MOSES – Modularizing a Geospatial Mind: Modular Onto-Logic Embeddings for Spatial AI Reasoning

Sean Tucker

Abstract

We introduce **MOSES** (Modular Onto-Logic Spatial Embedding System), a framework for transparent, interpretable, and modular reasoning in geospatial AI. MOSES composes three baseline **Statically Implied Models (SIMs)**: the **Spatiotemporal Embedding Model (STEM-GLE)**, the **Geospatial Ontological Embedding (GOE)**, and the **Geospatial Poly-Linear Embedding (GPLE)**. These SIMs are deterministic, algebra-compatible vector representations of space, type, and geometry. Each includes a shared stem_vector derived from STEM-GLE, enabling model-integration and vector-native referencing in systems like Weaviate.

This foundation supports **Prompt-Readable Vector Logic**, allowing human-AI collaboration over embedded spatial knowledge. Cognitively, MOSES is grounded in theories of modular intelligence and co-referencing, offering a novel approach to spatial AI systems that are symbolic, scalable, and spatially aware.

1. Introduction

Geospatial AI remains dominated by opaque, statistically trained models with limited modularity and interpretability (Mai et al., 2022; Bommasani et al., 2021). These models excel at tasks like classification or retrieval but struggle with symbolic reasoning, traceability, or user-guided logic. Especially in infrastructure, disaster response, or environmental planning, systems must be accountable, interpretable, and adaptable across domains (Janowicz et al., 2020; Cai & Wang, 2020).

To address this, we propose MOSES—a modular architecture for **Spatial AI Systems (SPAIS)**—built from **Statically Implied Models (SIMs)**. SIMs are deterministic embeddings with five core properties (Tucker, 2025a):

- Determinism
- Decomposability
- Algebra Compatibility
- Cross-Domain Reasoning
- Prompt-Readability

These SIMs function as reusable, modular units of spatial knowledge. Each is anchored by a **stem_vector**, derived from the **Spatiotemporal Embedding Model (STEM-GLE)**, which encodes time-space coordinates as a math-native embedding.

We compose three such SIMs into MOSES:

- **STEM-GLE** (spatiotemporal anchor)
- **GOE** (semantic type)
- **GPLE** (geometric extent)

These are **baseline types**—extensible by logic layer, geometry, or domain—providing modular depth and breadth.

Cognitively, MOSES draws on theories of modular mind (Fodor, 1983), multiple intelligences (Gardner, 1983), distributed processing (Rumelhart & McClelland, 1986), and embodied cognition (Clark & Chalmers, 1998). It proposes that spatial AI can be made more intelligible and modular by composing SIMs through shared references, mimicking how the human brain integrates modular but co-referenced systems.

2. Background: SIMs and Geospatial Reasoning

SIMs were proposed to fill a critical void in geospatial AI: interpretable, interoperable, and algebra-compatible embeddings (Tucker, 2025a). Unlike black-box learned embeddings, SIMs use deterministic logic to encode structured knowledge, much like coordinate systems or symbolic ontologies.

SIMs enable reusable vector components with clear semantics and decomposable structure. In GIS, this approach mirrors longstanding concerns over **semantic reference systems** (Kuhn, 2003) and aligns with the rise of **vector-based GIS architectures** (Yan et al., 2021).

SIMs offer:

- A bridge between structured data and vector AI
- Algebra-native reasoning (e.g., vector joins)
- LLM compatibility via prompt-readable logic

In MOSES, SIMs form the substrate of symbolic-spatial intelligence. Their integration is anchored through **STEM**, which encodes spatial-temporal positions in vector space.

3. The MOSES SIM Stack

3.1 STEM-GLE: Spatiotemporal Embedding Model

The foundational SIM, STEM-GLE encodes spatial and temporal coordinates into an 8D vector:

STEM(lat, lon, alt, t) = [

sin(lat), cos(lat),

sin(lon), cos(lon),

alt/h,

sin(2πt/T), cos(2πt/T)

]

Where h is a normalization factor (e.g., 9000m) and T is the time cycle (e.g., 24h). This deterministic embedding supports time-aware reasoning and real-time spatial proximity logic (Tucker, 2025b).

3.2 GOE: Geospatial Ontological Embeddings

GOE encodes what an entity *is*—such as a bridge, subway station, or hospital. It includes a stem_vector to spatially ground the entity. This enables queries such as:

"Find all GOE:type=bridge near STEM:point"

GOEs support symbolic and semantic filtering, allowing LLMs to reason with vector-typed knowledge (Smith & Mark, 2001).

3.3 GPLE: Geospatial Poly-Linear Embeddings

GPLE encodes extent, path, or zone—such as:

- A subway line
- A flood zone polygon
- An evacuation route

Each GPLE also includes a stem_vector as centroid or anchor. It enables path-based joins (e.g., "find GOE:schools inside GPLE:flood_zone") and topological logic such as upstream/downhill.

These three SIMs—type, time, and shape—form the MOSES core. Each is modular, prompt-readable, and algebra-compatible.

4. Spatial Anchoring, Vector Databases, and the Architecture of Reasoning

The architectural core of MOSES is the shared spatial embedding known as the stem_vector. This vector, derived from STEM-GLE, anchors all SIMs in a common space-time reference frame, enabling:

- Vector-native joins
- Latent model integration
- Retrieval-augmented reasoning

4.1 The stem_vector as a Latent Key

The stem_vector provides a deterministic spatial anchor for all geo-based SIMs. Its continuous, math-native form allows:

- Cross-SIM co-referencing of entities that share space
- Algebraic reasoning (e.g., similarity, vector joins)
- Decomposability for explainable alignment

Unlike brittle foreign keys, the stem_vector enables semantic joins across time, geometry, and type—through latent spatial continuity.

4.2 Vector Database Integration

Vector databases like Weaviate enable real-time querying and reasoning over stem_vector-indexed SIMs. For example:

1. GOE hospitals and GPLE evacuation zones are indexed by their stem_vector
2. A query can retrieve all GOEs near a GPLE zone, using cosine similarity
3. The result is a cross-type spatial join without explicit relationships

This architecture mirrors **spatial interaction models** and **latent reference systems** (Oshan et al., 2020; Kuhn, 2003) but re-implements them in vector-native space.

4.3 Retrieval-Augmented Generation (RAG) Over SIMs

In MOSES:

- SIMs are indexed in a vector DB
- A user prompt (e.g., "schools near bridges in flood zones") is parsed
- Matching SIMs are retrieved via vector proximity

- The LLM composes logic-aware outputs

This enables prompt-driven, multi-SIM reasoning, grounded in deterministic embeddings.

4.4 Cognitive Justification: Co-Referencing as Mind Integration

In human cognition, spatial attention, object classification, and planning are handled by modular yet co-referenced systems (Fodor, 1983; Gardner, 1983).

MOSES emulates this:

- Each SIM is a modular intelligence unit
- The shared stem_vector provides cognitive co-referencing
- The vector DB acts as a distributed working memory

This architecture aligns with **Embodied Cognition**, **Distributed Mind**, and **Multiscale Reasoning** (Clark & Chalmers, 1998; Oshan et al., 2019).

5. Applications

MOSES applications can be made wherever vector data analysis, reasoning, and AI integration is possible. It includes:

- **AI Planning Agents** reasoning over infrastructure, zoning, and hazards using SIM-based logic
- **LLMs** prompting: *"Find cafes (GOE) uphill (STEM) from the flood area (GPLE) and open now (time-aware)."*
- **Environmental Monitoring** of moving entities across vector-anchored zones with traceable reasoning

Wherever the stochastic and the static can inform each other, MOSES supports synergy: nuance with numeric certainty, probability with precise positioning, and intuition with deduction.

5.1 A Path to Spatial AI Systems (SPAIS)

MOSES allows SIM types to be added for deeper and broader insights. Its intelligence is as granular and expansive as the SIM/STEM architecture of the world features exposed to it.

Shared SIM embeddings from varied sources allow:

- Optimized SIM combinations for SPAIS design
- Curated SIMs by domain experts

- Experiments with spatial cognition in LLM pipelines

6. Future Extensions

MOSES can expand through:

- **New SIM Types**: emissions, economics, mobility, environmental metrics
- **GeoMesh Base Layer**: an Earth-wide mesh (~1m resolution) for standardized anchoring and fast lookup
- **SIM Generators & Sync Tools**: converting GIS or ontology files into reusable SIMs

SIM Sync Tools will support transitions from relational and NoSQL geodata systems, increasing adoption across legacy infrastructure.

7. Conclusion

MOSES offers a new paradigm for spatial AI: modular, cognitively aligned, and symbol-compatible. By composing reusable SIMs grounded in a shared spatial index (STEM-GLE), it enables interpretable and algebra-ready reasoning across space, time, and concept.

As SIMs are published and adopted, spatial AI systems can be built as transparent, testable architectures—capable of answering not just *what is*, but *why*, *where*, and *how*.

References

- Bommasani, R., et al. (2021). On the Opportunities and Risks of Foundation Models. arXiv:2108.07258.
- Cai, L., & Wang, J. (2020). A survey of explainable AI: Interpretability, fairness, and robustness. arXiv:2006.11371.
- Clark, A., & Chalmers, D. (1998). The extended mind. *Analysis*, 58(1), 7–19.
- Fodor, J. A. (1983). *The Modularity of Mind: An Essay on Faculty Psychology.* MIT Press.
- Gardner, H. (1983). *Frames of Mind: The Theory of Multiple Intelligences.* Basic Books.
- Janowicz, K., et al. (2020). GeoAI: Spatially Explicit Artificial Intelligence Techniques. *IJGIS*.
- Kuhn, W. (2003). Semantic reference systems. *IJGIS*, 17(5), 405–409.
- Mai, G., et al. (2022). Toward a theory of spatial information observability. *Transactions in GIS*, 26(2), 867–884.
- Oshan, T. M., et al. (2019). A primer for working with large, open geospatial datasets. *Geographical Analysis*, 51(1), 90–111.
- Rumelhart, D. E., & McClelland, J. L. (1986). *Parallel Distributed Processing: Explorations in the Microstructure of Cognition.* MIT Press.
- Smith, B., & Mark, D. M. (2001). Geographic categories: An ontological investigation. *IJGIS*, 15(7), 591–612.
- Tucker, S. (2024). A systematic review of geospatial location embedding approaches. *arXiv:2401.10279*.
- Tucker, S. (2025a). SIM: Statically Implied Models for Embedding Spatiotemporal Knowledge. *arXiv preprint*.
- Tucker, S. (2025b). STEM – Stabilizing the Stochastic with the Static: A Deterministic Spatiotemporal Embedding Model for Infrastructure-Aware Reasoning. *arXiv preprint*.
- Yan, B., Mai, G., & Janowicz, K. (2021). Vector-based geographic information systems (V-GIS).