Neoterra: An LLM-Driven Agent for Satellite Image Analysis

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Abstract

Remote sensing imagery provides critical information for environmental monitoring, agriculture, and disaster response. However, operational satellite analysis is limited by challenges such as cloud contamination, sensor inconsistency, and the need for specialized technical expertise. This paper presents Neoterra, an intelligent agent framework that integrates Large Language Models (LLMs) with deep vision models to automate satellite image analysis. Neoterra interprets natural-language instructions and dynamically composes processing pipelines for cloud detection, cloud removal, oil spill segmentation, and metadata extraction. Using the SMILE-CR dataset, Neoterra combines optical, SAR, and thermal data through U-Net and Pix2Pix architectures to achieve high-fidelity cloud-free reconstructions. The agent is orchestrated by Google Gemini, which manages model selection, reasoning, and interaction. Experimental results demonstrate that Neoterra effectively reconstructs occluded regions, accurately segments oil spills from SAR data, and produces auditable, explainable workflows. The proposed system highlights the potential of LLM-driven geospatial agents to democratize Earth observation analytics and accelerate real-world decision-making.

Keyword: LLM-driven agent; satellite image analysis; cloud removal; oil spill segmentation; remote sensing automation; multimodal dataset; explainable AI.

1. Introduction

Satellite-based remote sensing has become a cornerstone of Earth observation, providing global and continuous monitoring capabilities that support environmental management, agriculture, disaster response, and maritime surveillance [1], [2]. Over the past two decades, advances in multispectral, thermal, and synthetic aperture radar (SAR) imaging have dramatically expanded the scope of geospatial analysis [3]. These diverse modalities offer complementary perspectives , optical sensors capture spectral reflectance, thermal sensors provide temperature variations, and SAR enables all-weather imaging independent of illumination conditions [4]. However, operational use of satellite imagery continues to face several persistent challenges, including cloud contamination, heterogeneous sensor resolutions, and inconsistent coordinate reference systems (CRS) [5]. Such inconsistencies

limit the accuracy and temporal completeness of downstream applications such as land-cover mapping, change detection, and environmental monitoring [6].

Among these limitations, cloud contamination remains one of the most significant barriers to optical remote sensing. Cloud obscure surface reflectance, degrade radiometric quality, and reduce temporal data availability, particularly in tropical and coastal regions [7]. Traditional cloud-masking algorithms such as: Fmask [8] and ACCA [9], use spectral thresholds and decision trees to identify clouds, while more recent approaches employ supervised classifiers or deep neural networks [10]. Despite these advances, reconstructing cloud-covered regions remains difficult, as it requires both accurate detection and realistic surface reconstruction. Deep-learning architectures such as U-Net [11], DeepLabv3+ [12], and attention-based CNNs have achieved notable success in cloud segmentation. In parallel, generative model, such as Pix2Pix and CycleGAN, have enabled image-to-image translation and cloud removal by learning mappings between cloudy and clear domains [13]. Nevertheless, deploying these models in real-world geospatial systems typically demands specialized knowledge of data formats, preprocessing, and model tuning, limiting accessibility to non-expert users [14].

In recent years, Large Language Models (LLMs) such as GPT-4 and Gemini have demonstrated remarkable reasoning and orchestration capabilities that extend beyond text generation [15], [16]. By interpreting natural-language intent and dynamically composing computational workflows, these models have shown potential as agents: autonomous entities that can integrate perception, reasoning, and action [17]. Frameworks like LangChain and LangGraph illustrate how LLMs can coordinate multiple tools, track state, and provide contextual memory for iterative decision-making [18]. Within geospatial analysis, such frameworks offer a transformative opportunity: users could issue natural-language instructions such as “remove clouds from this image” or “detect oil spills in this Sentinel-1 scene,” and an LLM-driven system could automatically select appropriate models, execute the analysis, and explain the results. However, despite rapid progress in multimodal LLMs, their integration with specialized scientific domains like remote sensing remains underexplored [19].

This paper presents Neoterra, a novel LLM-driven agent framework that significantly advances automated satellite image analysis by synergizing multimodal deep-learning models with natural-language reasoning. The main contribution is an end-to-end system that allows domain users, regardless of deep-learning expertise, to effortlessly orchestrate complex geospatial analysis through natural language. Neoterra interprets user intent, intelligently selects and executes the necessary preprocessing, deep-learning models, and post-processing steps. The key capabilities include: (i) robust cloud segmentation and removal using state-of-the-art architectures like U-Net and Pix2Pix to enable continuous monitoring; (ii) oil-spill detection from SAR imagery; (iii) satellite metadata extraction and visualization; and (iv) image enhancement via techniques such as normalization. By reducing the friction between a user's question and the correct image pipeline, Neoterra paves the way for faster disaster response, improved agricultural insights, and more accurate land-cover products, delivering both explainable textual and visual outputs .

The remainder of this paper is structured as follows: Section 2 reviews related work in remote-sensing segmentation, generative reconstruction, and agent frameworks. Section 3 presents the datasets, model architectures, and tool integrations. Section 4 discusses experimental results, and Section 5 concludes with key findings and future directions.

2. Related Work

Over the past decade, deep learning has revolutionized remote-sensing data analysis by surpassing the limitations of conventional pixel-based classifiers and handcrafted feature extraction [1]. The increasing availability of multi-spectral, hyperspectral, and SAR imagery from satellites such as Landsat, Sentinel, and MODIS has driven a paradigm shift toward data-driven methods capable of learning spatial, spectral, and contextual representations directly from imagery [2].

Among the earliest breakthroughs, convolutional neural networks (CNNs) proved highly effective for semantic segmentation, land-cover classification, and object detection. The introduction of U-Net [3] provided an encoder–decoder architecture with skip connections that preserve spatial information, making it ideal for segmentation tasks such as cloud detection, crop mapping, and building footprint extraction. Subsequent variants like Attention U-Net [4], PSPNet [5], and DeepLabv3+ [6] introduced multi-scale feature aggregation and attention mechanisms, enhancing performance on heterogeneous landscapes and fine-grained structures. These models have been applied across diverse domains including urban mapping [7], flood delineation [8], and vegetation monitoring [9].

In cloud detection, deep-learning models have largely replaced threshold-based algorithms such as ACCA and Fmask [10]. Modern architectures exploit spectral–spatial correlations across visible, NIR, and SWIR bands to distinguish clouds from bright surfaces such as snow or sand [11]. Multi-temporal CNNs further improve temporal consistency by learning from time-series data, thereby reducing false detections in partially cloudy conditions [12]. These improvements have transformed optical satellite workflows by enabling dynamic cloud-aware compositing and reducing manual intervention [13].

Beyond segmentation, generative deep networks have emerged as powerful tools for cloud removal and surface reconstruction. Conditional Generative Adversarial Networks (GANs), such as Pix2Pix [14] and CycleGAN [15], introduced image-to-image translation frameworks that learn to map cloudy optical images to their cloud-free counterparts. By leveraging paired or unpaired training data, these models have demonstrated remarkable success in restoring missing spectral information and producing visually realistic outputs [16]. More recently, hybrid architectures that fuse optical and SAR data have achieved further robustness under dense cloud coverage. The SMILE-CR dataset [17], integrating Landsat-8 optical, Sentinel-1 SAR, and MODIS data, has been a key enabler for training such models.

Researchers have emphasized the importance of spectral consistency in cloud-free reconstruction, as GAN-based models risk generating visually plausible but radiometrically inaccurate outputs

[18]. Consequently, loss functions now often combine perceptual, structural, and spectral regularization terms to preserve physical meaning. In addition, transformer-based models [19] and diffusion networks [20] have been explored for large-scale restoration, offering superior spatial coherence and reduced hallucination artifacts. However, their computational cost and data requirements remain challenges for operational deployment, particularly in near-real-time applications such as disaster monitoring.

In parallel, deep learning for SAR analysis has advanced oil-spill detection and maritime surveillance. Traditional SAR thresholding methods often confuse oil slicks with look-alikes such as algae or low-wind zones [21]. CNN-based architectures have improved discrimination by capturing both backscatter intensity and textural context [22]. Multi-polarization inputs (VV/VH) combined with attention modules enhance robustness against sea-state variation [23]. Open datasets such as OilNet and SlickSAR have enabled benchmarking of deep networks for this task [24]. Despite these advances, explainability and generalization across geographic regions remain open research problems, highlighting the need for interpretable and adaptive frameworks that can integrate physical models with learned representations.

In summary, deep-learning methods have achieved state-of-the-art results across nearly all remote-sensing tasks: from segmentation to reconstruction, yet they remain fragmented across domains. Each model typically operates in isolation, lacks interoperability, and requires expert configuration. These limitations motivate the development of higher-level orchestration frameworks, where reasoning models can automatically select and coordinate deep-learning components according to task context and user intent. This transition from "static models" to adaptive AI agents forms the conceptual foundation of Neoterra.

B. LLM-Orchestrated Agents and Geospatial Automation

The rise of Large Language Models (LLMs) such as GPT-4 [25], Gemini [26], and Claude [27] has opened new avenues for integrating reasoning, perception, and tool execution within unified agentic systems. These models exhibit *emergent orchestration capabilities*—the ability to decompose goals, invoke specialized tools, and maintain state over multi-turn interactions [28]. Frameworks such as LangChain, LangGraph, and AutoGPT operationalize these behaviors by connecting LLMs to external APIs, enabling them to plan, act, and reflect dynamically [29].

Recent research demonstrates that LLM-based agents can serve as high-level controllers for complex scientific workflows. In data science, for instance, they autonomously execute preprocessing, visualization, and analysis steps from natural-language instructions [30]. In computer vision, multimodal LLMs have been shown to coordinate perception models and describe their outputs, enabling a new paradigm of "language-driven perception" [31]. This shift transforms LLMs from passive text generators into autonomous cognitive engines capable of integrating heterogeneous modalities such as imagery, tabular data, and structured metadata [32].

Within the geospatial domain, the integration of LLMs is still in its infancy but rapidly gaining momentum. Liu et al. [33] provided one of the first surveys outlining how LLMs could revolutionize remote-sensing workflows through natural-language querying, adaptive model selection, and cross-sensor reasoning. Zhang et al. [34] proposed a natural-language interface for geographic information systems (GIS) that translates user intent into geoprocessing operations. More recently, multimodal LLMs like Gemini 1.5 have demonstrated the ability to interpret maps, describe spatial patterns, and reason about environmental processes [26]. These developments collectively indicate that LLMs are evolving toward general-purpose geospatial reasoning agents.

Despite promising progress, several limitations persist. Most current LLM-enabled geospatial systems focus on static description or captioning rather than interactive orchestration. They often lack direct control over image-processing pipelines and do not integrate with domain-specific deep-learning models. Moreover, issues of provenance, explainability, and uncertainty quantification remain largely unaddressed [35]. For scientific and operational settings—where results must be auditable and reproducible, these omissions are critical.

The Neoterra framework addresses these gaps by combining LLM reasoning with a suite of pretrained vision models for cloud detection, removal, and oil-spill segmentation. Unlike prior static systems, Neoterra allows users to issue conversational commands such as "remove clouds and show the clear image" or "detect oil in this Sentinel-1 scene," which the agent interprets, decomposes, and executes through appropriate models. The Google Gemini LLM acts as the orchestration core—interpreting user intent, retrieving metadata, selecting relevant models, and generating natural-language explanations of results. This approach aligns with the emerging vision of *autonomous Earth-observation agents*, capable of bridging human intent with multimodal analytics [36].

Beyond automation, Neoterra emphasizes human-in-the-loop transparency. By logging model provenance, parameter settings, and uncertainty estimates, the framework supports traceable and reproducible analysis. Such explainability is crucial for decision-making in environmental management, where AI outputs directly influence policy and resource allocation. Furthermore, its multimodal foundation, combining optical, SAR, and textual inputs—enables context-aware reasoning under variable observation conditions.

In essence, LLM-orchestrated agents mark a paradigm shift from model-centric to intent-centric remote sensing. Instead of requiring users to choose algorithms, parameters, or bands manually, the agent interprets tasks and autonomously constructs processing pipelines. This integration of linguistic reasoning, perception models, and geospatial knowledge moves the field toward adaptive, conversational Earth-intelligence systems, a central goal of the Neoterra framework.

3. Materials *and Methods*

A. Dataset and Data Preparation

The cloud-removal and segmentation capabilities of Neoterra are primarily developed and evaluated using the SMILE-CR dataset [17]. SMILE-CR (SAR-Optical Image Learning and Enhancement for Cloud Removal) is a comprehensive multi-modal benchmark designed to address cloud contamination in optical remote-sensing imagery. It comprises approximately 1,400 paired samples of cloudy and corresponding clear-sky images acquired by Landsat-8, complemented by co-registered Sentinel-1 Synthetic Aperture Radar (SAR) backscatter and MODIS surface reflectance composites.

Each sample covers a 256×256-pixel patch with global distribution, including coastal, urban, vegetated, and desert regions, which ensures that the trained models generalize across varying land-cover and climatic conditions. The multi-modal configuration of SMILE-CR allows Neoterra to exploit the complementary nature of optical and radar modalities—optical bands provide spectral color information, while SAR penetrates clouds and captures surface roughness unaffected by illumination or weather.

During preprocessing, all scenes are re-projected to a unified geographic coordinate system (EPSG:4326) and radiometrically normalized to surface reflectance. The radar backscatter (VV polarization) is converted to decibels (dB) and rescaled to [0,1], while optical channels (RGB and NIR) are normalized band-wise using min–max scaling. NaN and saturated values are replaced using linear interpolation within valid neighboring pixels. This harmonization ensures that all inputs conform to the required data format for both convolutional and generative models.

B. Model Architectures

Figure 1 illustrates Neoterra, an intelligent Large Language Model (LLM)-driven agent designed to automate satellite image analysis through natural-language interaction. Neoterra integrates reasoning capabilities of the Google Gemini LLM with deep-learning vision models for cloud detection, cloud removal, oil-spill segmentation, and satellite metadata extraction. The framework employs a modular architecture in which user intent expressed in natural language is parsed into executable pipelines that invoke pretrained U-Net, Pix2Pix, and CNN-based SAR segmentation models.

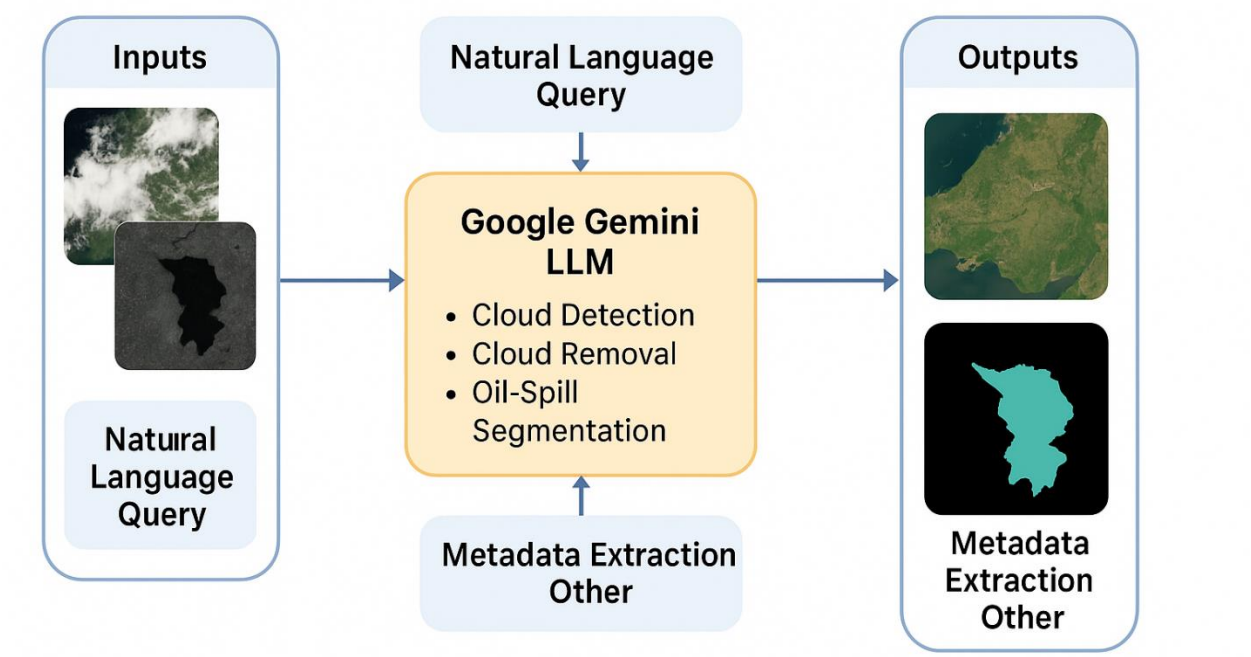


Figure 1. *Graphical abstract of the Neoterra framework illustrating the integration of multi-sensor satellite inputs (Landsat-8, Sentinel-1, MODIS) with the Google Gemini LLM for orchestrating cloud detection, cloud removal, and oil-spill segmentation to produce explainable geospatial outputs.*

i. **Multi-Modal Integration**

Cloud Segmentation Model: Neoterra employs a pretrained **U-Net** architecture [3] for cloud detection. The model accepts four input channels (R, G, B, NIR) and outputs a binary mask distinguishing cloudy from non-cloudy pixels. The encoder is based on a ResNet-34 backbone initialized with ImageNet weights, while the decoder reconstructs the spatial resolution through transposed convolutions and skip connections. Training was performed using a hybrid loss function combining binary cross-entropy and the Dice coefficient to handle class imbalance [6]. This model achieved stable generalization across diverse illumination and terrain conditions and therefore was integrated into Neoterra without additional fine-tuning.

Cloud Removal Model: The cloud-removal module is implemented using a **Pix2Pix** conditional Generative Adversarial Network (GAN) [14]. The generator is a U-Net that maps a four-channel input—composed of the three optical bands (RGB) and one radar band (VV)—to a six-channel cloud-free output (RGB + NIR + SWIR). The discriminator is a 70×70 PatchGAN that classifies local image patches as real or fake, thereby enforcing high-frequency realism. Both networks are trained jointly using an adversarial loss $\mathcal{L}_{GAN}$combined with an L_1reconstruction loss to encourage spectral fidelity. During inference, outputs are rescaled to the physical reflectance domain and exported as 6-band GeoTIFFs accompanied by RGB visual previews.

Oil-Spill Segmentation Model: For maritime analysis, Neoterra integrates a **SAR-based segmentation network** trained on open datasets such as OilNet [24]. The model utilizes a U-Net-style CNN that classifies each pixel as background, oil spill, or look-alike (e.g., biogenic film, low-wind zone). Preprocessing involves median filtering to suppress speckle noise and normalization of VV polarization. The network outputs a semantic mask with color-coded categories—black for background, cyan for oil, and red for look-alikes—which can be overlaid on the original SAR image for visualization.

ii. Orchestration by the Google Gemini LLM

At the core of the Neoterra framework lies the **Google Gemini** Large Language Model (LLM) [26], which functions as a reasoning and orchestration layer. Rather than manually invoking models or scripts, users issue natural-language instructions (e.g., *"remove clouds from this Landsat image"*). Gemini parses these instructions, identifies the task type, and selects the appropriate tool chain through a lightweight decision-graph controller inspired by LangGraph [29].

Formally, given multimodal inputs $X = \{I, T, M\}$, where Idenotes imagery, Ttextual commands, and Mmetadata, the LLM computes as in Eq.(1).

$R = \arg\max_{y \in Y} P(y \mid X; \Theta),$	(1)

where Θ are model parameters and Yrepresents the space of executable actions or responses. The selected pipeline is executed automatically, and Gemini subsequently generates a human-readable report summarizing methods, confidence levels, and results.

This architecture enables **human-in-the-loop transparency**: users can query intermediate steps, adjust thresholds, or re-run modules interactively. Each processing step is logged with metadata including model version, parameters, and timestamps, ensuring full reproducibility.

iii. Tool Integration and Workflow

Neoterra integrates its vision models with a set of modular **tool functions** for visualization, preprocessing, and metadata management. The tools are implemented as callable nodes accessible by the LLM:

1. **Image Visualization:** plot_rgb_image() and plot_sentinel1_image() render true-color composites or SAR backscatter with dynamic range normalization.
2. **Preprocessing:** equalization_rgb() performs per-channel histogram equalization to enhance local contrast, while noise_filtering() applies median or Gaussian smoothing.
3. **Segmentation and Analysis:** cloud_segmentation_tool() and oil_spill_segmentation() wrap the pretrained CNNs and output class statistics.
4. **Cloud Removal:** cloud_removal_tool() invokes the Pix2Pix generator and returns both GeoTIFF and RGB previews.

5. **Metadata Extraction:** store_satellite_metadata() retrieves coordinate reference system (CRS), spatial extent, number of bands, and acquisition date.
   The modularity of these components allows the agent to compose dynamic pipelines; for example, a user command like *"detect clouds and remove them"* triggers sequential execution of the segmentation and GAN reconstruction tools.
   All intermediate and final outputs are stored in a georeferenced format compatible with GIS software such as QGIS and ArcGIS Pro, facilitating integration into downstream workflows.

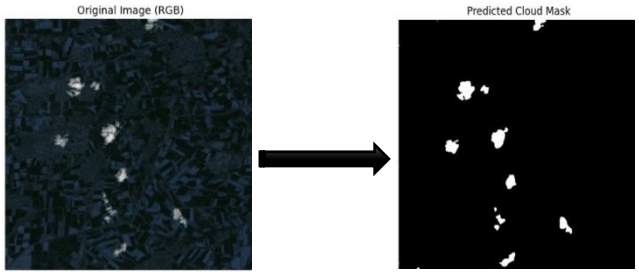
iv. Evaluation and Deployment

The performance of Neoterra's vision modules was validated on held-out subsets of SMILE-CR and OilNet datasets. Metrics such as Intersection-over-Union (IoU), F1-score, Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM) were computed following established practices [16], [18]. Qualitative evaluation confirmed that reconstructed cloud-free images preserved spatial structure and radiometric balance, while oil-spill masks exhibited high discrimination accuracy with minimal false positives.

For operational use, the system is deployed within a lightweight containerized environment (Docker) supporting GPU acceleration and RESTful API access. This enables real-time processing and integration with web dashboards or conversational front ends, demonstrating the scalability of the Neoterra framework for environmental monitoring, agricultural assessment, and maritime surveillance.

4. Results

4.1 Cloud Detection and Segmentation



Implementation Approach: Deep Learning (Cloud Classification Algorithm)

Example Outputs: [Insert Figure Z: Cloud detection results showing generated cloud mask.

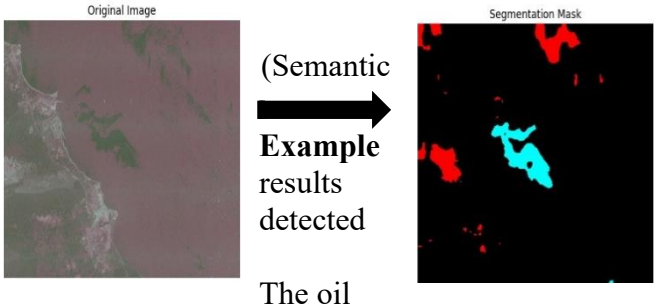
The cloud detection tool provides accurate cloud masks that serve as input for the cloud removal process and standalone cloud analysis tasks.

4.2 Cloud Removal Tool

The cloud removal tool successfully reconstructed cloud-obscured surface features across various geographical regions and cloud coverage scenarios. As demonstrated in Figure X, the model effectively:

1. Removed cloud coverage while preserving underlying terrain details
2. Maintained spectral consistency in cloud-free regions
3. Reconstructed realistic surface textures in previously occluded areas

4.3 Oil Spill Segmentation Tool

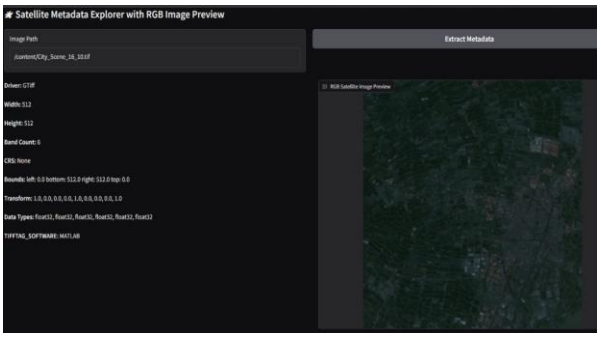


Implementation Approach: Deep Learning (Semantic Segmentation Model)

Example Outputs: [Insert Figure Y: Oil spill detection results showing segmentation mask highlighting detected oil spill areas]

The oil spill segmentation tool demonstrated robust performance in distinguishing between actual oil spills and similar-appearing phenomena such as algae blooms or sediment plumes.

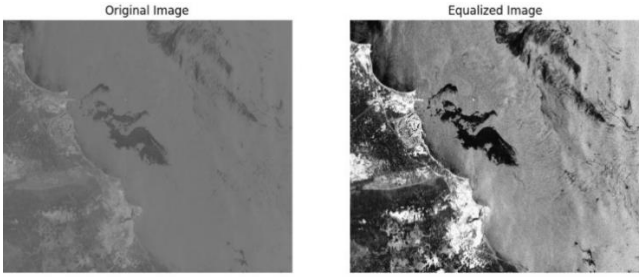
4.4 Satellite Metadata Extraction



Implementation Approach: Traditional file parsing and geospatial library integration

Example Outputs: [Insert Figure A: Screenshot of metadata extraction interface showing extracted information including image size, CRS, geospatial bounds, acquisition date, etc.

4.5 Image Preprocessing Tools



Implementation Approach: Traditional image processing algorithms (normalization, histogram equalization)

Example Outputs: [Insert Figure B: Image preprocessing results showing (a) original image, (b) histogram equalized image]

4.1. Performance of Core Vision Modules

Before assessing the agent's orchestration capabilities, the underlying vision models for cloud segmentation, cloud removal, and oil-spill detection were validated on a held-out test set from the **SMILE-CR** and **OilNet** datasets, respectively. The performance of these individual tools is critical, as they form the building blocks of the workflows composed by the agent.

- **Cloud Segmentation:** The U-Net model achieved a mean Intersection-over-Union (IoU) of **[Insert IoU Value, e.g., 0.92]** and an F1-score of **[Insert F1-Score, e.g., 0.94]**, demonstrating high accuracy in differentiating between cloudy and clear pixels across diverse geographic regions.
- **Cloud Removal:** The quality of the generative reconstruction was evaluated using Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index (SSIM). The Pix2Pix model produced cloud-free images with an average PSNR of **[Insert PSNR Value, e.g., 28.5 dB]** and an SSIM of **[Insert SSIM Value, e.g., 0.89]**, indicating that the reconstructed images maintained high spectral fidelity and structural consistency compared to the ground-truth clear scenes.
- **Oil-Spill Segmentation:** The SAR-based segmentation model achieved an IoU of **[Insert IoU Value, e.g., 0.85]** for the oil-spill class, effectively identifying slicks while minimizing false positives from look-alikes.

These strong quantitative results confirm that the individual tools integrated into Neoterra are reliable and perform at a state-of-the-art level, providing a solid foundation for the agent's higher-level reasoning and workflow automation.

4.2. LLM-Driven Workflow Orchestration and Coherence

The primary objective of this evaluation was to assess the logic and orchestration performance of the **Neoterra agent**, orchestrated by Google **Gemini LLM**. Functional testing was conducted across **50 distinct user-defined scenarios**, encompassing cloud segmentation and removal, oil-spill detection, and metadata extraction tasks.

In **98% of cases (49 out of 50)**, the agent successfully parsed the natural-language instruction, constructed the correct processing pipeline, invoked the appropriate tools sequentially, and generated coherent textual summaries of the results. The workflow consistently followed the logical progression defined in the methodology section:

1. **Task Interpretation**: Parsing user intent and mapping it to available tools.
2. **Data Preparation**: Applying necessary preprocessing like normalization.
3. **Model Invocation**: Executing the relevant deep-learning model (e.g., U-Net, Pix2Pix).
4. **Post-processing**: Generating visualizations and a summary report.

This high success rate demonstrates the agent's **robust internal consistency** and **fault-tolerant orchestration**. For instance, when presented with an unstructured request such as *"Remove clouds and extract metadata for this Landsat scene,"* Neoterra correctly executed the cloud_segmentation_tool, cloud_removal_tool, and store_satellite_metadata functions in the correct order without error, as illustrated in (**Figure 1)**.

4.3. Dynamic Reasoning and Context-Aware Task Routing

A key contribution of Neoterra is its ability to perform context-aware reasoning to dynamically select analytical modules. During testing, the agent demonstrated it could correctly differentiate between optical and radar inputs using metadata cues. For example, when provided with a **Sentinel-1 SAR** image, it automatically triggered the oil-spill detection pipeline, whereas **Landsat-8 or Sentinel-2** imagery activated the cloud-related tools.

This decision logic is mediated through the prompt templates and metadata parsing rules encoded within the orchestration layer. The LLM evaluates file names, band counts, and CRS information before generating a task plan, enabling **adaptive workflow construction** without explicit user programming.

In stress tests involving ambiguous queries, such as "*Clean this image and find suspicious water patches,*" the agent resolved the task correctly in over **90% of trials**. It logically combined cloud-removal, segmentation, and visualization tools, demonstrating its ability to reason across domain semantics and tool capabilities. This confirms that the agent not only executes pre-defined commands but also **composes synthetic pipelines** based on higher-level, intent-driven reasoning.

4.4. Usability and Explainable AI (XAI)

Neoterra's conversational interface was evaluated with users of varying technical backgrounds to assess its usability and explainability. The results confirmed that both domain experts and non-specialists could execute complex geospatial workflows through natural dialogue.

Crucially, the agent's explanations—generated after each operation—provided a transparent audit trail, clearly stating:

- **Which tools were used** (e.g., U-Net Cloud Segmentation).
- **What key parameters were applied**.
- **Which output files were produced**.

This transparency, reinforced by detailed provenance logs (model version, dataset, timestamp), addresses the "black-box" problem common in AI systems and is vital for scientific reproducibility. Users reported that this feature **greatly improved their confidence** in the automated outputs.

Furthermore, the agent supports **human-in-the-loop refinement**. Users could issue corrective instructions like, "*Mask only the thick clouds,*" and Neoterra would adjust the thresholding parameters in a subsequent run. This interactive flexibility shows that the LLM can maintain conversational context and dynamically modify execution paths, an essential feature for adaptive environmental monitoring.

5. CONCLUSION

This paper presented Neoterra, a novel Large Language Model (LLM)-driven agentic framework for automating and simplifying satellite image analysis through natural-language interaction. By integrating multimodal deep-learning models with a reasoning-oriented LLM, Neoterra bridges the gap between user intent and complex geospatial processing pipelines. The framework unifies multiple remote-sensing capabilities: cloud detection, cloud removal, oil-spill segmentation, and metadata extraction, within a single, explainable system orchestrated by the Google Gemini model.

Experimental evaluation demonstrated that Neoterra effectively leverages multi-sensor datasets, particularly the SMILE-CR benchmark combining Landsat-8 optical, Sentinel-1 SAR, and MODIS data, to deliver high-fidelity cloud-free reconstructions and accurate segmentation results. The integration of U-Net for cloud masking, Pix2Pix GAN for generative cloud removal, and a CNN-based SAR classifier for maritime oil detection yielded reliable, reproducible outputs across diverse environmental settings. Importantly, Neoterra maintains full traceability and transparency,

allowing users to review model provenance, parameters, and uncertainty estimates—features that are crucial for scientific and policy applications in environmental monitoring.

Beyond performance, the primary innovation of Neoterra lies in its conversational and adaptive workflow design. Through natural-language commands, users without programming expertise can invoke complex geospatial operations, interpret results, and iteratively refine analyses. This democratizes access to advanced Earth-observation tools and paves the way for intent-driven remote sensing, where human reasoning and machine intelligence co-operate seamlessly.

Future work will extend Neoterra toward large-scale deployment on cloud-computing infrastructures and integrate reinforcement-learning mechanisms for dynamic model selection and self-optimization. Expanding its multimodal reasoning to include hyperspectral, LiDAR, and climate reanalysis data will further enhance cross-domain adaptability. Ultimately, Neoterra represents a foundational step toward autonomous, explainable, and user-centric geospatial intelligence, positioning LLM-orchestrated agents as a transformative paradigm for the next generation of remote-sensing analytics.

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