

Latent Field Reduction of Earth Observation Foundation Model

Advances in Representation Learning for Earth Observation

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Earth Observation Foundation Model

- ▷ **FM4CS:** Foundational Model for Climate and Society, encodes satellite images into 768-dimensional latent vectors v using a ViT architecture.
- ▷ **Data:** Sentinel-3 SLSTR daily measurements over Norway (2018), 4 optical + 2 thermal bands, 2–3 km resolution.
- ▷ **Latent Field:** Latent vectors form a spatially resolved, abstract vector field $v(x)$ of satellite data across the region.

(Reference 1)

Latent Vector Field Embedding

- ▷ **Idea:** Analyze latent field via dimensionality reduction of vectors v .
- ▷ **Problem:** Traditional methods treat vectors as point cloud → ignore domain and continuity of underlying structure.
- ▷ **Solution:** Treat vectors as samples from a continuous field and find embedding $u(x)$ of the field in a lower dimensional vector space using Graph Kernel Operators (GKO).

Graph Kernel Operator

- ▷ **Graph construction:**
 - Sample set of random latent vectors $v(x_i)$ as node features.
 - Nearest neighbors connected by edges.
 - Edges equipped with attributes containing positional encoding of nodes.

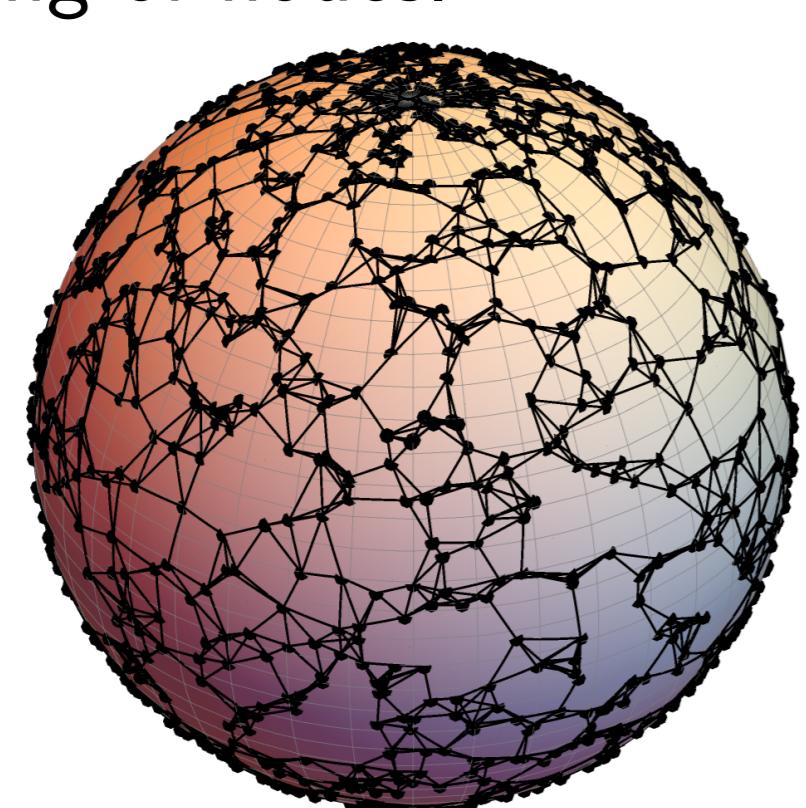


Figure 1: Visualization of graph, constructed using discrete latent vector field realizations for GKO-based dimensionality reduction.

Architecture

- Lifting: Single linear layer P projects nodes into a intermediate dimensional vector space H

$$Pv(x_i) = h_i \in H. \quad (1)$$

- Message-Passing: Information from neighboring nodes is iteratively passed

$$h_i^{(t+1)} = \sigma \left(Wh_i^{(t)} + \sum_{j:(i,j) \in E(i,j)} K_{ij} h_j^{(t)} \right), \quad (2)$$

using a kernel matrix K_{ij} that is predicted based on edge attributes.

- Final node features $h^{(T)}$ are projected into low-dimensional space with using a linear layer Q

$$Qh_i^{(T)} = \hat{u}(x_i) \quad (3)$$

(Reference 2)

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Experiments

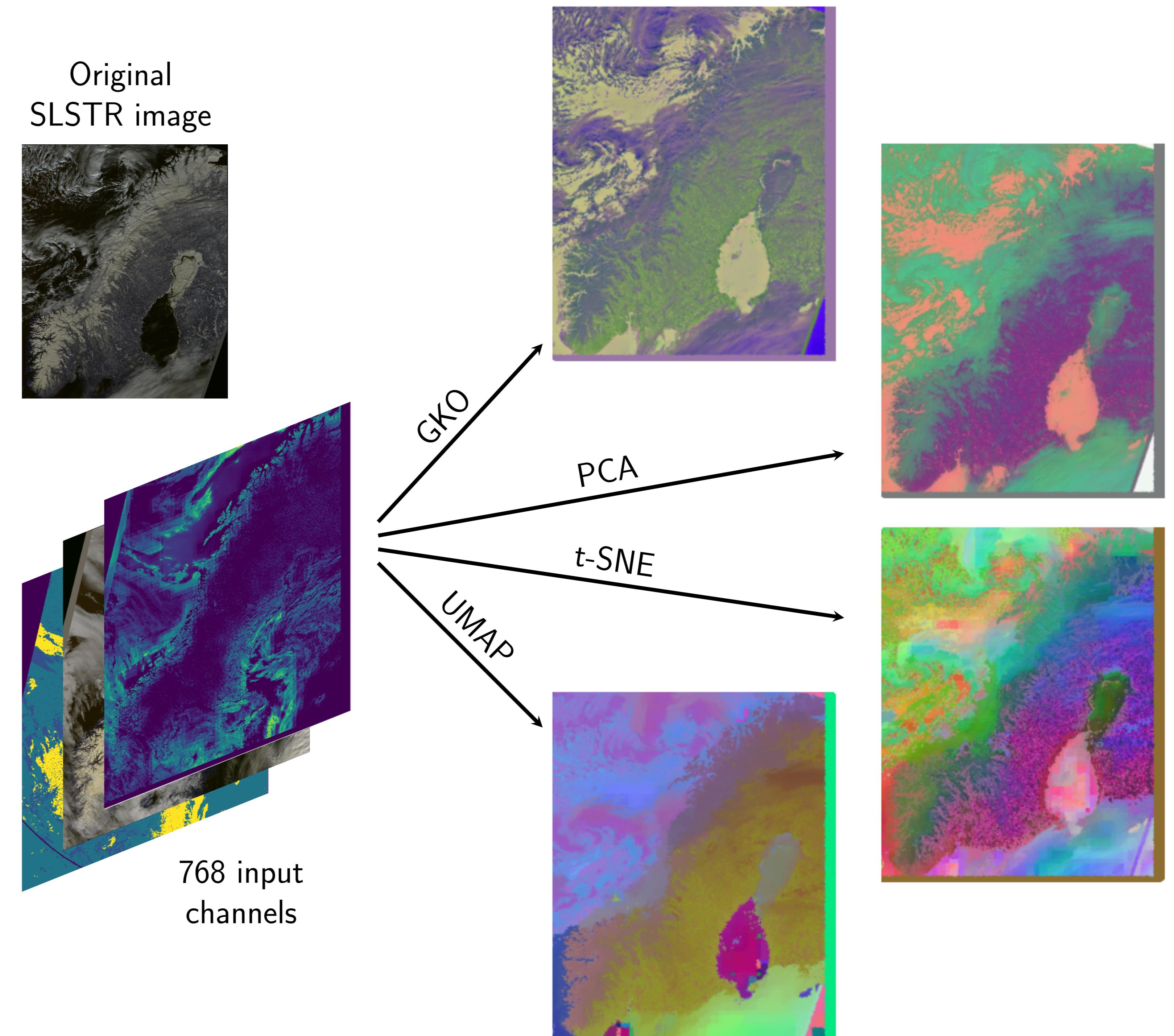


Figure 2: 100,000 randomly sampled vectors from FM4CS' latent space representation of Scandinavia for 01.04.2018 are reduced from 768 to 3 dimensions. For comparison, this is done using our GKO method, as well as classical methods (PCA, t-SNE, UMAP). Results are displayed by interpreting each of the 3 dimensions as an RGB color-channel.

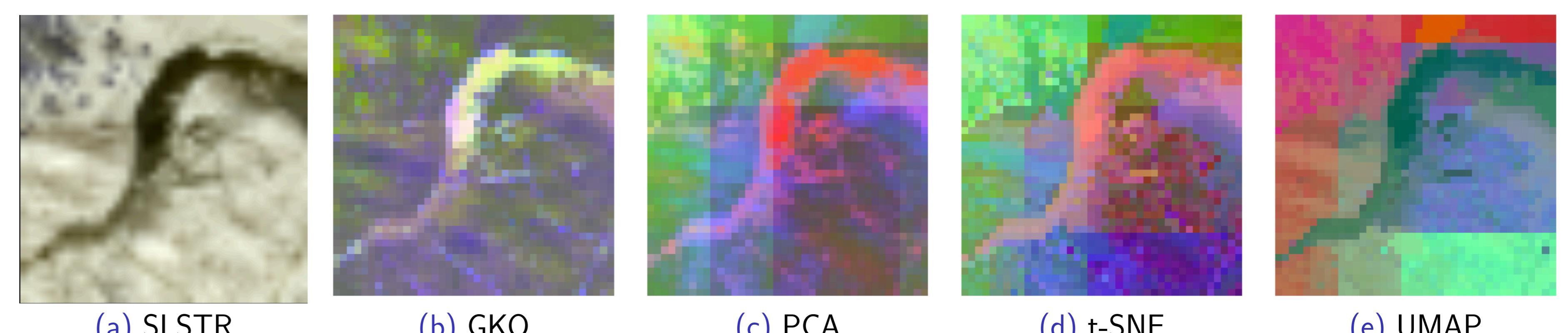


Figure 3: Dimensionality reduction for densely sampled 1600 latent vectors for a small region, representing a “zoom” into a small region of interest. Plots compare (3a) the original SLSTR image and (3b-3e) reduction for the same samples across methods.

Main Results

▷ Conceptual Advantage:

- Traditional methods view data as point cloud; GKO view vectors as discrete realizations of a continuous field. This guarantees **continuous embeddings**.
- Due to its graph structure and positional encodings, GKO-based dimensionality reduction is **domain-aware**.

▷ Practical Observations:

- GKO method is efficient and scalable.
- Resulting images are closer to original SLSTR images → increases interpretability.
- Traditional methods contain artifacts due to overclustering and underlying image-patch structure; GKO is the only method to overcome these issues.

References 1

FM4CS presentation:
<https://nr.no/en/publication/10255345/>

References 2

Z. Li, et al., *Neural Operator: Graph Kernel Network for Partial Differential Equations*, arXiv preprint arXiv:2003.03485, 2020. [Online]. Available: <https://arxiv.org/abs/2003.03485>