# Autonomous Spatial Intelligence: A Comprehensive Technical Report on Agentic AI Methods, Architectures, and Evaluation

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## Abstract

The convergence of Agentic Artificial Intelligence and Spatial Intelligence marks a pivotal frontier in the pursuit of creating machines that can autonomously operate in the physical world. While agentic systems demonstrate increasingly sophisticated capabilities in planning and tool use, their ability to perceive, reason about, and interact with complex spatial environments remains a significant bottleneck. This technical report addresses a critical gap in the existing literature by providing a unified taxonomy that systematically connects the architectural components of agentic AI with the functional requirements of spatial intelligence. We review over 500 papers spanning foundational agentic architectures [Yao et al., 2023b, Shinn et al., 2023, Yao et al., 2023a, Wei et al., 2022], embodied AI systems [Wang et al., 2023a, Driess et al., 2023, Brohan et al., 2023, Ahn et al., 2022], vision-language-action models [Team et al., 2024, Kim et al., 2024, Liu et al., 2023b, Alayrac et al., 2022], graph neural networks for spatial reasoning [Kipf and Welling, 2017, Velickovic et al., 2018, Hamilton et al., 2017, Wu et al., 2019a], world models [Hafner et al., 2023, 2021, Yang et al., 2024, Hu et al., 2023a], and geospatial foundation models [Jakubik et al., 2024, Bastani et al., 2023b, Cong et al., 2022, Mendieta et al., 2023]. Through comprehensive analysis of state-of-the-art methods, industry applications from Palantir, ESRI, Foursquare, Google, and Waymo, and evaluation benchmarks, we provide a foundational reference for researchers and practitioners. By synthesizing these disparate research areas and outlining a forward-looking research roadmap, this paper aims to accelerate the development of robust, safe, and effective spatially-aware autonomous systems.

## 1 Introduction

The evolution of Artificial Intelligence is marked by a paradigm shift from specialized models to goal-oriented, self-directed agents capable of complex decision-making in dynamic environments [McCarthy et al., 1955, Newell et al., 1956, Turing, 1950]. This field, which we term **Agentic AI**, represents a significant leap towards creating machines that can operate with a higher degree of autonomy [Wang et al., 2024b, Xi et al., 2023, Weng, 2023]. The foundational work on large language models [Brown et al., 2020, OpenAI, 2023, Chowdhery et al., 2022, Touvron et al., 2023, Team and Google, 2023, Anthropic, 2024] has enabled a new generation of AI agents that can reason, plan, and execute complex tasks through natural language interfaces [Wei et al., 2022, Kojima et al., 2022, Wang et al., 2022].

Concurrently, the ability for these agents to perceive, comprehend, and act within the physical world, a capability we define as **Spatial Intelligence**, has become a primary bottleneck and a critical area of research [Chen et al., 2024a, Yang et al., 2025, Thompson et al., 2025]. The convergence of these two domains is essential for developing AI systems that can effectively and safely navigate real-world complexities, from autonomous vehicles [Sun et al., 2020, Caesar et al., 2020, Wilson et al., 2023, Hu et al., 2023b, Jiang et al., 2023] and robotic assistants [Brohan et al., 2023, Driess et al., 2023, Team et al., 2024] to large-scale urban planning [Zheng et al., 2014, Jin et al., 2023, Li et al., 2018] and disaster response systems [Gupta et al., 2019a, Christie et al., 2018, Bastani et al., 2023a].

Despite rapid progress in both agentic systems and spatial reasoning, the research landscape remains fragmented. Numerous surveys have independently covered topics such as Large Language Model agents [Yao et al., 2023b, Wang et al., 2024b, Huang et al., 2024, Gao et al., 2023, Patil et al., 2023, Qin et al., 2024], embodied AI [Wang et al., 2023a, Driess et al., 2023, Duan et al., 2022, Amin and Kiela, 2024], multimodal large language models [Liu et al., 2023b, Alayrac et al., 2022, Li et al., 2023b, Bai et al., 2023, Wang et al., 2024c], graph neural networks [Wu et al., 2019a, Kipf and Welling, 2017, Velickovic et al., 2018, Hamilton et al., 2017, Xu et al., 2019, Battaglia et al., 2018], spatio-temporal prediction [Jin et al., 2023, Li et al., 2018, Yu et al., 2018, Wu et al., 2019b, Bai et al., 2020], world models [Hafner et al., 2023, 2021, 2019, Yang et al., 2024, Hu et al., 2023a], and geospatial analysis [Jakubik et al., 2024, Cong et al., 2022, Manas et al., 2021, Bastani et al., 2023b, Mendieta et al., 2023]. However, a comprehensive synthesis that bridges the architectural components of agentic AI with the functional requirements of spatial intelligence is notably absent. This disconnect hinders a holistic understanding of the challenges and opportunities at the intersection of these fields, slowing progress toward building truly world-aware autonomous agents.

This technical report aims to fill this critical gap. We provide a formal definition of Agentic AI, focusing on the core components of memory, planning, and tool use, and a structured taxonomy of Spatial Intelligence, categorizing tasks across navigation, scene understanding, manipulation, and geospatial analysis. Our primary contributions are:

1. A novel, unified taxonomy that connects agentic architectures with spatial intelligence tasks, providing a structured framework for understanding and categorizing research in this interdisciplinary area.
2. A comprehensive review of over 500 papers covering state-of-the-art methods, evaluation benchmarks, and real-world industry applications, synthesizing findings from previously disparate fields.
3. A forward-looking analysis of the open challenges and a research roadmap to guide future work in developing more capable, robust, and safe spatially-aware agentic systems.

# 2 A Taxonomy of Spatial Intelligence

We define **Spatial Intelligence** as an agent's ability to perceive, reason about, and interact with the physical world. We propose a taxonomy that categorizes spatial tasks into four key domains, each with distinct challenges and methodological approaches.

## 2.1 Navigation

Navigation encompasses the ability to plan and execute paths in physical or simulated environments. This domain has seen remarkable progress through vision-language navigation (VLN) [Anderson et al., 2018, Chen et al., 2019, Hong et al., 2020, Krantz et al., 2020, Ku et al., 2020], which requires agents to follow natural language instructions in realistic environments. The Room-to-Room (R2R) benchmark [Anderson et al., 2018] established a foundational evaluation framework, while subsequent work has extended to continuous environments [Krantz et al., 2020], outdoor settings [Chen et al., 2019], and cross-lingual scenarios [Yan et al., 2020].

Point-to-point navigation has been advanced through the Habitat platform [Savva et al., 2019, Szot et al., 2021, Puig et al., 2024], which provides high-fidelity simulation environments for training and evaluating embodied agents. Object-goal navigation [Batra et al., 2020, Chaplot et al., 2020a, Ramakrishnan et al., 2022] requires agents to navigate to specific object categories, while image-goal navigation [Zhu et al., 2017]

uses visual targets. Zero-shot object navigation (ZSON) [Majumdar et al., 2022, Gadre et al., 2022] leverages vision-language models to navigate to novel objects without task-specific training.

Semantic mapping approaches [Gupta et al., 2019b, Chaplot et al., 2020b, Huang et al., 2023] build spatial representations that enable more efficient navigation. VLMaps [Huang et al., 2023] creates open-vocabulary 3D semantic maps by fusing CLIP features with depth information, enabling natural language queries about spatial locations. Recent work on visual navigation transformers [Shah et al., 2023b,a] has demonstrated impressive generalization across diverse environments through large-scale pretraining.

## 2.2 Scene Understanding

Scene understanding involves perceiving and reasoning about the objects, relationships, and context of 3D environments. This domain spans multiple levels of abstraction, from low-level perception to high-level semantic reasoning.

**3D Reconstruction and Representation.** Neural Radiance Fields (NeRF) [Mildenhall et al., 2020, Barron et al., 2021, 2022] have revolutionized novel view synthesis by representing scenes as continuous volumetric functions. More recently, 3D Gaussian Splatting [Kerbl et al., 2023] has emerged as a faster alternative with explicit scene representations. These representations enable agents to build detailed mental models of their environments.

**3D Object Detection and Segmentation.** Point cloud processing through PointNet [Qi et al., 2017a] and PointNet++ [Qi et al., 2017b] established foundational architectures for 3D understanding. Subsequent work has developed more sophisticated approaches including Point Transformers [Wu et al., 2022, 2024b], voxel-based methods [Shi et al., 2020, Zhou and Tuzel, 2018], and hybrid approaches. Indoor scene understanding has been advanced through datasets like ScanNet [Dai et al., 2017], Matterport3D [Chang et al., 2017], and S3DIS [Armeni et al., 2016].

**Scene Graphs.** Scene graph generation [Xu et al., 2017, 2020, Krishna et al., 2017b] provides structured representations of objects and their relationships, enabling higher-level reasoning about spatial configurations. Visual Genome [Krishna et al., 2017a] established a large-scale dataset for this task, while recent work has explored 3D scene graphs [Armeni et al., 2019, Rosinol et al., 2020] for more complete environmental understanding.

**Spatial Reasoning Benchmarks.** CLEVR [Johnson et al., 2017] introduced compositional visual reasoning, while GQA [Hudson and Manning, 2019] extended this to real-world images. NLVR2 [Suhr et al., 2019] focuses on grounded language understanding, and SpatialVLM [Chen et al., 2024a] specifically targets spatial reasoning in vision-language models. Recent benchmarks like REM [Thompson et al., 2025] and EmbodiedBench [Yang et al., 2025] evaluate spatial reasoning in embodied contexts.

## 2.3 Manipulation

Manipulation encompasses the ability to interact with and modify objects in the environment. This domain is critical for robotic applications and requires tight integration of perception, planning, and control.

**Robotic Manipulation.** Transporter Networks [Zeng et al., 2021] introduced a spatial action representation for pick-and-place tasks. CLIPort [Shridhar et al., 2022] combined this with CLIP for language-conditioned manipulation. More recent work has developed general-purpose manipulation policies through large-scale imitation learning [Brohan et al., 2022, 2023, Team et al., 2024, Kim et al., 2024].

**6D Pose Estimation.** Accurate object pose estimation is fundamental for manipulation. PoseCNN [Xiang et al., 2018] established a baseline approach, while recent work has developed foundation models for pose estimation [Wen et al., 2024, Labbé et al., 2022] that generalize to novel objects without retraining.

**Task and Motion Planning.** Integrating high-level task planning with low-level motion planning remains a key challenge [Ghallab et al., 2004, Garrett et al., 2021]. LLM-based planners [Song et al., 2023, Huang et al., 2022b,a] have shown promise in generating task plans from natural language, while approaches like SayCan [Ahn et al., 2022] ground these plans in robotic affordances.

**Dexterous Manipulation.** Learning dexterous manipulation skills, particularly for multi-fingered hands, has been advanced through simulation [Akkaya et al., 2019, Chen et al., 2022] and real-world learning [Wu et al., 2024a]. TidyBot [Wu et al., 2023a] demonstrated household tidying through LLM-guided manipulation.

### 2.4 Geospatial Analysis

Geospatial analysis involves reasoning about large-scale geographic data, from satellite imagery to urban sensor networks. This domain has seen rapid advancement through foundation models and graph neural networks.

**Remote Sensing Foundation Models.** Prithvi [Jakubik et al., 2024] introduced a geospatial foundation model pretrained on NASA's Harmonized Landsat Sentinel-2 data. SatMAE [Cong et al., 2022] and SatCLIP [Klemmer et al., 2023] developed self-supervised approaches for satellite imagery. Scale-MAE [Reed et al., 2023] addressed the multi-scale nature of remote sensing data. These models enable transfer learning across diverse geospatial tasks including land use classification [Sumbul et al., 2019, Helber et al., 2019], change detection [Zhang et al., 2018], and building damage assessment [Gupta et al., 2019a].

**Spatio-Temporal Graph Networks.** Traffic forecasting has been revolutionized by graph neural networks that model spatial dependencies between sensors. DCRNN [Li et al., 2018] introduced diffusion convolution for traffic prediction, while STGCN [Yu et al., 2018] combined graph convolution with temporal convolution. Graph WaveNet [Wu et al., 2019b] learned adaptive adjacency matrices, and AGCRN [Bai et al., 2020] introduced attention mechanisms. These approaches have been extended to broader urban computing applications [Jin et al., 2023, Atluri et al., 2018].

**Urban Computing.** Smart city applications leverage spatial AI for traffic management [Li et al., 2018, Yu et al., 2018], crime prediction [Watson et al., 2021], air quality monitoring, and urban planning [Zheng et al., 2014]. The integration of multiple data sources—sensors, social media, satellite imagery—enables comprehensive urban intelligence [Allam and Dhunny, 2020, Anghelescu and Ionescu, 2019].

## 3 Core Components of Agentic AI

Agentic AI systems are characterized by their ability to act autonomously to achieve goals. We identify three core components that enable this autonomy, drawing from the unified framework proposed by Wang et al. [2024b] and subsequent analyses [Xi et al., 2023, Weng, 2023, Huang et al., 2024].

### 3.1 Memory Systems

Memory enables agents to store and retrieve information from past experiences, supporting both short-term reasoning and long-term knowledge accumulation.

**Short-Term Memory.** In-context learning [Brown et al., 2020, Min et al., 2022] allows agents to adapt to new tasks through examples provided in the prompt. Chain-of-thought prompting [Wei et al., 2022, Kojima et al., 2022] enables step-by-step reasoning within a single context window. Self-consistency [Wang et al., 2022] improves reasoning by sampling multiple reasoning paths.

**Long-Term Memory.** Retrieval-augmented generation (RAG) [Lewis et al., 2020, Guu et al., 2020] extends agent knowledge through external retrieval. Generative Agents [Park et al., 2023] demonstrated emergent social behaviors through memory streams and reflection. MemGPT [Packer et al., 2023] introduced hierarchical memory management for extended conversations. Recent work on agentic memory [Xu et al., 2025] explores more sophisticated memory architectures.

**Spatial Memory.** For embodied agents, spatial memory is critical for navigation and manipulation. Cognitive mapping approaches [Gupta et al., 2019b, Chaplot et al., 2020b] build metric maps of environments. Semantic mapping [Huang et al., 2023, Chen et al., 2023a] adds language-grounded understanding to spatial representations.

### 3.2 Planning Systems

Planning enables agents to decompose high-level goals into executable action sequences. This capability is essential for complex spatial tasks that require multi-step reasoning.

**Chain-of-Thought Planning.** CoT prompting [Wei et al., 2022] elicits step-by-step reasoning from language models. Zero-shot CoT [Kojima et al., 2022] demonstrated that simple prompts like "Let's think step by step" can improve reasoning. Self-consistency [Wang et al., 2022] aggregates multiple reasoning paths for more robust planning.

**Tree-Based Planning.** Tree of Thoughts [Yao et al., 2023a] generalizes CoT by exploring multiple reasoning paths in a tree structure, enabling deliberate search and backtracking. Graph of Thoughts [Besta et al., 2023] further extends this to arbitrary graph structures. These approaches are particularly valuable for complex spatial planning tasks.

**Iterative Refinement.** Reflexion [Shinn et al., 2023] enables agents to learn from failures through verbal self-reflection. Self-Refine [Madaan et al., 2023] iteratively improves outputs through self-feedback. These approaches are critical for robust planning in uncertain environments.

**Hierarchical Planning.** LLM-Planner [Song et al., 2023] decomposes high-level goals into subgoals for embodied agents. Inner Monologue [Huang et al., 2022a] uses language as an interface between planning and perception. RAP [Hao et al., 2023] treats planning as reasoning with world models.

**Classical Planning Integration.** Recent work has explored combining LLMs with classical planners [Valmeekam et al., 2023, Guan et al., 2023, Liu et al., 2023a] to leverage the complementary strengths of neural and symbolic approaches.

### 3.3 Tool Use and Action

Tool use extends agent capabilities through external APIs, code execution, and physical actuators.

**API and Tool Integration.** Toolformer [Schick et al., 2023] trained language models to decide when and how to use tools. MRKL [Karpas et al., 2022] proposed a modular architecture combining LLMs with specialized modules. Gorilla [Patil et al., 2023] and ToolLLM [Qin et al., 2024] scaled tool use to thousands of APIs. ART [Paranjape et al., 2023] automates multi-step reasoning and tool use.

**Code Generation.** Program-aided language models [Gao et al., 2023] use code as an intermediate representation for reasoning. Code as Policies [Liang et al., 2023] generates executable robot policies as Python code. This approach enables more complex and dynamic behaviors than direct action prediction.

**ReAct Architecture.** ReAct [Yao et al., 2023b] interleaves reasoning traces with actions, creating a synergistic loop between thinking and acting. This architecture has become foundational for agentic systems, enabling agents to create, maintain, and adjust plans while interacting with environments.

### 3.4 Multi-Agent Systems

Multi-agent architectures enable collaboration and specialization among multiple AI agents.

**Collaborative Frameworks.** AutoGen [Wu et al., 2023c] provides a framework for building multi-agent conversations. CAMEL [Li et al., 2023a] explores role-playing for cooperative task completion. MetaGPT [Hong et al., 2023a] assigns different roles (architect, engineer, etc.) to agents for software development.

**Multi-Agent Coordination.** Research on multi-agent reinforcement learning [Zhang et al., 2021, Hernandez-Leal et al., 2019, Yuan et al., 2023] provides foundations for coordinated behavior. Multi-agent geosimulation [Borges et al., 2014] applies these concepts to spatial domains.

## 4 State-of-the-Art Methods

### 4.1 Vision-Language-Action Models

Vision-Language-Action (VLA) models represent a paradigm shift in robotics, directly mapping visual observations and language instructions to robot actions through end-to-end learning.

**Proprietary VLA Models.** RT-1 [Brohan et al., 2022] demonstrated that transformer-based policies trained on large-scale robot data can generalize across tasks. RT-2 [Brohan et al., 2023] extended this by co-training on web-scale vision-language data, enabling emergent capabilities like reasoning about novel objects. PaLM-E [Driess et al., 2023], a 562B parameter model, integrates continuous sensor data directly into a language model for embodied reasoning.

**Open-Source VLA Models.** Octo [Team et al., 2024] provides an open-source generalist robot policy trained on the Open X-Embodiment dataset. OpenVLA [Kim et al., 2024] offers a 7B parameter open-source alternative with strong performance. These models democratize access to VLA capabilities and enable community-driven research.

**Multimodal Foundation Models.** LLaVA [Liu et al., 2023b,c] pioneered visual instruction tuning for multimodal understanding. Flamingo [Alayrac et al., 2022] introduced few-shot learning for vision-language tasks. BLIP-2 [Li et al., 2023b] efficiently bootstraps vision-language pretraining. Qwen-VL [Bai et al., 2023, Wang et al., 2024c] and InternVL [Chen et al., 2024b] provide strong open-source alternatives. GPT-4V [OpenAI, 2023,?] and Gemini [Team and Google, 2023] represent the frontier of proprietary multimodal capabilities.

## 4.2 Embodied AI Agents

Embodied AI agents operate in physical or simulated environments, requiring tight integration of perception, reasoning, and action.

**Open-Ended Exploration.** Voyager [Wang et al., 2023a] demonstrated open-ended exploration in Minecraft through LLM-driven curriculum learning and skill library construction. MineDojo [Fan et al., 2022] provides a benchmark suite for open-ended embodied agents. DEPS [Wang et al., 2023b] uses language descriptions to enable efficient exploration.

**Grounded Language Agents.** SayCan [Ahn et al., 2022] grounds language models in robotic affordances by combining LLM planning with learned value functions. Code as Policies [Liang et al., 2023] generates executable robot code from language instructions. LLM-Planner [Song et al., 2023] enables few-shot grounded planning for embodied agents.

**Simulation Environments.** Habitat [Savva et al., 2019, Szot et al., 2021, Puig et al., 2024] provides high-fidelity simulation for embodied AI research. iGibson [Shen et al., 2021, Li et al., 2021] offers interactive environments with realistic physics. AI2-THOR [Kolve et al., 2017] enables research on interactive visual AI. Gibson [Xia et al., 2018] provides real-world scanned environments.

## 4.3 Graph Neural Networks for Spatial Intelligence

Graph Neural Networks (GNNs) provide powerful tools for modeling spatial relationships and dependencies.

**Foundational Architectures.** Graph Convolutional Networks (GCN) [Kipf and Welling, 2017] introduced spectral convolution on graphs. Graph Attention Networks (GAT) [Velickovic et al., 2018] added attention mechanisms for adaptive aggregation. GraphSAGE [Hamilton et al., 2017] enabled inductive learning on large graphs. Graph Isomorphism Networks (GIN) [Xu et al., 2019] provided theoretical analysis of GNN expressiveness.

**Geometric GNNs.** Geometric deep learning [Han et al., 2024, Bronstein et al., 2021] extends GNNs to handle geometric data with equivariance properties. E(n) Equivariant GNNs [Satorras et al., 2021] preserve Euclidean symmetries. These approaches are critical for molecular modeling, protein structure prediction, and physical simulation.

**Spatio-Temporal GNNs.** Traffic forecasting has driven innovation in spatio-temporal graph learning. DCRNN [Li et al., 2018] models traffic as diffusion on a graph. STGCN [Yu et al., 2018] combines graph and temporal convolutions. Graph WaveNet [Wu et al., 2019b] learns adaptive graph structures. AGCRN [Bai et al., 2020] introduces node-specific patterns. These methods have been surveyed comprehensively [Jin et al., 2023, Atluri et al., 2018].

**GNN + LLM Integration.** Recent work explores combining GNNs with LLMs for enhanced reasoning. GraphGPT [Tang et al., 2024] aligns graph encoders with language models. LLM-GNN [Chen et al., 2023b, He et al., 2023] uses LLMs to enhance graph learning. GNN-RAG [Wang et al., 2024a] combines graph retrieval with language generation. This integration holds promise for spatial reasoning tasks that require both structural and semantic understanding.

## 4.4 World Models

World models learn predictive representations of environments, enabling planning through imagination.

**Model-Based Reinforcement Learning.** Dreamer [Hafner et al., 2019] introduced latent imagination for model-based RL. DreamerV2 [Hafner et al., 2021] achieved human-level performance on Atari through discrete world models. DreamerV3 [Hafner et al., 2023] demonstrated mastery across diverse domains with a single algorithm. DayDreamer [Wu et al., 2023b] transferred world models to real robots.

**Video Prediction Models.** Video prediction provides a form of world modeling through pixel-space forecasting. Genie [Bruce et al., 2024] learns controllable world models from internet videos. Sora [Brooks et al., 2024] demonstrates impressive video generation capabilities. WorldDreamer [Yang et al., 2024] generates world models for autonomous driving.

**World Models for Autonomous Driving.** GAIA-1 [Hu et al., 2023a] generates realistic driving videos conditioned on actions. UniSim [Yang et al., 2023b] provides a unified simulator for real-world interaction. DriveWorld [Min et al., 2024] learns structured world models for driving. These approaches enable scalable training of autonomous driving systems.

**LLM-Based World Models.** Recent work explores using LLMs as world models for planning [Hao et al., 2023, Guan et al., 2023]. LLMs can predict state transitions and outcomes, enabling model-based planning without explicit environment models.

### 4.5 Autonomous Driving Systems

Autonomous driving represents a critical application domain for spatial AI, requiring integration of perception, prediction, and planning.

**End-to-End Driving.** UniAD [Hu et al., 2023b] unifies perception, prediction, and planning in a single model. VAD [Jiang et al., 2023] vectorizes scene representation for efficient planning. DriveVLM [Tian et al., 2024] integrates vision-language models for driving. EMMA [Waymo, 2024] from Waymo demonstrates end-to-end multimodal driving.

**BEV Perception.** Bird's-eye-view (BEV) representations have become standard for autonomous driving perception. LSS [Philion and Fidler, 2020] introduced lift-splat-shoot for BEV generation. BEVFormer [Li et al., 2022, Yang et al., 2023a] uses transformers for BEV feature extraction. These representations enable unified perception across multiple cameras.

**Datasets and Benchmarks.** nuScenes [Caesar et al., 2020] provides a large-scale multimodal dataset. Waymo Open Dataset [Sun et al., 2020] offers high-quality sensor data. Argoverse 2 [Wilson et al., 2023] includes HD maps and diverse scenarios. KITTI [Geiger et al., 2012] remains a foundational benchmark.

## 5 Industry Applications

The convergence of agentic AI and spatial intelligence has enabled transformative applications across industries.

### 5.1 Geospatial Intelligence Platforms

**Palantir.** Palantir Technologies [Palantir, 2023, Bailey, 2021, Freeman, 2021] has pioneered the integration of AI with geospatial analysis for government and commercial applications. Their platforms enable analysis of satellite imagery, sensor data, and geographic information for defense, logistics, and urban planning applications.

**ESRI.** ESRI [ESRI, 2023] provides the ArcGIS platform, which has increasingly integrated AI capabilities for geospatial analysis. Their GeoAI tools enable automated feature extraction, land use classification, and spatial pattern recognition. Recent integration of foundation models [Jakubik et al., 2024] enables more sophisticated analysis.

**Google Earth and Maps.** Google [Google, 2023] has deployed AI extensively for mapping, navigation, and location-based services. Their systems process satellite imagery at global scale, enable real-time traffic prediction, and power location-based recommendations.

### 5.2 Location Intelligence

**Foursquare.** Foursquare [Foursquare, 2023, Krumm, 2017] provides location intelligence through analysis of movement patterns, points of interest, and spatial behavior. Their platforms enable businesses to understand customer behavior, optimize site selection, and target marketing based on location.

**Smart City Applications.** Urban computing [Zheng et al., 2014, Allam and Dhunny, 2020] leverages spatial AI for traffic management, public safety, resource optimization, and urban planning. Cities worldwide are deploying AI-powered systems for real-time monitoring and decision support.

### 5.3 Autonomous Vehicles

**Waymo.** Waymo [Waymo, 2023, 2024] has deployed autonomous vehicles at scale, demonstrating the viability of spatial AI for real-world transportation. Their systems integrate perception, prediction, and planning for safe navigation in complex urban environments.

**Tesla.** Tesla [Tesla, 2023] has pursued a vision-based approach to autonomous driving, leveraging large-scale data collection from their vehicle fleet. Their systems demonstrate the potential for scalable spatial AI through fleet learning.

### 5.4 Enterprise Spatial AI

The integration of spatial AI with enterprise data systems enables new applications in business intelligence and decision support.

**Data Integration.** Combining spatial data with enterprise systems like Snowflake, SAP, and Salesforce enables location-aware business analytics. This integration supports applications like sales territory optimization, supply chain planning, and customer segmentation based on geographic patterns.

**Automated GIS Analysis.** AI agents can automate complex GIS workflows that previously required teams of specialists. This includes automated feature extraction, change detection, and spatial pattern analysis at scale.

**Real-Time Sensor Analytics.** Processing millions of sensor data points in real-time enables applications like predictive maintenance, environmental monitoring, and smart infrastructure management.

## 6 Evaluation Benchmarks

Comprehensive evaluation is essential for measuring progress in spatial AI. We categorize existing benchmarks by their focus areas.

### 6.1 Navigation Benchmarks

Vision-language navigation benchmarks include R2R [Anderson et al., 2018], RxR [Ku et al., 2020], and REVERIE [Qi et al., 2020]. Object-goal navigation is evaluated through Habitat ObjectNav [Batra et al., 2020] and SOON [Zhu et al., 2021]. Continuous navigation benchmarks [Krantz et al., 2020] extend discrete graph-based evaluation.

### 6.2 Manipulation Benchmarks

ALFWorld [Shridhar et al., 2021] provides text-based household tasks. BEHAVIOR [Srivastava et al., 2021] offers realistic household activities. RLBench [James et al., 2020] provides diverse manipulation tasks. Meta-World [Yu et al., 2020] enables multi-task evaluation.

### 6.3 Spatial Reasoning Benchmarks

CLEVR [Johnson et al., 2017] tests compositional visual reasoning. GQA [Hudson and Manning, 2019] evaluates real-world visual reasoning. SpatialVLM [Chen et al., 2024a] specifically targets spatial reasoning. REM [Thompson et al., 2025] evaluates embodied spatial reasoning in MLLMs.

### 6.4 Integrated Agent Benchmarks

AgentBench [Liu et al., 2023d] provides comprehensive LLM agent evaluation. WebArena [Zhou et al., 2023] tests web-based agent capabilities. OSWorld [Xie et al., 2024] evaluates computer use agents. Embodied-Bench [Yang et al., 2025] comprehensively evaluates embodied MLLMs. SafeAgentBench [Yin et al., 2025] focuses on safe task planning.

### 6.5 Geospatial Benchmarks

BigEarthNet [Sumbul et al., 2019] provides multi-label land use classification. fMoW [Christie et al., 2018] tests temporal reasoning in satellite imagery. xBD [Gupta et al., 2019a] evaluates building damage assessment. SpaceNet [Van Etten et al., 2018] focuses on building and road extraction.

## 7 Open Challenges and Future Directions

Despite significant progress, several fundamental challenges remain for spatial AI agents.

### 7.1 Robust Spatial Representation

Developing representations that capture the complexity of 3D environments and generalize across different scenes remains challenging [Mildenhall et al., 2020, Kerbl et al., 2023, Dai et al., 2017, Chang et al., 2017]. Current approaches often struggle with novel viewpoints, lighting conditions, and scene compositions. Foundation models for 3D understanding [Hong et al., 2023b, Xu et al., 2024] represent promising directions.

### 7.2 Long-Horizon Planning

Creating agents that can plan over extended time horizons and decompose complex spatial tasks into manageable sub-goals is essential for real-world applications [Song et al., 2023, Huang et al., 2022b, Hao et al., 2023, Valmeekam et al., 2023]. Current LLM-based planners often struggle with tasks requiring many sequential steps or complex spatial reasoning.

### 7.3 Safe and Reliable Operation

Ensuring that agents operate safely, especially in safety-critical applications, is paramount [Yin et al., 2025, Bai et al., 2022, Hendrycks et al., 2021, Ganguli et al., 2022, Amodei et al., 2016]. This includes robust handling of uncertainty, graceful degradation under distribution shift, and alignment with human values.

### 7.4 Sim-to-Real Transfer

Bridging the gap between simulation and the real world remains a key challenge for deploying embodied agents [Zhao et al., 2020, Tobin et al., 2017, James et al., 2019, Savva et al., 2019, Shen et al., 2021]. Domain randomization, system identification, and real-world fine-tuning are active research areas.

### 7.5 Multi-Modal Integration

Effectively integrating information across modalities—vision, language, audio, touch, proprioception—is essential for robust spatial intelligence. Current approaches often struggle to leverage complementary information across modalities.

### 7.6 Scalable Data Collection

Training capable spatial AI agents requires large-scale, diverse data. Approaches like Open X-Embodiment [Collaboration, 2023] demonstrate the value of data sharing, but scaling data collection for embodied AI remains challenging.

# 8 Conclusion

This technical report has provided a comprehensive overview of the intersection of Agentic AI and Spatial Intelligence, reviewing over 500 papers spanning foundational architectures, state-of-the-art methods, industry applications, and evaluation benchmarks. We have proposed a unified taxonomy connecting agentic components (memory, planning, tool use) with spatial intelligence domains (navigation, scene understanding, manipulation, geospatial analysis).

The convergence of large language models, vision-language models, graph neural networks, and world models is enabling a new generation of spatially-aware autonomous agents. Industry applications from Palantir, ESRI, Foursquare, Google, Waymo, and others demonstrate the transformative potential of these technologies.

Key challenges remain in robust spatial representation, long-horizon planning, safe operation, and sim-to-real transfer. Addressing these challenges will require continued collaboration across the AI, robotics, and geospatial communities.

By providing this synthesis, we aim to create a foundational reference for researchers, developers, and practitioners, fostering a more integrated approach to building the next generation of autonomous spatial intelligence.

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