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Exploring power of AI and DL for Land Classification for Data Scarce Rural Regions

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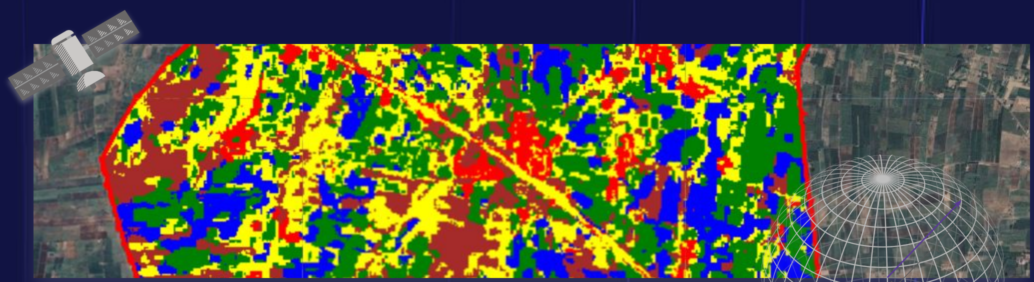
Abstract

Mapping the complex landscape of rural India is challenging due to fragmented land holdings, small plot sizes, and spectral similarity between several operational land use types, like unpaved roads and barren fields. Traditional Remote Sensing using only spectral bands often fails to capture these nuances. This study evaluates Google Satellite Embedding V1 - an foundational model trained to recognize spatial texture and context - against standard pixel-based spectral classification. We tested three temporal windows (1, 3, and 10 years) to identify the optimal period for rural mapping. Results show that Embeddings successfully capture the unique texture of rural landscapes, outperforming spectral bands by **17.2%** in accuracy when using a 3-year aggregation window, specifically in distinguishing village roads from fallow lands.



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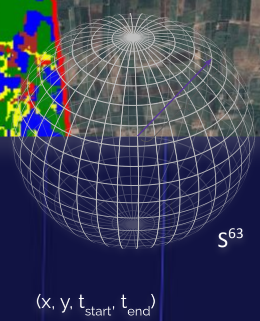
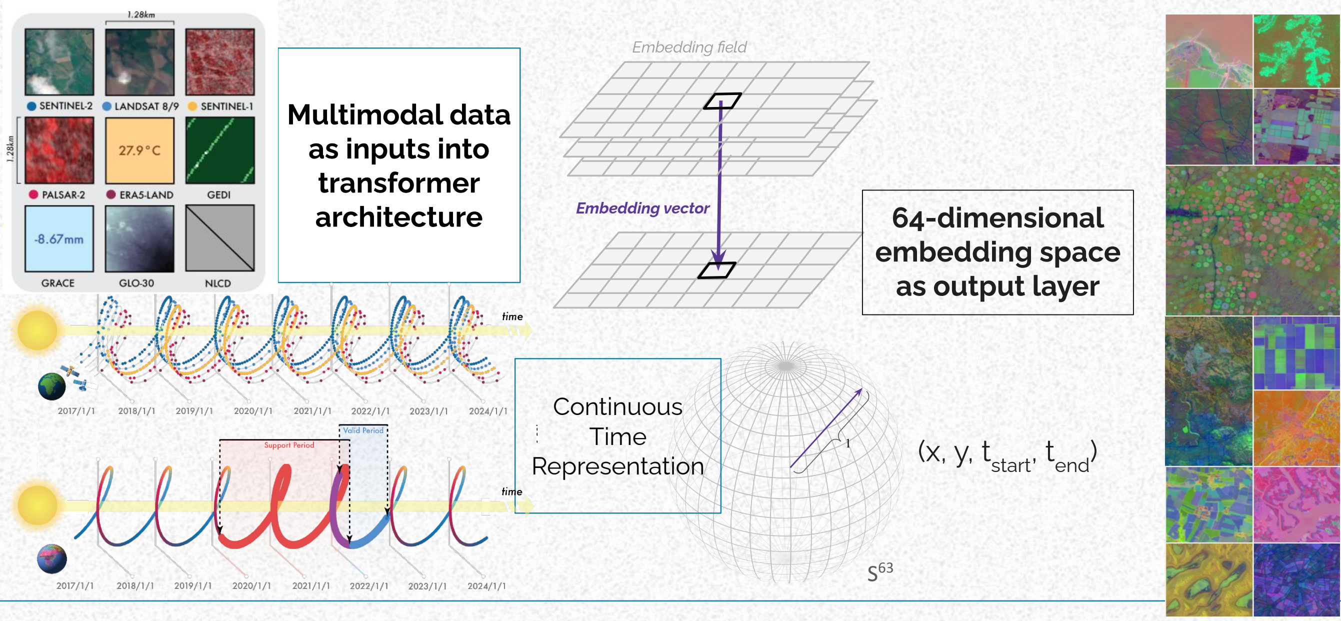


INTRODUCTION

Crop water optimization in Maharashtra requires precise land use maps. However, the texture of rural India presents unique remote sensing challenges:

- **Fragmentation:** Small, irregular farm plots create mixed pixels.
- **Spectral Confusion:** Mud roads, built-up village centers, and dry barren land often share identical spectral signatures.

Objective: To demonstrate that Satellite Embeddings (which see texture and context) are superior to Spectral Bands (which see only gray level) for mapping the heterogeneous landscape of rural India.



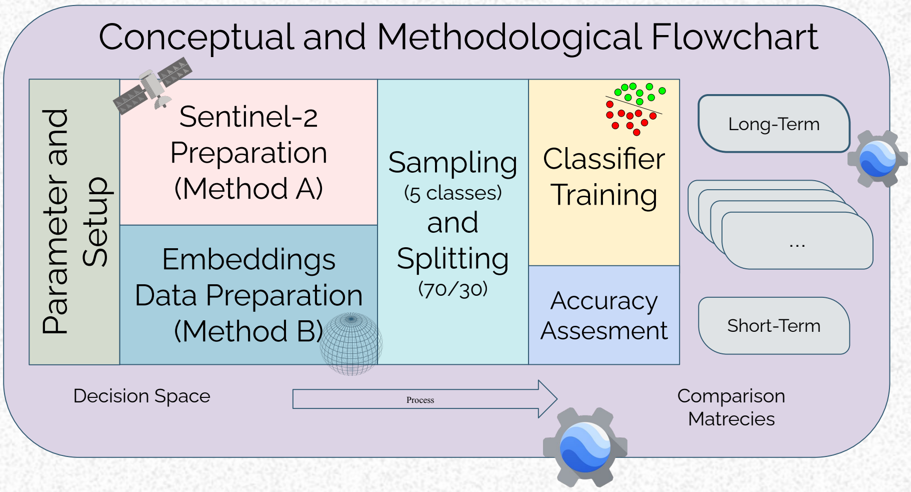
What are Satellite Embeddings?

Unlike traditional remote sensing that relies solely on pixel gray level (spectral bands), Embeddings are product of Google AlphaEarth foundation model that use deep learning to encode spatial texture and context into 64-dimensional vectors. This allows the model to **see** structural shapes (like linear roads vs. scattered scrubland) that spectral sensors miss. (Brown et al., 2024)

STUDY AREA, METHODS AND MATERIALS

Figure 1 Study Area:
Loni Devkar Village, Indapur Taluka, Pune District, Maharashtra.
Source: Survey Of India

Data & Models:
Baseline: Sentinel-2 (SR) Median Composites (Bands B2, B3, B4, B8, B11, B12).
Proposed: Google Satellite Embeddings (V1) - 64-dimension texture vectors.
Classifier: Supervised K-Nearest Neighbors (KNN) trained on google earth and drone based GT points (Road, Crop, Built-up, Water, Barren).



Temporal Experiment:
We analyzed how temporal depth impacts the model's ability to see texture:
Short-term: 1 Year (2020)
Mid-term: 3 Years (2020–2023)
Long-term: 10 Years (2014–2024)

RESULTS

The analysis identifies the 3-year aggregation as the optimal window, achieving 70.8% accuracy—a significant 17.2% improvement over the spectral baseline. While 10-year composites suffered from land-use change artifacts, the 3-year Embedding model successfully captured stable rural textures, distinguishing unpaved roads from fallow land.

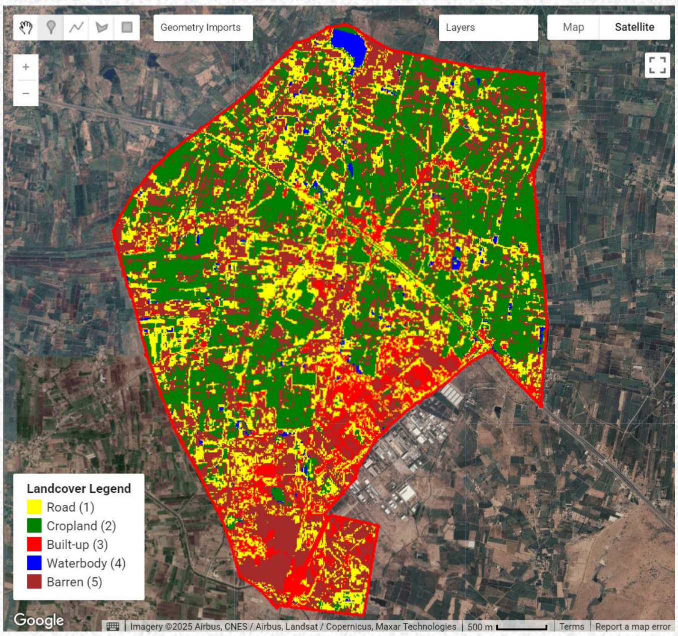


Figure 2.1 Classification , Sentinel-2 (3 Years)

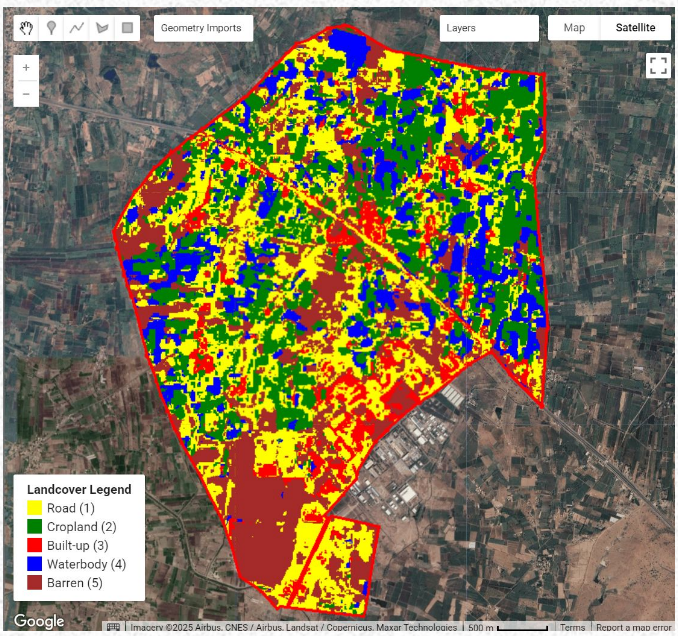


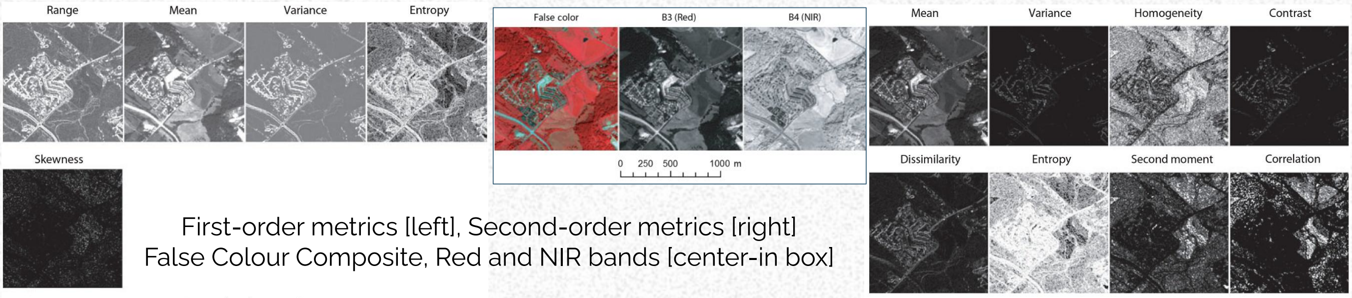
Figure 2.2 Classification , Google Embedding

Table 1. Choice of Temporal Span on overall accuracy

Temporal Window	Sentinel-2 *(Spectral Only)*	Google Embeddings *(Texture + Spectral)*	Performance Gain
1 Year (2020)	55.6%	64.0%	+11.4%
3 Years (2020–23)	53.6%	**70.8%**	**+17.2%**
10 Years (2014–24)	51.7%	60.7%	+9.0%

DISCUSSION

1. Texture and Spatial context Advantage: Embeddings outperformed Sentinel-2 in every scenario, in terms of overall accuracy. This is attributed to the model's ability to recognize spatial texture. A road and a barren field may have the same color (spectrum), but the Embedding model recognizes the linear shape of the road vs. the amorphous shape of the field.



First-order metrics [left], Second-order metrics [right]
False Colour Composite, Red and NIR bands [center-in box]

Figure 3 Kernel Based texture in Remote Sensing (Warner, 2011)

2. **3-Year span as optimum window:**

- 1-Year data was too noisy due to sparse cloud-free observations.
- 10-Year data suffered from temporal ghosting. Land use changes over a decade (e.g., a farm becoming a building in the southeast) confused the training set.
- 3-Year data provided enough stability to remove noise but was short enough to maintain land cover consistency.

CONCLUSIONS

1. **AI/DL Superiority:** Just like every other fonts in technology, RS-based AlphaEarth Embeddings provide a robust alternative to raw spectral bands, improving classification accuracy by up to 17%.
2. **Optimal Window:** A dynamic temporal aggregation is recommended for complex Indian agrarian regions.
3. **Impact:** This improved mapping accuracy will directly enhance the precision of the Crop Water Optimization decision support system currently under development at RuDRA lab, C-TARA.

1. Brown et al., 2024 – AlphaEarth Foundations (arXiv:2407.08723)
2. Gorelick et al., 2017 – Google Earth Engine (RSE 202, 18–27)
3. Spatial Thoughts, 2024 – Satellite Embedding Deep Dive (YouTube Workshop)
4. Warner, 2011 – Kernel-Based Texture in RS Classification (Geography Compass 5:781–798)
5. CodeRepo - tinyurl.com/somdeep-CMInDS

Acknowledgement

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