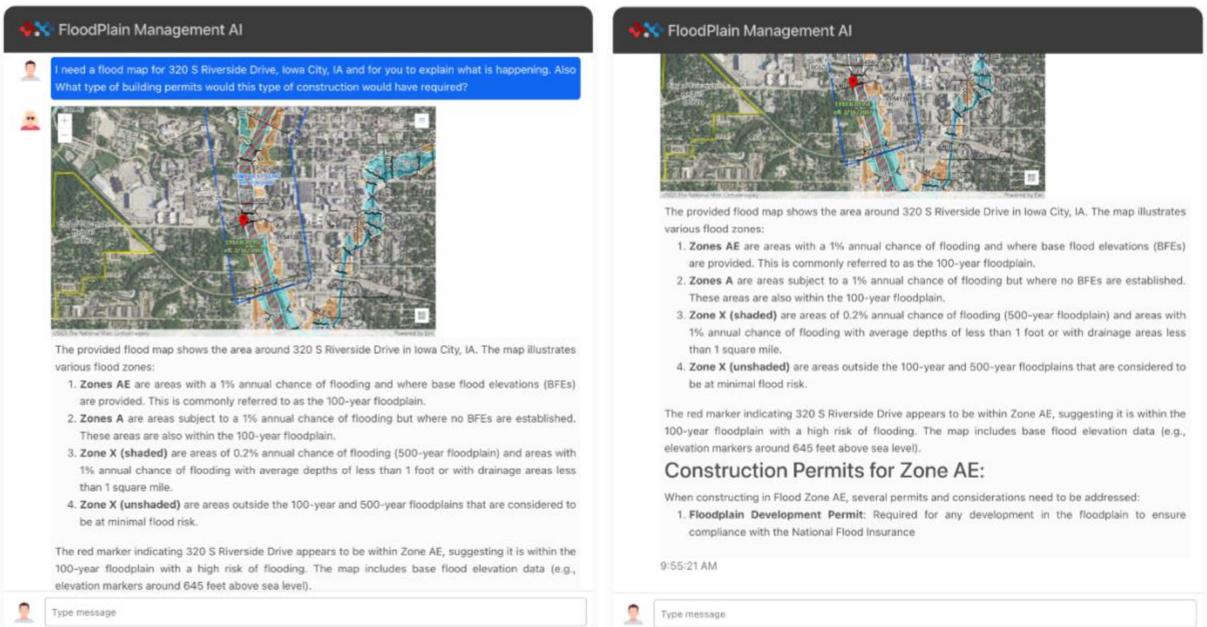

Figure 8: Multimodal FEMA flood zone map for 320 S Riverside Drive, Iowa City, IA: Risk Zones and Construction Implications

Thirdly, the ability to interpret flood maps and other complex data enhances the analytical tools available to floodplain managers. The AI's ability to process and explain visual data supports more informed risk assessments and planning decisions. This can lead to more effective flood mitigation measures and safer community development. Moreover, the positive user experience reported by stakeholders indicates that the AI Assistant is accessible and user-friendly. The intuitive interface and natural language processing capabilities facilitate seamless interaction, which is essential for widespread adoption and integration into existing workflows.

The system offers several advantages that contribute to its potential as a valuable tool in floodplain management:

- **Expert Knowledge Access**: It provides access to comprehensive and up-to-date knowledge, including technical information, regulatory guidance, and best practices.
- **Efficiency and Time Savings**: By quickly providing precise answers, it can reduce the time required to locate and interpret information from multiple sources.
- **Location-Specific Assistance**: The ability to deliver state-specific guidance ensures that information is relevant and compliant with local regulations.

- **Enhanced Data Interpretation**: The capability to interpret flood maps and other complex data supports advanced analytical tasks, aiding in risk assessment and planning.
- **Continuous Learning Potential**: The AI models can be updated and fine-tuned with new data, allowing it to evolve and maintain relevance as regulations and knowledge change.
- **User-Friendly Interface**: The conversational interface enables users to interact with the AI Assistant using natural language, reducing barriers to adoption and facilitating ease of use.

5.1. Limitations

Despite the benefits demonstrated, several limitations were observed that need to be addressed. One limitation is the dependency on the currency and completeness of the data used to train the models. The AI Assistant occasionally provided outdated information due to changes in regulations that occurred after the last data update. This highlights the importance of regularly updating the data sources and embeddings to ensure that the AI Assistant provides the most current information.

Another limitation is the AI's struggle with interpreting complex legal language or providing definitive answers on complex legal matters. Legal interpretation often requires human expertise to consider context, precedents, and nuances that may not be fully captured by AI models. Therefore, while the AI Assistant can provide general guidance, critical legal decisions should involve consultation with legal professionals.

The AI Assistant's performance is also highly dependent on the quality and completeness of the curated data used for training and embeddings. Incomplete or inaccurate data can lead to erroneous responses. Additionally, instances were noted where the AI Assistant did not fully capture the nuances of complex regulatory scenarios or required improvement in handling ambiguous or poorly formulated queries. This indicates a need for enhanced natural language understanding and possibly the incorporation of mechanisms for clarification or request for additional information from the user.

The study itself has limitations that should be acknowledged. The evaluation focused on specific aspects of the system performance, and additional testing across a broader range of scenarios and with a more diverse user base could provide a more comprehensive assessment. The data sources used were curated and may not encompass all relevant information, suggesting that expanding the data sources could enhance the AI Assistant's capabilities. Furthermore, the rapid evolution of AI technologies means that models like GPT-4 may be superseded by more advanced models. Ongoing adaptation and updates are necessary to maintain the relevance and effectiveness of the system.

5.2. Future Enhancements

To enhance the utility of the Floodplain Manager AI and address its limitations, several potential improvements can be considered. Establishing processes for regular updates of data sources and embeddings is essential. Integrating automated data harvesting from authoritative sources, such as FEMA and state agencies, can help ensure that the AI Assistant reflects the most current regulations and guidelines. Enhancing the AI Assistant's natural language processing abilities to better handle ambiguous or poorly formulated queries can improve user experience. Implementing mechanisms for clarification, such as asking follow-up questions when the AI Assistant is uncertain about a query, can help the AI provide more accurate responses.

Integrating the AI Assistant with real-time databases and external systems, such as the National Levee Database or live flood monitoring tools, could expand its capabilities and provide users with more comprehensive information. This would allow the AI Assistant to offer real-time data on flood conditions, further aiding risk assessment and decision-making. Incorporating user feedback mechanisms can facilitate continuous improvement. Allowing users to report inaccuracies or suggest enhancements can help developers refine the AI Assistant's performance and address user needs more effectively. Additionally, expanding the AI Assistant's knowledge base to include more specialized areas of floodplain management, such as climate change impacts, sustainable development practices, and advanced hydrological modeling, can increase its value to practitioners.

Longitudinal studies assessing the long-term impact of the AI Assistant on floodplain management practices and outcomes would provide valuable insights. Developing training programs to help users maximize the benefits of the AI Assistant can facilitate adoption and integration into professional workflows. Collaborative efforts involving floodplain managers, policymakers, and AI experts can guide the development of new features and ensure that the AI Assistant meets the evolving needs of the field. Expanding the AI Assistant's capabilities to cover related areas, such as emergency response planning and community education, can further enhance its utility. Exploring the application of similar AI technologies in other areas of environmental management and disaster risk reduction can extend the benefits demonstrated in this study to broader contexts, contributing to improved resilience and sustainability efforts.

5.3. Ethical and Practical Considerations

When deploying AI technologies in professional practices, several ethical and practical considerations must be addressed. The reliance on AI should not replace human expertise but rather complement it. The AI Assistant should be viewed as a tool that supports floodplain managers, providing information and assistance while recognizing that critical decisions, especially those involving legal compliance and public safety, require human judgment.

Data privacy and security are also critical considerations. Ensuring that user data and interactions with the system are secure and that privacy is maintained is essential. Compliance with data protection regulations must be upheld to protect sensitive information. Transparency in how the AI generates responses can build trust among users. Providing explanations or citations for the information provided can help users understand the reasoning behind the AI Assistant's responses. Additionally, addressing potential biases in the AI models is important to ensure fair and equitable assistance to all users.

6. Conclusion

The development of Floodplain Manager AI represents a significant advancement in the application of AI to environmental management, specifically in the domain of floodplain management. This study demonstrated that leveraging advanced AI technologies, such as large language models and embeddings, can effectively address key challenges faced by floodplain managers, including efficient information retrieval, provision of location-specific guidance, and interpretation of complex data like FEMA flood maps. The evaluation of the AI Assistant revealed that fine-tuning AI models and integrating embeddings substantially improve performance. The GPT-4 model, especially when fine-tuned and augmented with embeddings, achieved high accuracy in answering floodplain management questions and providing detailed, relevant information. The AI Assistant's ability to offer state-specific guidance and interpret flood maps using multimodal capabilities underscores its potential as a valuable tool for practitioners.

Despite its strengths, the AI Assistant has limitations, particularly concerning the currency of data and handling of complex legal interpretations. Regular updates of data sources and enhancements in natural language processing can mitigate these issues. The AI Assistant should be viewed as a complementary tool that supports, rather than replaces, the expertise of floodplain managers. The positive feedback from users indicates that the AI Assistant enhances decision-making processes and contributes to more effective floodplain management practices. By providing timely, accurate, and accessible information, it aids in mitigating flood risks and improving community resilience. Future work should focus on updating data sources, refining natural language understanding, integrating real-time data, and expanding the AI Assistant's capabilities to cover more specialized areas. Collaborative efforts between AI developers and floodplain management professionals will be essential in evolving the AI Assistant to meet the dynamic needs of the field.

Author Contributions

Vinay Pursnani: Software, Investigation, Writing – original draft, Visualization, Methodology, Validation. **Yusuf Sermet:** Supervision, Conceptualization, Methodology, Validation, Writing - Review & Editing. **Ibrahim Demir:** Conceptualization, Supervision, Validation, Writing - Review & Editing, Project administration, Funding acquisition

Funding

This project was funded by the National Oceanic & Atmospheric Administration (NOAA) via a cooperative agreement with The University of Alabama (NA22NWS4320003) awarded to the Cooperative Institute for Research to Operations in Hydrology (CIROH).

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to improve the flow of the text, correct any potential grammatical errors, and improve the writing. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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