

RS-Agent: Automating Remote Sensing Tasks through Intelligent Agent

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Abstract

The unprecedented advancements in Multimodal Large Language Models (MLLMs) have demonstrated strong potential in interacting with humans through both language and visual inputs to perform downstream tasks such as visual question answering and scene understanding. However, these models are constrained to basic instruction-following or descriptive tasks, facing challenges in complex real-world remote sensing applications that require specialized tools and knowledge. To address these limitations, we propose RS-Agent, an AI agent designed to interact with human users and autonomously leverage specialized models to address the demands of real-world remote sensing applications. RS-Agent integrates four key components: a Central Controller based on large language models, a dynamic toolkit for tool execution, a Solution Space for task-specific expert guidance, and a Knowledge Space for domain-level reasoning, enabling it to interpret user queries and orchestrate tools for accurate remote sensing task. We introduce two novel mechanisms: Task-Aware Retrieval, which improves tool selection accuracy through expert-guided planning, and DualRAG, a retrieval-augmented generation method that enhances knowledge relevance through weighted, dual-path retrieval. RS-Agent supports flexible integration of new tools and is compatible with both open-source and proprietary LLMs. Extensive experiments across 9 datasets and 18 remote sensing tasks demonstrate that RS-Agent significantly outperforms state-of-the-art MLLMs, achieving over 95% task planning accuracy and delivering superior performance in tasks such as scene classification, object counting, and remote sensing visual question answering. Our work presents RS-Agent as a robust and extensible framework for advancing intelligent automation in remote sensing analysis. Our code will be available at <https://github.com/IntelliSensing/RS-Agent>.

1. Introduction

By aligning visual and textual information, Multi-modal Large Language Models (MLLMs) (Radford et al., 2021, Sun et al., 2023) have made considerable progress across diverse remote sensing image interpretation tasks, including image captioning (Tao et al., 2023), visual question answering (Bashmal et al., 2023), and semantic scene understanding (Hu et al., 2025, Kuckreja et al., 2023), making remote sensing data more accessible to non-expert users. However, despite these advancements, MLLMs still face challenges in consistently handling multiple tasks across diverse remote sensing image modalities and resolutions. Firstly, remote sensing data encompass a wide range of modalities with varying resolutions. Consequently, general-purpose models lack the flexibility to quickly accommodate new modalities without computationally expensive re-training. In addition, most existing MLLMs are primarily optimized for instruction-following or descriptive tasks, such as image captioning and visual question answering. These generalist models typically do not provide expert-level responses comparable to those specialized models customized for specific tasks (Sun et al., 2021, Li et al., 2021a, Wang et al., 2022, Zhu et al., 2022). These challenges emphasize the necessity for an expert-aware system capable of interacting with human users, and automatically utilizing specialized models to address the demands of real-world remote sensing applications.

It is believed that AI Agent (Xi et al., 2025) is a promising solution to these challenges. AI agents are autonomous systems capable of understanding user intent, planning multi-step

tasks, invoking appropriate tools, and refining their decisions based on intermediate outcomes (Reed et al., 2022, Park et al., 2023, Wang et al., 2024d). Recent advancements in agent frameworks—often powered by large language models—have demonstrated strong potential in coordinating multiple tools, decomposing complex tasks, and flexibly adapting to diverse user goals through modular design (Ruan et al., 2023, Xi et al., 2025). These agents can bridge the gap between high-level semantic instructions and low-level tool execution operations. Despite growing interest, such agent-based approaches remain largely underexplored in the remote sensing domain. Although a few works in the remote sensing field use the term “agent” in their paper (Du et al., 2023, Liu et al., 2024, Zhu et al., 2024), they primarily focus on specific tasks and fail to propose a general-purpose agent. RS-ChatGPT (Guo et al., 2024a) integrates ChatGPT (Brown et al., 2020) with a collection of pre-trained remote sensing networks to perform tasks such as object detection, scene classification, and image captioning. However, RS-ChatGPT encounters limitations when scaling to a broader range of tools or addressing tasks that demand specialized domain knowledge.

In this paper, we propose Remote Sensing Agent (RS-Agent), an initial yet substantial step towards bridging this gap by building an AI agent specifically designed for professional remote sensing applications. As illustrated in Fig. 1, RS-Agent consists of four main components: **(i)** Central Controller that utilizes LLM to interpret user queries, plans complex tasks, perform tool execution, memorizes interaction history, aggregates intermediate results, and retrieves relevant knowledge; **(ii)** Toolkit that integrates the state-of-the-art (SOTA) methods for various remote sensing applications, including image denois-

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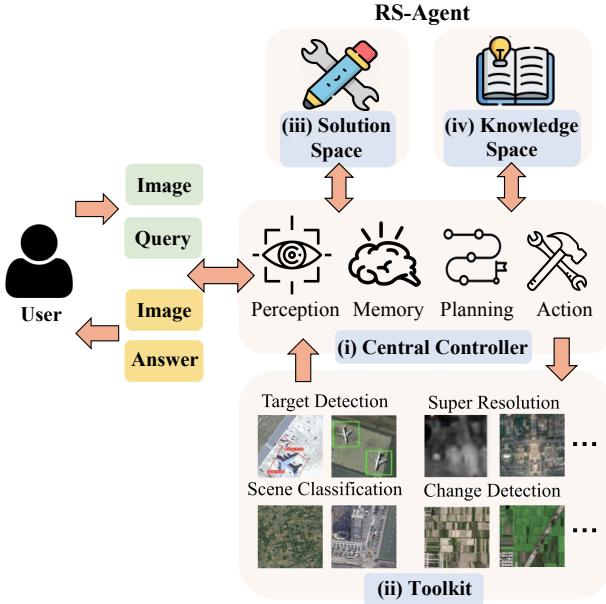


Figure 1. The schematic diagram of the RS-Agent. RS-Agent consists of four main components: a Central Controller based on LLM, which comprehends user queries, maintains historical context, plans tool usage, aggregates results; a Solution Space that provides well-defined solutions to user-submitted problems; a Knowledge Space offering domain-specific knowledge in remote sensing; and a Toolkit integrating state-of-the-art methods for remote sensing tasks.

ing, super-resolution, detection, captioning, scene classification, etc, as illustrated in Table 8 and Figure 3; (iii) Solution Space that provides task-specific, professional solutions to guide tool selection and execution; (iv) Knowledge Space that offers domain-specific expertise and theoretical support for remote sensing tasks.

The core functionality of RS-Agent lies in its ability to accurately interpret user instructions and convert them into precise and executable workflows. To this end, we design a carefully structured agent architecture that integrates modular system prompts with a long-term memory mechanism. This design empowers the Central Controller to accurately interpret user intent and dynamically plan workflows by leveraging current inputs, tool outputs, and contextual memory. Robustness and adaptability are critical for such systems, especially when handling diverse and ambiguous user instructions. Recent studies have emphasized the importance of stable task-level decision-making under varying task distributions and execution contexts (Wang et al., 2024a, Lv et al., 2024). In the Solution Space, to empower RS-Agent with the ability to reason and operate like a professional remote sensing analyst, we build a Solution Database that stores professional knowledge on how to use various remote sensing tools effectively. We further propose a Task-Aware Retrieval method to retrieve and comprehend expert knowledge, enabling accurate tool selection and step-by-step task decomposition tailored to the user’s query. To address the domain knowledge limitations of general-purpose models (Brown et al., 2020, Touvron et al., 2023, Bai et al., 2023), we develop a dedicated Knowledge Database, tailored to remote sensing targets. Building on this, we propose DualRAG, a novel retrieval-augmented generation method that enables the agent to retrieve more relevant and accurate domain-specific knowledge.

RS-Agent accurately interprets user intent and offers flexible integration of new tools to support emerging applications. We

conduct extensive experiments across 9 datasets and 18 remote sensing tasks. Experiments reveal that the RS-Agent significantly enhances task planning accuracy—achieving over 95% accuracy, substantially outperforming the SOTA baseline RS-ChatGPT (Guo et al., 2024a). Furthermore, by coordinating multiple tools, RS-Agent consistently surpasses single-model performance across diverse applications, including scene classification, remote sensing visual question answering, and object counting. In addition, the proposed DualRAG method markedly improves the quality of domain-specific knowledge retrieval. It is also worth noting that this work does not aim to develop new LLM architectures. Instead, RS-Agent is designed to be compatible with both open-source and proprietary LLMs. We validate the generality and adaptability of our framework through experiments with several state-of-the-art models, including ChatGPT (Brown et al., 2020), LLaMA (Touvron et al., 2023), Qwen (Yang et al., 2024), and DeepSeek (Guo et al., 2025), demonstrating the generality and adaptability of our framework.

The contributions of this paper are summarized as follows:

- **RS-Agent: The Comprehensive Agent Framework For Remote Sensing Applications.** We present RS-Agent, a novel architecture designed to interpret user queries and orchestrate diverse tools for accurate and efficient remote sensing task execution. Its four core components—Central Controller, toolkit, Solution Space, and Knowledge Space—work in concert, seamlessly interacting and complementing one another to enable robust, adaptive performance across a wide range of applications.
- **Innovative Task Planning Solution Space with Task-Aware Retrieval method.** To enhance the agent’s task planning accuracy, we propose an innovative Task-Aware Retrieval method. By retrieving and understanding expert-level task solutions, RS-Agent is able to emulate the decision-making and tool selection processes of professional remote sensing analysts.
- **Knowledge Space with DualRAG to Retrieve Professional Domain Knowledge.** To strengthen RS-Agent’s domain-specific knowledge, we propose DualRAG, a retrieval augmented generation method that assigns weights to extracted keywords and performs dual path retrieval, thereby enhancing the accuracy and relevance of knowledge retrieval.
- **Superior Performance on Various Applications** Extensive experiments have demonstrated that RS-Agent consistently surpasses previous SOTA Multimodal Large Language Models across a range of remote sensing applications, and significantly boosts the task planning accuracy. These results establish RS-Agent as a major step forward in adapting AI agents to the remote sensing field, and, for the first time, present a comprehensive and modular architecture tailored for remote sensing applications.

2. Related Works

2.1 Remote Sensing Multimodal Large Language Models

The integration of Multimodal Large Language Models (MLLMs) into remote sensing has opened new opportunities for human-AI interaction in earth observation tasks. MLLMs

aim to bridge visual and semantic spaces, enabling the processing and interpretation of remote sensing imagery based on natural language inputs. Early applications of MLLMs in remote sensing primarily focused on a limited set of tasks, such as image captioning (Shi and Zou, 2017, Wang et al., 2020b) and visual question answering (VQA) (Lobry et al., 2020). As research progressed, MLLMs began to support a broader range of vision-language tasks (Wang et al., 2025), each addressing specific challenges in remote sensing interpretation. RSGPT (Hu et al., 2025) integrates both image captioning and VQA. GeoChat (Kuckreja et al., 2023) extended this capability to visual geo-localization via interactive dialogue. LHRB-Bot (Muhtar et al., 2024) is a general-purpose MLLM built upon large-scale datasets and a novel multi-level vision-language alignment strategy, achieving state-of-the-art performance in classification, visual question answering, and visual grounding tasks. EarthVQANet (Wang et al., 2024c) introduces a novel multi-task framework combining semantic segmentation and VQA to enhance spatial reasoning in remote sensing imagery. SkySenseGPT (Luo et al., 2024) leveraged knowledge graphs to enhance relational reasoning and complex target understanding. Beyond single-image interpretation tasks, a number of MLLM-based models have also been developed to address the interpretation of multi-scene remote sensing data. ChangeCLIP (Dong et al., 2024) filled a critical gap by tackling change captioning between multi-temporal images. SkyEyeGPT (Zhan et al., 2025) introduced video captioning for remote sensing. UniRS (Li et al., 2024) further advanced the field by integrating single-frame, bi-temporal, and video inputs into a unified model designed specifically for temporal remote sensing analysis.

Despite these advances, most existing MLLM models remain limited in their ability to generalize across tasks. They often focus on interpreting a particular image modality or handling a fixed group of vision-language problems, rather than offering a unified solution. Moreover, when new tasks are introduced, these models typically require costly retraining, limiting their scalability. To address these challenges, we introduce RS-Agent, a scalable agent framework which supports diverse tasks across multiple modalities through dynamic tool orchestration, task planning, and expert-level reasoning.

2.2 AI Agent

AI agents are autonomous systems designed to perceive their environment, process information, make decisions, and execute actions to achieve specific objectives (Wu et al., 2023). Equipped with the ability to learn from interactions, adapt to new data, and continuously improve performance, these agents are capable of functioning effectively across a wide range of application domains (Park et al., 2023, Durante et al., 2024).

While AI agents have been widely explored in general domains, their application in the field of remote sensing remains limited. Only a few agent-based systems have been proposed, typically addressing some specific defined tasks. TreeGPT (Du et al., 2023), for instance, is designed for forestry applications, enabling individual tree segmentation and ecological parameter estimation from remote sensing imagery. Change-Agent (Liu et al., 2024) focuses on bi-temporal image analysis, supporting both change detection and change captioning, and enables interactive change interpretation based on user instructions. (Zhu et al., 2024) proposes a LLM-guided multi-agent system for remote sensing image generation. RS-ChatGPT (Guo et al.,

2024a) represents a more general-purpose attempt. By combining ChatGPT with a suite of pre-trained remote sensing image processing models, it can handle seven tasks such as object detection, scene classification, and image captioning in response to user queries. However, those agent models are limited by a relatively narrow toolkit, which restricts its ability to fully address complex, domain-specific requirements. Additionally, they often face challenges in flexible task planning and occasionally fail in reasoning or tool selection.

To address these issue, RS-Agent enhances tool diversity by incorporating a rich set of remote sensing tools, enabling more effective support for complex and multi-tool tasks. Besides, RS-Agent employs a task-aware retrieval strategy to access pre-defined task solutions, significantly improving the accuracy and efficiency of tool utilization. Furthermore, RS-Agent integrates a knowledge graph-based RAG technique, effectively broadening its Knowledge Database in the remote sensing domain, thereby enhancing the model’s performance in handling diverse remote sensing tasks.

2.3 Retrieval-Augmented Generation

Large Language Models (LLM) excels in generating fluent text thanks to large-scale pre-training. However, their performance on domain-specific tasks—such as those in remote sensing—is limited by the lack of relevant or up-to-date training data. To mitigate this, Retrieval-Augmented Generation (RAG) has emerged as a promising approach, enabling language models to access external, domain-specific knowledge sources (Kennevog et al., 2024).

RAG frameworks typically employ dense or sparse retrieval mechanisms to fetch relevant documents from a large corpus (Gao et al., 2023a, Gao et al., 2023b, Chan et al., 2024), which are then fused with the input prompt of LLM to guide the generation process. While effective for general use, they often fall short on complex queries requiring multi-hop reasoning or capturing comprehensive global information (Tang and Yang, 2024). To improve this, knowledge graph-based RAG has been introduced (Edge et al., 2024, Guo et al., 2024b, Zhu et al., 2025), integrating structured entity-relation data into retrieval to support more accurate and semantically rich responses.

Among them, LightRAG (Guo et al., 2024b) proposed a light-weight framework that combines graph-based indexing with keyword-guided queries. It constructs a combined vector by concatenating generated keywords from query, capturing their semantic connections. While LightRAG introduces an efficient retrieval framework and leverages graph-based indexing, it suffers from two major drawbacks: (1) it treats all generated keywords equally, ignoring their varying importance in representing the query’s intent; and (2) it constructs a single concatenated query from all keywords, which may obscure the semantic distinctiveness of loosely related or heterogeneous concepts. This often results in reduced retrieval coverage and suboptimal relevance, particularly for complex, multi-aspect queries.

To address this, we propose DualRAG, which introduces a dual retrieval strategy. It combines both holistic query-based and decomposed keyword-based retrieval, enhanced by a dynamic weight allocation mechanism. This design improves both relevance and diversity in retrieval, especially for complex or heterogeneous queries.

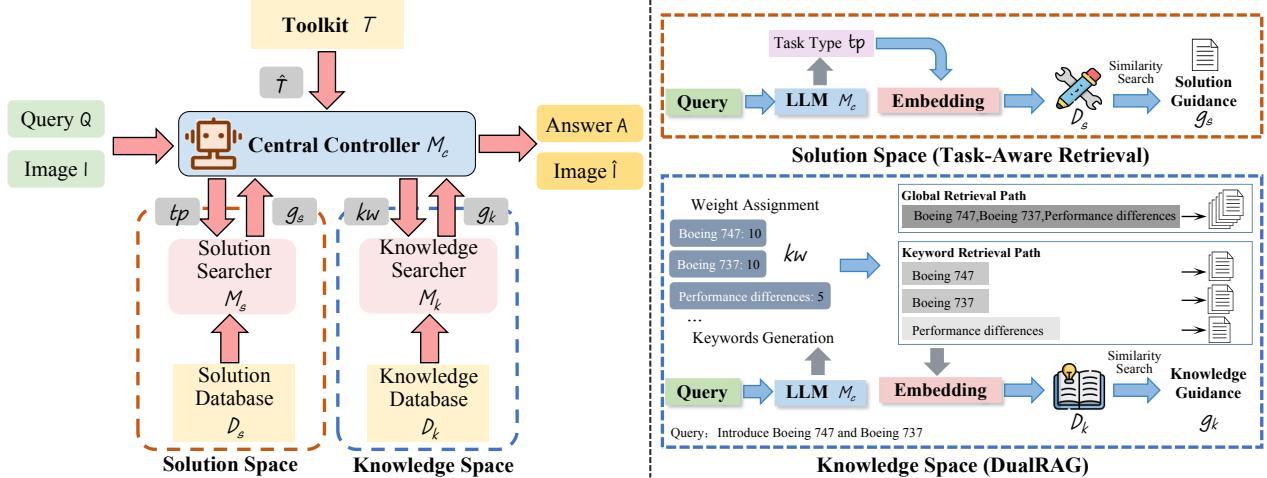


Figure 2. Framework of RS-Agent. The left side shows the overall architecture, including key components like the Central Controller, Solution Space, Knowledge Space, and Toolkit. The right side details the Solution Searcher M_s and Knowledge Searcher M_k . The M_s uses Task-Aware Retrieval method for solution guidance g_s generation. The M_k adopts a DualRAG strategy to retrieve relevant documents.

3. Remote Sensing Agent (RS-Agent)

In this section, we first illustrate the overall architecture and workflow of RS-Agent, followed by detailed introductions to its four core components and our proposed techniques.

3.1 Overall Architecture

The Remote Sensing Agent (RS-Agent) is designed to autonomously handle a broad range of remote sensing applications by first interpreting user queries, then planning tasks and executing appropriate image processing tools. To achieve this, RS-Agent is designed with four core components: the Central Controller, Solution Space, Knowledge Space, and Toolkit, as shown in Figure 2.

The end-to-end workflow proceeds as follows: the Central Controller first parses the user query Q and the associated remote sensing image I . It then consults the Solution Space and Knowledge Space to retrieve expert solutions and relevant knowledge. Based on this guidance, it formulates a task plan and dynamically invokes specific tools from the Toolkit to process the input image I . The final outputs—a response A and processed image \hat{I} —are then synthesized and returned to the user. The four core components of RS-Agent are illustrated as follows:

- **Central Controller:** Serves as the decision-making core of the agent. The Central Controller first interprets the user instruction Q and analyzes the input image I . It then consults both the Solution Space (for task-specific strategies) and the Knowledge Space (for domain-specific reasoning support) to construct an executable task plan. Based on this plan, it dynamically invokes the appropriate tools from the Toolkit. Once tool outputs (e.g., processed image data or intermediate analysis results) are received, the Controller synthesizes a final response A and processed image \hat{I} for the user.
- **Toolkit:** A collection of state-of-the-art remote sensing tools for various applications. These tools are invoked based on the Central Controller’s planning.
- **Solution Space:** This module serves as a repository of expert-defined task workflows and tool sequences. When

Algorithm 1 The workflow of RS-Agent.

Input: The user query Q and the input remote sensing image I ;
Output: Answer A generated by the RS-Agent; Processed remote sensing image \hat{I} (if required by the task, i.e., object detection results, etc);

- 1: Central controller M_c receives user query Q and determines the task type tp ;
- 2: Transmits tp to solution searcher M_s ;
- 3: M_s searches through the Solution Database D_s , and retrieves the most relevant documents d as Solution Guidance g_s ;
- 4: Based on query Q and Solution Guidance g_s , M_c selects the appropriate tools \hat{T} from Toolkit T ;
- 5: **if** \hat{T} contains knowledge_search **then**
- 6: The Central Controller M_c generates a set of keywords kw and sends them to the Knowledge Searcher M_k , which employs the DualRAG strategy to search the Knowledge Database D_k and retrieve relevant context as Knowledge Guidance g_k .
- 7: **else**
- 8: Invoke \hat{T} to process the image I , and get the corresponding outputs and \hat{I} ;
- 9: **end if**
- 10: M_c compiles the final answer A from the output of \hat{T} ;
- 11: **return** A and \hat{I} ;

the Controller identifies the nature of the query, it queries the Solution Space to retrieve similar cases or templates, which inform the tool selection and parameter settings. The Solution Space thereby provides procedural guidance and accelerates task planning.

- **Knowledge Space:** Complementing the Solution Space, the Knowledge Space stores structured remote sensing knowledge, such as definitions, operational principles, or region-specific metadata. During task planning, the Controller queries this space to resolve ambiguities, validate tool parameters, or retrieve explanatory information, particularly for reasoning-intensive tasks.

A detailed workflow of RS-Agent is shown in Algorithm 1. Given a user instruction Q (e.g., “How many airplanes are parked in this image? And what are their categories?”), the

RS-Agent workflow begins with the Central Controller M_c analyzing the input query to determine the corresponding task type tp . The task type tp is then forwarded to the Solution Searcher M_s to retrieve relevant solution documents g_s from the Solution Database D_s . These documents contain task-specific solutions that assist M_c in planning the task, for example, executing object detection first, followed by category recognition. Based on the solution documents g_s , M_c selects and executes an appropriate set of tools \hat{T} to process the input image. If the user instruction requires specialized domain knowledge (e.g., “Provide professional information about the Boeing 747”), M_c generates a set of query-relevant keywords kw , and uses the Knowledge Searcher M_k to retrieve Knowledge Guidance g_k from the Knowledge Database D_k with the DualRAG strategy. Finally, M_c integrates the results from tool execution and generates the final response A . We provide a more detailed workflow in the Appendix.

3.2 Central Controller

The Central Controller M_c serves as the brain of the RS-Agent to manage multi-step reasoning and tool execution through modular interfaces. We build M_c using a large language model and leverage the LangChain framework (Chase, 2022) to support task decomposition, context management, and dynamic tool invocation. To improve task planning accuracy, the Central Controller M_c adopts a structured, two-stage prompt-based reasoning process to guide precise task execution.

Stage 1. Task Inference and Solution Retrieval. Upon receiving the user input Q , M_c first infers the task type tp by analyzing the semantic intent of the query and all the supported tasks, with the following task classification prompt:

```
System: You are an expert in remote sensing. Your task is to
       classify the following user query into one of the
       predefined task categories: {supported tasks}.
User Input: {Q}
```

The task type tp serves as the basis for subsequent task planning. Once the task type tp is identified, it is forwarded to the Solution Searcher module M_s , which retrieves a candidate solution g_s —a task-specific guideline outlining expert-recommended strategies for solving the problem.

Stage 2. Task Planning and Tool Execution. Leveraging the retrieved g_s and the original Q , the Central Controller M_c constructs a detailed task plan by selecting the most appropriate tools and arranging them into a logical, step-by-step workflow tailored to the user’s intent. To facilitate the memory mechanism, M_c incorporates prior dialogue history to ensure accurate, context-aware reasoning. The structure of this planning prompt is as follows:

```
System: You are an intelligent remote sensing assistant. Given
       the following context, your task is to efficiently call
       tools and provide a precise answer based on the user's
       needs.
User Input: {Q}
Solution Guidance: {solution guidance}
Conversation History: {conversation_history}
```

In this way, the Central Controller M_c effectively translates high-level user intent into executable actions grounded in domain expertise and tool capabilities. Empowered by M_c , RS-Agent is able to engage in interactive dialogue, accurately interpret user queries, and determine the most appropriate course of action to fulfill the task.

3.3 Toolkit

The Toolkit T serves as the action engine of RS-Agent, comprising a collection of 18 tools tailored for specific remote sensing applications such as image caption (Wang et al., 2020a), scene classification (Xu et al., 2023), super resolution (Lin et al., 2020), etc. Details of the available tools are provided in Table 8 and illustrated in Figure 3. All tools are invoked through API-based interfaces, allowing for efficient and modular integration. This modular design ensures that the Toolkit can be continuously extended with additional tools, allowing RS-Agent to keep pace with emerging tasks, methods, and challenges in the remote sensing domain.

3.4 Solution Space

In the RS-Agent architecture, the Solution Space plays a critical role in supporting accurate task planning by compensating for the lack of domain-specific solution strategies in large language models (LLMs). While LLMs have shown impressive capabilities in natural language understanding and reasoning, they often struggle with remote sensing tasks that require specialized knowledge and precise procedural guidance. This limitation is especially evident when task instructions are ambiguous, underspecified, or implicitly formulated (Qin et al., 2023; Shapira et al., 2023)—scenarios common in real-world remote sensing applications.

To address this limitation, we introduce the Solution Space, which supports accurate task planning and enhances the robustness of decision-making. It comprises two key components: the Solution Database D_s , which stores expert-curated solutions for various remote sensing tasks, and the Solution Searcher M_s , which assists the Central Controller in retrieving the most appropriate solution based on user queries.

3.4.1 Solution Database To provide RS-Agent with a reliable source of task-solving knowledge, we construct a curated Solution Database $D_s = \{d_s^1, d_s^2, \dots\}$, which stores expert-defined solutions for commonly encountered remote sensing tasks. This database acts as a structured knowledge base that guides task planning and tool invocation within the RS-Agent framework.

Each solution document in D_s is manually designed and structured, containing high-level task descriptions, recommended tools, required input formats, and expected outputs. For instance, the solution for the task Super Resolution specifies: “To solve this kind of task, you should directly use tool super_resolution_2x to get the answer. The input to this tool should be the image path.” Likewise, the solution for Knowledge Search reads: “To solve this kind of task, you should directly use tool knowledge_search to get the answer. The input to this tool should be the keywords of the query.”

To support efficient retrieval, these solution documents are encoded into dense vector representations using a sentence-level embedding model, allowing the system to semantically match user queries with the most relevant solution.

3.4.2 Solution Searcher with Task-Aware Retrieval To enable RS-Agent to accurately locate the most relevant solution for a given task, we design the Solution Searcher, a module dedicated to retrieving appropriate entries from the Solution Database. To enhance its effectiveness, we propose a Task-Aware

Retrieval method, which augments the capabilities of large language models by integrating Retrieval-Augmented Generation (RAG) into the solution selection process.

As illustrated in the top right corner of Figure 2, the Task-Aware Retrieval method consists of two key steps: Task Inference, which identifies the underlying task type based on the user query, and Solution Retrieval, which uses this task type to retrieve the most relevant solution document from the database.

Task Inference: When a user query Q is received, the Central Controller M_c first interprets the user’s intent and infers the underlying tp using a system prompt designed to guide task recognition. This step can be viewed as a query rewriting process, where the LLM reformulates or abstracts the input into a semantically meaningful task label, enabling more structured downstream retrieval.

Solution Retrieval: The inferred tp is then passed to the M_s , which retrieves relevant strategies from D_s to support tool selection and reasoning. To achieve the retrieval, each solution document in D_s and the task type tp are encoded into a dense vector representation with a sentence embedding model (Chen et al., 2024). Then Solution Searcher M_s employs the FAISS algorithm (Jégou et al., 2022), a high-performance vector similarity search algorithm f_s , to find the most relevant documents, and form the Solution Guidance $g_s = d$:

$$d = f_s(tp, D_s, 1). \quad (1)$$

Here, the parameter 1 indicates that only the top-1 most relevant document is retrieved. This structured approach serves as critical support for the LLM in selecting the most appropriate tools from the available Toolkit, and generating the workflow. By combining retrieval and generation, the Task-Aware Retrieval method equips RS-Agent to read and understand human-defined tool solutions and handle complex remote sensing tasks.

3.5 Knowledge Space

The Knowledge Space is designed to strengthen RS-Agent’s ability to handle user queries (Q) that require specialized domain knowledge. It consists of two components: a structured Knowledge Database D_k , which stores curated remote sensing knowledge in an organized and queryable format; and a Knowledge Searcher M_k , which retrieves relevant knowledge documents from D_k based on the semantic content of the query.

3.5.1 Knowledge Database The Knowledge Database D_k serves as a structured repository of domain knowledge that supports RS-Agent in tasks requiring factual accuracy, technical terminology, or background-specific reasoning. It provides a foundation for semantic retrieval and reasoning, allowing the agent to access reliable information when responding to complex or knowledge-intensive queries. In this paper, to theoretically validate RS-Agent’s capability in retrieving and generating domain-specific knowledge, we construct a small-scale knowledge database D_k named RSpace for case-study. This curated dataset includes information on 65 types of aircraft, such as fighter jets, commercial airliners, drones, and helicopters. We adopt a knowledge graph-based storage structure (Guo et al., 2024b), in which each text chunk is processed by an LLM to extract entities and relational triples. These entities and relations are embedded into separate vector spaces, enabling structure-aware semantic retrieval. This representation supports multi-hop reasoning and domain-informed query expansion, facilitating more accurate and context-rich responses.

3.5.2 Knowledge Searcher with DualRAG The Knowledge Searcher is responsible for retrieving the most relevant knowledge documents from the Knowledge Database D_k to support RS-Agent in answering domain-specific queries. To accurately locate the required information, we propose an enhanced retrieval approach named DualRAG.

As illustrated in the bottom right of Figure 2, DualRAG consists of two components: Keyword Generation and Weight Assignment, and Dual-Path Retrieval. The first component extracts important keywords from the user query and assigns weights to reflect their relevance. The second combines global semantic search with weighted keyword-level retrieval. Together, they ensure that the retrieved knowledge is both comprehensive and focused, enabling the agent to respond with accurate, knowledge-grounded answers.

Keyword Generation and Weight Assignment: Given a query Q , the Knowledge Searcher M_k jointly generates a set of keywords and assigns a relevance weight to each one:

$$\{(kw_i, w_i)\}_{i=1}^m = M_k(Q), \quad \text{where } w_i \in [1, 10]. \quad (2)$$

The format of the keyword generation prompt is shown below:

System: You are a helpful assistant tasked with identifying keywords from the user’s query. For each keyword, assign an importance score (1-10) based on its relevance.

User Input: {Q}

Each tuple (kw_i, w_i) represents a keyword kw_i and its corresponding importance weight w_i , higher weights reflecting higher semantic contribution. The weight assignment is based on the LLM’s understanding of the context and helps guide the knowledge retrieval process in the next stage. And m denotes the total number of extracted keyword-weight pairs.

Dual-Path Retrieval: To enhance the relevance and coverage of the retrieved knowledge documents, our DualRAG adopts a dual-path retrieval strategy that combines global and keyword-level search.

In the global retrieval path, the generated kw_i are concatenated to form a single string:

$$kw_{\text{global}} = \text{Concat}(kw_1, kw_2, \dots). \quad (3)$$

This string is used to retrieve the top- N documents from the Knowledge Database D_k via similarity search algorithm f_k :

$$d_{\text{global}} = f_k(kw_{\text{global}}, D_k, N). \quad (4)$$

This path captures the overall semantic structure and inter-keyword dependencies.

In the keyword retrieval path, each kw_i is treated as an individual query. The number of the retrieved knowledge documents n_i is allocated based on the assigned weight w_i :

$$n_i = \frac{w_i}{\sum_m w_m} \times N, \quad (5)$$

where we retrieve more knowledge documents for the keywords with higher importance weight. Then, each kw_i retrieves its own top- n_i documents:

$$d_{\text{keyword}} = \bigcup_{i=1}^m f_k(kw_i, D_k, n_i), \quad (6)$$

where m is the number of keywords. This approach helps retrieve more detailed information and ensures that all meaningful aspects of the query are taken into account.

The retrieved documents form the Knowledge Guidance $g_k = d_{\text{global}} \cup d_{\text{ind}}$, which provides the LLM with domain-specific knowledge. By combining both retrieval paths, DualRAG achieves a better balance between semantic coherence and informational diversity, addressing the limitations of single-query strategies like that in LightRAG (Guo et al., 2024b).

4. Experiments

In this section, we first present the implementation details of RS-Agent. We then evaluate its task planning accuracy, and demonstrate the generalizability of the RS-Agent architecture through experiments conducted on a variety of both open-source and proprietary LLMs. Furthermore, we experimentally demonstrate that by coordinating multiple tools, RS-Agent consistently outperforms single-model baselines across a range of challenging applications, including scene classification, remote sensing visual question answering, and object counting. We also validate the effectiveness of the proposed Task-Aware Retrieval and DualRAG methods with ablation studies. Finally, we provide qualitative results to further illustrate the performance of RS-Agent.

4.1 Implementation Details

To ensure the flexibility and generalizability of RS-Agent, we build the Central Controller with LangChain framework (Chase, 2022) and general-purpose large language models. Unless otherwise specified, RS-Agent uses the Qwen 2.5 32B-Instruct model (Yang et al., 2024), balancing the model capability with inference speed.

Within the Task-Aware Retrieval method, we employ the open-source m3e-base (Chen et al., 2024) model as the embedding model to convert textual data into vectors. These embeddings are then indexed using the FAISS (Jégou et al., 2022) algorithm, enabling efficient retrieval of relevant information. For DualRAG method, we return the top- N most relevant knowledge documents, with $N=30$.

RS-Agent currently includes a toolkit of 18 specialized tools designed to support diverse remote sensing tasks. These span from low-level vision operations such as denoising and super-resolution, to high-level semantic tasks like scene classification, object detection, and building damage assessment.

4.2 Task Planning Accuracy

A core capability of RS-Agent is its ability to accurately plan tasks and invoke the appropriate tools in response to user queries. In this section, we evaluate the task planning accuracy of RS-Agent.

4.2.1 Task Planning Accuracy Compared to SOTA Agent Dataset.

We construct a dedicated dataset to evaluate RS-Agent’s task planning capabilities, measuring accuracy by whether the first tool invoked matches the correct one for the query. To ensure a fair comparison with RS-ChatGPT (Guo et al., 2024a), we adopt seven core tasks from RS-ChatGPT: scene classification, land use segmentation, object detection, image captioning, edge detection, object counting, and instance segmentation. For each task, we create average 20 query-solution

pairs, including both clear and intentionally ambiguous instructions to assess the model’s ability to interpret user intent, resolve ambiguity, and select the appropriate tool.

Results: As shown in Table 1, RS-Agent consistently outperforms RS-ChatGPT in task planning accuracy across various LLMs used as the Central Controller. For example, when using the gpt-3.5-turbo-1106 model, RS-Agent boosts the average accuracy from 72.66% to 84.89%, achieving a substantial gain of 12.23%. Similar improvements are observed with gpt-3.5-turbo (+5.76%) and gpt-4o-mini (+7.19%). These results demonstrate that RS-Agent exhibits superior task comprehension and decision-making ability, allowing it to reliably select appropriate tools and execute tasks more effectively.

4.2.2 Task Planning Accuracy with Different LLMs To evaluate RS-Agent’s adaptability, we evaluate its task planning accuracy when paired with different closed-source (GPT series) and open-source LLMs. This analysis helps reveal whether RS-Agent can maintain or improve performance as the underlying model changes.

Datasets. To comprehensively evaluate RS-Agent’s task planning accuracy across different LLM configurations, we construct a new dataset tailored to the full toolkit currently supported by our system. Specifically, we define a set of 18 distinct tasks and design 20 query-solution pairs for each, resulting in a total of 360 evaluation instances. These queries span a diverse range of task types and complexity levels, and include both well-specified and ambiguous instructions to assess the model’s robustness in understanding intent and selecting the appropriate tool. Unlike the previous dataset, which was based on the RS-ChatGPT toolkit for comparative evaluation, this dataset fully leverages RS-Agent’s expanded capabilities and provides a more comprehensive assessment of its performance under different LLM configurations.

Results. As shown in Table 2, RS-Agent demonstrates robust tool selection accuracy across both proprietary and open-source LLMs. Notably, open-source models such as Qwen2.5-72B (98.61%) and 32B (97.78%) perform on par with or even better than ChatGPT series. This result highlights that well-tuned open-source models can match the reasoning capabilities of state-of-the-art commercial models in task planning scenarios.

Moreover, within the same model family, increasing parameter size generally correlates with improved accuracy. For instance, Qwen2.5 shows a consistent accuracy rise from 14B (96.94%) to 72B (98.61%), and LLaMa 3.1 from 8B (75.28%) to 70B (94.72%). However, this performance gain often comes at the cost of inference speed. For example, while Qwen2.5-72B achieves high accuracy, its processing speed is only 16.24 tokens/s, compared to 69.61 tokens/s for Qwen2.5-14B. Taking both accuracy and speed into account, Qwen2.5-14B and 32B emerge as balanced choices for practical deployment. Interestingly, LLaMa 3.1-8B yields suboptimal performance (75.28%), suggesting that smaller variants in some model families may not generalize well for tool planning.

In summary, from the above results We can observe that the model performance varies significantly across different tasks, especially those with unclear tool boundaries. This highlights the need for clearer task definitions and more robust planning strategies in future work.

Table 1 Comparison of Task Planning Accuracy with SOTA RS-ChatGPT

Task	gpt-3.5-turbo-1106		gpt-3.5-turbo		gpt-4o-mini	
	RS-ChatGPT	RS-Agent (Ours)	RS-ChatGPT	RS-Agent (Ours)	RS-ChatGPT	RS-Agent (Ours)
Object Counting	47.37%	94.74%	97.74%	100%	100%	100%
Object Detection	78.95%	84.21%	52.63%	89.47%	42.11%	94.74%
Land Use Segmentation	90.48%	95.24%	95.24%	95.24%	90.48%	90.48%
Image Captioning	42.86%	57.14%	85.71%	61.90%	100%	95.24%
Scene Classification	90.48%	85.71%	80.95%	100%	100%	90.48%
Instance Segmentation	57.89%	78.95%	78.95%	68.42%	89.47%	100%
Edge Detection	100%	100%	84.21%	100%	94.74%	100%
Average Accuracy	72.66%	84.89%	82.01%	87.77%	88.49%	95.68%

Table 2 Task Planning Accuracy of our RS-Agent when equipped with Different LLMs

Task	ChatGPT			LLaMa 3.1		Qwen2.5		DeepSeek	
	3.5-turbo-1106 (87.71t/s)	3.5-turbo (65.03t/s)	4o-mini (58.87t/s)	8B (100.78t/s)	70B (17.71t/s)	14B (69.61t/s)	32B (36.77t/s)	72B (16.24t/s)	r1:70B (18.25t/s)
Cloud Removal	95.00%	95.00%	100%	100%	100%	100%	95.00%	100%	100%
Image Dehazing	30.00%	95.00%	100%	100%	100%	100%	100%	100%	75.00%
Super Resolution	100%	100%	100%	0%	100%	100%	100%	100%	95.00%
Denoising	90.00%	100%	100%	100%	100%	100%	100%	100%	90.00%
Image Captioning	55.00%	45.00%	90.00%	15.00%	60.00%	70.00%	80.00%	80.00%	10.00%
Object Detection	75.00%	60.00%	95.00%	30.00%	90.00%	90.00%	85.00%	100%	85.00%
Optical Plane Classification	100%	100%	100%	100%	100%	100%	100%	100%	95.00%
Scene Classification	20.00%	90.00%	100%	80.00%	90.00%	90%	100%	100%	50.00%
SAR Detection	30.00%	100%	100%	75.00%	95.00%	100%	100%	100%	100%
SAR Plane Classification	100%	100%	100%	100%	100%	100%	100%	100%	90.00%
Knowledge Search	100%	100%	100%	100%	80.00%	100%	100%	100%	10.00%
Building Damage Detection	100%	100%	100%	100%	100%	95.00%	100%	100%	100%
Building Extraction	10.00%	70.00%	100%	55.00%	100%	100%	100%	100%	100%
Road Extraction	15.00%	55.00%	100%	65.00%	100%	100%	100%	100%	100%
Horizontal Detection	20.00%	55.00%	100%	95.00%	100%	100%	100%	100%	100%
Rotated Detection	15.00%	35.00%	100%	85.00%	90.00%	100%	100%	100%	100%
Semantic Segmentation	60.00%	100%	100%	80.00%	100%	100%	100%	100%	80.00%
Land Use Classification	15.00%	100%	100%	75.00%	100%	100%	100%	95.00%	95.00%
Average Accuracy	57.22%	82.50%	99.17%	75.28%	94.72%	96.94%	97.78%	98.61%	81.94%

¹ “B” denotes the number of parameters in billions.

² Numbers in parentheses (t/s) indicate model inference speed in tokens per second on NVIDIA RTX4090 GPUs.

Table 3 Object counting accuracy on DOTA dataset. Our RS-Agent is compared with two other MLLM-based models.

Method	Absolute Accuracy	Interval Match	Relative Error
GeoChat	17.65%	74.61%	0.65
LHRS-Bot	14.92%	60.78%	0.56
RS-Agent (Ours)	33.30 %	75.98%	0.28

4.3 Performance on Remote Sensing Tasks

Both agents and multimodal large language models (MLLMs) aim to perform multiple tasks through natural language interaction. To demonstrate the advantages of RS-Agent, we evaluate its performance on three representative remote sensing applications: object counting, visual question answering (VQA), and scene classification.

4.3.1 Object Counting Object counting is the task of estimating the number of target objects within a given image. It is particularly useful in remote sensing for applications such as counting vehicles for traffic analysis, or assessing infrastructure density in urban planning, where accurate quantification of objects is critical for resource management.

Datasets. We use the validation set from DOTAv1 (Xia et al., 2018) to assess the object counting ability. The set contains 458 images and 1,099 questions. For the object counting task, we used the prompt: “What is the number of the object? Answer the question using a number.” The object could be any one of

15 typical remote sensing target types, such as plane, ship and bridge.

Metric. We evaluate object-counting performance using three metrics: absolute accuracy, interval-matching accuracy, and relative error. Absolute accuracy measures the percentage of predictions that exactly match the ground truth. Interval-matching accuracy considers a prediction correct if it falls within the same predefined range as the ground truth. The intervals are: 0, 1–10, 11–100, 101–1000, and > 1000. Relative error e_r quantifies the deviation of the prediction from the ground truth and is computed as follows:

$$e_r = \frac{1}{N} \sum_{i=1}^N \log \left(1 + \frac{|gt_i - p_i|}{gt_i} \right), \quad (7)$$

where gt_i represents the ground truth of the i -th test case, p_i denotes the model prediction of this case, and N is the total number of counting problems, which is 1,099.

Results. As presented in Table 3, RS-Agent outperforms both GeoChat (Kuckreja et al., 2023) and LHRS-Bot (Muhtar et al., 2024) across all evaluation metrics. It achieves an absolute accuracy of 33.30%, significantly surpassing GeoChat (17.65%) and LHRS-Bot (14.92%). Its interval-matching accuracy reaches 75.98%, slightly higher than GeoChat (74.61%) and notably better than LHRS-Bot (60.78%). In terms of relative error, RS-Agent achieves a score of 0.28—substantially lower than GeoChat (0.65) and LHRS-Bot (0.56)—indicating more precise and consistent predictions. These results demonstrate the robustness and reliability of RS-Agent in ob-

ject counting tasks.

4.3.2 Visual Question Answering Visual Question Answering (VQA) is a task designed to assess a model’s ability to understand visual content and answer corresponding natural language questions. It primarily evaluates the model’s capabilities in visual perception, language comprehension, and cross-modal reasoning.

Datasets. We evaluate VQA performance using the widely adopted RSVQA-LR dataset (Lobry et al., 2020), which comprises image–question–answer triplets tailored for remote sensing visual question answering. The dataset includes 772 satellite images and 77,232 question–answer pairs, covering four question types: presence, comparison, rural/urban classification, and counting.

Compared Methods. We compare RS-Agent with two groups of multimodal large language models: (1) general-purpose models trained on broad, non-specialized corpora, e.g., LLaVA-1.5 (Liu et al., 2023), MiniGPTv2 (Chen et al., 2023), InstructBLIP (Dai et al., 2024), mPLUG-Owl2 (Ye et al., 2023) and QWen-VL-Chat (Bai et al., 2023) and (2) remote sensing-specific models fine-tuned on domain-specific remote sensing datasets, e.g., RSVQA (Lobry et al., 2020), SkyEyeGPT (Zhan et al., 2025), LHRS-Bot (Muhtar et al., 2024) and GeoChat (Kuckreja et al., 2023).

In our experiment, we adopt a multi-tool invocation approach. RS-Agent leverages a set of tools, including super-resolution, denoising, and GeoChat to handle different types of questions in the RSVQA dataset. The system retrieves appropriate strategies from D_s using the Task-Aware Retrieval mechanism to generate accurate responses.

Results. We compared the performance of different methods in the RSVQA-LR dataset in rural/urban classification, presence detection, and comparison tasks. As shown in Table 4, using multi-tool invocation, RS-Agent achieves a higher accuracy in the RSVQA-LR dataset compared to MLLMs such as GeoChat and LHRS-Bot.

In a zero-shot setting, RS-Agent achieves state-of-the-art results with 97.00% on Rural/Urban, 91.07% on Presence, and 90.58% on Comparison tasks, yielding an average accuracy of 90.88%—the highest among all models tested. Moreover, RS-Agent’s capability to dynamically select and invoke appropriate tools based on question type suggests promising potential for broader applications in remote sensing VQA beyond the RS-VQA dataset.

4.3.3 Scene Classification Scene Classification in remote sensing aims to categorize satellite or aerial images into pre-defined scene types. It evaluates a model’s ability to capture spatial patterns, textures, and contextual cues from large-scale images.

Datasets. For evaluation, we utilized the RSSDIVCS (Li et al., 2021b) dataset, AID (Xia et al., 2017) dataset, and UCMerced (Yang and Newsam, 2010) dataset. The AID comprises a substantial collection of aerial images sourced from Google Earth, spanning 30 classes. The UCMerced consists of 2100 images across 21 land use scene categories.

To perform this task, RS-Agent is prompted with: “Identify the scene depicted in this image.” For GeoChat (Kuckreja et al.,

2023) and LHRS-Bot (Muhtar et al., 2024), the prompt used is: “Classify the image within one of the given classes: dense residential area, ..., school. Answer with one word or short phrase.”

For scene classification, RS-Agent employs a Vision Transformer (ViT-B16)(Dosovitskiy et al., 2020) pretrained with self-supervision on the unlabelled ImageNet dataset(Deng et al., 2009) as the backbone. The model is then fine-tuned on remote sensing imagery to function as the scene classifier. Training is conducted on the RSSDIVCS dataset (Li et al., 2021b), which comprises 70 scene categories, each containing 800 images at a resolution of 256×256 pixels. We use 80% of the images from each category for training.

Results. As shown in Table 5, RS-Agent consistently outperforms baseline models across all datasets. On the RSSDIVCS (Li et al., 2021b) dataset, it achieves 98.00% accuracy, significantly higher than GeoChat (51.43%) and LHRS-Bot (63.85%). On AID (Xia et al., 2017), RS-Agent reaches 96.88%, surpassing GeoChat (72.03%) and LHRS-Bot (91.29%). Similarly, on the UCMerced (Yang and Newsam, 2010) dataset, RS-Agent attains 98.63%, outperforming GeoChat (84.43%) and LHRS-Bot (96.63%).

These results clearly indicate that RS-Agent outperforms the other compared models across all three datasets, showcasing its superior performance in scene classification tasks.

4.4 Effectiveness of the Task-Aware Retrieval method

As mentioned in Section 3.4, the Task-Aware Retrieval method obtains g_s through Task Inference and Solution Retrieval. To evaluate the effectiveness of Task-Aware Retrieval method in enhancing task planning accuracy, we perform an ablation study. For ablation study, we use the following models, which progressively incorporate the task inference and the solution retrieval:

- **Baseline:** The RS-Agent without the Solution Space.
- **Baseline+ T_{inf} :** The RS-Agent with Solution Space, where we only perform the Task Inference.
- **Baseline+ S_{retr} :** The RS-Agent with Solution Space, where we only retrieves task-specific guidance by directly using Q as the retrieval input, allowing LLM to leverage external knowledge when interpreting the task.
- **Baseline+ T_{inf} + S_{retr} :** Our full RS-Agent network.

Evaluation tasks. To fully evaluate the task planning accuracy of the models, we perform experiments on two kinds of remote sensing applications. The first category is single-tool tasks, which focus on simpler tasks requiring only one tool. The second category is multi-tool tasks, designed to test the RS-Agent’s ability to handle more complex remote sensing needs by coupling multiple tools together.

Results. As shown in Table 6, the baseline performs well in tasks like Land Use Segmentation (95.24%) but has low performance in Object Counting (10.53%) and Object Detection (15.79%), with single-tool accuracy at 69.06% and multi-tool accuracy at 84.24%.

Only adding Task Inference boosts performance, especially in Object Counting (52.63%) and Object Detection (36.84%),

Table 4. Visual Question Answering Accuracy on RSVQA-LR datasets. Top: general-purpose MLLMs; bottom: models tailored for remote sensing.

Method	Rural/Urban	Presence	Compare	Avg.
LLaVA-1.5 (Liu et al., 2023)	59.22%	73.16%	65.19%	65.86%
MiniGPTv2 (Chen et al., 2023)	60.02%	51.64%	67.64%	59.77%
InstructBLIP (Dai et al., 2024)	62.62%	48.83%	63.92%	59.12%
mPLUG-Owl2 (Ye et al., 2023)	57.99%	74.04%	65.04%	65.69%
QWen-VL-Chat (Bai et al., 2023)	62.00%	47.65%	54.64%	58.73%
RSVQA (Lobry et al., 2020)	90.00%	87.47%	81.50%	86.32%
SkyEyeGPT (Zhan et al., 2025)	88.93%	88.63%	75.00%	84.16%
LHRS-Bot (Muhtar et al., 2024)	89.07%	88.51%	90.00%	89.19%
GeoChat (Kuckreja et al., 2023)	94.00%	91.09%	90.33%	90.70%
RS-Agent (Ours)	97.00 %	91.07 %	90.58 %	90.88 %

Table 5 Scene classification accuracy on RSSDIVCS, AID, UCMerced, compared with two MLLM models.

Model	RSSDIVCS	AID	UCMerced
MiniGPTv2 (Chen et al., 2023)	-	52.60%	62.90%
Qwen-VL-Chat (Bai et al., 2023)	-	52.60%	62.90%
LLaVA-1.5 (Liu et al., 2023)	-	51.00%	68.00%
GeoChat (Kuckreja et al., 2023)	51.43%	72.03%	84.43%
LHRS-Bot (Muhtar et al., 2024)	63.85%	91.29%	96.63%
RS Agent (Ours)	98.00 %	96.88 %	98.63 %

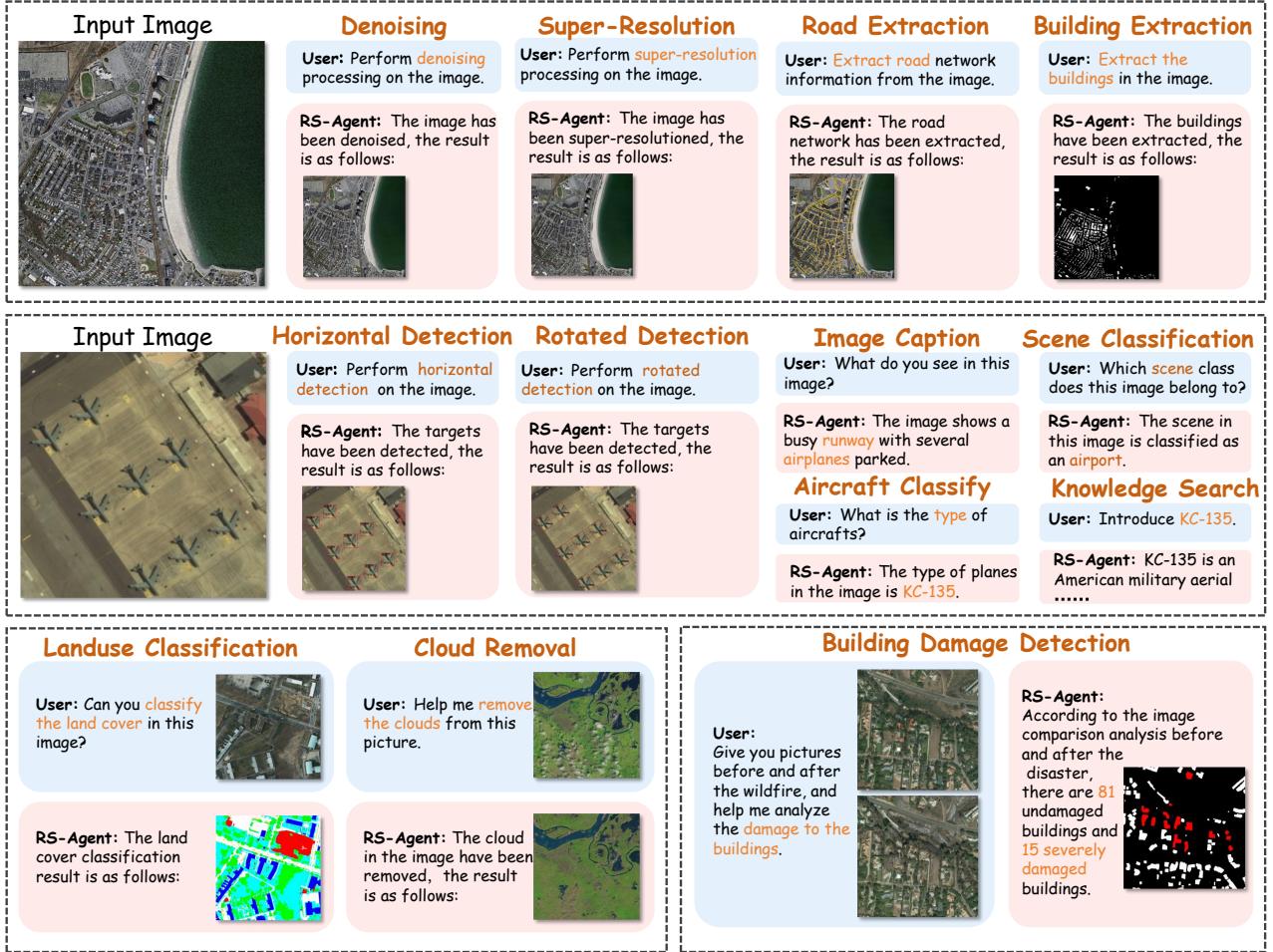


Figure 3. Qualitative result of RS-Agent. This figure shows several key tools that highlight the core capabilities of RS-Agent. The input image represents the image input by the user. The blue box shows the user’s request, and the red box shows the RS-Agent’s reply.

raising single-tool accuracy to 82.01%, raising multi-tool ac-

curacy to 84.34%. Only adding Solution Retrieval further im-

Table 6 Ablation Study of Task-Aware Retrieval method on Single-Tool Tasks and Multi-Tool Tasks

Method	Object Counting	Object Detection	Land Use Segmentation	Image Captioning	Scene Classification	Instance Segmentation	Edge Detection	Single-Tool Accuracy	Multi-Tool Accuracy
Baseline	10.53%	15.79%	95.24%	85.71%	76.19%	100%	94.74%	69.06%	84.24%
Baseline+ T_{inf}	52.63%	36.84%	95.24%	95.24%	95.24%	100%	100%	82.01%	84.34%
Baseline+ S_{ret}	52.63%	31.58%	100%	80.95%	52.38%	94.74%	94.74%	73.38%	84.57%
Baseline+ $T_{inf}+S_{ret}$	100%	84.21%	90.48%	95.24%	100%	84.21%	100%	93.53%	90.88%

Table 7 Win rates of LightRAG v.s. RS-Agent with DualRAG across two datasets and four evaluation dimensions.

Mode	Dimensions	RSaircraft		Mix	
		LightRAG	RS-Agent(Ours)	LightRAG	RS-Agent(Ours)
Local	Comprehensiveness	41.00%	58.00%	48.40%	51.60%
	Diversity	43.40%	56.40%	50.00%	50.00%
	Empowerment	43.40%	56.40%	50.80%	49.20%
	Overall	42.80%	57.20%	50.80%	49.20%
Global	Comprehensiveness	40.40%	59.60%	48.80%	51.20%
	Diversity	43.60%	56.40%	46.80%	53.20%
	Empowerment	39.20%	60.80%	51.60%	48.40%
	Overall	39.60%	60.40%	49.20%	50.80%
Hybrid	Comprehensiveness	36.80%	63.20%	46.40%	53.60%
	Diversity	37.00%	62.00%	44.80%	55.20%
	Empowerment	35.60%	64.40%	47.60%	52.40%
	Overall	36.00%	64.00%	47.20%	52.80%

proves performance, particularly in tasks like Land Use Segmentation (100%) and Instance Segmentation (94.74%), with single-tool accuracy at 73.38%, with multi-tool accuracy at 84.57%.

Combining both components achieves the best results, including 100% accuracy in Object Counting and Scene Classification, with single-tool accuracy at 93.53% and multi-tool accuracy at 90.88%. This demonstrates that the two components work synergistically to enhance task planning accuracy.

Overall, these results demonstrate that while RS-Agent performs well even without Task-Aware Retrieval method, incorporating Task-Aware Retrieval method substantially enhances its capability, particularly in complex, multitool scenarios, by improving both task interpretation and execution.

4.5 Effectiveness of the DualRAG method

In this Section, to verify the effectiveness of DualRAG method, we perform an in-depth comparison between RS-Agent with DualRAG and LightRAG (Guo et al., 2024b).

Datasets. In this study, we utilize two datasets: the RSaircraft dataset, which we have specifically constructed for remote sensing applications, and the Mix dataset from the UltraDomain benchmark (Qian et al., 2024), a general-domain RAG dataset. The RSaircraft dataset focuses on aircraft-related information, tailored for remote sensing tasks, and was built by systematically collecting and processing structured data from publicly available sources. The Mix dataset, on the other hand, consists of a diverse collection of literary, biographical, and philosophical texts, representing a broad range of disciplines such as cultural studies, historical analysis, and philosophical discourse. The inclusion of both datasets allows us to evaluate the performance of DualRAG in both domain-specific (remote sensing) and general-domain contexts.

Metric. Following the approach outlined in LightRAG (Guo et al., 2024b), we employ GPT-4o-mini as an automated evaluator to assess model responses across four dimensions: Comprehensiveness, Diversity, Empowerment, and Overall quality.

The evaluation is carried out in a pairwise comparison setting, where the judge selects the superior response between two candidates. The usage of keywords follows three modes: Local, Global, and Hybrid, as defined in LightRAG.

Results. Table 7 presents the win rates of LightRAG (Guo et al., 2024b) compared to our RS-Agent with DualRAG across two datasets (RSaircraft and Mix) and four evaluation dimensions. RS-Agent consistently outperforms LightRAG across nearly all settings, with particularly substantial improvements observed on the RSaircraft dataset.

In the RSaircraft dataset, RS-Agent with DualRAG shows significant advantages across all four dimensions. For example, in the Local mode, RS-Agent achieves a 17.00% higher win rate in Comprehensiveness (58.00% vs. 41.00%). The performance gap remains consistent in other dimensions, with RS-Agent outscoring LightRAG by 13.00% in Diversity and Empowerment (56.40% vs. 43.40%). These results are mirrored across different modes, indicating that RS-Agent’s response quality remains strong under both limited and broad contextual retrieval settings. The most pronounced improvement is seen in the Hybrid mode, where RS-Agent exceeds LightRAG by 26.40% in Comprehensiveness (63.20% vs. 36.80%), 25.00% in Empowerment (64.40% vs. 35.60%), and 28.00% in Overall win rate (64.00% vs. 36.00%).

In the Mix dataset, while the improvements are smaller, RS-Agent with DualRAG still demonstrates a clear edge. In Comprehensiveness, RS-Agent achieves 51.60% compared to 48.40% for LightRAG. Similarly, RS-Agent shows slight but consistent improvements in Diversity (55.20% vs. 44.80%) and Empowerment (52.40% vs. 47.60%). While the margins are not as wide as on RSaircraft, RS-Agent still outperforms LightRAG in all dimensions across different modes, reinforcing its ability to generate more comprehensive, diverse, and empowering responses in a general domain.

Overall, these quantitative gains validate the effectiveness of DualRAG’s design. By leveraging a more flexible and informative retrieval process, DualRAG is able to consistently pro-

Table 8 Functions and example inputs for the updated Toolkit.

Tool	Function	Example Input
cloud_removal (Pan, 2020)	Cloud removal from satellite images	Remove the clouds in this image.
image_dehazing (Luo et al., 2023)	Haze removal from images	Dehaze this foggy image.
super_resolution (Wang et al., 2021)	Image super-resolution (2x)	Enhance the resolution of this image.
denoising (Vaksman et al., 2020)	Image denoising	Remove noise from this image.
caption (Kuckreja et al., 2023)	Geo-specific VQA and captioning	What is in this remote sensing image?
optical_detection (Ultralytics, 2023)	Optical image target detection	Detect objects in this optical image.
optical_plane_type	Aircraft type recognition in optical images	What type of aircraft is in this image?
scene	Scene classification	What is the scene category of this image?
sar_detection (Zhou et al., 2024)	Target detection in SAR images	Find the objects in this SAR image.
sar_plane_type	Aircraft type recognition in SAR images	Identify the aircraft in this SAR image.
knowledge_search	Aircraft info retrieval via Knowledge Database	Who manufactures Boeing 747?
building_damage_detection (Zheng et al., 2021)	Building damage assessment	Which buildings are damaged?
building_extraction (He et al., 2023)	Building extraction from images	Extract all buildings from the image.
road_extraction (Hetang et al., 2024)	Road extraction from images	Extract roads from the scene.
horizontal_object_detection (Wang et al., 2024b)	Horizontal bounding box detection	Detect objects using horizontal boxes.
rotated_object_detection (Wang et al., 2024b)	Rotated object detection	Detect objects using rotated boxes.
semantic_segmentation (Wang et al., 2024b)	Pixel-wise semantic segmentation	Segment the different regions in this image.
land_use_classification (Wang et al., 2022)	Land use categorization	What are the land use types in this image?

duce higher-quality, more engaging responses. The robustness of its performance across different evaluation modes and datasets demonstrates its potential as a strong and generalizable improvement over existing retrieval-augmented generation methods.

4.6 Qualitative Results

As shown in Table 8, RS-Agent offers a comprehensive suite of tools tailored to address a wide range of remote sensing challenges, from low-level vision tasks (e.g., denoising, super-resolution) to high-level image interpretation (e.g., scene classification, object detection, building damage detection). In Figure 3, we illustrate several representative tasks that showcase the core capabilities and practical applicability of the system, a demonstration of the user interface is also provided in Appendix Figure 5.

Each tool demonstrates strong performance, producing fluent, accurate, and contextually appropriate responses. Outputs are not only visually and semantically aligned with the input queries, but also exhibit robustness across various image types and modalities. Beyond accuracy, RS-Agent also excels in interpreting natural language instructions, even when they are underspecified or ambiguous. For example, a vague query such as “What do you see in this image?” is correctly interpreted as an image description task, and the system autonomously invokes the appropriate image captioning model to produce a detailed and relevant response.

This ability reflects RS-Agent’s strong task planning capabilities, which allow it to bridge the gap between user intent and technical execution. Rather than relying solely on keyword matching, the agent demonstrates a deeper understanding of task semantics, enabling flexible adaptation to open-ended or imprecise instructions. Furthermore, the toolkit is inherently modular and extensible, allowing new tools to be seamlessly integrated as the task landscape evolves—thereby ensuring long-term scalability, adaptability, and generalizability across diverse remote sensing scenarios.

5. Conclusion

We propose RS-Agent, an advanced AI agent tailored for remote sensing, capable of seamlessly integrating diverse remote sensing tools to address a wide range of tasks across different imaging modalities. Our novel agent architecture is designed for user queries interpretation, complex task planning,

tool execution, and history memorization. The novel agent architecture is designed to interpret user queries, perform complex task planning, execute appropriate tools, and maintain interaction history. Our proposed Task-Aware Retrieval method significantly improves task planning accuracy, enhancing both efficiency and reliability in complex scenarios. Additionally, the DualRAG mechanism equips RS-Agent with access to a specialized knowledge database, allowing it to handle complex technical queries. Extensive experiments show that RS-Agent consistently outperforms state-of-the-art multimodal large language models across multiple remote sensing benchmarks. Furthermore, RS-Agent efficiently integrates with new tools while keeping the capability to activate previously learned tools. Overall, RS-Agent demonstrates strong potential to streamline remote sensing workflows, reduce reliance on domain experts, and enable more accessible, high-quality analysis in real-world applications.

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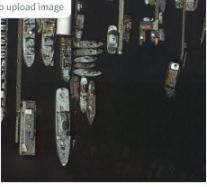
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Appendix

User	<code>Locate and mark the planes visible in this image.</code>
Prompt 1	<p>Given the question: "<code>{Query}</code>", identify the most relevant task type from the following list(Return the result as an array):</p> <ul style="list-style-type: none"> -Object_Counting: Tasks that involve counting the number of specific objects in the image. -Object_Detection: Tasks that involve identifying and determining the location of specific objects in the image. -Landuse_Segmentation: Tasks that involve segmenting different land use types in the image. . . . <p>Return the result as an array. Please return only the task types in the correct order based on their relevance to the question. If more than one task type applies, list them in order in an array. Do not provide any explanations or additional text.</p>
RS-Agent	<code>[Object Detection]</code>
Solution Searcher	<p>Input: [Object Detection] Output: To solve this kind of task, you should directly use tool `classify_image` to determine image type, then use `optical_detection` or `sar_detection` to get answer.</p>
Prompt 2	<p>You are an intelligent assistant named RS-Agent, which can handle moving target detection, aircraft detection, counting and recognition, road network extraction, building extraction, post-disaster assessment of buildings, target detection, super-resolution, denoising and other remote sensing tasks.</p> <p>Your task is to efficiently call tools and provide precise answers based on the user's needs. You can maintain context across multiple turns of conversation and directly answer the user's questions using the results from the tools. Please respond in the language the user is using, and ensure your answers are concise, natural, and appropriate, reflecting your professionalism and friendliness as an intelligent assistant.</p> <p>User Input: <code>{Query}</code> Solution Guidance: <code>{Solution Guidance}</code> Conversation History: <code>{conversation_history}</code></p>
RS-Agent	<p>The user wants to perform detection on an image located at `../test.jpg`. Before proceeding with the detection, it's important to determine the image type.</p> <p>Action: <code>classify_image</code> Action Input: <code>../test.jpg</code> To solve your problem, I need to call the tool <code>classify_image</code>, which is currently running... I have got the output of the tool and am generating the answer... Observation: <code>Optical image</code> Thought: The image has been classified as an optical image. The next step is to perform detection on this optical image.</p> <p>Action: <code>optical_detection</code> Action Input: <code>../test.jpg</code> To solve your problem, I need to call the tool <code>optical_detection</code>, which is currently running... image 1/1 .../result.jpg: 1024x1024 162.5ms Speed: 9.9ms preprocess, 162.5ms inference, 26.7ms postprocess per image at shape (1, 3, 1024, 1024) I have got the output of the tool and am generating the answer... Observation: <code>{'message': '3 planes', 'extract_image_path': '../result.jpg'}</code> Thought: The optical detection tool has identified that there are 3 planes in the image located at `../result.jpg`.</p> <p>Final Answer: <code>The image contains 3 planes, the processed image path is '../result.jpg'.</code></p>

Figure 4. Illustration of the RS-Agent workflow with detailed prompt. The RS-Agent uses prompt1 to infer the task type of the query, while the Solution Searcher retrieves the Solution Guidance for that task. The RS-Agent then uses prompt2 to plan the workflow, execute the tools, and provide the final answer to the query.

RS-Agent



Clear Image
Expand Imagebox

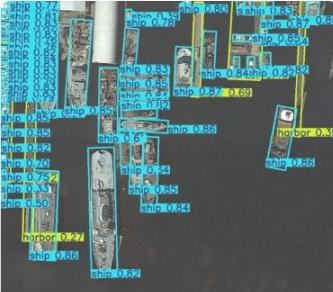
Enter your question to RS-Agent

Send
Clear Chat

Close Agent Thought Chain

How many ships are in this image?

There are 54 ships in this image. Here is the processed image with bounding boxes around the detected ships:



To solve your problem, I need to call the tool optical_detection, which is currently running...
I have got the output of the tool and am generating the answer...

Example

Click here to upload image	Click here to upload question
	How many planes are in this image?
	How many ships are in this image?
	Classify the image into the following categories: church, beach, dense residential area, tank.



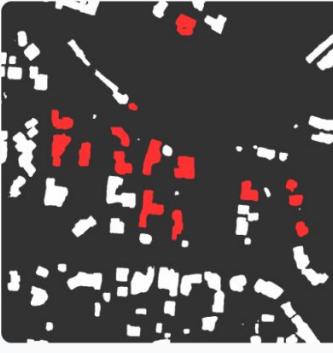


Clear Image
Close Expandbox

Enter your question to RS-Agent

How is the damage to buildings after wildfires?

After assessing the buildings in the provided images, there are 81 undamaged buildings and 15 buildings that have suffered severe damage from the wildfires. You can view the processed image with the assessment



To solve your problem, I need to call the tool building_damage_detection, which is currently running...
I have got the output of the tool and am generating the answer...

Figure 5. The user interface of the RS-Agent. Users can upload remote sensing images and interpret remote sensing data through natural language. The example shows object detection and building damage detection task.