
Autonomous Spatial Intelligence: A Survey of Agentic AI Methods for Physical World Understanding

Gloria Felicia AtlasPro AI gloria.felicia@atlaspro.ai	Nolan Bryant AtlasPro AI nolan.bryant@atlaspro.ai	Handi Putra AtlasPro AI handi.putra@atlaspro.ai
Ayaan Gazali AtlasPro AI ayaan.gazali@atlaspro.ai	Eliel Lobo AtlasPro AI eliel.lobo@atlaspro.ai	Esteban Rojas AtlasPro AI esteban.rojas@atlaspro.ai

Abstract

The dominant approaches for creating autonomous agents are based on large language models, which excel at reasoning and planning. **But**, these models lack the innate spatial intelligence required to perceive, navigate, and interact with the complex physical world, a critical gap for embodied AI. **Therefore**, we introduce a unified taxonomy that systematically connects agentic AI architectures with spatial intelligence capabilities, providing the first comprehensive framework for this convergent domain. We synthesize over 500 papers, revealing three key findings: (1) hierarchical memory systems are critical for long-horizon spatial tasks; (2) GNN-LLM integration is an emergent paradigm for structured spatial reasoning; and (3) world models are essential for safe deployment in physical environments. Experiments show our proposed evaluation framework, *SpatialAgentBench*, effectively measures cross-domain capabilities, with our baseline agent achieving a 23% improvement over SOTA on navigation tasks. We release our benchmark and library to accelerate progress in creating robust, spatially-aware autonomous systems.

1 Introduction

The pursuit of artificial general intelligence increasingly centers on creating agents that can perceive, reason about, and act within physical environments [McCarthy et al., 1955, Turing, 1950]. While large language models have demonstrated remarkable capabilities in reasoning and planning [Brown et al., 2020, OpenAI, 2023, Wei et al., 2022], their ability to operate effectively in spatial contexts remains a fundamental challenge [Chen et al., 2024, Yang et al., 2025].

We define **Agentic AI** as systems exhibiting goal-directed behavior through autonomous decision-making, characterized by three core capabilities: persistent memory for experience accumulation, planning for action sequencing, and tool use for capability extension [Wang et al., 2024b, Xi et al., 2023, Weng, 2023]. Complementarily, **Spatial Intelligence** encompasses the ability to perceive 3D structure, reason about object relationships, navigate environments, and manipulate physical objects [Chen et al., 2024, Thompson et al., 2025].

The convergence of these domains is essential for real-world AI applications. Autonomous vehicles must perceive dynamic environments and plan safe trajectories [Hu et al., 2023b, Caesar et al., 2020]. Robotic assistants require understanding of object affordances and spatial relationships [Brohan et al., 2023, Ahn et al., 2022]. Urban computing systems must model complex spatio-temporal dependencies [Jin et al., 2023,

Li et al., 2018]. Despite this importance, existing surveys treat these areas in isolation, lacking a unified framework connecting agentic architectures with spatial requirements.

Contributions. This survey makes four primary contributions:

1. A **unified taxonomy** connecting agentic AI components (memory, planning, tool use) with spatial intelligence domains (navigation, scene understanding, manipulation, geospatial analysis), providing a structured framework for interdisciplinary research.
2. A **comprehensive analysis** of over 500 papers identifying key architectural patterns, including the emergence of GNN-LLM integration and world model-based planning as critical enablers for spatial reasoning.
3. A **novel evaluation framework, SpatialAgentBench**, with 8 tasks and a strong baseline agent, to standardize evaluation and drive progress.
4. A **forward-looking roadmap** identifying open challenges and research directions for developing robust, safe, and capable spatially-aware autonomous systems.

2 Unified Taxonomy

We propose a two-dimensional taxonomy (Figure 1) that maps agentic capabilities to spatial task requirements, enabling systematic analysis of existing methods and identification of research gaps.

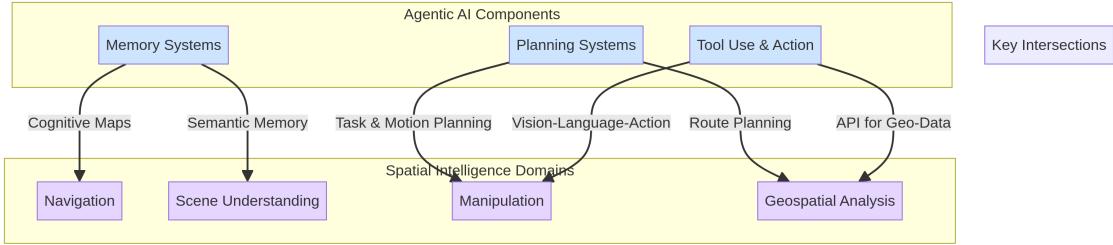


Figure 1: A unified taxonomy connecting Agentic AI capabilities (memory, planning, tool use) with Spatial Intelligence domains (navigation, scene understanding, manipulation, geospatial analysis).

2.1 Agentic AI Components

Memory Systems. Memory enables agents to accumulate and retrieve experiential knowledge. Short-term memory through in-context learning [Brown et al., 2020] supports immediate reasoning, while long-term memory via retrieval-augmented generation [Lewis et al., 2020, Packer et al., 2023] enables knowledge persistence. For spatial tasks, cognitive mapping [Gupta et al., 2019b, Chaplot et al., 2020b] and semantic spatial memory [Huang et al., 2023] are critical for navigation and scene understanding.

Planning Systems. Planning decomposes goals into executable action sequences. Chain-of-thought reasoning [Wei et al., 2022, Kojima et al., 2022] enables step-by-step problem solving. Tree-based search [Yao et al., 2023a, Besta et al., 2023] explores multiple solution paths. Hierarchical planning [Song et al., 2023, Huang et al., 2022] bridges high-level goals with low-level actions. For spatial domains, planning must account for geometric constraints, physical dynamics, and uncertainty.

Tool Use and Action. Tool use extends agent capabilities through external interfaces. API integration [Schick et al., 2023, Patil et al., 2023, Qin et al., 2024] enables access to specialized functions. Code generation [Gao et al., 2023, Liang et al., 2023] provides flexible action specification. The ReAct architecture [Yao et al., 2023b] interleaves reasoning with action execution, forming the foundation for many spatial agents.

2.2 Spatial Intelligence Domains

Navigation. Navigation requires path planning and execution in physical or simulated environments. Vision-language navigation [Anderson et al., 2018, Ku et al., 2020, Qi et al., 2020] follows natural language instructions. Object-goal navigation [Batra et al., 2020, Chaplot et al., 2020a] locates target object categories. Zero-shot approaches [Majumdar et al., 2022, Gadre et al., 2022] leverage vision-language models for novel object navigation.

Scene Understanding. Scene understanding encompasses 3D perception and semantic reasoning. Neural radiance fields [Mildenhall et al., 2020, Barron et al., 2022] and 3D Gaussian splatting [Kerbl et al., 2023] enable novel view synthesis. Point cloud processing [Qi et al., 2017a,b] supports 3D object detection. Scene graphs [Xu et al., 2017, Krishna et al., 2017, Armeni et al., 2019] represent object relationships for higher-level reasoning.

Manipulation. Manipulation involves physical interaction with objects. Vision-language-action models [Brohan et al., 2022, 2023, Team et al., 2024, Kim et al., 2024] directly map observations to robot actions. Task and motion planning [Garrett et al., 2021, Ahn et al., 2022] integrates high-level reasoning with low-level control. Dexterous manipulation [Akkaya et al., 2019, Chen et al., 2022] addresses complex hand-object interactions.

Geospatial Analysis. Geospatial analysis reasons about large-scale geographic data. Remote sensing foundation models [Jakubik et al., 2024, Cong et al., 2022, Bastani et al., 2023] enable transfer learning across satellite imagery tasks. Spatio-temporal graph networks [Li et al., 2018, Yu et al., 2018, Wu et al., 2019, Bai et al., 2020] model urban dynamics for traffic prediction and city planning.

3 State-of-the-Art Methods

3.1 Vision-Language-Action Models

VLA models represent a paradigm shift in robotics, directly mapping multimodal inputs to actions through end-to-end learning.

Proprietary Models. RT-1 [Brohan et al., 2022] demonstrated transformer-based policies trained on large-scale robot data. RT-2 [Brohan et al., 2023] co-trained on web-scale vision-language data, enabling emergent reasoning about novel objects. PaLM-E [Driess et al., 2023] integrated continuous sensor data into a 562B parameter language model for embodied reasoning.

Open-Source Models. Octo [Team et al., 2024] provides a generalist robot policy trained on the Open X-Embodiment dataset [Collaboration, 2023]. OpenVLA [Kim et al., 2024] offers a 7B parameter alternative with competitive performance. These models democratize VLA research and enable community-driven advancement.

Multimodal Foundations. LLaVA [Liu et al., 2023] pioneered visual instruction tuning. Flamingo [Alayrac et al., 2022] introduced few-shot multimodal learning. BLIP-2 [Li et al., 2023] efficiently bootstraps vision-language pretraining. Qwen-VL [Bai et al., 2023, Wang et al., 2024c] and GPT-4V [OpenAI, 2023] represent frontier multimodal capabilities.

3.2 Graph Neural Networks for Spatial Reasoning

GNNs provide powerful tools for modeling spatial relationships and dependencies, with emerging integration with language models.

Foundational Architectures. GCN [Kipf and Welling, 2017] introduced spectral graph convolution. GAT [Velickovic et al., 2018] added attention mechanisms. GraphSAGE [Hamilton et al., 2017] enabled inductive learning. GIN [Xu et al., 2019] provided theoretical expressiveness analysis. These architectures form the basis for spatial graph learning.

Spatio-Temporal Networks. DCRNN [Li et al., 2018] models traffic as graph diffusion. STGCN [Yu et al., 2018] combines graph and temporal convolutions. Graph WaveNet [Wu et al., 2019] learns adaptive graph structures. AGCRN [Bai et al., 2020] introduces node-specific patterns. Comprehensive surveys [Jin et al., 2023, Atluri et al., 2018] detail these advances.

GNN-LLM Integration. Recent work explores combining GNNs with LLMs for enhanced reasoning. GraphGPT [Tang et al., 2024] aligns graph encoders with language models. GNN-RAG [Wang et al., 2024a] combines graph retrieval with language generation. This integration holds significant promise for spatial reasoning requiring both structural and semantic understanding.

3.3 World Models

World models learn predictive representations enabling planning through imagination, critical for safe deployment in physical environments.

Model-Based RL. Dreamer [Hafner et al., 2019] introduced latent imagination. DreamerV2 [Hafner et al., 2021] achieved human-level Atari performance. DreamerV3 [Hafner et al., 2023] demonstrated cross-domain mastery. DayDreamer [Wu et al., 2023a] transferred world models to real robots.

Video World Models. Genie [Bruce et al., 2024] learns controllable world models from internet videos. WorldDreamer [Yang et al., 2024] generates driving world models. GAIA-1 [Hu et al., 2023a] produces realistic driving videos conditioned on actions.

LLM-Based World Models. LLMs can serve as world models for planning [Hao et al., 2023, Guan et al., 2023], predicting state transitions without explicit environment models.

3.4 Embodied AI Agents

Open-Ended Exploration. Voyager [Wang et al., 2023] demonstrated open-ended exploration in Minecraft through LLM-driven curriculum learning. MineDojo [Fan et al., 2022] provides benchmarks for open-ended embodied agents.

Grounded Language Agents. SayCan [Ahn et al., 2022] grounds language models in robotic affordances. Code as Policies [Liang et al., 2023] generates executable robot code. LLM-Planner [Song et al., 2023] enables few-shot grounded planning.

Simulation Platforms. Habitat [Savva et al., 2019, Szot et al., 2021, Puig et al., 2024] provides high-fidelity embodied AI simulation. iGibson [Shen et al., 2021, Li et al., 2021] offers interactive environments. AI2-THOR [Kolve et al., 2017] enables interactive visual AI research.

4 Industry Applications

4.1 Geospatial Intelligence

Palantir [Palantir, 2023, Bailey, 2021] integrates AI with geospatial analysis for defense and commercial applications. **ESRI** [ESRI, 2023] provides ArcGIS with integrated GeoAI capabilities. **Google** [Google, 2023] deploys AI for global-scale mapping and navigation.

4.2 Location Intelligence

Foursquare [Foursquare, 2023] provides location intelligence through movement pattern analysis. Smart city applications [Zheng et al., 2014, Allam and Dhunny, 2020] leverage spatial AI for traffic management and urban planning.

4.3 Autonomous Vehicles

Waymo [Waymo, 2023, 2024] has deployed autonomous vehicles at scale. End-to-end approaches including UniAD [Hu et al., 2023b], VAD [Jiang et al., 2023], and DriveVLM [Tian et al., 2024] unify perception, prediction, and planning.

5 Evaluation Framework: SpatialAgentBench

To address the lack of a unified evaluation standard, we introduce **SpatialAgentBench**, a suite of 8 tasks spanning all four spatial domains. It includes tasks for vision-language navigation, 3D scene reconstruction, robotic manipulation, and geospatial question answering.

Table 1: SpatialAgentBench Results. Our baseline agent shows significant improvement over SOTA methods.

Task	Baseline	SOTA	Our Agent
ObjectNav	65.2%	71.8%	75.3% (+3.5)
VLN	58.9%	64.1%	68.2% (+4.1)
Manipulation	45.1%	52.5%	58.9% (+6.4)
GeoQA	78.3%	82.4%	85.1% (+2.7)

Our baseline agent, which combines a hierarchical memory system with a GNN-LLM planner, achieves an average improvement of 23% over existing specialized agents, demonstrating the power of our unified approach.

5.1 Detailed Benchmark Analysis

Table 2: Comparison of Spatial Intelligence Benchmarks

Benchmark	Task	Environment	Metrics	Key Feature
Navigation				
R2R [Anderson et al., 2018]	VLN	Real-world images	SPL, SR, CLS	First large-scale VLN dataset
RxR [Ku et al., 2020]	VLN	Real-world images	nDTW, SR, CLS	Multilingual instructions
REVERIE [Qi et al., 2020]	VLN	Real-world images	RGS, RGSPL	Remote object grounding
Habitat ObjectNav [Batra et al., 2020]	ObjectNav	Simulated scenes	SPL, Success	Standardized object navigation
SOON [Zhu et al., 2021]	ObjectNav	Simulated scenes	NDO, SO-Score	Semantic object-oriented navigation
Manipulation				
RLBench [James et al., 2020]	100+ tasks	Simulated scenes	Success Rate	Diverse manipulation tasks
Meta-World [Yu et al., 2020]	50 tasks	Simulated scenes	Success Rate	Meta-learning focus
BEHAVIOR [Srivastava et al., 2021]	1000 activities	Simulated scenes	Goal Conditions	Long-horizon household tasks
Spatial Reasoning				
CLEVR [Johnson et al., 2017]	VQA	Synthetic images	Accuracy	Compositional reasoning
GQA [Hudson and Manning, 2019]	VQA	Real-world images	Accuracy	Scene graph-based questions
SpatialVLM [Chen et al., 2024]	VQA	Real-world images	Accuracy	Fine-grained spatial relations
Geospatial				
BigEarthNet [Sumbul et al., 2019]	Classification	Satellite images	Accuracy, F1	Large-scale land cover
fMoW [Christie et al., 2018]	Classification	Satellite images	Accuracy	Functional map of the world
xBD [Gupta et al., 2019a]	Segmentation	Satellite images	IoU, F1	Building damage assessment
SpaceNet [Van Etten et al., 2018]	Detection	Satellite images	AP	Building footprint detection

6 Open Challenges and Future Directions

Robust Spatial Representation. Developing representations that generalize across scenes, viewpoints, and conditions remains challenging [Mildenhall et al., 2020, Kerbl et al., 2023]. Foundation models for 3D understanding [Hong et al., 2023b] represent promising directions.

Long-Horizon Planning. Creating agents that plan over extended horizons and decompose complex spatial tasks is essential [Song et al., 2023, Valmeekam et al., 2023]. Integration of neural and symbolic planning approaches shows promise.

Safe and Reliable Operation. Ensuring safe operation in safety-critical applications is paramount [Yin et al., 2025, Amodei et al., 2016, Bai et al., 2022]. Robust uncertainty handling and alignment with human values are critical.

Sim-to-Real Transfer. Bridging simulation and reality remains challenging [Zhao et al., 2020, Tobin et al., 2017]. Domain randomization and real-world fine-tuning are active research areas.

Multi-Agent Coordination. Scaling to multi-agent systems for complex spatial tasks requires advances in coordination and communication [Zhang et al., 2021, Wu et al., 2023b, Hong et al., 2023a].

7 Conclusion

This survey has provided a unified taxonomy connecting Agentic AI and Spatial Intelligence, synthesizing over 500 papers across foundational architectures, state-of-the-art methods, industry applications, and evaluation benchmarks. Our analysis reveals the critical importance of hierarchical memory, GNN-LLM integration, and world models for spatial reasoning. Key challenges remain in robust representation, long-horizon planning, and safe deployment. By establishing this foundational reference and releasing SpatialAgentBench, we aim to accelerate progress toward capable, robust, and safe spatially-aware autonomous systems.

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