Self-Supervised Hyperspectral-LiDAR Pretraining for Large-Scale Remote Sensing Foundation Models

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Abstract

The fusion of hyperspectral imaging and light detection and ranging (LiDAR) data has become a cornerstone for high-fidelity Earth observation, yet the development of large-scale foundation models that jointly represent these modalities remains an open systems challenge. This paper examines the architectural, infrastructural, and governance dimensions of self-supervised pretraining for hyperspectral-LiDAR remote sensing models. Current approaches in single-modality self-supervised learning, such as contrastive and masked autoencoding methods, provide a foundation for multi-modal pretraining, but they face significant hurdles when applied to hyperspectral-LiDAR data due to differences in spatial resolution, spectral continuity, and point cloud sparsity. We analyze the structural trade-offs involved in designing a unified pretraining framework, including modality alignment strategies, band ordering effects, and the computational demands of processing high-dimensional spectral channels alongside geometric LiDAR features. A system-level perspective is adopted to discuss infrastructure requirements for large-scale pretraining, including data acquisition pipelines, normalization protocols, and distributed training architectures. Robustness and fairness issues arising from geographic biases and sensor variability are examined, along with policy implications for open data repositories and model governance. The paper argues that self-supervised pretraining offers a sustainable path toward reducing manual annotation effort, but its deployment in operational remote sensing systems must account for domain shifts, calibration drift, and ethical considerations. Through cross-domain comparisons with natural image foundation models, we identify key gaps and propose a research agenda for building truly reciprocal hyperspectral-LiDAR foundation models. The conclusions emphasize that progress hinges on community-wide coordination of benchmark datasets, standardized evaluation protocols, and transparent reporting of pretraining data composition.

Keywords

Self-supervised learning, foundation models, hyperspectral imaging, LiDAR, remote sensing, multi-modal fusion, large-scale pretraining, data governance, robustness, fairness.

1. Introduction

The remote sensing community has witnessed a paradigm shift toward large-scale pretrained models that can serve as versatile backbones for a wide array of downstream tasks. Early successes in natural language processing and computer vision have inspired a wave of foundation models tailored to Earth observation data, ranging from optical imagery to synthetic aperture radar. Hyperspectral imaging, which captures hundreds of narrow contiguous spectral bands, and light detection and ranging, which provides precise three-dimensional structural information, represent two of the most information-rich modalities available for environmental monitoring, urban planning, and precision agriculture. Their joint utilization enables a holistic characterization of surface materials, vegetation health, and

terrain morphology that neither modality can achieve alone. However, the construction of a single foundation model that can effectively pretrain on large-scale hyperspectral-LiDAR data presents unique systemic challenges that go beyond simply concatenating existing single-modality pretraining pipelines. The spatial and spectral heterogeneity of hyperspectral sensors, the irregular sampling of LiDAR point clouds, and the substantial differences in their data distributions require novel architectural and algorithmic innovations. Self-supervised learning, which leverages the intrinsic structure of unlabeled data to learn representations, offers a promising route to circumvent the prohibitively expensive manual annotation of multi-modal remote sensing datasets. This paper adopts a systems engineering perspective to dissect the design space of self-supervised hyperspectral-LiDAR pretraining, focusing on the interplay between representation learning objectives, network architectures, computational infrastructure, and socio-technical governance.

2. Background and Related Work

The emergence of foundation models in remote sensing has been driven by the availability of large-scale satellite and airborne datasets and the success of transformer-based architectures. Early efforts in single-modality pretraining for optical remote sensing, such as SatMAE [1] and SpectralGPT [2], demonstrated the feasibility of masked autoencoding and contrastive objectives on multispectral and hyperspectral imagery. These models built upon fundamental advances in self-supervised learning, including SimCLR [3], MoCo [4], DINO [5], and DINOv2 [6], which established that alignment of features from different augmentations or views can produce highly transferable representations. For LiDAR data, self-supervised methods have largely focused on point cloud understanding, employing contrastive learning between spatial transforms or occupancy-based masked modeling. However, the fusion of these two modalities in a pretraining context is still nascent. The challenge lies in designing pretext tasks that respect both the spectral continuity of hyperspectral data and the geometric sparsity of LiDAR while also capturing their cross-modal relationships. Early work on band ordering strategies for hyperspectral-LiDAR fusion networks [7] has highlighted that the sequential arrangement of spectral and LiDAR inputs significantly affects classification accuracy, a factor that must be considered in pretraining pipelines. Additionally, the survey by Zhu et al. [8] catalogs the landscape of large-scale pretrained models for remote sensing and underscores the absence of unified multi-modal pretraining efforts. The work of Li et al. [9] reviews self-supervised learning specifically for hyperspectral image classification and notes that most methods remain single-modal. Cong et al. [10] applied contrastive learning to remote sensing image pairs, but their approach did not incorporate three-dimensional point cloud data. These gaps motivate the need for a systematic investigation into pretraining architectures and system-level considerations for hyperspectral-LiDAR fusion.

3. Methodological Framework for Multi-Modal Self-Supervised Pretraining

Designing a self-supervised objective that can leverage both hyperspectral and LiDAR data simultaneously requires careful consideration of the representation space. A common approach is to train separate encoders for each modality and then enforce alignment between their outputs using a contrastive loss that maximizes mutual information between corresponding scene patches. This loosely mirrors the architecture of multimodal contrastive learning in natural language and vision, where pairs of image and text are aligned. However, the alignment between a hyperspectral cube and a LiDAR depth map or point cloud is not as straightforward. The hyperspectral sensor captures rich spectral signatures, whereas LiDAR provides geometric structure, and the two modalities often have different spatial resolutions

and ground footprints. A robust pretraining framework must therefore include a dense registration stage that matches each hyperspectral pixel to a set of LiDAR points within a local neighborhood, a process that introduces computational overhead and potential misalignment errors. An alternative strategy is to project both modalities into a common embedding space using cross-attention transformer layers, where the model learns to predict masked patches from one modality using the other as context. This masked multi-modal autoencoding approach has shown promise in early experiments, but it demands large training budgets and careful tuning of masking ratios to avoid trivial solutions. The band ordering aspect, as studied in recent work [12], becomes particularly relevant here because the transformer's self-attention mechanism treats each spectral channel as a separate token; the arrangement of those tokens relative to LiDAR-derived tokens can affect the model's ability to learn cross-modal interactions. Empirical investigations have demonstrated that interleaving spectral bands with LiDAR features in a structured manner yields improved downstream classification performance compared to simple concatenation [12]. This finding has direct implications for pretraining design: the ordering of input tokens must be considered as a learnable hyperparameter or as part of the positional encoding scheme. Furthermore, the high dimensionality of hyperspectral data necessitates efficient attention mechanisms, such as factorized or linear attention, to prevent the quadratic computational cost from becoming prohibitive during large-scale pretraining.

4. System-Level Considerations: Infrastructure, Scalability, and Data Governance

The deployment of a self-supervised hyperspectral-LiDAR foundation model at scale requires a robust computational infrastructure that can handle petabytes of raw data. Hyperspectral imagers, such as those aboard the AVIRIS or PRISMA missions, produce data cubes with hundreds of bands, each at typical spatial resolutions of 30 meters or finer. LiDAR surveys, acquired from airborne or spaceborne platforms, generate point clouds with billions of points. The preprocessing pipeline must include georeferencing, radiometric calibration, atmospheric correction, and co-registration, all of which must be automated and parallelized across distributed computing clusters. Cloud-based architectures, such as those provided by Amazon Web Services or Google Earth Engine, have become essential for managing the scale of remote sensing data, but they introduce latency and cost constraints that affect the feasibility of iterative pretraining experiments. Moreover, the storage and retrieval of paired hyperspectral-LiDAR datasets is complicated by data licensing and access restrictions. Many government-operated sensors have open data policies, but commercial providers often impose usage limitations that can hinder reproducibility and fair benchmarking. This data governance issue is central to the sustainability of foundation model research. Without a coordinated effort to create a large, publicly available, and well-curated hyperspectral-LiDAR pretraining corpus, progress will remain fragmented. The creation of such a corpus requires institutional agreements on metadata standards, data format harmonization (e.g., converting all hyperspectral data to a common spectral reference and all LiDAR to structured tile grids), and the adoption of a common coordinate reference system. The United States Geological Survey's Landsat and the European Space Agency's Sentinel programs serve as models for open data, but their spectral and spatial resolutions differ from those typical of hyperspectral-LiDAR systems. A foundation model trained solely on airborne data may not generalize to satellite-borne sensors, and vice versa, raising questions about transferability and domain adaptation. Therefore, any system-level design must include a curriculum learning strategy that exposes the model to a diverse range of sensors and acquisition conditions.

5. Structural Trade-Offs in Fusion Architecture and Pretraining Objectives

One of the most significant trade-offs in constructing a hyperspectral-LiDAR foundation model is the choice between early, intermediate, and late fusion. Early fusion concatenates raw data at the input level, but it suffers from severe modality imbalance: LiDAR data, often represented as digital elevation models or intensity rasters, have far fewer channels than the hyperspectral cube, potentially drowning out the LiDAR contribution. Late fusion, in contrast, processes each modality independently and combines predictions only at the decision layer, which fails to capture fine-grained cross-modal interactions. Intermediate fusion, where features from each modality are merged at several layers of a deep network, has become the de facto standard in supervised settings, but its application in self-supervised pretraining is underexplored. The transformer architecture naturally supports intermediate fusion through cross-attention modules, but the optimal depth and placement of these fusion layers remain an open research question. Another trade-off relates to the choice of pretraining objective. Contrastive objectives that encourage global scene-level alignment between hyperspectral and LiDAR representations may ignore local details that are critical for tasks like land cover classification. Masked autoencoding objectives, which reconstruct masked patches from both modalities, force the model to reconstruct spectral signatures from geometric cues and vice versa, fostering a deeper understanding of modality complementarity. However, the reconstruction loss must be balanced across modalities to prevent the model from over-learning the easier modality. For hyperspectral data, reconstruction of the full spectrum is a high-dimensional regression problem, whereas LiDAR reconstruction may involve predicting depth values or occupancy grids. The relative weighting of these losses is a hyperparameter that significantly impacts the quality of learned representations. Furthermore, the use of data augmentations, which are crucial for contrastive learning, must be adapted to preserve the physical meaning of spectral and geometric signals. Random crops and color jitter for hyperspectral data must respect the sensor's spectral response, and point cloud augmentations such as rotation and scaling must be applied in a physically plausible manner. These constraints complicate the design of augmentation pipelines and necessitate domain knowledge integration.

6. Robustness, Fairness, and Policy Implications

The robustness of a hyperspectral-LiDAR foundation model is intimately tied to the diversity and representativeness of its pretraining data. Geographic biases are a persistent challenge in remote sensing: most high-quality paired datasets originate from temperate regions with extensive ground truth, leaving tropical, arid, and polar ecosystems underrepresented. A model pretrained predominantly on North American or European landscapes may perform poorly on other regions, leading to systematic errors in global-scale applications. Self-supervised pretraining, by avoiding reliance on human annotations, can reduce some biases but cannot overcome geographic sampling imbalances. Robustness also depends on the model's ability to handle sensor drift, atmospheric variability, and seasonal changes. A foundation model should ideally be calibrated to produce invariant representations across different acquisition times and conditions. This requirement pushes toward data augmentation strategies that simulate environmental perturbations during pretraining, but such augmentations must be grounded in physical models to avoid introducing artifacts. Fairness considerations extend beyond geographic equity to include the types of downstream tasks that the model enables. If the foundation model is biased toward urban mapping because pretraining data are dominated by city scenes, rural communities may receive less accurate

environmental monitoring services. Policy frameworks for Earth observation foundation models are only beginning to emerge. The open science movement advocates for releasing model weights and training data, but concerns about dual-use applications, such as precision targeting in military contexts, call for access restrictions and accountability mechanisms. The authors of recent diffusion-based geospatial models [18] have highlighted the potential for misuse of high-resolution synthetic views, a concern that similarly applies to hyperspectral-LiDAR models that could be used to infer material composition or structural vulnerabilities. Transparent documentation of data sources, model limitations, and intended use cases, akin to model cards, should become standard practice. Furthermore, funding agencies and international consortia should invest in creating representative benchmark datasets that include diverse ecosystems and sensor configurations, ensuring that foundation models serve global rather than parochial interests.

7. Future Directions and Cross-Domain Perspectives

Looking forward, the field of hyperspectral-LiDAR pretraining can learn valuable lessons from the natural language processing and computer vision communities. The success of large language models has been predicated on massive, diverse, and continually updated corpora, coupled with scalable learning algorithms and infrastructure. For remote sensing, a similar trajectory would require the establishment of a multi-modal data lake that ingests data from all major hyperspectral and LiDAR sensors worldwide, with automated quality control and annotation through weak supervision. Self-supervised pretraining can then be performed at regular intervals, with the model weights made publicly available under a license that encourages both academic and commercial use while preventing harmful applications. Another promising direction is the integration of temporal information: many remote sensing applications rely on time series analysis, and a foundation model that incorporates temporal self-supervised objectives, such as predicting future spectral changes from LiDAR-derived deformation, would add significant value. The development of neuro-symbolic approaches that embed physical laws of reflectance and geometry into the pretraining loss could improve sample efficiency and interpretability. Cross-domain comparison with medical imaging, where multi-modal fusion (e.g., MRI and CT) is common, reveals that domain-specific normalization and registration are critical bottlenecks that deserve more research attention. Finally, the community must invest in systematic benchmarking protocols that measure not only task accuracy but also computational cost, data efficiency, and fairness metrics. Only through such rigorous evaluation can we ensure that self-supervised hyperspectral-LiDAR foundation models deliver on their promise of transformative Earth observation capabilities.

8. Conclusion

This paper has presented a comprehensive systems-level analysis of self-supervised hyperspectral-LiDAR pretraining for large-scale remote sensing foundation models. The architectural and algorithmic challenges of fusing high-dimensional spectral data with three-dimensional geometric data under self-supervised objectives are substantial, but they are surmountable through careful design of multi-modal transformers, masking strategies, and physically informed augmentations. The critical role of band ordering in multi-modal networks, as demonstrated by recent empirical work, underscores the need for principled input formatting and positional encoding. System-level considerations, including data governance, computational infrastructure, and reproducibility, are as important as algorithmic innovations. Robustness and fairness concerns demand that pretraining data be representative of global landscapes and that models be transparently documented. Policy implications

around open data, dual-use risks, and accountability must be addressed proactively by the research community. By learning from parallel advances in other AI domains and by fostering collaborative efforts to build large-scale, curated, and accessible hyperspectral-LiDAR datasets, the remote sensing field can realize a new generation of foundation models that are both powerful and responsible. The path forward is interdisciplinary, requiring expertise from remote sensing, machine learning, systems engineering, and science policy.

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