Discrete Global Grid Systems as a Framework for Geometrically Rigorous and Spatially Explicit GeoAI: A Research Agenda*

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1 The Planar Fallacy in Global GeoAI

Spatially explicit modeling has become a desired property of geospatial AI (GeoAI) [1, 2]. However, I argue that our excitement must not overshadow critical challenges that emerge, and we must critically examine these [3]. As the field moves towards global systems and foundation models, we must apply the same critical mindset and skepticism that has always marked our discipline [4]. One critical issue with prominent current architectures is that they are fundamentally tied to flat 2D representations [5]. By failing to account for the Earth's true geometry, these planar assumptions introduce inherent geometric and geographic biases. This **"planar fallacy"** manifests through two primary failure modes: spatial sampling bias and the fallacy of planar adjacency.

2 Mechanisms and Evidence of Geometric Bias

The reliance on planar, Euclidean operations undermines the foundational pillars of predictability and reproducibility in GeoAI [3]. Below I describe two primary mechanisms through which this occurs.

Spatial Sampling Bias (SSB) and Kernel Non-Stationarity. The reliance on projected grids creates a nonstationary unit of observation [6]. Because a pixel's physical ground area varies by location (e.g. in a Mercator or UTM projection) count-based or density-weighted inference are effectively viewing the Earth through a distorted lens. In deep learning terms, this violates translation equivariance and breaks the assumption of spatial stationarity required for effective weight sharing. Standard 3×3 convolutional kernels or Vision Transformer (ViT) patches assume that a feature at one location is mathematically equivalent to the same feature elsewhere. However, as the physical footprint deforms with latitude (e.g. Mercator projection), the model must expend parameter capacity to learn "projection-invariance" rather than the underlying spatial processes. This bakes a structural bias into the model weights, where the "importance" of a signal becomes an unintended function of coordinate geometry.

The Fallacy of Planar Adjacency and Topological Rupture. While 2D Euclidean assumptions may suffice for local analysis, they collapse at global scales by forcing spherical interactions into a flat adjacency matrix. This computational constraint effectively prevents the realization of the geo-dipole, the fundamental unit of geographic interaction defined in [7]. This creates a topological "cliff" at the 180th meridian or along the edges of UTM zones. This rupture breaks the very spatial autocorrelation that "spatially explicit" models aim to capture [2, 8]. In a 2D grid, two points separated by $1\,\mathrm{km}$ at the date line may be treated as being $40.000\,\mathrm{km}$ apart if "clever workarounds" like padding are not applied. This prevents architectures from achieving geometrically coherent understanding of global phenomena, such as atmospheric circulation or trans-Pacific migration, effectively ignoring Earth's true connectivity.

The "planar fallacy" introduces structural noise that high resolution alone cannot resolve [9]. State-of-the-art models like AlphaEarth-Foundation rely on fine $10\,\mathrm{m}$ UTM grids [10], where areal distortion is considered minimal, i.e. it ranges from $-0.146\,\mathrm{m}^2$ to $0.08\,\mathrm{m}^2$ between the zone edges and central meridian in Florida (UTM zone 17). This seemingly small $0.23\,\%$ discrepancy still yields a spatial variance of $2.300\,\mathrm{m}^2\,\mathrm{km}^{-2}$. While relative error is projection-dependent and scale-invariant, absolute area error scales with cell size. For a $100\,\mathrm{m}$ grid, error reaches $8\,\mathrm{m}^2$ to $\sim 15\,\mathrm{m}^2$, roughly the size of a room or a small backyard shed. This means that pixel represent a varying physical reality based solely on their zone position, which matters in geospatial tasks like carbon credit verification.

The architecture of another state-of-the-art foundation model, Prithvi-WxC suggests that the industry is attempting to bypass distortions via "grid-free" coordinate-based tokenization [11]. While this enables mathematical equivalence across latitudes, such "coordinate-aware" interventions are model-specific workarounds rather than structural solutions. They still highlight a field-wide desire for rigor that remains constrained by a data supply chain inherited from paper-based navigation and storage constraints from early ages of computing [5]. In the era of high-performance computing and mature spherical statistics, legacy 2D representations like Mercator-derived grids are no longer technological necessities. Favoring the simplicity of flat grids over the Earth's actual geometry only allows outdated shortcuts to compromise the scientific integrity and global reach of GeoAI.

3 The DGGS Alternative: A Forward-Looking Research Agenda

To achieve the scientific rigor demanded by global-scale systems [3] we must transition toward uniform, spherical data architectures. Discrete Global Grid Systems (DGGS) provide a mathematically rigorous, multi-scale tessellation of the Earth's surface [12–14]. However, I argue that for GeoAI to pass the "representation test" [2], where the internal model architecture reflects the fundamental properties of geographic space, we must move beyond mere clever indexing methods

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and toward equal-area geodesic frameworks. While popular DGGS implementations like H3 (`https://h3geo.org`) and S2 `https://s2geometry.io/`) offer significant adjacency benefits, they often lack the area-equivalence required for unbiased scientific inference [6]. To resolve SSB, GeoAI must adopt equal-area tessellations (e.g. ISEA4H [15] or rHEALPix [16]). Uniform observation units ensure consistent physical extent from poles to equator. This enforces metric stationarity and translational equivariance, allowing kernels to learn universal geographic features instead of projection-specific artifacts.

DGGS further provides spatio-temporal persistence, as cell IDs serve as permanent, immutable references to the same physical ground area over time. By providing a seamless indexing structure, DGGS also eliminates the ”topological cliff” of 2D grids and fulfills the topological consistency pillar of the representation test. This lack of artificial edges natively captures trans-Pacific phenomena and enables continuous spatial autocorrelation without periodic padding. This architecture allows Spherical Graph Neural Networks (GNNs) to treat DGGS cells as nodes, ensuring the computation domain matches the Earth's geometry. However, this spherical transition requires a difficult and fundamental rethink of the GeoAI stack to overcome decades of flat-grid optimization. I propose four critical directions of inquiry to bridge geographic theory and computational practice:

- **Equal-Area Geodesic Frameworks:** GeoAI must adopt equal-area tessellations to ensure a stationary unit of observation. This is a prerequisite for achieving true translational equivariance across a curved surface.
- **Benchmarking Geodesic Infrastructure:** High accuracy on localized planar datasets often masks the structural failures of global grids. We need benchmarks to evaluate area-preservation, shape distortion, and indexing speed of different DGGS to balance geographic rigor with computational performance.
- **DGGS-Native Data Supply Chains:** We must move beyond lossy 2D re-projections. This requires ”Spherical Data Cubes” and cloud-native formats (evolving from COG or Zarr) that support multi-scale indexing directly in a spherical context.
- **Resolving the Hardware-Software Mismatch:** Current AI hardware is optimized for flat rectangular tensors. Developing native geodesic kernels and custom CUDA operations will eliminate the ”computational tax” of forcing curved geographic data into flat memory patterns.

In conclusion, the continued advancement of GeoAI requires deepening its support for scientific discovery through fundamental principles. Abandoning the planar paradigm in favor of geometrically rigorous architectures is not a technical optimization but a prerequisite for scientific integrity. By embracing the sphere through Discrete Global Grid Systems, GeoAI can finally move beyond “Deep Learning on Maps“ and toward a true “AI for the Earth.“

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