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Decoding spectral representation for Earth's matter via large language models: A new methodology for planetary cognition

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Dear Editor,

Reflectance spectra act as a common language for how light and matter interact. They capture the physical and chemical fingerprints of surface materials and translate them into high-dimensional data. These records link microscopic material composition to large-scale Earth system dynamics.[1] Imaging spectroscopy is taking a massive step forward today. New space missions like NASA's EMIT, Germany's EnMAP, and ESA's CHIME drive this progress. Satellites, aircraft, and ground sensors cooperatively generate vast hyperspectral datasets. Researchers are shifting from basic visual observations to highly precise quantitative measurements. A serious bottleneck has appeared alongside this data revolution. We collect spectral data much faster than we can actually analyze it.[2]

Despite abundant available information, accurately interpreting spectral signals remains extremely difficult. The mapping from spectra to surface materials is inherently complex, nonlinear, and ill-posed, complicated by mixed-pixel heterogeneity and environmental perturbations. Existing inversion methods face obvious limits. Physics-based radiative transfer models rely on idealized assumptions that fail to capture the complexity of natural environments. Standard machine learning techniques like Random Forests or CNNs depend heavily on local training data, lacking the generalization for global-scale variability. The field urgently requires a paradigm shift from task-specific algorithms to universal, robust representation learning.[3]

The AI for Science movement offers a highly promising solution to this problem. Recently, Transformer-based foundation models have successfully distilled multi-source heterogeneous observations into universally transferable Earth representations.[4] Existing models, however, remain oriented toward image understanding. When spatial texture becomes ambiguous, reasoning from spectral morphology to surface material semantics still demands new approaches. The strong capacity of Large Language Models (LLMs) for pure sequence-level semantics has offered us inspiration. We therefore propose Spectral LLMs. The geoscientific meaning of a spectral curve is jointly constrained by adjacent band responses and the overall spectral shape, much as words in natural language derive meaning from contextual relationships. The Transformer architecture underlying LLMs can further perform spectral tokenization, processing spectral signals into a usable interface that allows them to enter the representation space of LLMs. Figure 1 illustrates how these models take advantage of the "scaling law". Spectral LLMs can deeply decouple complex mixed signals and accurately understand the Earth's surface.

To make the "Cognitive Spectrum Earth" a reality, the scientific community should take immediate and coordinated action. We advocate building global, open-access spectral data infrastructure (AI-ready datasets) and collaboratively training general-purpose Spectral LLMs. Such a framework goes beyond mapping surface materials. It actively provides significant information for strategic mineral exploration, precision agriculture, and planetary health monitoring. The future of remote sensing lies not only in seeing the Earth with better eyes, but also in understanding it with a better mind.

SPECTRAL LLMs: TOWARDS A KNOWLEDGE-GUIDED SEMANTIC REPRESENTATION OF EARTH

The transition to intelligent spectral cognition hinges on a triad of capabilities: planetary-scale data integration, robust generalization, and autonomous reasoning. International space missions routinely collect vast amounts of information, but a deep divide separates these raw datasets from usable knowledge. Data scarcity is no longer the bottleneck; fragmentation is. Researchers first need to build a standardized, AI-ready spectral library capturing the global diversity of surface materials across climate zones, ecosystems, and observation chains. Beyond data accumulation, this requires systematic integration of complex and diverse spectral response patterns to overcome heterogeneous noise limiting cross-sensor interoperability.[5]

To address this, we must move beyond rigid physical a priori assumptions and manual parameter tuning. The Transformer architecture offers a solution by providing a more flexible, data-driven framework. These models convert and tokenize continuous spectral curves into ordered natural language sequences with local adjacent dependencies and full-spectrum context. Spectral LLMs use the self-attention mechanism of the Transformer architecture to examine local absorptions and full-spectrum combinations simultaneously, preserving a distinguishable representation space for spectral variations under different genetic backgrounds. When trained with tokenization and self-supervised learning on massive datasets, Spectral LLMs learn to effectively "read" the Earth's surface. They rebuild the potential mapping rules between photon interactions and material properties within a high-dimensional semantic space.

Large-scale Data-driven pretraining alone is not enough. This creates a black box lacking domain expert reasoning. Explicit expert knowledge needs to be progressively injected through subsequent fine-tuning, carrying interpretable geoscientific meaning and achieving deeper cognition. This knowledge represents the culmination of long-standing human experience and is currently scattered across scientific literature, technical reports, and open web resources. We propose a knowledge-guided framework. It structures and encodes geoscientific knowledge as text, while tokenized spectra are converted into spectral embeddings through the spectral encoder. Both are then aligned inside a unified embedding space. The model retrieves embedded knowledge matching the current spectral morphology, converting it into a geoscientific reference that links subtle spectral differences to possible material processes. By bridging the semantic gap between spectral vectors and discrete concepts, model outputs remain physically interpretable. This envisions a potential paradigm shift in Earth observation: from physics-driven modeling toward knowledge-aware autonomous cognition. Building Spectral LLMs will change how scientists decipher Earth's composition, providing a pathway to extract the hidden value in spectral data as a definitive planetary fingerprint.

TACKLING GLOBAL CHALLENGES: MINERALS, AGRICULTURE, AND PLANETARY HEALTH

Deploying Spectral LLMs injects intelligent momentum into addressing 21st-century "Grand Challenges": resource security, food crises, and ecologi-

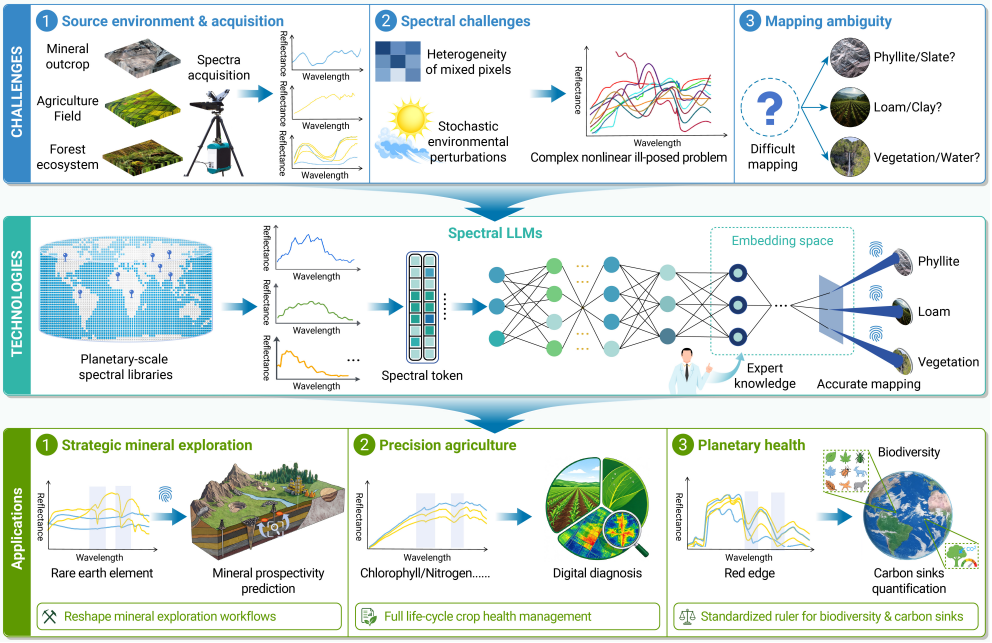


Figure 1. Intelligent mapping of spectra to surface materials enabled by LLMs for Spectrum Earth cognition.

cal deficits.

Strategic mineral exploration currently struggles with a severe bottleneck. Identifying deeply buried, physically concealed, and chemically complex resources remains extremely difficult. Spectral LLMs provide a new perspective on breaking detection boundaries. Their nonlinear deblending capabilities penetrate complex pixel mixtures and reveal faint signatures of key metals such as lithium, cobalt, and rare earth elements, enabling accurate mineral prediction. This shifts exploration from empirical assessment to data-driven targeting.

The agricultural sector benefits similarly, as the technology serves as a "digital stethoscope" for global plant life. These models decode the biochemical links between leaf spectra and specific stressors like chlorophyll, nitrogen, and water content. Consequently, farm management evolves from static observation to dynamic, full life-cycle health management. This enables precision fertilization and irrigation based on real-time data, helping to maintain stable food production under changing climatic conditions.

For planetary health, Spectral LLMs provide the first method for quantifying biodiversity and carbon sinks. By capturing subtle phenological variances in the Red Edge and SWIR bands, these models ground large-scale ecosystem assessments in solid material identification rather than superficial indices. This provides the credible scientific evidence required for global carbon budgeting and ecological restoration.

FUTURE OUTLOOK: EVOLVING TOWARDS A COGNITIVE EARTH

To fully realize the vision of an integrated "Cognitive Spectrum Earth", future technological evolution should converge on three strategic frontiers:

Bridging the scale chasm

We must break the transfer bottleneck between ground-truth spectra and satellite observations. This requires explicitly modeling physical processes—atmospheric transmission and sensor response functions—to achieve deep semantic alignment. The goal is a unified framework where a "spectral token" learned from a handheld spectrometer is mathematically consistent with one acquired from orbit.

Physics-Informed neuro-symbolic integration

Models driven purely by data are prone to producing illusions. Embedding radiative transfer priors and diagnostic band constraints directly into model architecture improves the synergy between physics and deep learning.

From specialists to generalists

Finally, Spectral LLMs should progressively move from task-specific tools toward universal platforms capable of reusing knowledge, extending to broader Earth observation scenarios through domain adaptation.

CONCLUSION

Proposing LLMs for spectral analysis goes far beyond a simple technological upgrade. It changes and reshapes the cognitive dimensions of Earth science. This framework responds to the urgent need for precise, global-scale material understanding. The systematic accumulation of planetary-scale data, combined with AI-based analytical capabilities, is driving a fundamental shift in spectral analysis. This transition moves from passively recording photon signals to actively interpreting the material composition that underlies those signals.

This methodology seamlessly integrates physical ground truth, domain expertise, and generative AI. It propels the evolution of remote sensing from simple visual perception toward deep material cognition. In critical domains ranging from strategic resource security to ecosystem governance, this intelligent framework stands ready to reshape operational workflows, providing the vital decision support systems necessary for a sustainable and resilient future. The era of "reading" the earth has ended; the era of "comprehending" it has begun.

REFERENCES

1. Roemer F. E., Buehler S. A., Brath M., et al. (2023). Direct observation of Earth's spectral long-wave feedback parameter. *Nat. Geosci.* **16**:416–421. DOI:10.1038/s41561-023-01175-6
2. Li C., Hong D., Zhang B., et al. (2024). Interpretable foundation models as decryptors peering into the Earth system. *The Innovation* **5**:100682. DOI:10.1016/j.xinn.2024.100682
3. Yuan Q., Shen H., Li T., et al. (2020). Deep learning in environmental remote sensing: Achievements and challenges. *Remote Sens. Environ.* **241**:111716. DOI:10.1016/j.rse.2020.111716
4. Bodnar C., Bruinsma W. P., Lucic A., et al. (2025). A foundation model for the Earth system. *Nature* **641**:1180–1187. DOI:10.1038/s41586-025-09005-y
5. Thoreau R., Risser L., Achard V., et al. (2024). Toulouse hyperspectral data set: A benchmark data set to assess semi-supervised spectral representation learning and pixel-wise classification techniques. *ISPRS J. Photogramm. Remote Sens.* **212**:323–337. DOI:10.1016/j.isprsjprs.2024.05.003

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AUTHOR CONTRIBUTIONS

Tong Zhu and Sheng Wang: Conceptualization, methodology, writing, and editing. Yongjun Xu: Editing, suggestions and supervision. Xiaohan Zhang and Wei Han: Writing. Jun Li and Lizhe Wang: Editing and supervision. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.