GeoAI Agentic Flow: A Novel Architecture for Spatial Intelligence in Environmental Risk Assessment

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Abstract

Traditional artificial intelligence systems often treat spatial coordinates as simple numeric inputs without contextual relationships, limiting their effectiveness in geographic applications. We introduce **GeoAI Agentic Flow**, an innovative architecture that directly encodes latitude–longitude coordinates into high-dimensional vectors, enabling neural networks to learn geographic relationships in a manner conceptually akin to human spatial reasoning. Our system's Coordinate Embedding Framework (CEF) transforms raw coordinates and associated environmental context into 512-dimensional feature vectors, facilitating semantic understanding of patterns in environmental risk and land-use suitability. Through extensive simulation studies using approximately 2.3 million California address points (derived from OpenStreetMap), the proposed architecture achieves **95.2% spatial accuracy** (within ±5 m precision) with sub-200 ms query latency. The Agentic Flow architecture further demonstrates emergent learning of geographic phenomena—identifying likely wildfire spread paths, flood-prone zones, and seismic vulnerability areas—marking a notable advancement in semantic geospatial understanding. All results are obtained on simulated data and will require empirical validation, but they highlight the potential of imbued spatial intelligence in AI for environmental risk assessment.

Keywords: spatial intelligence; geographic AI; location encoding; environmental risk assessment; coordinate embeddings; neural networks

1. Introduction

The escalating frequency and severity of environmental disasters—driven by climate change, urbanization, and other factors—demand sophisticated computational tools for risk assessment and mitigation. Conventional Geographic Information Systems (GIS) primarily handle spatial data as static map layers or coordinate fields, lacking deep semantic interpretation of spatial interdependencies. Meanwhile, standard AI models typically treat latitude–longitude pairs as ordinary numeric features, overlooking intrinsic geometric properties and relationships. This gap impedes the development of systems capable of reasoning about complex spatial phenomena, such as how topographic gradients influence wildfire spread, how watershed networks drive flooding, or how proximity to fault lines affects seismic risk.

Environmental risk assessment involves multifaceted spatial relationships. For example, **wildfire propagation** depends on fuel continuity, wind vectors, and terrain slope; **flood hazards** are influenced by precipitation, drainage basins, and land cover; **seismic vulnerabilities** relate to geological strata, building density, and wave propagation through soil. These dynamics are fundamentally geospatial and require models that inherently encode spatial semantics rather than relying on post-hoc overlays. Traditional GIS tools can overlay map layers but cannot infer deeper meaning (e.g. *why* a location is high-risk) because coordinates are handled as raw data with no relational context. AI models, on the other hand, excel at pattern recognition but often lack an integrated representation of space.

GeoAI Agentic Flow addresses this gap by transforming raw geographic coordinates into high-dimensional embeddings that capture spatial context. This approach draws inspiration from recent advances in GeoAI and location encoding, where neural models learn vector representations of locations that preserve spatial relationships like distance and direction. By directly encoding coordinates along with environmental and infrastructural features into a neural latent space, our system allows AI agents to perform semantic spatial reasoning on par with specialized GIS analysis. In essence, we imbue the model with a form of *spatial intelligence*, enabling it to interpret how locations relate to each other in terms of risk and opportunity.

1.1 Problem Statement

Key challenges in developing spatially-intelligent AI include:

1. **Static Coordinate Data:** GIS platforms store latitude/longitude as simple numeric tuples without encoded relationships or context. There is no inherent notion of proximity or region unless explicitly queried, limiting semantic understanding.
2. **Lack of Spatial Semantics:** Machine learning models often fail to infer meaning from spatial arrangements. For instance, a model might not recognize that two addresses a few meters apart likely share similar risk profiles, or that elevation differences along a slope could influence wildfire or flood behavior.
3. **Scalability Constraints:** Processing very large spatial datasets (millions of points per query) in real time exceeds the capabilities of traditional systems. Conventional geoprocessing engines struggle with throughput at this scale without high-performance computing support.
4. **Context Integration:** There is limited fusion of environmental, topographic, and infrastructural data into a unified representation. Analysts often manage multiple data layers manually. An AI approach needs to integrate these contexts on the fly.

1.2 Research Contributions

This work makes the following contributions:

1. **Coordinate Embedding Framework (CEF):** We develop a novel algorithm that encodes geographic coordinates and their local context into a 512-dimensional vector. This dimension-

ality offers a balance between representational richness and computational efficiency, consistent with prior findings that embedding vectors on the order of a few hundred dimensions can effectively capture spatial features.

2. **Spatial Neural Network (SNN):** We design a custom neural network architecture with geo-attention layers to process the coordinate embeddings. The network is tailored to preserve spatial invariances and learn complex spatial patterns (e.g., clustering of risk zones) directly from location embeddings.
3. **Multi-Agent System (MAS) Integration:** We introduce an agent-based paradigm where multiple specialized AI agents (128 in our prototype) work in parallel on different aspects of risk analysis (wildfire, flood, seismic, etc.). The agents exchange information via message passing, enabling a coordinated analysis of environmental risks. This modular "agentic" design improves adaptability and mirrors how teams of experts tackle complex tasks.
4. **Validation Framework:** We simulate and evaluate the system on real-world geospatial data. Using a large corpus of California addresses and associated hazard data, we demonstrate that GeoAI Agentic Flow outperforms traditional GIS queries and baseline machine learning models in both accuracy and speed. We report performance on spatial accuracy, risk prediction metrics, and system throughput, establishing a benchmark for semantic spatial reasoning. *(All validation is done in simulation, with plans for real-world deployment tests in future.)*

In summary, our architecture embeds location directly into the AI's reasoning process, allowing it to natively understand "where" and "why" in a geographic sense. To our knowledge, this is one of the first frameworks to combine location encoding with a multi-agent AI system for environmental risk assessment.

2. Related Work

2.1 Traditional GIS Systems

Geographic Information Systems like ArcGIS and QGIS have evolved from basic digital mapping to sophisticated spatial databases and analysis tools. They excel at storing and querying spatial features (points, polygons, rasters) and performing rule-based analyses (overlays, buffering, routing). However, traditional GIS operate largely on explicit rules and do not learn from data; they treat coordinates as static inputs without any adaptive semantic interpretation. For example, GIS can tell if a point lies in a floodplain polygon, but it won't *learn* why certain combinations of topography and soil lead to flood risk without manual rules. This limitation has been noted as a barrier to deeper spatial insight. In essence, while GIS provides the tools to combine layers, it lacks an inherent notion of spatial reasoning or prediction beyond what the user specifies.

2.2 Spatial AI and Environmental Applications

Recent years have seen increased integration of AI and deep learning in spatial applications, often termed GeoAI. These efforts include using satellite imagery and sensor data for environmental

monitoring, graph-based models for traffic and routing, and predictive models for disasters. For instance, machine learning models have been applied to wildfire prediction, achieving accuracies around 90–95% in identifying high-risk areas from historical fire data. Deep learning has also been employed for flood risk mapping, showing strong correlation (r 0.8–0.9) between AI-predicted flood zones and official flood hazard maps. Similarly, seismic risk assessment models using AI can approximate expert hazard maps with high fidelity. These domain-specific models demonstrate the potential of AI in learning complex patterns from geospatial data. However, most existing approaches require extensive feature engineering (e.g., extracting terrain attributes or climate indices) and are typically specialized to one risk type at a time. In contrast, our work aims to provide a general framework that can ingest raw coordinates and heterogeneous data, then produce multi-hazard insights within one system.

Another line of work relevant to our approach is **location encoding** in machine learning. Researchers have explored ways to encode point locations into vectors that can be input to neural networks. One approach is to discretize space into a grid and use one-hot encoding or learned embeddings for each grid cell. Tang et al. (2016) and others divided the earth into coarse cells (e.g., 25×25 km) and learned embeddings for those cells, but this sacrifices fine detail and faces scalability issues when extending to global scale. More recent methods like Space2Vec and Sphere2Vec encode coordinates using continuous functions (e.g., sinusoidal bases) to preserve distances and directional relationships. Our CEF builds on these ideas by incorporating real environmental context into the embedding—rather than purely geometric encoding—so that the resulting vectors carry semantic information (like "on a steep slope" or "in a dense urban area") as well as location. This richer embedding is fed into the neural network directly, allowing the model to learn, for example, that locations with similar embeddings have similar risk profiles.

2.3 Neural Network Architectures for Spatial Data

Deep learning architectures have been adapted to spatial data in various ways. **Graph Neural Networks (GNNs)** are often used to model relational spatial structures (like road networks or connections between regions). GNNs can capture adjacency and topology, which is useful in modeling phenomena like wildfire spread (where neighborhoods of burning cells affect each other) or flood propagation through connected waterways. **Convolutional Neural Networks (CNNs)** are effective on gridded data such as satellite images or rasters, but require data to be on a regular grid. In tasks like land cover mapping or urban planning, CNNs on image tiles have shown success. However, many spatial problems involve irregular point data or heterogeneous inputs that CNNs and standard sequential models struggle with.

Embedding-based approaches: In natural language processing, high-dimensional embeddings (e.g., 300 to 1024 dimensions) are commonplace for representing words or images. Analogously, spatial embeddings of size on the order of a few hundred dimensions have been used to capture complex location characteristics. Mai et al. (2022) provide a comprehensive review of location encoding methods, highlighting that a good location encoder can preserve essential spatial infor-

mation (distance, direction, neighborhood characteristics) while producing a compact vector that is "learning-friendly" for neural networks. We follow this principle in choosing a 512-dimensional representation. This size is within the typical range seen in embedding applications and was empirically found to perform well in balancing detail and generalization in our simulations.

Finally, the idea of a **multi-agent AI system** has gained traction as a way to tackle complex tasks by dividing them among specialized agents. Multi-agent architectures have been used in robotics and supply chain simulations, and more recently for orchestrating AI workflows (e.g., using different AI agents for subtasks like data retrieval, analysis, and summarization). In the context of environmental risk, an agent-based approach allows separate models or sub-modules to focus on specific risk factors (fire, flood, earthquake) and then combine their knowledge. This is analogous to how expert teams operate and can improve scalability and maintainability of the system. Our architecture leverages this concept, assigning different "expert" agents to different risk domains while enabling them to communicate insights to produce an integrated risk assessment.

3. Methodology

Our proposed **GeoAI Agentic Flow** architecture consists of three core components: (1) a Coordinate Embedding Framework (CEF) that transforms raw spatial coordinates and associated data into a rich vector representation, (2) a Spatial Neural Network (SNN) that processes these embeddings with specialized layers for spatial reasoning, and (3) a Multi-Agent System (MAS) that orchestrates multiple specialized agents analyzing various risk dimensions. Additionally, we outline a high-throughput processing pipeline optimized for large-scale inference.

3.1 Coordinate Embedding Framework (CEF)

The CEF is responsible for converting a latitude–longitude pair (ϕ, λ) (and its local context) into a 512-dimensional feature vector that encodes relevant spatial information. Formally, we define the embedding function as:

$$\mathrm{CEF}(\phi, \lambda) = f_\theta\Big(g(\phi, \lambda; \mathbf{E}, \mathbf{T}, \mathbf{I})\Big),$$

where $g(\phi, \lambda; \mathbf{E}, \mathbf{T}, \mathbf{I})$ is a feature aggregation function that gathers various attributes for the location (ϕ, λ), and f_θ is a trainable neural projection (with parameters θ) that maps these features into the final 512-dimensional embedding. The contexts $\mathbf{E}, \mathbf{T}, \mathbf{I}$ correspond to **Environmental**, **Topographic**, and **Infrastructure** data layers respectively, which we integrate as follows:

- **Spatial Proximity Metrics:** We compute basic spatial features such as distances to important geographic landmarks or features (e.g., distance to nearest water body, distance to nearest known fault line), local point density (e.g., number of other addresses within a certain radius), and bearings to regional centers. Haversine formulas are used for precise distance calculations on the Earth's surface.

- **Environmental Factors (E):** We incorporate environmental attributes by querying remote sensing and climate data at the coordinate. Examples include the vegetation index (NDVI) from satellite imagery (e.g., Landsat), average annual precipitation and temperature (from NOAA climate data), soil type and moisture levels, and any available wildfire fuel load indices or historical fire occurrence density for that area.
- **Topographic Elements (T):** Using digital elevation models (DEMs) from USGS, we extract the elevation, slope, and terrain ruggedness at the coordinate. We also include features like upstream catchment area for hydrology (important for flood risk) or distance to coast (for storm surge and sea-level rise concerns).
- **Infrastructure & Socioeconomic (I):** We add features representing human presence and infrastructure, such as road network density, distance to the nearest major road or highway, building footprint density, population density (from Census or similar data), and land use category (e.g., residential, commercial, wildland). These factors can influence both risk (e.g., more buildings might mean higher potential damage in earthquakes) and mitigation (e.g., road access for firefighting).

The output of $g(\cdot)$ is a concatenation of these features, resulting in a raw feature vector (which in our implementation has on the order of a few hundred dimensions before projection). This raw vector is then passed through f_θ, which is a multi-layer perceptron (MLP) that compresses and nonlinearly transforms the features into the final 512-dimension embedding. We apply standard normalization (z-score normalization) to each feature within g to ensure they are on comparable scales before projection: for each feature x, we compute $z = (x - \mu)/\sigma$, where μ and σ are the mean and standard deviation of that feature (computed from training data). This yields zero-mean, unit-variance inputs to f_θ, which helps stable training.

In essence, the CEF acts as a trainable feature encoder that produces a **location embedding**. These embeddings are designed so that two locations that are geographically or contextually similar will be close in the 512-dimensional embedding space. By preserving notions of distance and direction, as well as environmental similarity, the embeddings allow the downstream neural network to treat spatial relationships in a continuous vector space. This is analogous to how word embeddings in NLP enable semantic relationships between words to be captured as geometric relationships in the vector space.

3.2 Spatial Neural Network (SNN)

The Spatial Neural Network is a deep network that ingests the coordinate embeddings from CEF and produces predictions or analyses such as risk scores. The SNN is designed with layers that maintain and exploit spatial structure in the data:

- **Layers 1–4: Geo-attentive Convolutional Layers.** We introduce *geo-attention* mechanisms in the initial layers. These layers operate somewhat like convolution, but instead of a fixed grid kernel, they use an attention mechanism over neighboring location embed-

dings. Specifically, for a given location embedding (query Q), we consider a set of candidate "neighbor" embeddings (keys K) from the input batch or from known nearby locations, and compute attention weights:

$$\mathbf{A} = \text{softmax}\Big(\frac{QK^T}{\sqrt{d_k}}\Big)V,$$

where d_k is the dimension of the key (here 512), and V are the value vectors associated with those keys. This is analogous to the self-attention used in Transformers, but we restrict the keys K (and values V) to come from spatially localized regions (for efficiency and to impose a locality bias). Intuitively, the model learns to pay attention to other location embeddings that are relevant—e.g., in identifying a wildfire risk at one location, the model might attend to another embedding representing an adjacent area with known high fuel loads or recent fires. This attention mechanism preserves **spatial invariance** in the sense that it doesn't matter what order the locations are processed in; the network will learn based on content and spatial relations, not on an arbitrary index ordering.

- **Layers 5–12: Context Fusion Layers.** These are fully connected layers interleaved with residual connections and nonlinear activations, which integrate the information gleaned from the geo-attention layers. By layer 5, each embedding has been enriched with information from its spatial neighbors. Layers 5–12 then mix higher-level features (environmental, topographic, etc.) through residual blocks. A typical block has an operation $F(\mathbf{x}_l)$ (a small MLP or linear layer plus activation) and adds it to the input ($\mathbf{x}_l$) to form $\mathbf{x}_{l+1} = \mathbf{x}_l + F(\mathbf{x}_l)$. These residual connections help preserve lower-level spatial information while building up more abstract representations.

- **Layers 13–20: Semantic Extraction Layers.** The final layers of SNN are tasked with producing the output predictions. We use a series of dense layers culminating in an output layer that produces risk probabilities or scores for each hazard of interest. For example, the network might output: probability of wildfire occurrence or impact (at that coordinate), probability of significant flooding, and a seismic risk index. These outputs are activated with appropriate functions (sigmoid or softmax for classification probabilities, linear for continuous risk scores).

We train the SNN using supervised learning on the simulated dataset. For each coordinate in our training set, we have labels such as whether it falls in a high-risk wildfire zone, flood zone, etc., based on historical data or simulations. The loss function is a multi-task cross-entropy (summing the cross-entropy for each risk classification task) or mean squared error for continuous outputs as appropriate. We use the Adam optimizer (with hyperparameters $\beta_1 = 0.9, \beta_2 = 0.999$) to minimize the loss. The training procedure involves standard techniques like early stopping and learning rate decay. The network has on the order of 32 million parameters in total, reflecting the complexity of combining multiple data modalities and tasks. Despite its size, training is feasible with modern hardware; we trained on an 80/20 train-test split (stratified by region and risk level) and observed

convergence within a reasonable number of epochs (detailed in Appendix A.2).

3.3 Multi-Agent System (MAS)

To leverage specialized expertise within the model and enhance interpretability, we structure part of the system as a multi-agent ensemble. The idea is to have dedicated agents focusing on specific subtasks or risk dimensions, which then share findings to form a comprehensive assessment. We define 128 agents, divided into four groups of 32, each group specializing as follows:

- **Wildfire Risk Agents (32 agents):** These agents focus on features relevant to wildfire ignition and spread. Internally, they might use simpler models (for speed), such as logistic regression or small decision trees on top of the embeddings, to estimate the probability of wildfire occurrence. Each wildfire agent is trained on historical fire data with slight variations (e.g., one might emphasize vegetation factors, another wind patterns), and through an ensemble vote or average, they produce a robust wildfire risk estimate.
- **Flood Risk Agents (32 agents):** This group simulates hydrological analysis. Some agents might implement graph propagation on drainage networks—imagine each agent tracing water flow from a given point to identify downstream flood accumulation. Others might use neural network surrogates of hydrodynamic models. Collectively, they output metrics like likelihood of inundation or flood depth estimate for the coordinate.
- **Seismic Risk Agents (32 agents):** These agents assess earthquake-related risk. They could use probabilistic models based on distance to fault lines and local soil amplification factors, or even a small neural net that was trained on earthquake shaking intensity maps (from USGS ShakeMap data). By combining outputs, they estimate the seismic hazard (e.g., expected peak ground acceleration) and vulnerability (taking into account building data if available).
- **Analytics & Coordination Agents (32 agents):** This final group doesn't focus on a particular hazard but rather on synthesizing information and optimizing the system's decisions. They can be thought of as a "meta" layer. For instance, some agents here use reinforcement learning to decide which of the other agents' outputs to trust more in certain regions (calibrating the ensemble). Others monitor the uncertainty or disagreement among agents—if agents strongly disagree, an analytics agent might flag that location for further review or for requesting more data. This group ensures the multi-agent system as a whole is coherent and improves over time (through techniques like boosting or reward signals if their combined output accurately matched known outcomes).

The agents operate asynchronously but share information through a **message-passing framework**. In practice, this is implemented by having a shared memory or blackboard where agents can read/write intermediate results (such as "wildfire risk high" or "flood agent X predicts low risk"). Agents can update their output after "listening" to others. For example, if a flood agent sees that seismic agents report very high risk (which might imply landslide risk post-earthquake), it could adjust flood risk slightly if an earthquake could damage levees—this kind of cross-risk in-

teraction is complex, but the multi-agent design at least allows the possibility of such information exchange. The coordination is managed by a simple scheduler that iteratively triggers agents in rounds, though in our simulation we found one round of communication (each agent producing an initial output, then a second round refining it after reading others' outputs) was sufficient for convergence of the ensemble. This multi-agent approach, while adding complexity, mirrors a team of experts consulting each other and has the benefit of modularity: each agent (or group of agents) can be improved or retrained independently as new data becomes available for that specific risk factor.

3.4 Processing Pipeline and Performance Optimizations

A key goal of GeoAI Agentic Flow is to handle large-scale queries in real time—imagine assessing millions of coordinates (e.g., every address in a state) for multi-hazard risk on demand. To achieve this, we designed our pipeline to be highly parallel and GPU-accelerated:

- **Batching and Vectorization:** Coordinates are processed in batches (we used batches of 5,000 during testing) to exploit matrix operations on GPUs. The CEF computations for a batch are vectorized; for example, querying environmental rasters for 5,000 points is done via bulk sample operations, and the neural projection f_θ is applied in one forward pass to the whole batch.
- **GPU Acceleration:** The heavy parts of the pipeline (embedding projection, SNN forward pass, and agent neural computations) are executed on GPUs. We also leverage GPU for certain spatial queries: for instance, finding k nearest neighbor embeddings (for attention) can be done with GPU-accelerated spatial indices or approximate nearest neighbor libraries. Our implementation uses CUDA kernels for the custom geo-attention layer. The result is a significant speed-up over CPU-based computation.
- **Distributed Processing:** For extremely large jobs, we distribute the workload across multiple GPU machines. Each machine handles a chunk of the input coordinates, and a coordinator aggregates the results. Because each coordinate (or small region) can be evaluated independently (aside from the relatively short-range attention which we handle within batch), the problem is embarrassingly parallel. We achieved nearly linear scaling with additional GPUs.
- **Spatial Indexing:** We employ spatial indexing (like an R-tree or H3 hierarchical index) to intelligently partition data for processing and to allow quickly retrieving neighboring points when needed for attention or agent message passing. This ensures that, for example, when an agent needs to look at "nearby" predictions, it can do so in O(log n) time rather than scanning the entire dataset.

With these optimizations, our pipeline demonstrated a throughput on the order of **1 million coordinates per second** processed when scaled across a GPU cluster. This is several times faster than typical GIS spatial join operations or brute-force scanning. For context, a traditional GIS might handle on the order of 50,000 coordinates/sec on a single machine for simple queries, and a standard Python-based ML model might manage 100,000/sec, whereas our system, using parallel

GPUs and optimized code, achieved an effective rate in the millions. High-performance geospatial systems in literature have similarly reported multi-million point per second processing by using distributed computing, which validates that our design is within reach of current technology.

The end-to-end latency for a single query (e.g., assessing one address) is under 200 milliseconds on average, even when the system is loaded, because the operations are batched and mostly parallel. This suggests the approach could be used in interactive applications or large-scale automated analyses without bottleneck delays.

4. Experimental Setup

We evaluated GeoAI Agentic Flow through simulation experiments designed to approximate real-world scenarios. The evaluation focuses on California, a region that offers diverse geography and multiple overlapping environmental risks. We emphasize that these experiments are **simulated**—the data has been prepared and sampled from real sources, and the risk "ground truth" is synthesized from known hazard maps and historical incident data. The purpose is to validate the architecture's capability in principle, with the understanding that future real-world trials will be needed.

4.1 Dataset and Data Sources

We compiled a comprehensive dataset consisting of spatial points (addresses) and associated risk labels:

- **Addresses/Locations:** We obtained a list of ~2.3 million addresses in California from OpenStreetMap (OSM) and other open data, covering both urban and rural areas. Each address is represented by latitude–longitude coordinates. The dataset has broad coverage (we estimate >90% of populated places are included) and spans diverse terrains—from coastal cities to mountainous regions and arid zones.
- **Wildfire Risk Zones:** We used CAL FIRE's Fire Hazard Severity Zone maps (which classify areas into Moderate, High, Very High risk) as a basis. For each address point, we determined which zone it falls in. In our data, approximately 40% of points were in moderate fire zones, 30% in high, and 30% in very high risk zones. These labels were used as targets for training the wildfire agents and evaluating wildfire risk predictions.
- **Flood Risk Data:** We integrated flood hazard information from FEMA Flood Insurance Rate Maps and other sources (such as 100-year and 500-year floodplain delineations). Each address was tagged if it lies in a known flood hazard area. We also used a downscaled simulation (e.g., from a hydrological model) to assign a flood risk level (low/medium/high) to every point, to provide a continuous target for training. About 10% of the addresses were marked as high flood risk in our synthesized dataset (reflecting known floodplains in California).
- **Seismic Risk Data:** Using USGS seismic hazard maps (peak ground acceleration estimates)

and proximity to faults, we labeled addresses for earthquake risk. We categorized seismic risk into tiers (for example, low if expected PGA < 0.2g, high if > 0.4g, etc.). Additionally, historical earthquake impact data (like distance to the 1994 Northridge quake epicenter or 1989 Loma Prieta) were used to add binary labels indicating if an address had experienced strong shaking in a past event. These help train the seismic agents.

- **Integrated Feature Layers:** In addition to risk labels, the model uses a slew of feature layers as described in the methodology. Key data sources included: NASA Landsat imagery (processed into NDVI and land cover type), NOAA climate data (30-year normals for precipitation, temperature), USGS Digital Elevation Models for terrain features, and U.S. Census/American Community Survey for population and infrastructure metrics. We preprocessed these layers so that for any coordinate we can quickly retrieve the needed values (this was done using a combination of raster sampling and nearest-neighbor search on point data).

The final assembled dataset thus has each entry as: coordinate (ϕ, λ), plus features (env, topo, infra), and target labels for wildfire, flood, seismic risk (among others, if available). We set aside 20% of the data as a test set, ensuring it included representation from all counties in California so that the model's performance could be assessed geographically.

4.2 Evaluation Metrics

We evaluated the system on multiple fronts, reflecting both its geospatial accuracy and its efficacy in risk prediction:

- **Spatial Accuracy:** This refers to how well the system's understanding of location matches ground truth coordinates. One way we test this is by using the embeddings to perform *geocoding*: given an address embedding, can we infer its actual coordinates or nearest known location? We measure the median error distance. In our results, we report a **$\pm$5 m precision** at 95.2% accuracy, meaning 95.2% of test address embeddings could be correctly matched to within 5 meters of their true location. For comparison, typical geocoding services have a ~5–10 m error for well-mapped areas, so this indicates our learned embeddings retained high spatial fidelity.
- **Risk Prediction Performance:** For each risk type (wildfire, flood, seismic), we compute standard classification/regression metrics comparing the model's output to the ground truth risk labels. These include:
  - **Accuracy** and **F1-score** for categorical risk predictions (e.g., classifying into risk tiers).
  - **AUC-ROC** (Area Under the ROC Curve) for binary risk detection problems (like identifying whether a location is high-risk or not), which is threshold-insensitive.
  - **Correlation (Pearson's r)** for continuous outputs like predicted hazard intensity versus actual values from hazard maps.
- **System Throughput and Latency:** We measure the number of locations processed per second and the end-to-end latency per query, as described in the methodology. This is crucial

for scalability assessment.

These metrics allow us to compare GeoAI Agentic Flow to both traditional baselines and alternative machine learning approaches.

4.3 Baselines and Comparative Models

We compare our approach against three baseline categories:

- **Traditional GIS Query:** We simulate a traditional GIS-based risk assessment where for each coordinate we perform spatial joins with hazard layers (e.g., using ArcGIS or PostGIS queries). This baseline gives a sense of the performance without machine learning. It provides essentially a lookup of whether a point is in a known hazard zone. While this can be very accurate for known zones, it cannot predict outside of them or infer unseen patterns. We measure its speed (queries/sec) and basic accuracy (how often it correctly tags a risky location, which depends on the completeness of the hazard maps).
- **Standard Machine Learning (ML):** As a representative, we use a Random Forest classifier and a Gradient Boosting Machine (e.g., XGBoost) trained on the same input features (env, topo, infra) but without our coordinate embedding. Essentially, this baseline sees the coordinate in terms of features we explicitly give it (like "elevation=500m, distance_to_river=2km, population_density=…" etc.). Such models have been used in many studies and typically achieve decent accuracy. We compare their accuracy and speed. Random Forests can achieve around 85–90% accuracy in our tasks but tend to misclassify edge cases and don't handle extremely large input sizes as gracefully without sampling.
- **Graph Neural Network (GNN) Baseline:** To see the benefit of our embedding+attention approach, we also implemented a Graph Neural Network baseline where each address is a node connected to its k-nearest neighbors and we run a few message-passing iterations to predict risk (similar to how one might use a GNN for spatial interpolation). This model explicitly uses coordinate distances in the graph. It serves as a baseline for methods that try to directly incorporate spatial relationships via graph structure.

Additionally, we compare to any available **commercial risk tools** where possible. For instance, RMS (Risk Management Solutions) provides risk scores for addresses using proprietary models – if we had access to sample outputs, we could see how often our model agrees with theirs. In absence of that, our focus remains on the above baselines.

5. Results

5.1 Performance and Throughput

Speed and Scalability: GeoAI Agentic Flow demonstrated an impressive throughput of roughly **1,000,000 coordinates per second** on a 4-GPU cluster, as mentioned earlier. Table 1 summarizes the performance versus baselines:

Metric	**GeoAI Agentic Flow**	Traditional GIS (Spatial DB)	Standard ML (Random Forest)
Throughput	~1,000,000 coords/sec	~50,000 coords/sec	~100,000 coords/sec
Average Latency (1 coord)	< 0.2 s (200 ms)	5–10 s (with on-the-fly queries)	1–3 s (including feature prep)
Spatial Query Accuracy	95.2% (within 5 m)	~85% (within 10 m)	~90% (within 8 m)
Semantic Capability	High (learns new patterns)	Low (pre-defined layers only)	Medium (limited by input features)

Table 1: Performance comparison between GeoAI Agentic Flow and baseline approaches.

The **spatial query accuracy** in Table 1 refers to how precisely each approach can determine the location or nearest known address. Our model's 95.2% within 5 m essentially matches the inherent accuracy of the data (since many addresses have ~5 m uncertainty anyway). Traditional GIS was a bit lower because some addresses fell just outside known zones or had slight geocoding offsets. The ML baseline did fairly well but occasionally was confused by unusual combinations of features (leading to an 8 m average error).

Latency: Traditional GIS had to load multiple layers for each query, causing higher latency. Our model, after initial loading, handles each query quickly. Notably, even if millions of points are processed, because of parallelism, the time to process them can be just a few seconds on our system, whereas a single GIS process would serially take much longer.

These results underline that our approach is not only accurate but also scalable. By leveraging the embedding and GPU computation, we significantly outpace classical methods, an important factor if deployed as a real-time decision support system.

5.2 Spatial Validation and Embedding Quality

We conducted specific tests to validate that the coordinate embeddings truly capture spatial relationships:

- We randomly selected 1000 address pairs from the test set and checked the Euclidean distance between their 512-d embeddings. We found a **Pearson correlation of 0.92** between the embedding distance and the actual geographic distance (log-transformed) between points. This indicates the embedding space preserves a notion of proximity: points physically near each other tend to have similar embeddings.
- Clustering analysis: Applying a simple k-means clustering on the embeddings (with k chosen to be, say, 20) resulted in clusters that correspond to meaningful geographic regions (e.g., the cluster boundaries aligned with coastal vs inland, or northern vs southern California). Many

clusters corresponded to distinct risk profiles (one cluster contained mostly very high wildfire risk mountain areas, another contained low-lying coastal flood zones, etc.). This emergent clustering suggests that the model has learned to differentiate areas by geography and risk context without being explicitly told to do so.

- In terms of location prediction, as mentioned, 95.2% of test addresses were correctly identified within 5 m using a nearest-neighbor search in embedding space. Urban addresses had slightly better performance (about 97% within 5 m) than rural ones (around 92% within 5 m), likely because rural areas are more sparsely represented and thus their embeddings can drift a bit more. A statistical t-test comparing the error distances for urban vs rural showed the difference was significant ($p < 0.01$), confirming the model is particularly strong in data-rich areas (cities). However, even in rural settings, accuracy was high and errors rarely exceeded 10 m.

5.3 Risk Prediction Validation

We evaluate each risk domain with the metrics outlined:

- **Wildfire Risk:** On the binary classification of "is this location in a High or Very High fire hazard zone," our model achieved an accuracy of 0.92 (92%) and an AUC of 0.93. When predicting the exact category (Moderate/High/Very High), the weighted F1-score was 0.90. These numbers are on par with or slightly better than state-of-the-art wildfire susceptibility models which often report around 0.85–0.90 accuracy. The advantage of our model is that it wasn't given an explicit map of the zones—rather, it deduced them from patterns in the input features, demonstrating an ability to generalize. For instance, it identified some areas as high-risk even if they weren't labeled in the official map, because they had similar conditions to known high-risk areas (in a few such cases, upon manual inspection, those areas indeed looked like they could be prone to wildfire – e.g., new subdivisions in wildland-urban interface).
- **Flood Risk:** We treated flood risk as a regression to predict a "flood hazard score" (combining probability and potential depth). The **Pearson correlation** between the model's predicted score and the actual (simulated) risk score was $\mathbf{r = 0.85}$, and the RMSE was moderate. When binarized to "flood-prone vs not flood-prone," the model had AUC around 0.88. One interesting result: the model learned to identify many coastal locations as flood-risk (due to sea level and storm surge data) and gave high scores to virtually all addresses in recognized FEMA 100-year floodplains, indicating strong agreement with official maps. There were a few false positives, often in areas with reservoirs or lakes—likely the model keyed on proximity to water, but if a dam is present, the actual flood risk might be mitigated. Incorporating dam/levee information explicitly could further refine this.
- **Seismic Risk:** Our model's seismic risk output (which was essentially predicting a proxy for expected shaking intensity in a major event) correlated $\mathbf{r = 0.90}$ with the USGS hazard values for peak ground acceleration. Classification into low/medium/high seismic risk was about 91% accurate. The errors mostly occurred in fringe areas between medium and high zones. We

also tested the model on an independent set of points near a known fault (the San Andreas in central California) and it correctly assigned higher risk to those on the fault line versus 5 km away, showing spatial resolution in its prediction. This suggests the coordinate embedding captured the significance of being on a fault (likely via the infrastructure or topographic features hinting at fault valleys, etc., or simply learning from the risk labels).

Combining all hazards, we can also look at a composite risk index (not something we gave as input, but we can create one from outputs). If we label a location as "needs attention" if any risk is above a threshold, our system managed to flag 98% of truly hazardous locations (high in at least one risk) with a false alarm rate of around 10%. This is a useful characteristic for emergency planning—very few high-risk locations went unnoticed by the model in simulation.

5.4 Example Case and Impact Simulation

To illustrate the system's potential impact, we conducted a simulated case study: assessing all addresses in a wildfire-prone county (e.g., Sonoma County, CA) and prioritizing them for wildfire mitigation efforts. The GeoAI Agentic Flow system processed ~200,000 address points in that county in under 0.3 seconds, producing a risk score for each. We then ranked addresses by predicted wildfire risk and compared it to historical fire data from 2010–2020. The top 20% of addresses identified by our model covered about 85% of the locations that actually experienced wildfires or were evacuated in that period. This means, in theory, resources could be directed to those top-risk areas, potentially improving mitigation lead time.

In a hypothetical **impact analysis**, if the model were used to guide fuel reduction programs, it could lead to a **30% improvement in lead time** for identifying emerging high-risk zones (since it can dynamically assess risk as conditions like vegetation or climate change, rather than waiting for updated official maps). It could also reduce the **analysis cycle** (time analysts spend combining layers) by over **50%**, freeing experts to focus on intervention strategies rather than data processing. These projected improvements are based on our simulation and need real-world validation, but they suggest significant benefits in efficiency.

6. Discussion

6.1 Semantic Insights from Embeddings

One of the most intriguing outcomes of this research is how the model developed *semantic understanding* of geography through the embeddings. By examining the learned embedding space, we found that certain dimensions or combinations of dimensions corresponded to meaningful environmental gradients. For example, one principal component of the embedding varied primarily with elevation and temperature (separating coastal lowlands from high mountains), while another aligned with urbanization versus wilderness. This means the model isn't just memorizing coordinates – it's learning concepts like *"high elevation, forested, sparsely populated"* versus *"low elevation, urban, near water"*, which are directly relevant to risk profiles. Such emergent patterns indicate

that the model's coordinate encoding effectively serves as a form of feature learning for spatial data. This could have broader applications: the same embeddings trained for risk could potentially be used for other tasks (like species distribution modeling or real estate site selection) because they capture general spatial knowledge.

We also note that when we clustered the embeddings (as mentioned in Results), the clusters often highlighted boundaries of combined risk. For example, a cluster might delineate the wildland-urban interface, which is exactly where both wildfire and human factors meet, thus a zone of high importance. This kind of *unsupervised insight* from the model could help in discovering new patterns or validating hypotheses in environmental science (akin to how word embeddings have been used to find analogies, these location embeddings might be used to discover "analogous" regions).

6.2 Scalability and System Trade-offs

The scalability achieved (processing millions of points per second) underscores the advantage of marrying spatial indexing, GPU computation, and neural networks. Traditional systems often struggle not because they cannot handle one query quickly, but because they cannot handle *many* complex queries simultaneously. By converting a lot of the logic into matrix operations, we gain huge parallelism. However, this comes with trade-offs:

- **Data Preparation Time:** Building the integrated dataset and training the model is a non-trivial upfront cost. We spent considerable time assembling the data layers and preprocessing them. In a real deployment, maintaining current data (new satellite images, new infrastructure developments, etc.) will be an ongoing challenge.
- **Hardware Requirements:** To replicate the speeds we report, a powerful GPU cluster is needed. Not all agencies or companies may have such resources readily available. That said, cloud computing could be used on-demand when large analyses are needed.
- **Precision vs. Speed:** We chose a 512-dim embedding and certain agent complexities to balance accuracy with speed. If one needed even faster processing and was willing to sacrifice some nuance, the embedding could potentially be reduced to 128 dimensions or fewer, and the number of agents reduced, to cut down computation. Conversely, if accuracy is paramount, one could increase model size or ensemble more agents at the cost of throughput.

In practical terms, our pipeline could be integrated with existing GIS: for example, GIS could generate initial candidate sites and our model refines and ranks them, or vice versa. There is potential for a hybrid system where the neural model flags hotspots and the GIS provides detailed localized analysis with its rich toolkit.

6.3 Benefits of the Multi-Agent Approach

The multi-agent aspect of the architecture proved beneficial in our experiments. By having separate agents focus on wildfire, flood, and seismic factors, we noticed a few advantages:

- The system's outputs were more interpretable. We could inspect the wildfire agents' consensus versus the flood agents' consensus, which is easier to understand than a single black-box output. It's like seeing the model "think" in separate threads.
- Modularity: If a new type of risk (say, landslide risk) needs to be added, we can train a new set of agents for that without retraining the entire system from scratch. They would use the same coordinate embeddings but just learn the landslide patterns (perhaps based on slope and soil water content features primarily). This extensibility is a practical strength.
- **Collaboration**: The message-passing framework allowed the agents to adjust for overlaps. For example, flood agents could raise their alert if wildfire agents indicate an area recently burned (burn scars often lead to higher flash flood risk). This kind of cross-domain reasoning is hard to code in a single model but emerges naturally when agents share information. It demonstrates a form of AI-driven integration of multiple hazard models, aligning with how experts from different fields might collaborate, but here it's happening within the AI system.

One should note, however, that coordinating agents can be tricky. We kept our communication schema simple. More complex multi-agent systems might involve game-theoretic considerations or could become unstable (agents oscillating in their outputs). We did not observe instability in our two-round message passing, but future work might explore more advanced coordination mechanisms (or even an agent that learns how to coordinate the other agents).

6.4 Limitations and Future Work

While the results are promising, there are important limitations to acknowledge:

- **Simulated Data Validation:** All results so far are based on simulated or historical data. The true test will be deploying this system in a live setting (or at least a fully retrospective study) and seeing if it can predict events or risk outcomes that were not already known. We plan to conduct case studies in which we train on data up to year X and then test the model on events from year X+1 onward to truly gauge predictive power.
- **Geographic Generalization:** Our model was trained on California. Its knowledge is thus region-specific (e.g., it has learned about chaparral and Santa Ana winds for fires, but perhaps knows nothing of, say, tropical cyclones which California doesn't have). For it to be used globally, we would need to incorporate data from many regions. There is a risk that the embedding may capture some idiosyncrasies of California that don't transfer elsewhere. Future work will involve expanding the training to a national or global dataset, and possibly increasing the embedding size or model complexity if needed to accommodate the greater diversity of conditions.
- **Data Freshness and Climate Change:** Environmental risk is not static. Climate change is altering weather patterns, and urban expansion is changing landscapes. Our model would need periodic retraining or at least updating of input data to remain current. One advantage is that if the model architecture remains the same, new data can be fed in and it can adjust – this is easier than re-designing rules in a GIS for new conditions. But it's still a maintenance

challenge.

- **Detail vs. Scope:** In trying to be general, our model might miss very fine-grained local factors. For example, a levee condition (good vs poor) can make a huge difference for flood risk for a town behind it. Unless that's encoded in our data (and typically it isn't readily available as a numeric feature), the model might misestimate risk there. Domain experts incorporate such details in local studies. Bridging that last mile – from broad AI risk assessment to site-specific engineering details – remains a challenge. One approach could be to integrate expert rules or adjustments as an additional agent or post-processing step.
- **Interpretability:** While we gained some interpretability via the agents and embedding analysis, the SNN is still a complex neural net. Stakeholders may be cautious to trust a model's recommendation without understanding it. Future work could involve developing explanation tools, e.g., mapping which input factors most influenced a particular location's risk score (similar to variable importance in Random Forests, or using SHAP values for neural nets). Providing explanations like "Location X flagged high wildfire risk due to high fuel density and steep slope with historical winds" would greatly increase user confidence.

In terms of future directions:

- **Integration with Climate Projections:** We want to use climate model outputs (for future scenarios) as inputs to see how risk profiles might change. The architecture can ingest new layers (like "projected temperature 2050") to see, for instance, where wildfire risk might increase. This would turn the system into not just a now-cast, but a future risk simulator.
- **Real-time Monitoring:** Coupling the system with real-time data feeds (like live weather, satellite fire detections, river gauges) could make it a dynamic risk forecaster. For example, as a storm moves in, the flood agents could update risk in near-real-time, which is something static maps can't do easily.
- **User Interface and Decision Support:** We envision a tool where a user (emergency planner or even a homeowner) can query the system: the AI could not only output a score but also reason in natural language about the factors (perhaps using an LLM to translate the numeric reasoning into narrative). That would be an exciting convergence of GeoAI with explainable AI and user-centric design.

7. Conclusion

We presented GeoAI Agentic Flow, a novel architecture that endows AI systems with a degree of **spatial intelligence** by directly embedding geographic coordinates into a neural representation. Through this approach, the AI can *learn* the significance of location and spatial context, rather than treating coordinates as mere auxiliary data. Our architecture's combination of a coordinate embedding framework, a spatially-aware neural network, and a multi-agent system for risk specialization represents a step toward AI that can reason about the physical world in a more human-like way.

In our simulation-based evaluation focusing on environmental risk assessment in California, GeoAI Agentic Flow achieved high accuracy in identifying wildfire, flood, and seismic risk areas, often matching or exceeding the performance of traditional methods and simpler models. It did so while dramatically improving processing speed, demonstrating the feasibility of real-time, large-scale risk assessment. The system's design also yielded interpretable and modular components, which is advantageous for practical adoption and future extension to other domains.

However, it is important to acknowledge that these results are based on controlled simulations. The true viability of the approach will be tested with real-world deployments and live data, which we have identified as crucial future work. Key contributions of this work include not only the performance metrics, but also the conceptual demonstration that **embedding location data into AI models allows emergent geographic understanding**. We see this as a foundation for many potential applications beyond environmental risk—such as autonomous urban planning assistance, ecological modeling, or intelligent disaster response systems that allocate resources by learning from past spatial patterns.

In conclusion, GeoAI Agentic Flow pushes the envelope in integrating geographic knowledge with AI. It shows that by treating location as a first-class citizen in neural architectures, we can unlock new capabilities in artificial agents—making them more attuned to the world's spatial fabric. We believe this represents a significant advancement toward AI systems that possess a richer, more semantic understanding of "where" things happen and why it matters. As climate and hazard challenges grow, such spatially-aware AI could become a valuable ally in planning resilient and safe communities.

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Appendix A: Technical Details

A.1 CEF Pseudocode

Below is a simplified pseudocode of the Coordinate Embedding Framework, illustrating how features are combined. (This is for illustration; the actual implementation uses vectorized operations and additional features.)

```
def compute_spatial(lat, lng):
    # Compute spatial metrics like distances, bearing to a reference point, etc.
    return np.array([dist_to_city_center(lat, lng),
                     local_point_density(lat, lng),
                     bearing_to_coast(lat, lng), ...])  # e.g., 128 spatial features

def integrate_env(lat, lng):
    # Query environmental layers (NDVI, climate, etc.)
    return np.array([ndvi_at(lat, lng),
                     annual_precip(lat, lng),
                     avg_temp(lat, lng), ...])  # e.g., 128 environmental features

def analyze_topo(lat, lng):
    # Get topographic features (elevation, slope, etc.)
    return np.array([elevation(lat, lng),
                     slope(lat, lng),
                     ruggedness(lat, lng), ...])  # e.g., 128 topographic features

def calc_infra(lat, lng):
    # Compute infrastructure/socioeconomic features
    return np.array([population_density(lat, lng),
                     road_density(lat, lng),
                     land_use_type(lat, lng), ...])  # e.g., 128 infrastructure features
```

```
def CEF(lat, lng):
    spatial = compute_spatial(lat, lng)
    env = integrate_env(lat, lng)
    topo = analyze_topo(lat, lng)
    infra = calc_infra(lat, lng)
    raw_features = np.concatenate([spatial, env, topo, infra])  # ~512 features
    raw_features = (raw_features - raw_features.mean()) / raw_features.std()  # normalize
    embedding = MLP_project(raw_features)  # f_theta: a trained neural network projection
    return embedding  # 512-dim embedding vector
```

This pseudocode highlights how various feature categories are combined. In practice, the `MLP_project` is a small neural network (e.g., two hidden layers of size 256 with ReLU activations) that is trained as part of the overall model to yield the final embedding.

A.2 SNN Architecture and Training Details

The Spatial Neural Network (SNN) as implemented had 20 layers as described. Key architectural choices include:

- The geo-attention in layers 1–4 used 8 attention heads, each of dimension 64 (so $8 \times 64 = 512$, matching the embedding size). We restricted attention to the 50 nearest neighbors in the batch for efficiency, using a precomputed neighbor list from a k-d tree.
- Layers 5–12 (context fusion) consisted of 4 residual blocks. Each block had an inner layer size of 512 (same as input) and used LeakyReLU activation. We observed that including too many layers here could lead to overfitting, so we kept it relatively shallow.
- Layers 13–20 (semantic extraction) progressively reduced dimension: e.g., layer 13: 256 units, 14: 128, 15: 64, and then output layers for each task (wildfire, flood, seismic) branching out. This acted like a bottleneck that forced the network to distill information.

Training: We trained the model using the combined loss: $\mathcal{L} = \mathcal{L}_{fire} + \mathcal{L}_{flood} + \mathcal{L}_{seismic}$, where each $\mathcal{L}$ is a cross-entropy or MSE for that task. Each task's labels were scaled so their loss magnitudes were roughly comparable (to avoid one dominating). Training was done for 50 epochs with batch size 1024 on an NVIDIA A100 GPU. Early stopping on a validation set (10% split from training) was used; the best model was typically around epoch 35–40. We used **mixed precision** training (FP16) to speed up training and reduce memory, which did not affect accuracy noticeably but allowed using larger batch sizes.

A.3 Implementation Optimizations

A few additional optimizations and engineering notes:

- We implemented a custom CUDA kernel for the attention in layers 1–4 to efficiently handle

the batched neighbor lookups and softmax computation. This yielded about 3× speedup for those layers compared to a naive PyTorch implementation.

- We made use of Faiss (Facebook AI similarity search library) to perform fast nearest-neighbor search for message passing between agents. For each agent's output, identifying the top relevant other-agent outputs was done via Faiss if needed.
- For spatial indexing, we used H3 (Uber's hexagonal grid indexing) to partition tasks among agents. Each agent could quickly retrieve all points in a given H3 cell to, say, sum up local risk or find neighbors.
- We found that **pre-training** the CEF's MLP on a simple task (like reconstructing coordinates or predicting one of the features) helped as an initialization. In effect, we did an unsupervised pre-training of the embedding such that it preserved distances; this is similar to ideas in representation learning where you first ensure the embedding contains the basics, then fine-tune for the actual task. This pre-training was done by training the MLP to predict the latitude and longitude (normalized) from the raw feature vector — which it could only do by learning to use those features effectively. After this pre-training (which reached ~0.99 correlation in lat/lon prediction), the MLP weights were used to initialize the full model training. This seemed to speed up convergence and possibly improved the spatial accuracy outcome.

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