

A Comprehensive Evaluation of Multimodal Large Language Models in Hydrological Applications

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Abstract

Large Language Models (LLMs) combined with visual foundation models have demonstrated remarkable advancements, achieving a level of intelligence comparable to human capabilities. In this study, we conduct an analysis of the latest Multimodal LLMs (MLLMs), specifically Multimodal-GPT, GPT-4 Vision, Gemini and LLaVa, focusing on their application in the hydrology domain. The hydrology domain holds significant relevance for AI intelligence applications, including flood management and response, water level monitoring, agricultural water discharge, and water pollution management. Our analysis involves testing these MLLMs on various hydrology-specific studies, evaluating their response generation, and assessing their suitability for real-time systems. We deliberately selected complex real-world scenarios to explore the potential of MLLMs in addressing hydrological challenges. Additionally, we carefully designed prompts to enhance the models' visual inference capabilities and their ability to comprehend context from image data. The findings from our analysis reveal effective human-computer interaction and inspire potential solutions for real-world hydrological inference systems that incorporate both textual and image data. Among the validated models, GPT-4 Vision stands out as the top performer among other MLLMs, showcasing unparalleled proficiency in inferring visual data. The results highlight the significant understanding, reasoning, and decision-making capabilities that multimodal foundation models bring to the domain of hydrology. This research contributes valuable insights into the potential applications of advanced AI models in addressing complex challenges within hydrological contexts.

Keywords: Large Language Models (LLMs), Hydrology, Intelligent Assistants, Multimodal LLMs.

This manuscript is an EarthArXiv preprint and has been submitted for possible publication in a peer reviewed journal. Please note that this has not been peer-reviewed before and is currently undergoing peer review for the first time. Subsequent versions of this manuscript may have slightly different content.

1. Introduction

Artificial Intelligence (AI) is becoming a groundbreaking technology with the potential to revolutionize various specific disciplines, and hydrology is no exception. Hydrology, which encompasses the scientific study of the movement of water on Earth, will benefit greatly from the revolutionary potential of AI (Pursnani et al., 2023). Such methods are increasingly being applied in hydrology to solve various problems such as rainfall-runoff modeling (Herath et al., 2021; Sit et al., 2021), water quality forecasting using deep learning (Wu et al., 2022), data augmentation (Demiray et al., 2021), and climate and hydrologic forecasting using AI (Slater et al., 2023). Large Language Models (LLMs) are a class of deep learning models that are trained on massive textual data to generate or understand human language which could be able to generate human-like language outputs.

Some prominent examples of LLMs include GPT-4 (Achiam et al., 2023) and BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2018). Nonetheless, it's important to acknowledge that the responses can occasionally be deceptive, incorrect, or false. Models like Mini-GPT4 (Zhu et al., 2023a) and LLaVA (Liu et al., 2023) have emerged, each endeavoring to replicate and extend GPT-4's achievements. These initiatives have explored the fusion of visual representations with the language model's input space, harnessing the original self-attention mechanism of language models to process complex visual information. In the realm of computer vision, ImageBERT (Qi et al., 2020) represents a promising intersection between visual and textual data, enabling improvements in vision and language tasks. In healthcare, Clinical BERT (Huang et al., 2020) leverages the analysis of clinical notes to predict hospital readmission.

In hydrology, the integration of AI has shown tremendous potential for advancing our understanding and management of water-related processes (Sermet and Demir, 2019). Leveraging the capabilities of LLMs in this domain introduces a novel dimension, where textual and visual information can be synthesized to enhance hydrological analyses and communication (Xiang and Demir, 2022). This study explores the convergence of hydrology and LLMs, with a particular focus on models such as GPT-4, Gemini, LLaVA, and MultimodalGPT. While conventional models have made significant contributions, the emergence of LLMs provides an unprecedented opportunity to process and interpret vast amounts of hydrological data in a more nuanced and context-aware manner. The integration of visual representations into language models signifies a paradigm shift in how hydrologists can approach complex datasets (Demir et al., 2022). These models not only inherit the language generation prowess of their predecessors but also harness advanced self-attention mechanisms to process intricate visual information.

The intersection of visual and textual data, exemplified by models like ImageBERT, opens new avenues for improving both vision and language tasks in hydrological research. As we delve into the capabilities of these LLMs, it is crucial to acknowledge the inherent limitations. While promising, the responses generated by these models may occasionally be deceptive, incorrect, or false. Balancing the enthusiasm for the potential breakthroughs with a realistic understanding of the model's limitations is essential for responsible and effective integration into hydrological research (Sermet and Demir, 2021).

1.1. LLMs and Vision Models in Flooding and Hydrology

Hydrology and flood detection involve complex processes that can benefit from the integration of advanced AI models (Sermet and Demir, 2018). The application of LLMs and vision models in flood detection and hydrology involves leveraging advanced language processing and computer vision technologies to enhance our understanding and management of water-related phenomena (Samuel et al., 2024a). MLLMs are pre-trained on a massive corpus of images and texts, thus can perform predictions even without further training or fine-tuning (Embedded, 2023).

Data Analysis and Interpretation: LLMs can be employed to analyze textual data related to hydrological studies. They can assist in interpreting data from sensors, reports, and other reliable government sources to extract valuable insights. Simultaneously, computer vision models, such as vision transformers with LLMs, can analyze satellite imagery and detect changes in land cover or water levels indicative of potential flooding (Li et al., 2023).

Real-time Monitoring: Combining LLMs with vision models allows for real-time monitoring of hydrological conditions. LLMs can process textual information from various sources, while vision models analyze images or video feeds from surveillance cameras or satellites (Samuel et al., 2024b).

Contextual Understanding: LLMs are powerful tools for understanding contextual information. They can generate summaries, answer questions, and provide context-specific details about hydrological events based on textual data. Vision models contribute by providing spatial context, identifying geographical features, land use changes, and patterns in satellite imagery crucial for hydrological assessments.

Decision Support Systems: LLMs can assist in generating reports, risk assessments, and decision-making documents. They can process complex data and information from sensor networks and remote sensing resources and provide recommendations for water resource mitigation and planning decisions (Alabbad et al., 2024) based on textual data. Vision models contribute to decision support by visualizing hydrological events, creating visual representations of flood-prone areas, changes in river courses, and other relevant spatial information.

Predictive Analytics: LLMs contribute to predictive analytics by understanding and generating insights from historical hydrological data. They process textual information related to weather patterns, river flows, and other variables. Vision models excel at recognizing patterns in visual data, identifying trends or anomalies in satellite imagery, aiding in predicting potential flood events (Li and Demir, 2024).

Communication and Reporting: LLMs facilitate effective communication by generating human-like responses to inquiries, integrated into chatbots or conversational interfaces to provide information about hydrological conditions. Vision models contribute to visual reporting by creating maps, charts, and visualizations that enhance the understanding of hydrological data.

This study aims to explore the synergies between hydrology and Multimodal LLMs (MLLMs), examining the contributions of models like GPT-4, Gemini, LLaVA, and Multimodal-GPT, and their implications for advancing our understanding of water-related processes. Additionally, we discussed the challenges and ethical considerations associated with integrating LLMs into

hydrological research, paving the way for a more informed and responsible use of AI in this critical scientific domain.

2. Background

In recent studies, the advancement of multi-modal based LLMs has shown significant improvement. The emergence of ChatGPT for text generation (OpenAI, 2022) and visual transformers-based diffusion models for image generation (Fan et al., 2022) sets the stage for AI-generated multi-modal tasks. This progress enhances the cognitive abilities and decision-making capabilities of machines, especially with open-source LLMs like Vicuna (Chiang et al., 2023), Flan-T5, Alpaca (Taori et al., 2023), and LLaMa (Touvron et al., 2023). Additionally, the availability of multi-modal data from various sensors, including audios, videos, and text, necessitates machines to adeptly handle multi-modal decision-making processes.

Several LLMs are continually being introduced, including DeepMind's Flamingo (Alayrac et al., 2022), Salesforce's BLIP (Li et al., 2022), Microsoft's KOSMOS-1 (Huang et al., 2023), Google's PaLM-E (Driess et al., 2023), and Tencent's Macaw-LLM (Lyu et al., 2023). Chatbots like ChatGPT and Gemini are examples of LLMs. However, not all multimodal systems are LLMs. For instance, text-to-image models like Stable Diffusion, Midjourney (Midjourney, 2024), and Dall-E are multimodal but lack a language model component. The integration of LLMs for visual reasoning has been influenced by the enhancement of visual models (Parisi et al., 2022; Gao et al., 2022; Schick et al., 2023). Several visual foundation models (Wu et al., 2023; You et al., 2023; Zhu et al., 2023b) are available to perform visual reasoning tasks, often incorporating task specific LLMs (Wang et al., 2023; Zhang et al., 2023; Zhu et al., 2022).

Visual reasoning models (Yu et al., 2019; Gao et al., 2019) are designed to generalize and perform well in decision-making on unseen data, as they are trained on real-world data. Text-based LLMs possess a profound understanding of other modalities and exhibit reasoning capabilities for audio and video. The integration of adapters allows text based LLMs to connect with visual models, facilitating multi-modal reasoning. This has led to the development of multi-modal LLMs such as BLIP-2 (Li et al., 2022), Flamingo (Alayrac et al., 2022), MiniGPT-4 (Zhu et al., 2023a), Video-LLaMA (Zhang et al., 2023), LLaVA (Liu et al., 2023), PandaGPT (Su et al., 2023), and SpeechGPT (Zhang et al., 2023). These models take images/videos as input and comprehend context across multiple modalities. The responses generated by these multi-modal LLMs rival human intelligence, as they can accept input in any modality and generate responses in the user-requested modality.

Vision-language multi-modal tasks are typically categorized into two groups: generation and vision-language understanding (VLU). In the generation models, responses can be output as text, image, or a combination of both. Text-to-image generation models like Dall-E, Midjourney, and Stable Diffusion create images based on textual input. Text generation models rely on text and produce multi-modal responses in both text and image formats. For instance, image captioning models can extract text-based information from images.

Vision Language Understanding (VLU) models demonstrate proficiency in two key tasks: classification and text-based image retrieval (TBIR). In the context of classification, these models engage in image-to-text retrieval. Given an image and a predefined pool of texts, the model aims to identify the text most likely to be associated with the provided image. This task is essential for understanding the content and context depicted in images. Text-based image retrieval is another critical aspect of VLU models. In this task, the model undergoes training in a joint embedding space that encompasses both images and text. When presented with a text query, the model generates an embedding for this query. Subsequently, it identifies all images whose embeddings closely align with the generated embedding for the given text query. This approach enables effective retrieval of relevant images based on textual input, showcasing the versatile capabilities of VLU models in bridging the gap between language understanding and visual content interpretation.

2.1. Evolution of Multi-modal LLMs

The multi-modal LLMs represents a significant advancement in AI technology, particularly in the field of natural language processing (NLP). These models have undergone several transformative stages, each marked by notable innovations and improvements. The researchers aim to achieve the evolution of any-to-any modality, enhancing AI generation techniques. Tang et al. (2023) introduced Composable Diffusion (CoDi), a novel generative model capable of producing responses in any combination of language, image, and audio modalities. However, this model lacks the reasoning and decision-making capabilities of LLMs. In contrast, the later-developed model Visual-ChatGPT integrates LLMs with visual foundation models, enabling accurate responses based on input images (Wu et al., 2023).

HuggingGPT (Shen et al., 2023) focuses on general AI across various domains and modalities. This model utilizes LLMs and selects the AI model based on functional descriptors and user requests within Hugging Face. It can handle AI tasks involving different modalities and domains. In 2022, InfoQ reported on DeepMind's Flamingo, a system that integrates separately pre-trained vision and language models, enabling it to answer questions about input images and videos. Furthermore, InfoQ covered OpenAI's GPT-4, which demonstrated the capability to process image inputs. Microsoft made advancements with two vision-language models: Visual ChatGPT, leveraging ChatGPT to engage various visual foundation models for tasks, and LLaVA, a fusion of CLIP for vision and LLaMA for language, incorporating an additional network layer to seamlessly connect the two. The model was trained end-to-end in visual instruction tuning.

Multi-modal LLMs demonstrate the ability to emulate human commonsense reasoning (Davis & Marcus, 2015) and employ Chain-of-Thought (CoT) for hydrology-specific tasks (Wei et al., 2022). CoT simulates responses based on sequences of events or data, generating domain-specific responses. Two techniques are used to induce Chain-of-Thoughts in conversation: Few-Shot-CoT and Zero-Shot-CoT. In Few-Shot-CoT (Zhang et al., 2022), automated Chain-of-Thoughts is provided to the model by prompting intermediate steps in reasoning. Pretrained LLMs also serve as excellent task-specific exemplars, functioning as zero-shot reasoners by simply adding "Let's

think step by step" before each answer (Kojima et al., 2022; Zelikman et al., 2022). Multimodal-CoT (Zhang et al., 2023) incorporates text and vision modalities into a two-stage framework that separates rationale generation and answer inference. This approach allows answer inference to leverage better-generated rationales based on multimodal information.

2.2. Multi-modal Reasoning and Response Generation

Multi-modal reasoning enables AI models to comprehend information across various modalities, facilitating a holistic understanding and the generation of responses that incorporate multiple domains. The hydrology domain-specific use cases are validated using the MultiModal-GPT (Gong et al., 2023), GPT-4 Vision (2023), and LLaVA: Large Language and Vision Assistant (Liu et al., 2023) in this paper. MultiModal-GPT utilizes a vision encoder to efficiently extract visual information and integrates a gated cross-attention layer for seamless interactions between images and text. Fine-tuned from OpenFlamingo, this model incorporates a Low-rank Adapter (LoRA) in both the gated-cross-attention and self-attention components of the language model. Notably, MultiModal-GPT employs a unified template for both text and visual instruction data during training, facilitating its ability to engage in continuous dialogues with humans.

In September 2023, GPT-4 Vision was introduced, allowing users to instruct GPT-4 for various MultiModal tasks. This large multimodal model, trained similarly to GPT-4 using texts and images from licensed sources, accepts images and texts as inputs to generate textual outputs. Aligning with existing general-purpose vision-language models (Anderson et al., 2018; Lu et al., 2019; Li et al., 2019; Alberti et al., 2019; Li et al., 2020; Tan & Bansal, 2019; Su et al., 2019; Zhou et al., 2020; Chen et al., 2020; Li et al., 2023; Deng et al., 2009; Zhou et al., 2016; Chen et al., 2015), GPT-4 Vision is versatile enough to handle single image-text pairs or single images for tasks like image recognition, object localization, image captioning, visual question answering, visual dialogue, dense caption, and more.

LLaVA represents a comprehensively trained large multimodal model designed to seamlessly integrate a vision encoder with a Large Language Model (LLM). This integration is aimed at achieving a broad scope of visual and language understanding for general-purpose applications. Notably, LLaVA utilizes the language-only GPT-4 as part of its architecture. In its operation, the model excels in generating multi-modal responses by leveraging machine-generated instruction-following data. This approach enables LLaVA to interpret and respond to inputs that involve both textual and visual elements, showcasing its proficiency in handling diverse modalities of information. One of the key strengths of LLaVA lies in its zero-shot capabilities, facilitated through the prompting of GPT-4. This makes the model provide accurate responses even when faced with complex and in-depth reasoning questions, a feature honed during its training process. This capability enhances the model's versatility and effectiveness in addressing a wide range of tasks that require a nuanced understanding of both language and visual content.

Limitations: MLLMs, combining language and vision models, bring considerable benefits but also pose notable limitations. Firstly, their complexity and resource demands are substantial, requiring extensive computational power for training and fine-tuning. Moreover, data

dependencies are critical; these models rely heavily on large, diverse datasets, and their performance is compromised when faced with limited or biased data. Despite excelling in specific tasks, their ability to generalize across various domains remains a challenge. Interpreting the representations generated by MLLMs is another challenge. Extracting meaningful insights from these models proves challenging, hindering transparency in decision-making processes. Furthermore, their domain specificity is a constraint; they thrive in areas with abundant multimodal data but may fail in less explored or niche domains. Ethical concerns arise due to perpetuation of biases from training data, raising questions about fairness and impartiality in outcomes. Additionally, these models exhibit limitations in contextual understanding, struggling with nuanced situations and subtle cues. Robustness against adversarial attacks is an ongoing challenge, and the high inference time for processing both language and vision concurrently can limit real-time applicability. The environmental impact of their computational demands also deserves attention, contributing significantly to carbon footprints. Acknowledging these limitations is essential for responsible deployment and ongoing research to address these challenges (Sajja et al., 2024).

The study of MLLMs encompasses the exploration and advancement of AI technologies capable of processing and generating information across multiple modalities, including text, images, and audio. Recent years have witnessed significant progress in this field, driven by the emergence of LLMs like ChatGPT for text generation and visual transformers-based diffusion models for image generation. These advancements have paved the way for AI-generated multi-modal tasks, with open-source LLMs such as Vicuna, Flan-T5, Alpaca, and LLaMa enhancing machines' cognitive abilities and decision-making capabilities. The availability of multi-modal data from various sensors further underscores the importance of developing LLMs capable of adeptly handling multi-modal decision-making processes. As a result, researchers continue to introduce new LLMs like DeepMind's Flamingo, Salesforce's BLIP, and Microsoft's KOSMOS-1, while also exploring integration with visual models to create multi-modal LLMs such as BLIP-2, Flamingo, MiniGPT-4, and others. This background study sets the stage for investigating the capabilities, applications, and challenges of MLLMs in hydrology and other domains.

3. Methodology

This study is designed to evaluate the application of MLLMs in hydrology, particularly for real-world scenario analysis such as flood management. The study involves an empirical assessment of four advanced MLLMs: MultimodalGPT, LLaVA, GPT-4 Vision, and Gemini. These models are evaluated based on their ability to interpret and generate responses from hydrology-specific multimodal data, involving both textual prompts and visual inputs as shown in Figure 1.

3.1. Input Data Preparation

The input for each MLLM consists of a visual element—an image depicting a hydrological scenario, such as a flood event—and a textual prompt that frames a question or a task related to the visual content. For instance, the model may be presented with an image of a flooded area and

asked to determine the number of buildings visible and assess their condition. To prepare input for a MLLMs capable of processing both images and textual questions about those images, a systematic approach involving image preprocessing, text preprocessing, and input combination is necessary. Initially, the image data undergoes preprocessing steps such as resizing to a fixed size suitable for the model, normalization of pixel values within an appropriate range typically between 0 and 1, and conversion into a format compatible with the model's input requirements, often involving tensors for deep learning frameworks. Following this, textual questions are subjected to tokenization, wherein they are broken down into tokens and converted into numerical IDs based on the model's vocabulary. Special tokens like [CLS] and [SEP] are inserted to delineate the beginning and end of the text sequence, with the sequence then padded or truncated to conform to a fixed length compatible with the model.

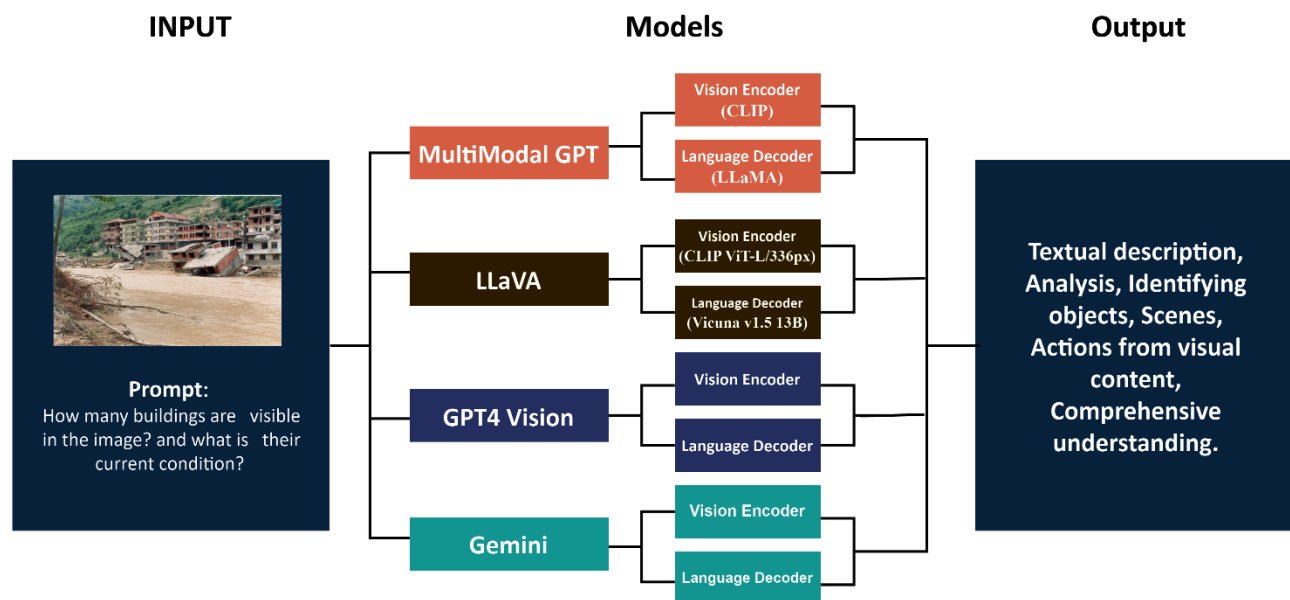


Figure 1: The workflow for MLLM benchmarking in hydrological tasks.

Moving forward, the prepared inputs are combined according to the requirements of the multimodal model being employed. Some models may necessitate separate inputs for the image and text portions, while others might accept a single input combining both modalities. In scenarios where separate inputs are required, the image tensor and tokenized text sequence are typically packed into a single data structure, such as a dictionary, before being fed into the model. This ensures that the model can effectively process both the visual and textual aspects of the input data in a cohesive manner. Ultimately, by following this structured approach to input preparation, practitioners can seamlessly integrate images and corresponding textual questions into multimodal GPT models, enabling them to generate contextually relevant and coherent responses.

3.2. Model Evaluation Process

The evaluation process will follow a specific structure where a case will be presented with an accompanying image and a clear prompt. The model's response to the prompt will be assessed based on accuracy, relevance, and understanding. Through this evaluation, we aim to explore how effectively the model integrates visual and textual information to comprehend the relationships implied by the user's input. Additionally, we assess its ability to provide accurate interpretations within the context of a hydrological application.

3.2.1. MultiModal-GPT

MultiModal-GPT is designed to facilitate human-level, multimodal dialogue between vision and language datasets, guided by the Unified Instruction Template. This template harmonizes both unimodal linguistic and multimodal vision-language data, providing structure to language-only tasks with a task description, input, and response format. The model leverages datasets such as Dolly 15k, curated for refining language model performance in instruction-based tasks like Alpaca GPT4. Similarly, vision-language tasks utilize a similar template with the incorporation of an image token, drawing from datasets like Mini-GPT4, A-OKVQA, COCO Caption, and OCR VQA for multimodal applications. From an architectural standpoint, MultiModal-GPT utilizes the OpenFlamingo infrastructure, comprising a vision encoder, spatial feature extractor via a perceiver resampler, and a language decoder. Pre-training involves a large number of image-text pairs to inform the model with powerful visual understanding. Low-Rank Adaptation (LoRA) is employed in the language decoder for fine-tuning against self-attention, cross-attention, and Feed-Forward Network (FFN) parts. This setup allows MultiModal-GPT to effectively integrate visual information into text, with the frozen OpenFlamingo model serving as its backbone.

3.2.2. LLaVA

LLaVA (Language and Vision for Instruction-Following with Vicuna and CLIP) integrates language and visual processing by generating multimodal language-image instruction-following data in two stages. Initially, multimodal language-image data is generated using the language-only GPT-4 model, collected through captions and bounding boxes describing various perspectives in visual scenes and individual objects. This dataset encompasses conversational Q&A about images, detailed image descriptions, and complex reasoning questions beyond visible features. To align vision and language modalities, a large-scale dataset is utilized and then fine-tuned using synthesized multimodal data, enhancing the model's generalization ability in processing and responding to natural multimodal instructions. LLaVA's performance is evaluated against GPT-4, employing metrics like accuracy, precision, recall, and F1 score across a synthetic multimodal dataset. Post-evaluation, LLaVA is refined for specific tasks such as science QA, showcasing its domain flexibility.

LLaVA architecture combines CLIP-based vision encoders with Vicuna-based language model decoders for feature extraction from visual inputs and textual inputs, facilitating task execution. The core of LLaVA training lies in "Visual Instruction Tuning," comprising pre-training for feature

alignment and end-to-end fine-tuning using the LLaVA-Instruct-158K dataset. By fusing language and vision input instructions, LLaVA develops multimodal instruction-following capabilities, representing a significant advancement in integrating language and vision processing for complex tasks.

3.2.3. GPT-4 Vision

GPT-4 Vision extends GPT-4's capabilities to understanding and processing visual data, introducing key stages in the visualization process. First, image preprocessing ensures standardization by resizing images to a consistent size and normalizing pixel values. This uniformity is crucial for optimizing model performance. Next, in Pixel Sequence Transformation, images are converted into sequences of pixels, akin to how language models operate on text, treating RGB values as tokens in a sequence. During Model Training, GPT-4 Vision is trained to predict pixels in a specific order, akin to predicting the next word in a sentence. This involves backpropagation and techniques like stochastic gradient descent to minimize prediction errors and assimilate patterns in image data. For image generation and classification tasks, the model predicts labels for images and generates them from seed pixel sequences. In classification, it produces a distribution of probabilities over potential labels, selecting the most probable. Lastly, for Multimodal Integration, GPT-4 Vision, capable of processing language, comprehends and describes images, answers questions based on visual content, and crafts stories integrating visual and textual elements. This holistic approach enables GPT-4 Vision to bridge the gap between visual and textual data, advancing multimodal understanding and generation capabilities.

3.2.4. Gemini

The next-generation development in multimodal AI systems introduces Gemini models, which enhance the transformer architecture to seamlessly integrate information across modalities. Designed to efficiently run on specialized hardware like Google TPUs, Gemini models excel in processing various media content, including text, audio, and visual data. With the capability to handle very long context lengths of up to 32,000 tokens, these models can process massive sequences of diverse data types, such as documents, high-resolution images, and lengthy audio files. Central to the efficiency of Gemini models are advanced attention mechanisms, which enable the models to focus their computation on the most relevant parts of input data, crucial for handling complex multimodal inputs and generating coherent outputs.

Gemini models are fine-tuned to process a wide range of input formats, from images and plots to PDFs and videos. They treat videos as sequences of frames and process audio signals at 16kHz, leveraging features directly from the Universal Speech Model to enhance content comprehension beyond mere text translation. The development of Gemini models involves innovative training algorithms and the design of custom datasets, facilitating the integration of mixtures of text, audio, and visual data. These models are delivered in two variants: Pro, optimized for efficient scaling up of pre-training, and Nano, compact and efficient for on-device applications like summarization and reading comprehension.

Gemini models can produce outputs in both text and images, utilizing discrete image tokens for visual content creation. They can respond to textual prompts with images or augment generated text outputs with appropriate visualizations. The infrastructure supporting Gemini is highly optimized and efficient, particularly in large-scale multimodal data processing using Google's TPUs, from architecture initialization to fine-tuning. These optimizations reduce resource requirements for pretraining and fine-tuning. In summary, Gemini models represent a significant advancement in AI, particularly in understanding and generating multimodal content. With broad applicability across various use cases requiring the integration of text, audio, and visual data, Gemini models pave the way for innovative solutions in diverse domains.

The methodology section outlines the approach taken to investigate MLLMs. The study first identifies relevant MLLMs, including those specialized in text generation, image generation, and multi-modal tasks, based on their capabilities and contributions to the field. Subsequently, the study delves into the integration of visual models with LLMs to develop MLLMs capable of processing and generating information across different modalities. To evaluate the performance and effectiveness of these MLLMs, a combination of qualitative and quantitative methods is employed. Tasks such as text-to-image generation, image captioning, visual question answering, and text-based image retrieval are undertaken to assess the models' capabilities comprehensively. Additionally, the study evaluates the generalization capabilities of MLLMs across various domains, assessing their proficiency in handling diverse datasets and tasks. Overall, the methodology encompasses a systematic exploration of MLLMs, aiming to provide insights into their potential applications, strengths, and limitations across a range of multimodal tasks and datasets.

4. Results

The study aims to enhance multimodal technologies to address various challenges related to flood management, water level monitoring, agricultural water discharge, and water pollution management. Efforts in flood management and response focus on leveraging advanced image description techniques to provide accurate and timely information about flood conditions, enabling more effective decision-making and response planning. Similarly, in water level monitoring, multimodal approaches are employed to integrate visual and textual data for real-time monitoring of water levels in rivers, lakes, and reservoirs, aiding in flood forecasting and early warning systems.

For agricultural water discharge, research emphasizes the development of multimodal models to monitor and manage the discharge of water in agricultural settings, optimizing irrigation practices and reducing water wastage. Additionally, efforts are directed towards using advanced image description mechanisms to detect and analyze water pollution sources, facilitating prompt intervention and mitigation measures. By integrating visual, textual, and audio data, multimodal technologies offer a comprehensive approach to address the complex challenges in hydrology, ultimately contributing to more efficient flood management, enhanced water level monitoring, sustainable agricultural practices, and effective water pollution management strategies.

In evaluating hydrology-related image samples, recent MLLMs such as MultimodalGPT, LLaVA, GPT-4Vision, and Gemini are utilized. These models are tested based on their ability to generate responses to textual prompts framing questions or tasks related to visual content. The generated textual descriptions are then compared across the models for accuracy, relevance, and understanding. This comparison helps assess the performance and effectiveness of each model in interpreting and generating contextually relevant descriptions for hydrology-related images. Below are examples illustrating both the images and textual descriptions generated by the MLLMs, providing insights into their respective capabilities and accuracies in interpreting visual content.

Table 1: Example of image-based recognition and response generation of MLLMs. GPT-4 Vision accurately identifies the crop as cornfield and assesses its condition.


<p>Question: What field is this?</p>	<p>Image Input:</p>	
<p>LLaVA:</p>	<p>This appears to be a field of corn that has been harvested. The stalks are left standing, which is common in some agricultural practices. The soil looks dry and cracked, which might indicate a period of drought or dry weather conditions. The field is situated under a partly cloudy sky, suggesting it might be a sunny day.</p>	
<p>GPT-4 Vision:</p>	<p>This is a corn (maize) field. However, it appears to be suffering from severe drought, as the soil is cracked and the corn plants are withered and brown, indicating they have not received adequate water for growth.</p>	
<p>MultiModal GPT:</p>	<p>A drought-stricken corn field in the Texas Panhandle.</p>	
<p>Gemini:</p>	<p>The image you sent is of a field of dried-up corn plants. This type of field is called a cornfield.</p>	

Table 2: Example of image-based recognition and response generation of MLLMs. GPT-4 Vision accurately identifies the collapsed building resulting from flooding in the image.


<p>Question: How many buildings are visible in the picture and what is their current condition?</p>	<p>Image Input: Image Source: Arman et al., 2010</p>	
<p>LLaVA:</p>	<p>There are two buildings visible in the picture, and they are in a dilapidated condition.</p>	
<p>GPT-4 Vision:</p>	<p>I can see several buildings in the image. In the foreground, there are two notably damaged buildings that are partially collapsed and appear to be sinking or tilting into the water. They are severely compromised and likely beyond repair. In the background, there are at least five other buildings visible. These buildings appear to be intact and in good shape, showing no obvious signs of damage. The scene suggests a natural disaster, possibly a flood or a landslide, which has caused the collapse of the closest structures.</p>	
<p>MultiModal GPT:</p>	<p>In the picture, you can see three buildings. Two of them are destroyed and one is still standing.</p>	
<p>Gemini:</p>	<p>There are eight buildings visible in the picture. All of them are severely damaged. Some of them are completely collapsed, while others are still standing but have large cracks in their walls.</p>	

Table 3: Example of image-based recognition and response generation of MLLMs. While all models generate responses, GPT-4 Vision stands out for its more accurate interpretation of the image, capturing all the details.


<p>Question: What is happening in the image? What is its severity?</p>	<p>Image Input:</p>	
<p>LLaVA:</p>	<p>The image shows a flooded neighborhood with houses and streets submerged in water. The severity of the flooding is evident, as it has caused significant damage to the area and disrupted the lives of the residents.</p>	
<p>GPT-4 Vision:</p>	<p>The image depicts a severe flooding event affecting a residential area. Numerous houses are partially submerged, and roads have become waterways. The floodwater appears to be widespread and deep in places, signaling a significant impact on the community. Infrastructure damage and displacement of residents are likely as a result of this natural disaster. The precise severity requires an on-the-ground assessment, but from the image, it is clear that there is substantial inundation which would require emergency response efforts and could have long-term repercussions for the area.</p>	
<p>MultiModal GPT:</p>	<p>The image is of a flooded city.</p>	
<p>Gemini:</p>	<p>The image shows a flood in a town. The water has risen above the first floor of the buildings. The severity of the flood is difficult to assess, but it is clear that it is a major disaster.</p>	

Table 4: Example of image-based recognition and response generation of MLLMs. LLaVA and GPT-4 Vision both produce comprehensive responses, yet GPT-4 Vision's output proves to be more relevant and exhaustive in addressing the question.

Question:
This is
happening in
front of me.
What should I
do?

**Image
Input:**



LLaVA: If you are witnessing a tornado in front of you, it is crucial to take immediate safety precautions. Here are some steps you should take:

- **Seek Shelter Immediately:** Tornadoes can be extremely dangerous. If you are in a vehicle, such as a car or truck, leave it immediately and seek shelter in a sturdy building.
- **Avoid Mobile Homes:** Mobile homes are particularly vulnerable to tornadoes and should be avoided.
- **Go to the Basement:** If you are in a house, go to the basement or the lowest level of the building. Avoid windows and doors.
- **Crouch Low to the Ground:** If you are in an open area with no shelter, crouch down as low to the ground as possible, protecting your head with your hands.
- **Avoid Trees and Power Lines:** If you are outside, avoid trees and power lines, as they can be dangerous during a tornado.
- **Listen to Local Authorities:** Pay attention to local news and emergency broadcasts for updates and instructions.
- **Stay Informed:** After the tornado has passed, stay informed about any potential aftershocks or additional hazards.

Remember, safety should always be your top priority. If you are in a situation where you are unsure of what to do, it is best to seek guidance from local authorities or emergency services.

**GPT-4
Vision:**

The image appears to show a tornado, which is a severe weather event that poses a significant risk to life and property. If you are in the vicinity of a tornado, it's crucial to take immediate action to ensure your safety. Here are some safety tips:

- **Seek Shelter Immediately:** If you're in a structure (such as a residence, school, or office building), go to a pre-designated shelter area such as a safe room, basement, storm cellar, or the lowest building level. If there is no basement, go to the center of an interior room on the lowest level (closet, interior hallway) away from corners, windows, doors, and outside walls. Put as many walls as possible between you and the outside.
- **Get Under Something Sturdy:** If possible, get underneath sturdy furniture such as a heavy table or desk and hold on to it.
- **Cover Yourself:** Protect your head and neck with your arms and put materials such as furniture cushions, mattresses, or blankets around or over you to protect from debris.
- **Don't Stay in a Mobile Home:** If you are in a mobile home, get out immediately and go to the nearest sturdy building or shelter. Mobile homes, even if tied down, cannot withstand tornado forces.
- **Do Not Try to Outrun a Tornado in a Vehicle:** If you're in a car or outdoors and cannot get to a building, as a last resort, find a ditch or low-lying area and lie flat, covering your head with your hand.

**MultiModal
GPT:**

A tornado is a violently rotating column of air that is in contact with both the surface of the Earth and a cumulonimbus cloud or, in rare cases, the base of a cumulus cloud. Tornadoes range in size from a few kilometers to over 200 kilometers (120 miles) in diameter.

Gemini:

If you see a tornado, you should immediately take shelter in a sturdy building. If you are in a car, you should pull over and seek shelter in a ditch or low-lying area. You should avoid windows and stay away from objects that can be blown around by the wind.

Table 5: Example of image-based recognition and value estimation using MLLMs. MultiModal GPT and Gemini provide arbitrary water discharge values in their responses, whereas LLaVA and GPT-4 Vision offer more realistic and contextually appropriate responses.


<p>Question: Give me the value of the water discharge in the image in cfs?</p>	<p>Image Input:</p>	
<p>LLaVA:</p>	<p>Based on the image, it is not possible to determine the exact value of the water discharge in cubic feet per second (cfs) without more information. However, the water is flowing over a dam, which suggests that there is a significant amount of water being discharged. To accurately determine the cfs value, one would need to measure the water flow rate at a specific point in the river, which is not visible in the image.</p>	
<p>GPT-4 Vision:</p>	<p>I'm sorry for any confusion, but as an AI, I'm unable to determine specific quantitative data such as the water discharge rate in cubic feet per second (cfs) from an image alone. This would require on-site measurements or data from monitoring equipment, which I do not have access to based on an image. Typically, water discharge rates are determined through a combination of flow measurements and hydrological models. Is there something else about the image you'd like to discuss or know about?</p>	
<p>MultiModal GPT:</p>	<p>The value of the water discharge in the image in cfs is 1,000</p>	
<p>Gemini:</p>	<p>900 cfs.</p>	

Table 6: Example of image-based recognition and analytics using MLLMs. Gemini demonstrates more accurate recognition of the number compared to other Multimodal LLMs.



<p>Question: How many people are there in the image?</p>	<p>Image Input:</p>	
<p>LLaVA:</p>	<p>There are five people in the image.</p>	
<p>GPT-4 Vision:</p>	<p>There are five people in this image. It appears they are standing in water, possibly a shallow river or stream, and wearing colorful clothing.</p>	
<p>MultiModal GPT:</p>	<p>A group of women washing their clothes in the river</p>	
<p>Gemini:</p>	<p>There are 6 people in the image.</p>	

Table 7: Example of image-based recognition and response generation of MLLMs. The GPT-4 Vision generates a detailed response, including the cause of dead fish and its impact.

<p>Question: What is happening in the image?</p>	<p>Image Input:</p>	
<p>LLaVA:</p>	<p>The image shows two fish, which appear to be dead, floating in a body of water. The water has a greenish hue, which could indicate algae growth or pollution. The fish are near the edge of the water, where there is some grass</p>	

and debris, suggesting that they may have been washed ashore or are in a shallow area. The exact cause of their death is not clear from the image alone, but it could be due to natural causes, disease, pollution, or other environmental factors.

GPT-4 Vision: The image shows a body of water, likely a pond or a lake, with multiple dead fish floating at the edge or partially submerged. It appears to be an environmental issue, possibly related to pollution or a lack of oxygen in the water, both of which can cause fish kills. The water surface is murky with visible algae or debris, which also suggests that the water quality might be poor. There's also some litter visible on the shore, which further indicates potential pollution issues in this area.

MultiModal GPT: Aquatic life in the pond. The fish are swimming in the pond.

Gemini: The image you sent me shows two dead fish floating on the shore of a pond. There are a few possible explanations for why the fish died:


Poor water quality: One possibility is that the water quality in the pond is poor. This could be due to factors such as pollution, low oxygen levels, or a buildup of ammonia from decomposing organic matter.

Disease: The fish could also have died from a disease. Fish can contract a variety of diseases, some of which can be very contagious.

Algal bloom: Another possibility is that the pond experienced an algal bloom. When algae die, they decompose and use up oxygen in the water. This can create a dead zone where fish and other aquatic organisms cannot survive.

Herbicides or pesticides: If herbicides or pesticides have been used near the pond, this could also be a cause of the fish kill. These chemicals can be toxic to fish and other aquatic organisms.

Table 8: Example of image-based recognition and response generation of MLLMs. The GPT-4 Vision is the clear winner in generating a detailed response on algal bloom compared to other Multimodal LLMs.

<p>Question: What is happening in the image?</p>	<p>Image Input:</p>	
<p>LLaVA:</p>	<p>The image shows a body of water with a large area of greenish-blue algae blooms. These blooms can occur naturally and can be caused by an excess of nutrients, such as nitrogen and phosphorus, which can come from agricultural runoff, sewage, or natural sources. The algae can produce toxins that can be harmful to humans, animals, and aquatic life. The presence of such blooms can also indicate poor water quality and can lead to oxygen depletion in the water, which can be harmful to aquatic ecosystems.</p>	
<p>GPT-4 Vision:</p>	<p>The image shows a coastal landscape where an algal bloom is apparent in the water. Algal blooms occur when there is an overgrowth of algae in a body of water, often due to excess nutrients such as phosphorus and nitrogen. This can happen because of runoff from agriculture or other sources of nutrient pollution. The water is visibly green and seems to be heavily populated by the algae, which is visible on the surface as a thick, green, foamy or scummy layer. In the background, there's a sandy beach leading to a forested area. The sky is clear, and it appears to be a sunny day, which can contribute to the rapid growth of algae by warming the water and promoting photosynthesis.</p>	
<p>MultiModal GPT:</p>	<p>The algae bloom in Lake Okeechobee, Florida, is the largest in recorded history.</p>	
<p>Gemini:</p>	<p>The image you sent shows green algae washing ashore on a beach. The specific type of algae appears to be Enteromorpha, also known as sea lettuce. It is a green marine alga that grows in shallow waters worldwide. There are a number of reasons why algae might wash ashore on a beach. Strong winds and currents can cause algae blooms to detach and drift towards the shore.</p>	

Additionally, changes in water temperature or nutrient levels can also cause algae blooms.

Tables 1-8 present the questions asked based on input images and the corresponding responses generated by multimodal LLMs, including LLaVA, GPT-4 Vision, MultiModal GPT, and Gemini. The key findings underscore the capabilities of these models in processing and interpreting complex multimodal data, which can significantly enhance various aspects of hydrological analysis and management. The evaluation demonstrated that GPT-4 Vision consistently outperformed the other models in terms of accuracy, relevance, and contextual understanding. This model's advanced visual and textual integration capabilities enable it to provide detailed, contextually rich responses. For example, GPT-4 Vision accurately assessed flood severity, identified drought-stricken crops, and provided detailed descriptions of environmental conditions. LLaVA and MultimodalGPT also showed promise but occasionally fell short in providing the same level of detail and accuracy as GPT-4 Vision. Gemini, while innovative, sometimes generated arbitrary values, indicating the need for further refinement in its response generation mechanisms.

5. Discussions

The successful application of MLLMs in this study indicates several promising implications for hydrology. In flood identification and management, these models can analyze patterns in data and provide predictions or suggestions for flood management. For instance, the models can identify floods, assess their severity, estimate the number of affected people and buildings, and suggest mitigation strategies. They can process images from various sources, including in-situ photographs, satellite images, and drones, to provide real-time insights and actionable suggestions for first responders and flood managers. In water quality assessment, MLLMs can analyze images of water bodies to detect indicators such as algal blooms, industrial runoff, dead fish, and other pollutants. This capability enhances real-time water pollution monitoring and response, providing critical information to environmental agencies and public health officials. For climate change analysis, they can integrate data from satellite images, climate models, and historical weather records to predict the impacts of climate change on hydrological cycles and water resources. This integrated analysis helps in understanding long-term trends and planning for future water resource management.

In water resource management, MLLMs can optimize the use of water resources by predicting rainfall, evaporation rates, and soil moisture levels. They can suggest optimal irrigation strategies for agriculture, thereby promoting sustainable agricultural practices and efficient water use. Hydropower generation can benefit from MLLMs by analyzing data on water flow, rainfall, and environmental factors to predict hydropower potential in specific areas. This can aid in the planning and optimization of hydropower projects, ensuring efficient energy production. Drought prediction is another critical area where MLLMs can be applied. By training on historical weather data and soil moisture levels, these models can forecast potential drought events, allowing for

proactive drought mitigation strategies. They can also identify drought conditions in images, providing immediate visual confirmation.

Streamflow forecasting can be enhanced by MLLMs through the analysis of rainfall, snowmelt, and other environmental data to predict river flow rates. This information is valuable for flood control, water supply planning, and navigation. In groundwater management, MLLMs can predict groundwater levels using data from various sources. This helps in the sustainable management of groundwater resources, ensuring their availability for future use. Wetland conservation efforts can be supported by MLLMs through the analysis of satellite imagery, climate data, and human activity. These models can assess the health of wetlands and suggest effective conservation strategies to maintain these crucial ecosystems.

Water demand forecasting can be improved by training MLLMs on population growth, climate data, and water usage patterns to predict future water demand. This information is essential for planning and managing water supply systems to meet future needs. Ecosystem health assessment can benefit from MLLMs by analyzing data on water quality, biodiversity, and other environmental factors. These models can provide insights into the health of aquatic ecosystems and suggest remediation efforts where necessary. They can also play a role in natural calamity detection by predicting the impact of natural disasters using climate models, satellite images, and historical data. This capability can enhance preparedness and response to natural calamities. In architectural matters within hydrology, MLLMs can be used to assist with the construction of dams and other hydrological infrastructure, supporting strategic planning and development.

6. Conclusion and Future Work

The potential impact of this study on flood detection and management is significant. By exploring the capabilities of MLLMs in the hydrology domain, this research offers insights into how advanced AI technologies can revolutionize flood monitoring, response systems, and water resource management. The analysis of MLLMs such as Multimodal-GPT, GPT-4 Vision, Gemini and LLaVA in processing hydrology-specific samples provides a foundation for developing intelligent systems capable of understanding and interpreting complex hydrological data in real-time. The findings suggest that MLLMs hold promise for enhancing human-computer interaction in flood management, offering accurate and contextually relevant insights for informed decision-making.

Moving forward, future research in hydrology, environmental analysis, and water resource management could focus on several directions to further leverage MLLMs and advance the field. One potential avenue is the development of MLLM-based systems for generating realistic flood scenarios based on textual descriptions. This could enhance predictive capabilities and aid in risk assessment and disaster preparedness. Additionally, research could explore the integration of MLLMs into decision support systems for improved water resource management, incorporating both textual and visual data to provide comprehensive insights. Furthermore, efforts could be directed towards addressing challenges such as model limitations, ethical considerations, and the environmental impact of MLLMs. Research on mitigating biases, improving interpretability, and

enhancing robustness against adversarial attacks would be valuable for ensuring responsible deployment of AI technologies in hydrology (Sajja et al., 2023). Additionally, investigating methods to optimize computational resources and reduce carbon footprints associated with MLLMs would be crucial for sustainable development.

The study sets the stage for the integration of MLLMs into flood detection and management systems, offering a glimpse into the transformative potential of AI in addressing complex hydrological challenges. By exploring future research directions and addressing key concerns, researchers can continue to advance the field and develop innovative solutions for sustainable water management in the face of climate change and increasing environmental pressures.

7. Acknowledgements

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).

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