POLITECNICO MILANO 1863 | DIPARTIMENTO DI INGEGNERIA CIVILE E AMBIENTALE

Foundation Models for Urban Intelligence: Why Geospatial Information Science Matters

07.09.2026 | **Maria Antonia Brovelli**,

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The most relevant question

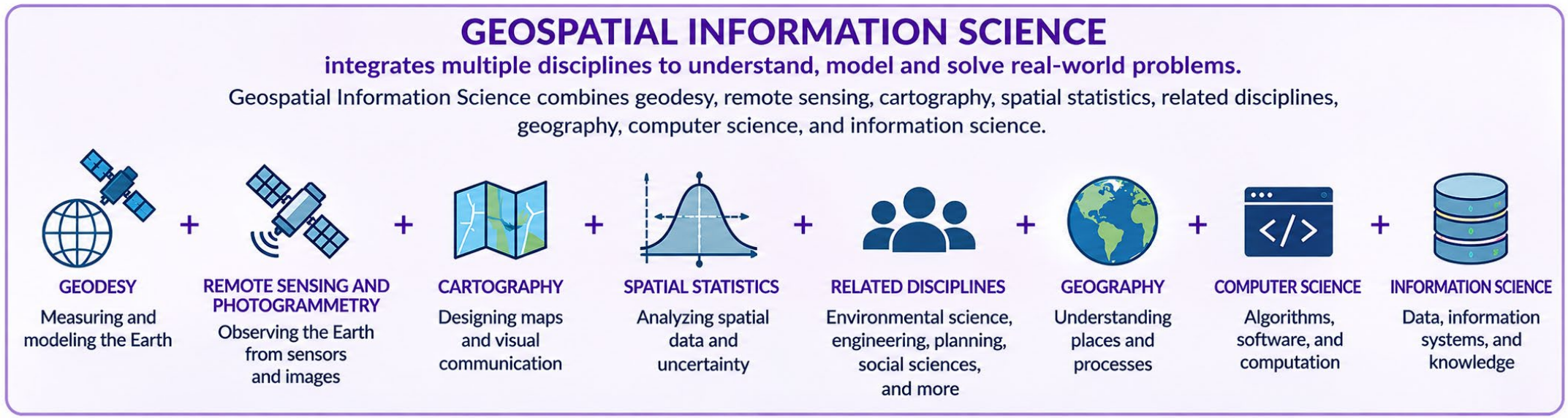
- When foundation models meet cities, is geographic information merely another modality—or does geography fundamentally change what the model has to learn?

My answer

- Geography cannot be added at the end. If we want foundation models to contribute to urban intelligence, geographic structure has to enter the representation itself.
- **A city is not an image with coordinates attached to it. It is a spatial, temporal, relational and governed system.**

Geospatial Information Science

Geospatial Information Science (GIScience) is the interdisciplinary scientific field that studies how geographic information about the Earth is acquired, represented, modelled, stored, shared, analysed, visualised, communicated and evaluated.



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GIScience versus GIS

Two sides of the same world

GIS

THE TECHNOLOGY & SYSTEM

GIS is the technology or information system used to capture, manage, analyse, and visualise geographic data.

CAPTURE
Collect geographic data from the real world

MANAGE
Store, organize, and maintain geographic data

ANALYSE
Explore, query, and analyze spatial patterns

VISUALISE
Present and share results through maps and apps

KEY CHARACTERISTICS

Tools & Software
e.g., QGIS, ArcGIS, PostGIS

Data Management
Databases, formats, standards

Applications
Mapping, analysis, modeling, visualization

Users
Practitioners, analysts, decision-makers

VS

GIScience

THE SCIENTIFIC DISCIPLINE

GIScience is the scientific discipline that studies the principles underlying geographic information, GIS technologies, and spatial reasoning.

THEORY
Developing models, concepts, and formal theories

METHODS
Designing algorithms, models, and analytical methods

SPATIAL REASONING
Understanding how people think about space and place

RESEARCH
Advancing knowledge through empirical and theoretical investigation

KEY FOCUS AREAS

Foundations
Ontology, semantics, data models

Methods & Models
Spatial statistics, uncertainty, AI, simulation

Cognition & Society
Human spatial cognition, VGI, ethics, policy

Interdisciplinary
Geography, computer science, statistics, social sciences, etc.

COMPLEMENTARY, NOT COMPETING

GIS provides the tools and infrastructure.
GIScience provides the knowledge and principles.
Together, they advance our understanding and ability to solve spatial problems.

Smarter Cities

Environmental Sustainability

Disaster Management

Public Health

Better Decisions for a Better World

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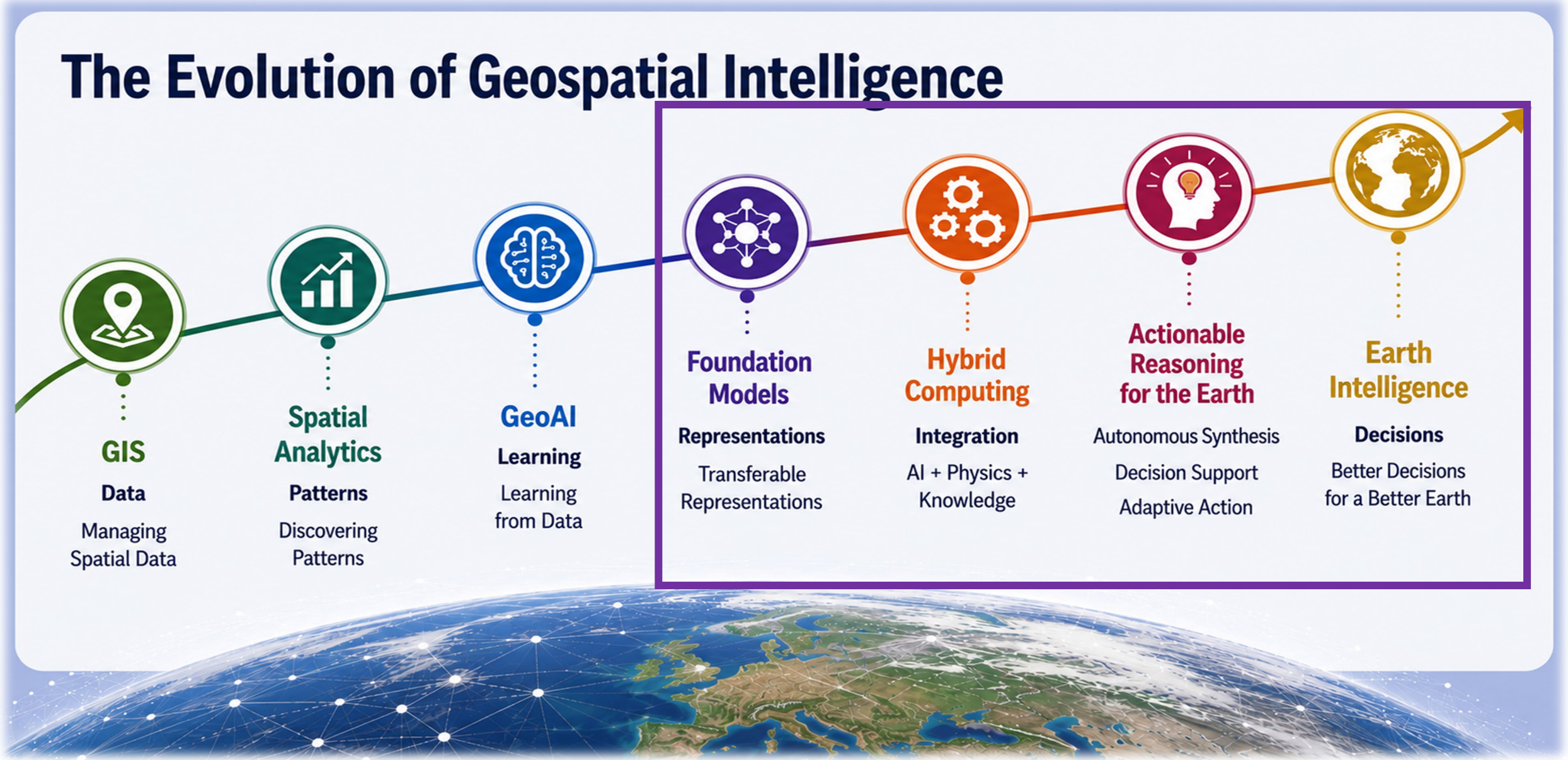

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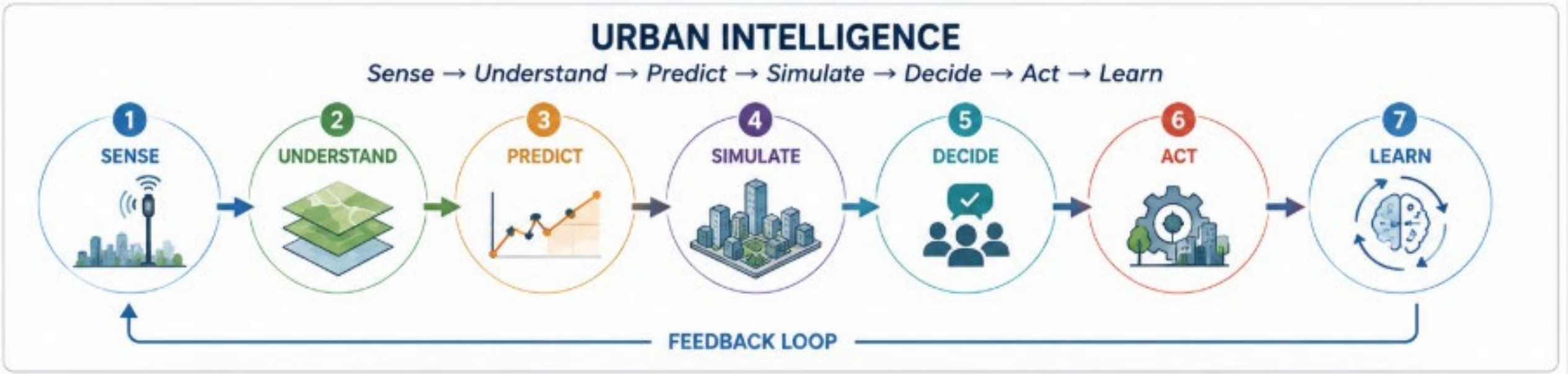
Urban Intelligence

Urban Intelligence: capacity to integrate observations, data, models, domain knowledge, and human expertise to understand, predict, simulate, and support decisions about urban systems.



Urban intelligence is not equivalent to producing a prediction; it requires explanation, spatial context, uncertainty, and actionable decisions.

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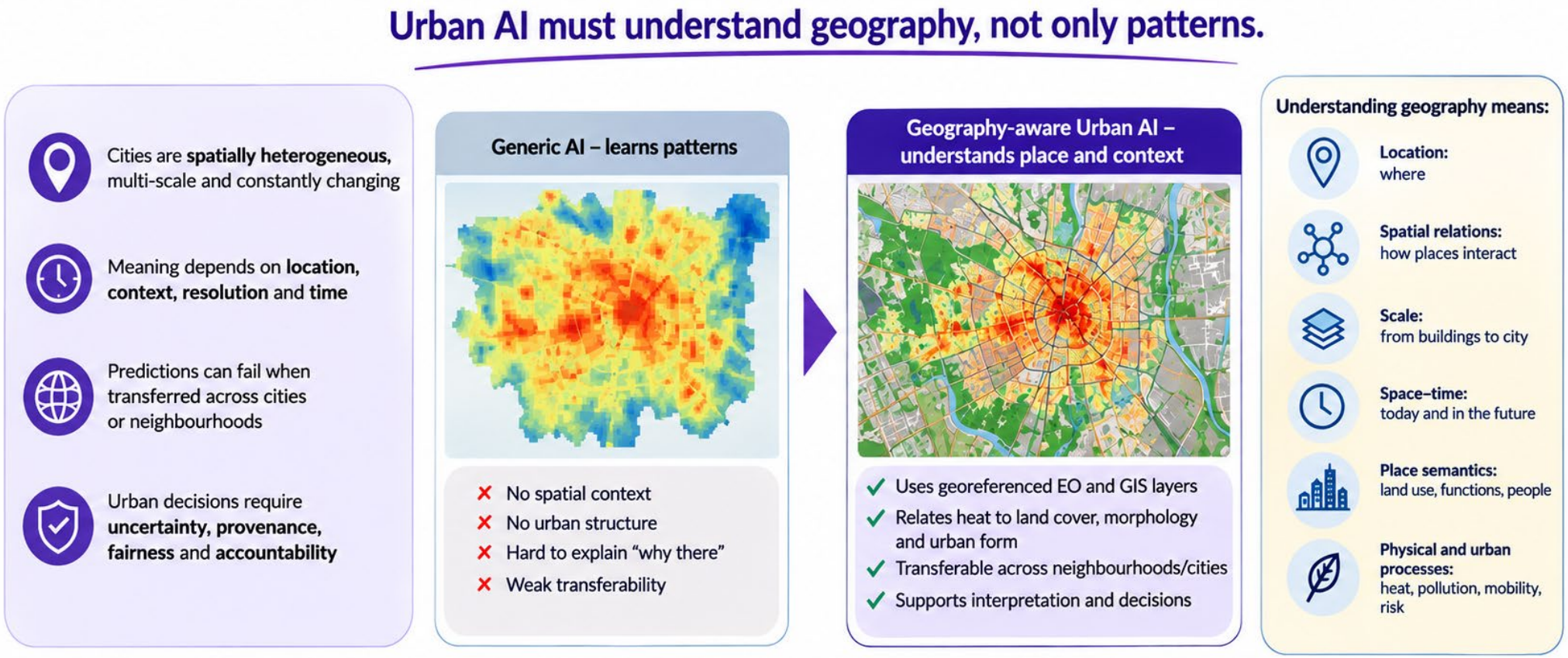
Why Generic AI Is Not Enough for Cities

If this is what we mean by Urban Intelligence, then simply applying a generic foundation model to urban data is not enough. Cities create scientific problems that are deeply geographic.



Geography is not metadata added after the model has been trained; it has to be part of the representation itself.

Generic AI predicts; GIScience-grounded Urban AI explains, transfers and supports decisions

Image generated with the assistance of OpenAi's ChatGPT , based on author-provided content.

Urban Foundation Models

Large-scale, pretrained AI models that learn transferable general-purpose representations and spatiotemporal reasoning capabilities of urban systems from diverse, multimodal, multiscale, and spatiotemporal urban data and that can be adapted to generate predictions and insight related to multiple urban applications.

From Foundation Models to Urban Geospatial Foundation Models

Geospatial Science provides a fundamental methodological framework for **grounding** these models in geographic reality by integrating spatial reasoning, geospatial data representations, rigorous analytical methods, and effective mechanisms for spatial communication. This foundation enables models to capture the spatial structure, context, scale, and heterogeneity of urban phenomena, thereby enhancing their geographic validity, interpretability, and practical applicability.

What does this geographic grounding add in practice? Let us look at urban applications before we move to the taxonomy.

Urban Applications: What GIScience Adds

Different applications stress different GIScience capabilities. Therefore, there is probably no meaningful notion of a universally 'best' Urban Foundation Model independent of task, geography and decision context.

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1. Urban Heat Islands

What does the FM provide, and what does GIScience add to turn that output into urban intelligence?

GIScience builds the urban-climate representation; the FM learns transferable relationships; GIScience turns outputs into place-based action.

Geospatial representation

- LST / thermal anomalies
- vegetation, canopy, NDVI
- imperviousness, morphology
- LCZs, land use, meteo time series
- CRS, resolution, spatial units

FM contribution

- reusable representations
- multimodal fusion
- prediction / gap filling
- downscaling
- transfer to new cities

GIScience reasoning

- spatial drivers of heat
- scale and modifiable areal unit problem (MAUP) control
- uncertainty mapped in space
- exposure / vulnerability overlays
- intervention areas and monitoring

Urban intelligence outcome

Where is heat risk concentrated, why there, who is exposed, and what should be cooled first?

+ DOMAIN EXPERTISE ACROSS THE CHAIN: URBAN CLIMATE

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4. Urban Air Quality

What does the FM provide, and what does GIScience add to turn that output into urban intelligence?

GIScience defines pollutant geography and exposure context; the FM learns nonlinear patterns; GIScience validates what the predictions mean.

Geospatial representation

- NO_2, $PM_{2.5}$, O_3, AOD
- sensors and emissions
- roads, industry, land use
- meteorology, terrain, dispersion context
- station geography and scale

FM contribution

- fuse sparse sensors + EO
- learn source–weather relations
- gap-fill / downscale
- short-term forecasting
- transfer to undersampled areas

GIScience reasoning

- exposure surfaces by population
- source-area interpretation
- station bias and uncertainty
- regulatory
- policy monitoring in space and time

Urban intelligence outcome

Who breathes what, when, from which sources, and which intervention reduces exposure?

+ DOMAIN EXPERTISE ACROSS THE CHAIN: AIR POLLUTION/ATMOSPHER

GIScience & EO → Foundation model → GIScience reasoning → Urban intelligence

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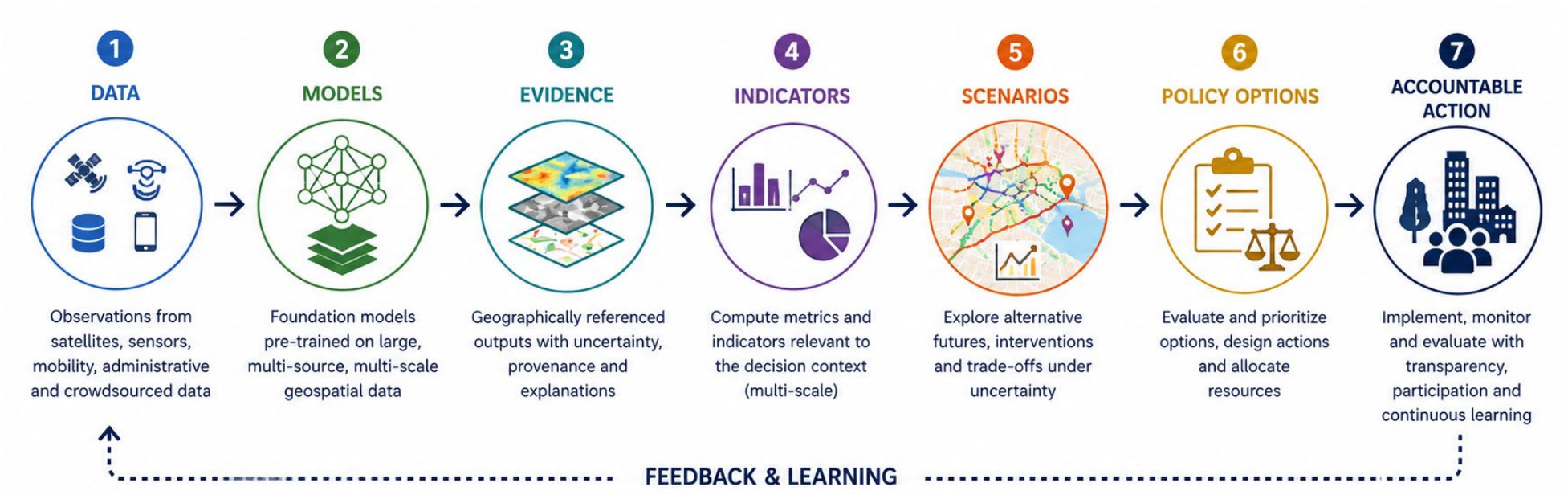
A Trusted Geospatial Decision Chain for Urban Intelligence

Urban Intelligence is not about blindly applying generic AI to city data. On the opposite, it relies on trusted geospatial decision chains that link data and models to actionable evidence, policy choices, and responsible outcomes. Foundation Models can contribute by generating predictions or insights but GIScience is essential to convert these outputs into geographically sound evidence, relevant indicators, and robust decisions.



This should not be viewed as a fixed sequence but as a flexible framework. Depending on the urban challenge, steps may overlap or merge. Model output is a starting point—it must be translated into geographically grounded evidence before it can support accountable governance.

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Representation-centered taxonomy of Urban (Geospatial) Foundation Models

We propose a **representation-centred, GIScience-grounded taxonomy of Urban Foundation Models**. In this framework, the geographic dimension is not treated as an additional attribute of an otherwise generic foundation model. Rather, it is considered **constitutive of the urban representation itself**. Urban phenomena are inherently spatially referenced, scale-dependent, relational, heterogeneous and dynamic; consequently, geographic structure forms part of the conceptual foundation of an UFM.

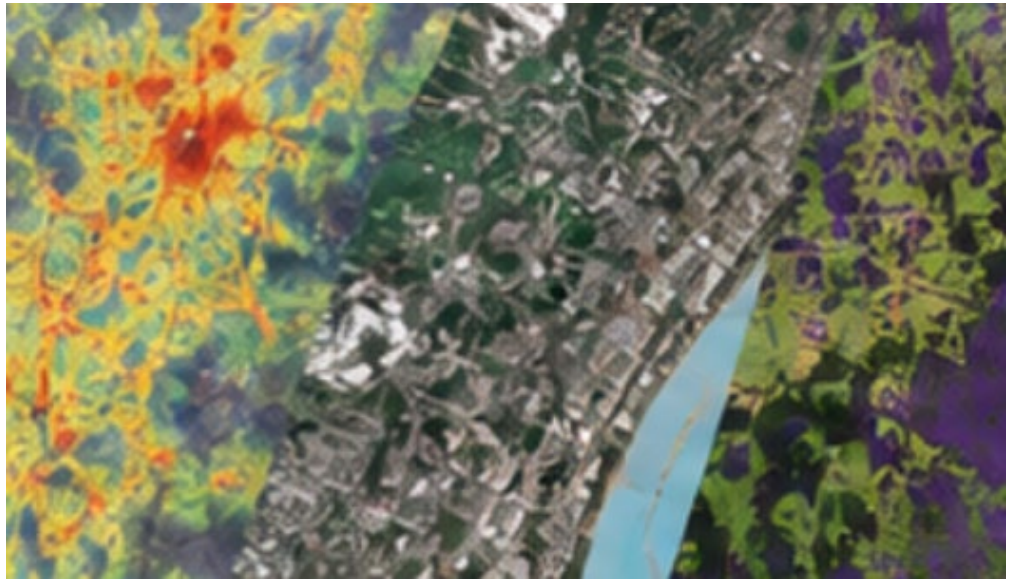
Accordingly, we use simply the term **Urban Foundation Model (UFM)** in this keynote. The qualifier **geospatial** may be omitted once this definition has been established, because **geospatial grounding is assumed to be intrinsic** to the family rather than an optional model characteristic.

The taxonomy is intended to provide a **parsimonious organization of the major representational paradigms currently emerging in urban foundation models**, rather than an exhaustive or mutually exclusive classification. Models are assigned to families according to their **dominant geographic representational principle**, rather than solely according to input modality, architecture or downstream application. **A model may therefore belong to more than one family when it explicitly combines different forms of geographic representation**.

Representation-centered taxonomy of Urban Foundation Models

We expect progressive convergence across the proposed families (representational archetypes rather than rigid model classes), with future models increasingly integrating **continuous fields, geographic objects, 3D scenes, networks, trajectories, spatiotemporal processes, language and domain knowledge within unified architectures**.

Earth-observation, environmental and urban-field GFMs



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Earth-observation, environmental and urban-field GFMs

Place-, object- and geovector-centric GFMs

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3D, cross-view and scene-centric GFMs

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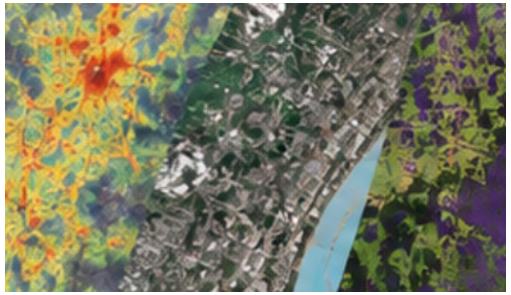


FIELDS

OBJECTS AND PLACES

GEOMETRY AND SCENES

RELATIONS AND PROCESSES

KNOWLEDGE AND DECISIONS

The future UFM may not choose between these five geographic languages; it may have to speak all five.

Multimodality, generative capability, reasoning, adaptation, transferability and interaction with external tools are **cross-cutting properties** rather than as independent model families.

Representation-centered taxonomy of Urban Foundation Models

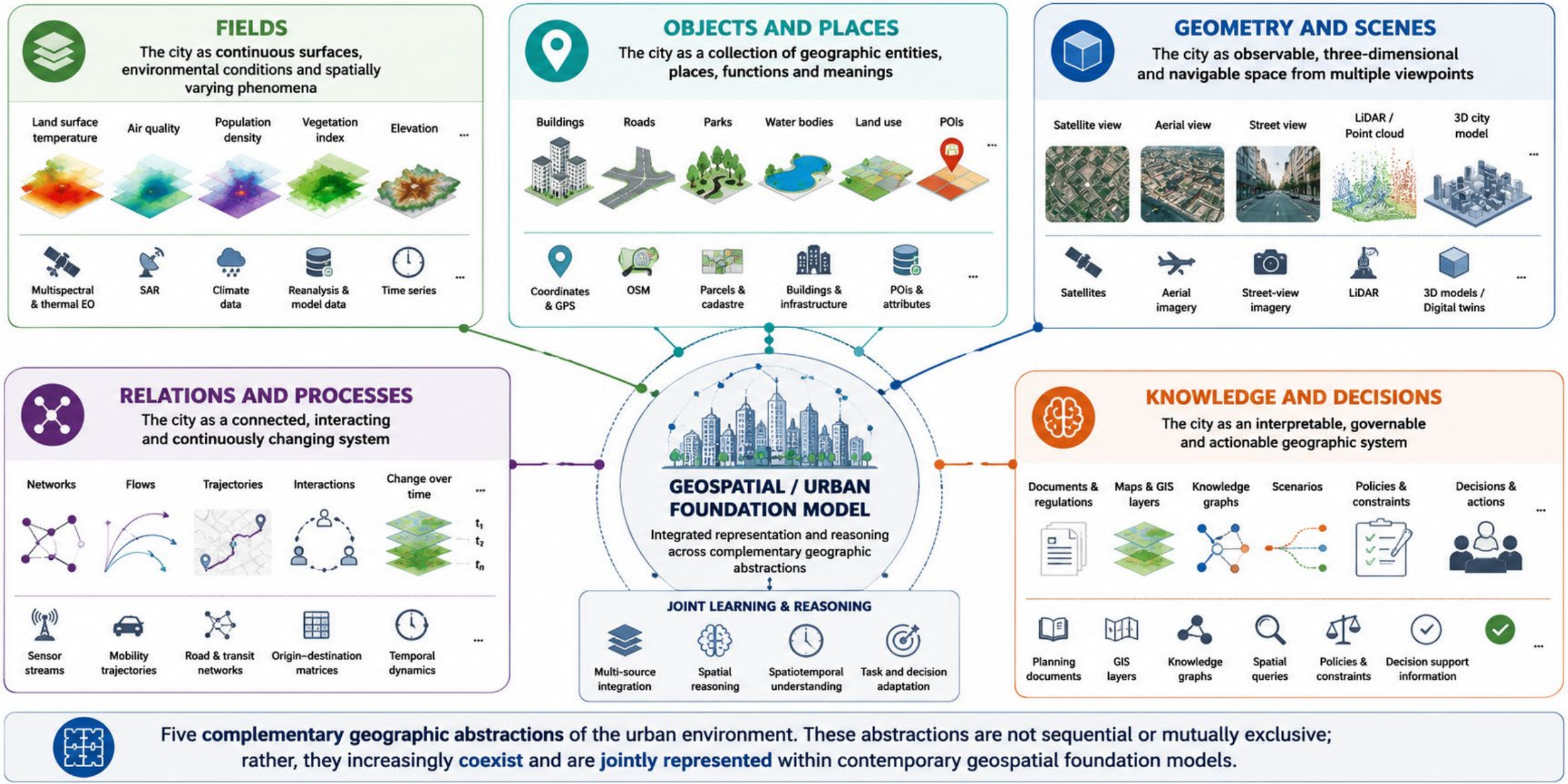
Family	Dominant geographic object or representation	Geographic conception of the city	Includes
Earth-observation, environmental and urban-field GFMs	Continuous geographic fields and raster representations	**Fields** — the city as continuous surfaces, environmental conditions and spatially varying phenomena	Optical, SAR, multispectral, hyperspectral and thermal imagery; climate layers; land-cover products; multitemporal EO data
Place-, object- and geovector-centric GFMs	Discrete geographic entities, vector objects and their semantic relationships	**Objects and places** — the city as a collection of geographic entities, places, functions and meanings	Coordinates, POIs, OSM, parcels, buildings, roads, land-use classes, urban functions, place embeddings, semantic graphs
3D, cross-view and scene-centric GFMs	Urban geometry, scenes and multiple 3D geometry, scenes, viewpoints, and embodied observations	**Geometry and scenes** — the city as observable, three-dimensional and navigable space represented from multiple viewpoints	Satellite, aerial and street-view imagery; video; LiDAR; point clouds; meshes; 3D city models; digital twins
Spatiotemporal process, mobility and network GFMs	Time series, trajectories, flows, graphs, and evolving spatial relations	**Relations and processes** — the city as a connected, interacting and continuously changing system	Sensor streams, spatiotemporal grids, traffic networks, road graphs, trajectories, mobility flows, origin–destination matrices, infrastructure networks
Geospatial language, knowledge and planning FMs	Textual, symbolic, relational and decision-oriented representations grounded in geographic context	**Knowledge and decisions** — the city as an interpretable, governable and actionable geographic system	Regulations; planning documents; maps; GIS layers; spatial queries; indicators; knowledge graphs; scenarios; planning constraints; spatial reasoning; policy and decision-support information

Representation-centered taxonomy of Urban Foundation Models

- Family membership is determined by the **dominant representational** principle rather than by the mere presence of a particular data modality. Secondary family memberships may be assigned when a model explicitly integrates multiple geographic representations.

- The taxonomy **does not classify UFMs primarily according to neural architecture or data modality**, but according to the form of geographic reality that their representations are designed to encode.

- These should not be interpreted as a strict progression. Rather, they are **complementary geographic abstractions**, which increasingly coexist within the same foundation model.



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A proposed GIScience-centred evaluation framework for Urban Foundation Models

Building on established requirements for foundation models, GeoAI, spatial reasoning, responsible geospatial AI, and urban computing, we propose a multidimensional framework for assessing the urban geospatial maturity of GFMs.The proposed framework evaluates UFMs from **three** complementary perspectives:

1. **eligibility criteria** determine whether a model should be considered an Urban Foundation Model. These are conditions and not scored quality dimensions. Therefore, they decide if a model can be considered a UFM

2. **GIScience dimensions** evaluate the extent to which the model explicitly represents and reasons about geographic properties of urban systems

3. **foundation-model and deployment dimensions** assess whether the model exhibits the generality, adaptability, robustness and operational maturity expected of a foundation model

Eligibility criteria

CRITERION	DEFINITION
E1. Urban relevance	The model is pretrained, adapted, or systematically evaluated on urban phenomena, urban geographic data, or urban tasks, either as its primary domain or within a broader geospatial domain.
E2. Geospatial grounding	Geographic structure is constitutive of the model representation rather than incidental metadata.
E3. Foundation-model behaviour	The model provides reusable representations or capabilities beyond a single predefined task and supports adaptation to multiple downstream problems.
E4. Documented evidence	Sufficient public information exists to assess the model consistently.

GIScience maturity dimensions I

G1–G6: core geographic representation and reasoning

ID	Dimension and definition
G1	**Explicit geographic grounding —** Model-level encoding, preservation or exploitation of geographic position and spatial context.
G2	**Scale and resolution awareness —** Ability to account for spatial extent, granularity, GSD, aggregation and scale effects.
G3	**Spatial dependence and geographic non-stationarity —** Representation of neighbourhood effects, spatial dependence and geographically varying relationships.
G4	**Temporal dynamics and spatiotemporal interaction —** Modelling of temporal evolution, dynamics and space-time interactions.
G5	**Topology and network structure —** Representation of adjacency, connectivity, containment, paths and network relations.
G6	**Geographic semantics —** Association of geographic entities and patterns with place, function, meaning and urban context.

Georeferenced input alone cannot justify model-level geographic grounding. The dimensions require evidence that geography shapes the representation, objective, inference or validated reasoning capability.

GIScience maturity dimensions II

G7–G11: trust, transfer and operational geographic use	
ID	Dimension and short definition
G7	**Uncertainty —** Estimation, calibration and communication of uncertainty in model outputs.
G8	**Provenance and data lineage —** Traceability of data sources, time, quality, processing history, licensing and lineage.
G9	**Geographic generalisation and transferability —** Maintaining or adapting performance across unseen cities, regions, sensors, scales and contexts.
G10	**Spatial and social fairness —** Evaluation and mitigation of disparities across territories, populations and data-coverage conditions.
G11	**Operational geospatial interoperability —** Official workflow integration with GIS formats, standards, data models and operational infrastructures.

Third-party post-processing is not a model capability unless it is part of the official released workflow. G11 requires preserved geographic reference and standard GIS-ready exchange.

Foundation-model and deployment maturity dimensions

F1–F8: foundation-model behaviour and deployment readiness

ID	Dimension and definition
F1	**Generality and adaptation capacity** — Reusable capabilities and efficient adaptation to new tasks, datasets, domains and applications.
F2	**Multimodal and cross-representational integration** — Alignment, fusion and joint exploitation of heterogeneous modalities and geographic representations.
F3	**Robustness and continual adaptation** — Reliability under noise, missing data, distribution shifts and evolving conditions, with updating.
F4	**Constraint-aware physical and behavioural plausibility** — Representation, enforcement or evaluation of physical, geometric, infrastructural, behavioural or institutional constraints.

F4 requires explicit constraints, targeted validity tests or constraint-aware training/inference.

Foundation-model and deployment maturity dimensions

F1–F8: foundation-model behaviour and deployment readiness

ID	Dimension and definition
F5	**Computational efficiency** — Practical training and inference performance in compute, memory, latency, energy and scalability.
F6	**Reproducibility and reusability** — Availability of code, weights, configurations, data and documentation for independent reuse.
F7	**Transparency and auditability** — Understandable, traceable and auditable behaviour through documentation, explanations and limitations.
F8	**Responsible and safe deployment** — Privacy, security, governance, human oversight, risk management and operational safeguards.

F4 requires explicit constraints, targeted validity tests or constraint-aware training/inference.

Scoring the dimensions

Score	Class	Definition	Typical evidence
0	**Not addressed**	The dimension is not addressed by the model, or no supporting evidence is available.	No relevant mechanism, experiment, output, documentation, or operational evidence.
1	**Claimed or implicit**	The dimension is mentioned, assumed, or indirectly present through the data or architecture, but is not explicitly operationalized or evaluated.	Conceptual claim; property inherited from the input data; indirect architectural support; no targeted evaluation.
2	**Partially addressed**	The dimension is explicitly considered through a relevant mechanism, dataset design, output, or evaluation, but evidence remains limited in scope or depth.	A dedicated mechanism with limited evaluation; one restricted context; descriptive analysis; limited transfer, robustness, or operational testing.
3	**Substantially demonstrated**	The model explicitly addresses the dimension and provides convincing empirical or operational evidence across multiple relevant settings.	Targeted experiments; ablations; multiple datasets, cities, scales, modalities, tasks, or evaluation settings; systematic documentation where appropriate.
4	**Comprehensively demonstrated**	The dimension is treated as a systematic model capability and is validated across diverse, realistic, and challenging conditions with strong evidence of robustness or operational maturity.	Cross-domain or cross-city validation; distribution-shift or stress testing; repeated temporal evaluation; calibrated uncertainty; interoperability in real workflows; extensive reproducibility evidence; operational deployment where relevant.

Adding Relevance

Label	Definition	Interpretation
C — Core	The dimension is central to the family's geographic representation and reasoning logic.	A model in this family should normally address this dimension. Its absence represents a significant limitation.
R — Relevant	The dimension is important for evaluating the family, but it does not define the family itself.	A model can still belong to the family without explicitly addressing this dimension, although its capabilities or applicability may be limited.
CR — Core Relevant	The dimension is relevant to the family in general, but becomes central for particular subfamilies, architectures, or applications.	Its importance depends on the specific model and use case. It should be evaluated carefully, but its absence is not always a fundamental weakness.
X — Contextual	The dimension can be useful for comparison or for specific applications, but it is not normally expected from the family.	Its absence is not necessarily a significant weakness.

Evaluation matrix

Family	Core dimensions	Relevant dimensions	Contextual dimensions
Earth-observation, environmental and urban-field GFMs	G1, G2, G3, G7, G8, G9, G11, F1, F3, F5, F6, F7, F8	G4 (CR), G6, G10, F2, F4	G5
Place-, object- and geovector-centric GFMs	G1, G2, G5, G6, G7, G8, G9, G11, F1, F2, F5, F6, F7, F8	G3, G10, F3, F4	G4
3D, cross-view and scene-centric GFMs	G1, G2, G7, G8, G9, G11, F1, F2, F5, F6, F7, F8	G3, G5, G6, G10, F3, F4(*)	G4
Spatiotemporal process, mobility and network GFMs	G1, G3, G4, G5, G7, G8, G9, G11, F1, F3, F5, F6, F7, F8	G2, G6, G10, F2(*), F4	
Geospatial language, knowledge and planning FMs	G1, G6, G7, G8, G9, G11, F1, F2, F3, F4, F5, F6, F7, F8		

(*) the requirement is relevant to the family in general but becomes core for specific subfamilies, model designs, or applications.

Eligible UFMs — Fields, Objects and Places

UFM #1	GitHub / model / embeddings	Open status
Prithvi-EO-2.0	GitHub · Hugging Face weights	**Open** — code + pretrained weights
TerraMind	GitHub · Hugging Face model	**Open** — code + pretrained weights
Copernicus-FM	GitHub · Hugging Face weights	**Open** — code + pretrained weights + associated data/embedding resources
THOR	GitHub · Hugging Face model	**Open** — code + pretrained weights
AlphaEarth Foundations	Official project · Earth Engine embeddings	**Partially open** — embeddings publicly available; model weights/training code not released
TESSERA	GitHub · GeoTessera embeddings	**Open** — code + model weights + global embeddings
Galileo	GitHub · Hugging Face models	**Open** — code + pretrained weights
AnySat	GitHub · Hugging Face model	**Open** — code + pretrained model
Panopticon	GitHub · Hugging Face weights	**Open** — code + pretrained weights
UrbanCLIP	GitHub	**Partially open** — public implementation and urban image-text data/resources; no explicit open-source license is visible in the main repository.
RobSense	GitHub Project	**Partially open** — The authors released code and weights on 23 May 2025.

UFM #2	GitHub / model / embeddings	Open status
CityFM	GitHub	**Partially open** — implementation + pretrained city models publicly available
PlaceFM	GitHub	**Partially open** — public training-free implementation
GeoLink*	GitHub	**Open** — implementation + pretrained checkpoints
ReFound	GitHub / PaddleSpatial	**Partially open** — implementation and associated resources publicly available

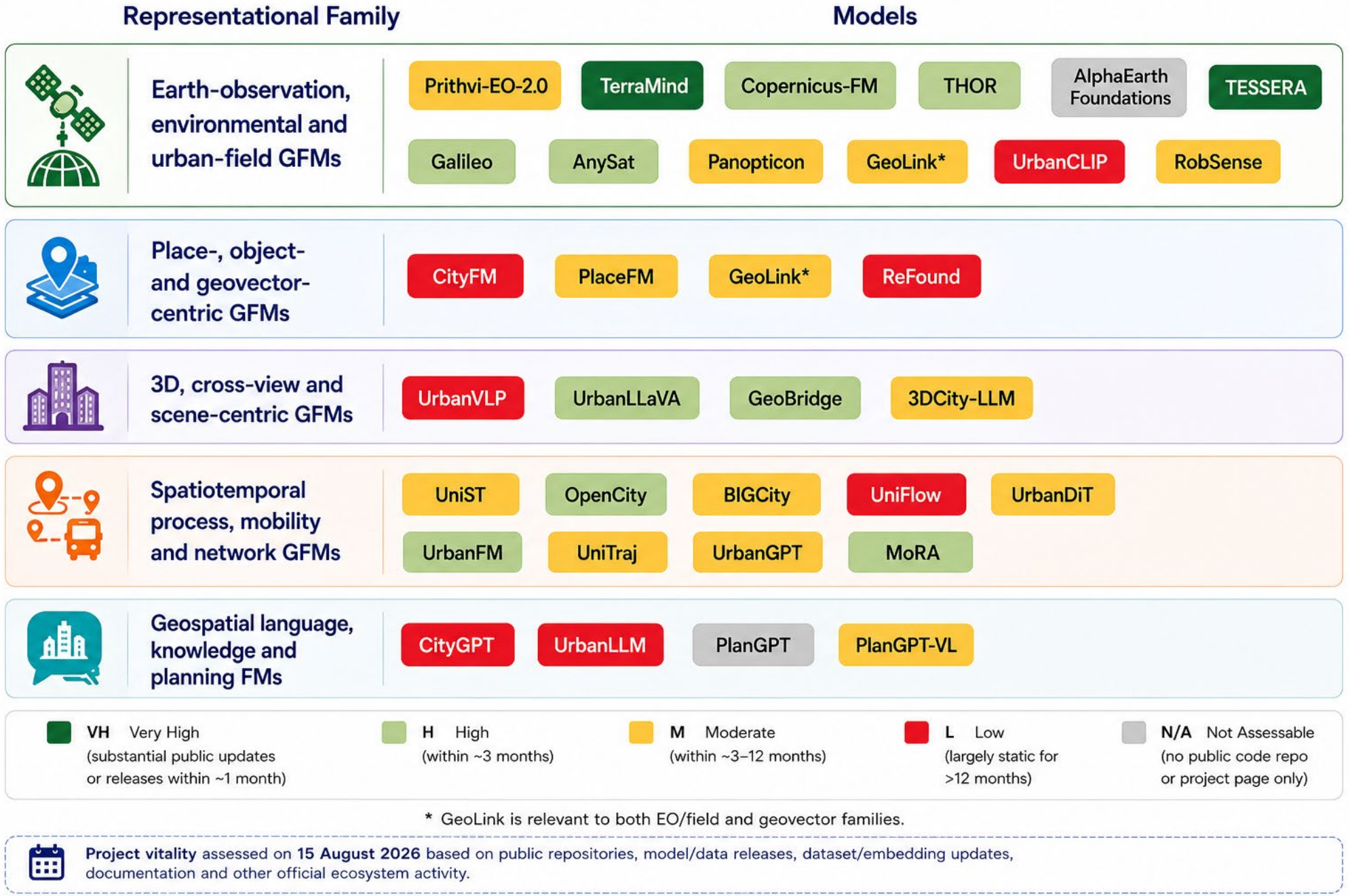
Eligible UFMs — Geometry, Processes, Knowledge and Decisions

UFM #3	GitHub / model / embeddings	Open status
UrbanVLP	GitHub	**Partially open** — official code public; pretrained checkpoint/release coverage limited
UrbanLLaVA	GitHub · Project	**Partially open** — code and data publicly available
GeoBridge	GitHub · Hugging Face model	**Partially open** — public code/model; some source imagery subject to redistribution restrictions
3DCity-LLM	GitHub	**Open** — code + model/data resources

UFM#5	GitHub / model / embeddings	Open status
CityGPT	GitHub · CityGPT data	**Partially open** — public framework, training/evaluation code and data resources
UrbanLLM	GitHub	**Partially open** — code/data public; standalone model-weight release limited
PlanGPT	GitHub / project · Project website	**Partially open** — public project/demo resources; complete underlying model stack not fully released
PlanGPT-VL	GitHub · Model	**Open** — public implementation + released model

UFM#4	GitHub / model / embeddings	Open status
UniST	GitHub	**Partially open** — official implementation + dataset/model resources
OpenCity	GitHub · Hugging Face model · Dataset	**Open** — code + pretrained model + datasets
BIGCity	GitHub · Hugging Face model	**Partially open** — implementation + weights + datasets publicly available
MoRA	GitHub Project	**Open** — MIT-licensed code + pretrained/distilled model and representation resources
UniFlow	GitHub	**Partially open** — public implementation and data resources
UrbanDiT	GitHub	**Partially open** — public implementation; pretrained release less complete
UrbanFM	GitHub	**Partially open** — implementation and WorldST resources public
UniTraj	GitHub	**Open** — implementation + pretrained model + trajectory resources
UrbanGPT	GitHub	**Open** — implementation + model/resource ecosystem

Eligible and Active Models



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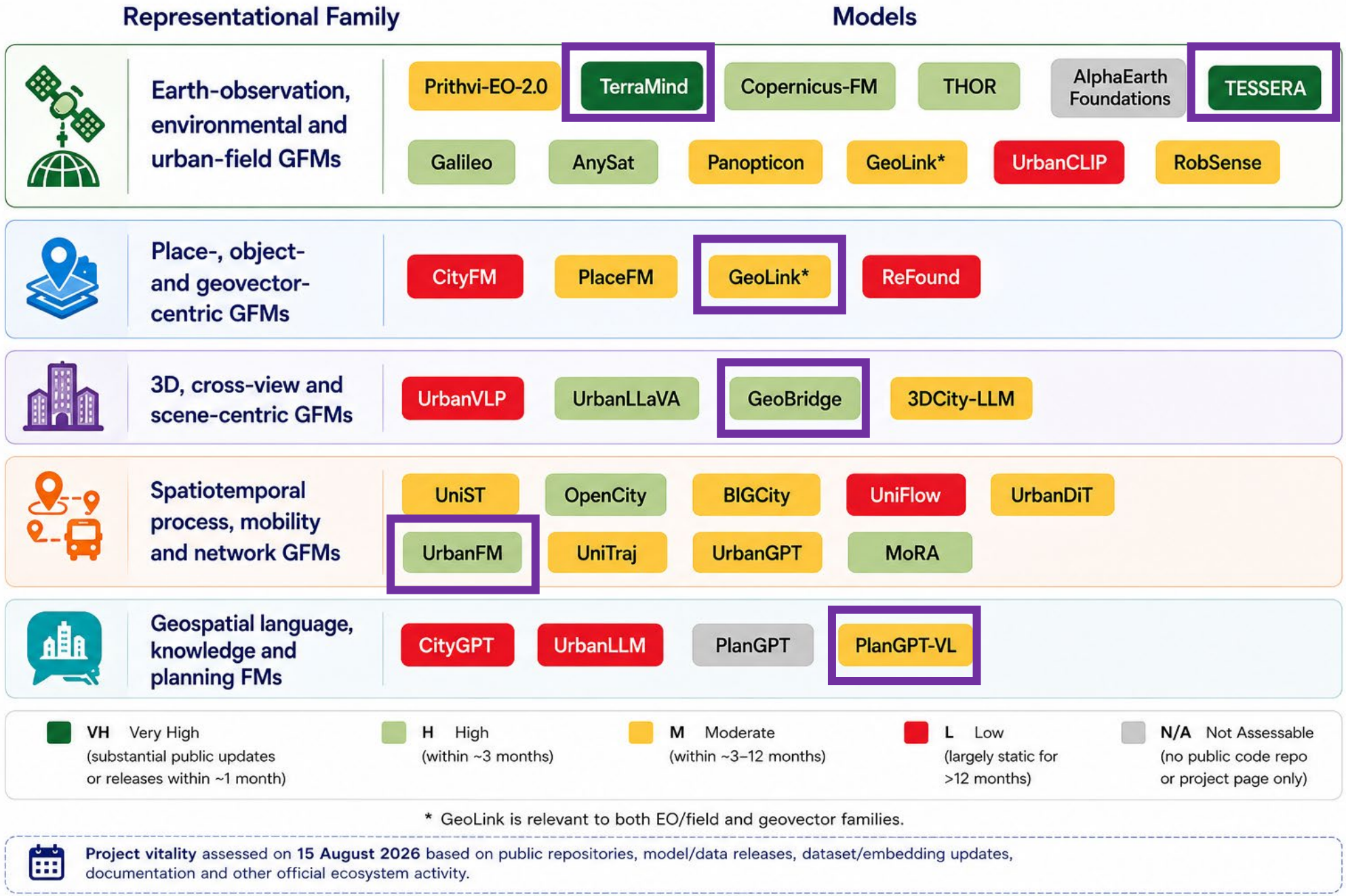
Eligible and Active Models

Selecting 6 models from the 5 families based on their vitality; both Terramind (model-centric, multimodal EO foundation-model approach) and Tessera (embedding-centric approach) were selected from family #1 because of their different approach



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Urban Foundation Models (UFMs):
Main Contributing Countries & Supporting Organisations

TerraMind (PANGAEA)

Pan-European (no single country lead)

Principal Organisations

- ESA Φ-lab
- IBM Research Europe
- FAST-EO consortium (DLR-MF, Forschungszentrum Jülich, KP Labs)
- ETH Zürich
- NASA IMPACT
- University of Iceland

TESSERA

United Kingdom (major contributor)

USA (dClimate Labs)

Finland (Aalto Univ.)

Principal Organisations

- University of Cambridge
- dClimate Labs (USA)
- Aalto University (Finland)
- University of Bristol
- NVIDIA (TESSERA v2)

GeoLink

China (major contributor)

Switzerland (EPFL)

Principal Organisations

- Peking University (Earth & Space Sciences; Urban & Environmental Sciences)
- Institute of Automation, Chinese Academy of Sciences
- EPFL (Switzerland)

GeoBridge

China (all contributors)

Principal Organisations

- Jilin University
- Wuhan University
- Zhongguancun Academy
- State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (Wuhan Univ.)

UrbanFM

China (Guangzhou & Hong Kong SAR)

Principal Organisations

- The Hong Kong University of Science and Technology (Guangzhou) – HKUST(GZ)
- The Hong Kong University of Science and Technology – HKUST

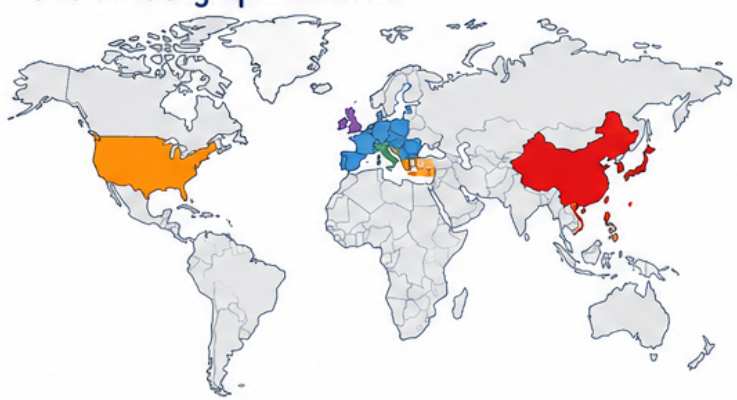
PlanGPT-VL

China (all contributors)

Principal Organisations

- Behavioral and Spatial AI Lab (BSAI Lab)
- Peking University & Tongji University
- Southern University of Science and Technology

Overall Geographic Pattern



- China leads: GeoLink, GeoBridge, UrbanFM, PlanGPT-VL
- United Kingdom leads: TESSERA
- Multinational European collaboration: TerraMind (IBM-ESA / FAST-EO)
- Switzerland contributes: TerraMind (major hub) & GeoLink
- Other contributors: USA, Finland, Italy, Poland, Iceland

Key Takeaways

- China is the largest overall contributor, leading 4 of the 6 models.
- The UK leads TESSERA, mainly through the University of Cambridge.
- TerraMind is a pan-European (IBM-ESA/FAST-EO) collaboration with major hubs in Switzerland, Germany and Italy.
- GeoLink has a Swiss component; TESSERA has limited US and Finnish participation.

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Robustness of the UFM evaluation across three LLMs

(Evaluators: GPT H · Claude Opus 5 H (run by L. Biagi) · Gemini 3.7 Flash (run by Q. Xu)

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	F1	F2	F3	F4	F5	F6	F7	F8
Count of Max Diff. = 0	2	4	0	4	4	4	1	3	3	1	2	1	2	1	1	1	3	2	1
Count of Max Diff. = 1	4	2	3	2	2	2	4	3	3	3	3	5	3	5	5	5	3	4	4
Count of Max Diff. = 2	0	0	3	0	0	0	1	0	0	2	1	0	1	0	0	0	0	0	1
Count of Max Diff. = 3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Count of Max Diff. = 4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

92% **of cases have** Max Diff ≤ 1

41 Max Diff = 0

64 Max Diff = 1

9 Max Diff = 2

0 Max Diff = 3

G3 **Spatial dependence and geographic non-stationarity** — Representation of neighbourhood effects, spatial dependence and geographically varying relationships (TerraMind, GeoBridge, UrbanFM)

G10 **Spatial and social fairness** — Evaluation and mitigation of disparities across territories, populations and data-coverage conditions (TerraMind, TESSERA)

Comparison of the UFM evaluation across three LLMs

(Evaluators: GPT H · Claude Opus 5 H (ran by L. Biagi) · Gemini 3.7 Flash ran by Q. Xu)

CONSENSUS SCORE PROFILE Mean ± Std Dev across GPT, Gemini and Claude

TerraMind G	**TerraMind F**	**GeoBridge G**	**GeoBridge F**
1.91±0.99	2.79±1.14	1.58 ±1.06	2.33±0.59
TESSERA G	**TESSERA F**	**UrbanFM G**	**UrbanFM F**
1.70±1.05	2.75±1.07	1.91±1.00	2.13±0.82
GeoLink G	**GeoLink F**	**PlanGPT G**	**PlanGPT F**
2.00±0.77	2.33±0.85	2.03±0.66	2.75±0.50

All-models
G = 1.70 ± 0.80
F = 2.28 ± 0.79

Model	Evaluator	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	F1	F2	F3	F4	F5	F6	F7	F8
GeoBridge (Family 3)	max diff	1	0	2	0	0	0	0	1	0	1	1	1	1	1	1	0	1	1	0

What could the GIScience-Centred Evaluation Show?

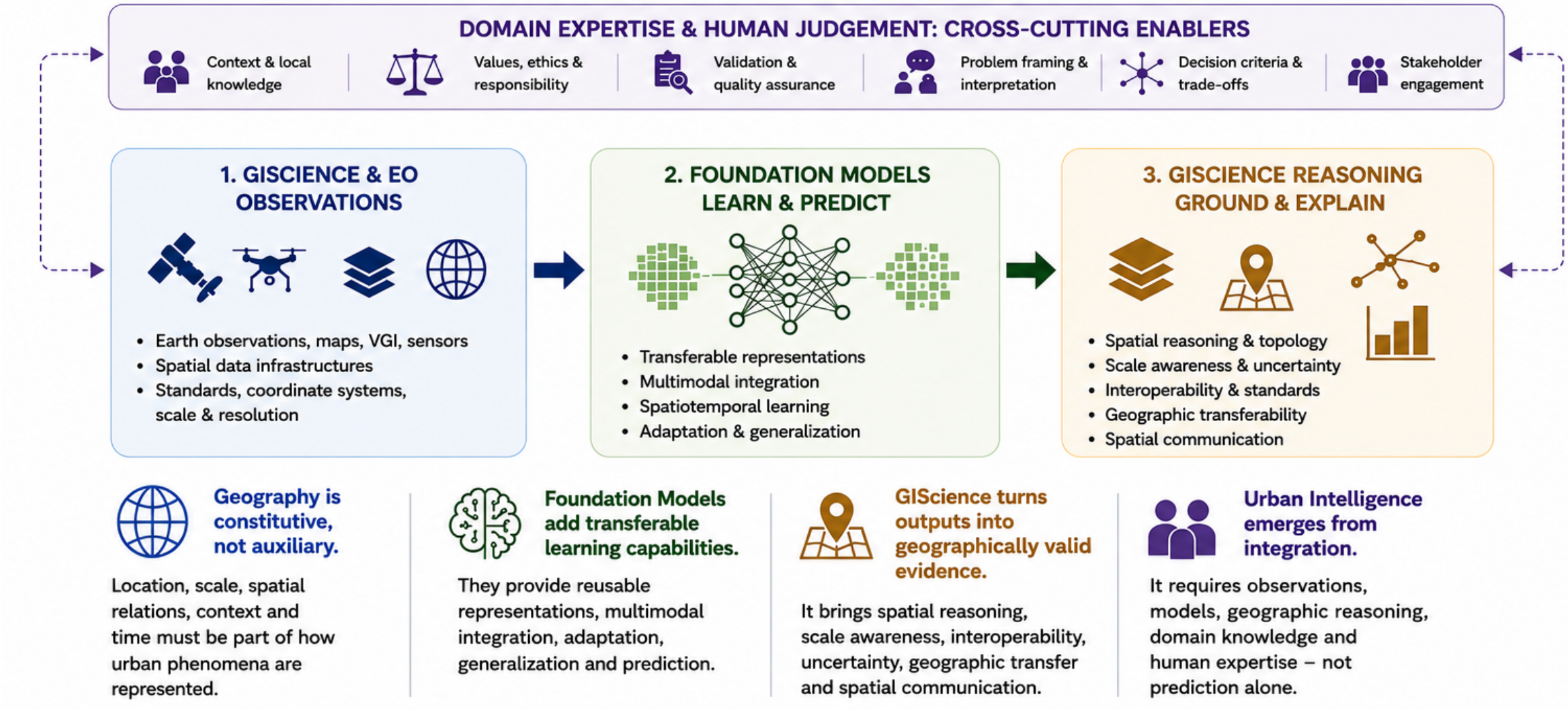
- **No single UFM is universally “best”; substantial room remains for improving their suitability across different urban applications and geographic contexts.**

- **Geospatial data ≠ geospatial intelligence.**
  Using EO, maps, coordinates, or trajectories does not automatically mean that a model explicitly understands **location, scale, topology, spatial dependence, or geographic context**.

- **GIScience maturity and FM maturity are different.**

- **Suggestions and comments on the framework are more than welcome**

Conclusions



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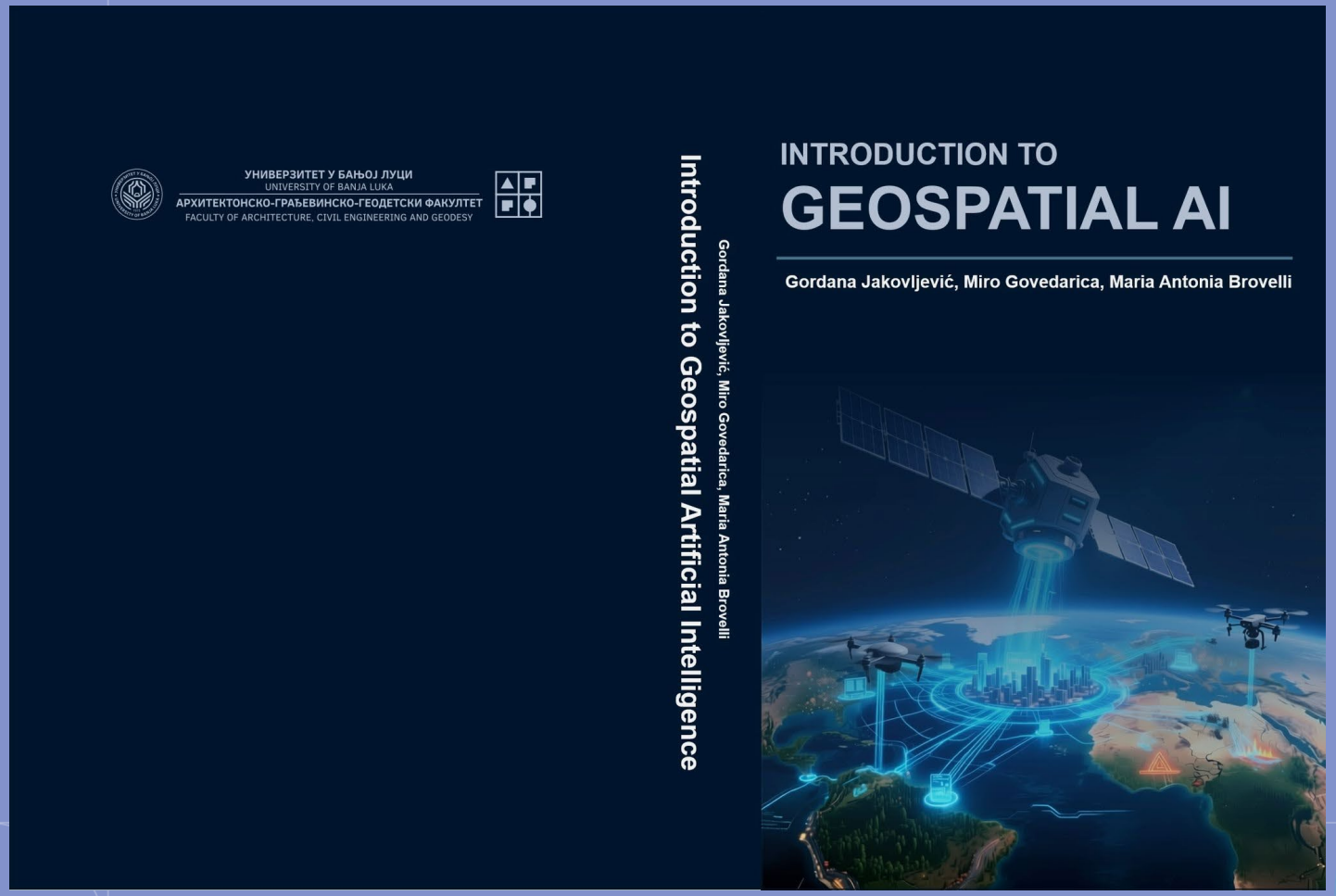

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Thanks for your attention

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