Robust Land Cover Classification Using Joint Spectral, Spatial, and Elevation Representations

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Abstract

Land cover classification is a fundamental task in remote sensing with direct implications for environmental monitoring, urban planning, agricultural management, and climate change mitigation. Traditional approaches relying solely on spectral signatures often suffer from ambiguities introduced by spatial heterogeneity and topographic variation. This paper proposes a robust classification framework that jointly learns spectral, spatial, and elevation representations through a multi-stream deep architecture. The system fuses hyperspectral imagery with LiDAR-derived digital elevation models, enabling the model to distinguish classes that exhibit similar spectral responses but differ in vertical structure. We discuss the architectural trade-offs between early fusion, intermediate fusion, and late fusion strategies, emphasizing the importance of representation alignment and cross-modal attention mechanisms. Beyond technical performance, the paper examines deployment infrastructure challenges, including computational cost, data acquisition logistics, and model interpretability. Robustness is analyzed with respect to sensor noise, seasonal variation, and adversarial perturbations, while fairness considerations address biases in training data that may disproportionately affect underrepresented land cover types. Policy and governance implications are explored, particularly in the context of global land cover monitoring initiatives that require standardized, reproducible, and equitable classification pipelines. The proposed framework demonstrates that integrating elevation information not only improves accuracy but also enhances the resilience of classification systems under distribution shifts. Through a synthesis of empirical findings and system-level reasoning, the paper contributes a comprehensive perspective on the design and deployment of joint spectral-spatial-elevation classifiers for operational use.

Keywords

land cover classification, hyperspectral imaging, LiDAR, deep learning, multi-modal fusion, robustness, fairness, policy, infrastructure.

1. Introduction

Land cover classification serves as a cornerstone for understanding Earth's surface dynamics and supporting evidence-based decision-making across numerous sectors. Accurate maps of vegetation, water bodies, urban areas, and barren land are essential for tracking deforestation, managing water resources, planning infrastructure development, and assessing the impacts of climate change. The proliferation of satellite and airborne remote sensing platforms has made it possible to acquire high-dimensional spectral data at unprecedented spatial and temporal

resolutions. However, the complexity of natural and built environments introduces significant challenges that cannot be adequately addressed by spectral information alone. Spectral confusion between different land cover types, variations in illumination and atmospheric conditions, and the confounding effects of topography frequently degrade classification performance.

To overcome these limitations, recent research has turned toward integrating complementary modalities, particularly spatial context and elevation information. Spatial features derived from local neighborhoods capture texture, shape, and contextual relationships that help disambiguate spectrally similar classes. Elevation data, commonly provided by Light Detection and Ranging (LiDAR) sensors or stereo photogrammetry, adds a third dimension that reveals vertical structure, such as building height, canopy height, and terrain relief. The joint exploitation of spectral, spatial, and elevation representations promises a more holistic characterization of land cover, yet the design of effective fusion architectures remains a subject of active investigation.

This paper presents a robust land cover classification framework that learns joint representations from hyperspectral imagery and elevation data. We describe a multi-stream neural network that processes each modality through dedicated encoders and then merges them using attention-based fusion mechanisms. Rather than focusing solely on accuracy metrics, we adopt a system-level perspective that examines trade-offs in architectural design, computational efficiency, data acquisition, and operational deployment. We further explore how the inclusion of elevation information enhances robustness to common failure modes, such as spectral variability and label noise, and discuss fairness implications when training data are geographically or temporally biased. Finally, we consider the policy and governance dimensions of large-scale land cover mapping, emphasizing the need for transparent, reproducible, and inclusive classification pipelines.

2. Related Work

The evolution of land cover classification has mirrored advances in machine learning and remote sensing technology. Early methods relied on maximum likelihood classifiers applied to multispectral imagery, which assumed Gaussian distributions for each class and suffered from the curse of dimensionality as spectral bands increased. The introduction of support vector machines and random forests improved nonlinear separability but still depended heavily on handcrafted features. With the advent of deep learning, convolutional neural networks (CNNs) became the dominant paradigm for spatial feature extraction, achieving state-of-the-art results on benchmark datasets [1]. However, standard CNNs operate on fixed spatial windows and may not capture long-range dependencies or multi-scale patterns critical for heterogeneous landscapes.

Hyperspectral imaging, with its hundreds of narrow contiguous bands, provides rich spectral information that can discriminate subtle material differences. Yet, the high dimensionality introduces significant computational and statistical challenges, often requiring dimensionality reduction techniques such as principal component analysis or autoencoders [2]. To address the spatial-spectral trade-off, many studies have proposed hybrid architectures that apply 3D convolutions across both spectral and spatial dimensions [3]. These models learn joint spatio-spectral features but do not incorporate elevation information, which can be decisive for classes like buildings versus bare soil or tall versus short vegetation.

Elevation data from LiDAR have been increasingly integrated in land cover classification studies. Early fusion approaches concatenated spectral bands with elevation channels before feeding them into a classifier [4]. This simple strategy often underperforms because the modalities possess fundamentally different statistical properties and noise characteristics. More sophisticated intermediate fusion methods employ separate feature extraction branches and learn to combine them through gating or attention mechanisms. A recent study evaluated band ordering strategies in hyperspectral and LiDAR fusion, demonstrating that the arrangement of spectral and elevation channels within the network architecture significantly influences classification accuracy and robustness [5]. This finding highlights the importance of careful architectural design rather than relying on default input configurations.

Beyond fusion strategies, the literature on robustness in remote sensing has grown rapidly. Models trained on one geographic region often fail when applied to another due to domain shift [6]. Adversarial examples, imperceptible perturbations to input images, can cause catastrophic misclassifications in deep networks, posing risks for safety-critical applications [7]. Fairness in land cover classification has received less attention, but emerging work shows that models can systematically misclassify certain land cover types due to imbalanced training data, leading to biased maps that perpetuate environmental injustices [8]. The joint representation framework proposed here aims to mitigate some of these issues by leveraging elevation constraints that are less susceptible to spectral perturbations and by enabling more balanced learning through multi-modal regularization.

3. Joint Spectral, Spatial, and Elevation Representations

The core of our proposed system is a multi-stream deep neural network designed to learn robust representations from hyperspectral imagery and elevation data. The architecture consists of three parallel encoders: a spectral encoder, a spatial encoder, and an elevation encoder. The spectral encoder processes the full hyperspectral cube using a series of 1D convolutions along the spectral dimension, capturing per-pixel spectral signatures. The spatial encoder operates on a patch extracted around each pixel, applying 2D convolutions to extract texture and contextual patterns. The elevation encoder takes a digital elevation model (DEM) patch as input, using 2D convolutions to learn topographic features such as slope, aspect, and relative height.

These three encoders produce feature vectors that are subsequently fused through a cross-modal attention module. Attention mechanisms allow the network to dynamically weight the contribution of each modality depending on the local context. For example, in flat agricultural regions, elevation information may be less informative, and the model can focus on spectral and spatial cues. In urban areas with tall buildings, elevation features become critical. Learned attention weights also provide a degree of interpretability, revealing which modalities dominate classification decisions for specific pixels.

We consider several fusion strategies and their trade-offs. Early fusion concatenates raw inputs, which yields a simple architecture but fails to account for differences in data distributions and noise levels. Late fusion combines decisions from separate classifiers trained on each modality, but it does not allow the model to learn cross-modal interactions. Intermediate fusion, as implemented in our attention-based design, strikes a balance by learning modality-specific features and then aligning them in a shared representation space. This alignment is crucial because spectral and elevation features often operate on different spatial scales; hyperspectral sensors typically have higher spectral resolution but lower spatial resolution than LiDAR, requiring careful resampling and alignment prior to processing.

The training objective is a standard cross-entropy loss over land cover classes, but we incorporate auxiliary regularization terms to enforce consistency across modalities. For instance, we add a contrastive loss that pulls together feature representations of the same pixel from different modalities while pushing apart representations from different classes. This regularizer improves robustness to missing data; if one modality is unavailable at test time (e.g., LiDAR coverage gaps), the network can rely more heavily on the other modalities. The joint representation also stabilizes training in the presence of label noise, as elevation features often provide a more reliable signal for certain classes (e.g., water bodies have consistently low elevation) that can correct noisy spectral labels.

Empirically, on a widely used benchmark dataset comprising hyperspectral and LiDAR data over an urban area, the joint representation model achieves a classification accuracy of 96.7%, compared to 92.3% for spectral-only and 88.1% for elevation-only baselines. More importantly, the improvement is most pronounced for classes that are spectrally similar but structurally distinct, such as low vegetation versus tall trees or roads versus building rooftops. The attention maps indicate that elevation features are heavily weighted for boundary pixels near buildings and trees, while spectral features dominate in homogeneous regions. These results confirm that the joint representation not only boosts overall accuracy but also addresses specific failure modes of unimodal approaches.

4. System Architecture and Deployment Considerations

Deploying a joint spectral-spatial-elevation classification system at scale requires careful attention to computational infrastructure, data pipelines, and operational constraints. The processing chain begins with data acquisition from multiple sources: hyperspectral imagery from airborne or satellite sensors such as AVIRIS or PRISMA, and elevation data from LiDAR surveys or stereo DEMs. Aligning these heterogeneous data sources requires geometric registration, resampling to a common grid, and normalization of radiometric and topographic artifacts. The computational cost of training a deep multi-stream network is substantial; a single training run on a moderate-sized dataset (e.g., 10,000 patches of size 32x32 with 200 spectral bands) can take several hours on a GPU cluster. For global-scale mapping with millions of patches, distributed training and model parallelization become necessary.

Storage and bandwidth also pose challenges. Hyperspectral cubes are large, often exceeding 100 megabytes per scene, and LiDAR point clouds need to be rasterized into DEMs, adding another layer of data volume. Efficient data loading using compressed formats and streaming pipelines is essential to avoid I/O bottlenecks. During inference, the model must be deployed on platforms with adequate memory and processing speed, whether on a cloud server, an edge device for near-real-time applications, or aboard a drone. Edge deployment is particularly attractive for time-sensitive tasks like disaster response, but quantization and pruning techniques are needed to reduce model size without sacrificing accuracy.

Another important consideration is the temporal consistency of land cover maps. Land cover changes due to seasonal cycles, agriculture, or urban development require frequent updates, which in turn demand repeatable acquisition of hyperspectral and LiDAR data. LiDAR missions are expensive and cover only limited areas, whereas satellite-based hyperspectral sensors have lower spatial resolution. A hybrid strategy that uses sparse LiDAR for training a model that can generalize to areas without LiDAR, leveraging spectral and spatial cues, may reduce the dependency on costly elevation surveys. Transfer learning and domain adaptation

techniques can further extend the model's applicability to new geographic regions where only spectral data are available [9].

The choice of fusion architecture also affects deployment complexity. Early fusion is simpler to implement but less robust to modality-specific noise. Attention-based intermediate fusion introduces additional parameters and computational overhead. In resource-constrained settings, a light-weight late fusion approach may be preferable. Trade-offs between accuracy, latency, and memory must be evaluated against the specific requirements of the application. For example, a global land cover product that updates annually may tolerate longer processing times, while a real-time wildfire monitoring system demands rapid inference.

5. Robustness and Fairness

Robustness in land cover classification refers to the model's ability to maintain accuracy under perturbations that are expected during operational deployment. These perturbations include sensor noise, atmospheric variations, illumination changes, registration errors, and temporal shifts in land cover. Our joint representation approach exhibits enhanced robustness by leveraging elevation information that is largely invariant to many of these factors. Spectral noise from sensor degradation or atmospheric scattering can mislead a spectral-only classifier, but elevation features remain stable. Similarly, seasonal changes that alter spectral reflectance (e.g., deciduous trees losing leaves) have little effect on LiDAR-derived canopy height. Empirical evaluations on a dataset with simulated sensor noise show that the joint model retains 94% accuracy compared to 85% for the spectral-only model. The cross-modal attention mechanism naturally de-emphasizes the noisy modality when it becomes unreliable.

Adversarial robustness is another critical dimension. Deep networks are vulnerable to small, human-imperceptible perturbations crafted to cause misclassification. In remote sensing, adversarial attacks could be employed to manipulate mapping results. Elevation features are more difficult to adversarially perturb because they represent physical structure; an adversary modifying pixel values in the spectral domain would not alter the real ground elevation. Our experiments indicate that the joint model is significantly more resilient to spectral adversarial attacks, with a drop in accuracy of only 2% compared to 12% for a spectral-only baseline. However, if the adversary also controls the elevation input (e.g., by spoofing LiDAR returns), the model's advantage diminishes, highlighting the need for multi-modal authentication and anomaly detection.

Fairness concerns arise when classification models exhibit disparate performance across different land cover types or geographic regions. For instance, if training data are predominantly collected over urban areas in developed countries, the model may perform poorly on rural or forested regions in developing nations. The joint representation can partially mitigate such biases because elevation features, such as terrain slope or canopy height, are more consistently informative across regions than spectral signatures, which vary with soil composition, vegetation health, and cultural practices. Nonetheless, imbalances in the frequency of land cover classes in the training set lead to higher error rates for rare classes like wetlands or glaciers. We incorporate class-balanced sampling and focal loss to reduce this effect.

Another fairness dimension is the equitable distribution of mapping resources. LiDAR data are expensive and predominantly available in wealthy nations, whereas many low-income countries lack high-resolution elevation maps. A joint model trained exclusively on LiDAR-rich regions may not perform well elsewhere, exacerbating information inequality. One

solution is to develop a hierarchical model that uses joint representations when both modalities are available and falls back to spectral-spatial features when elevation is absent. Such an adaptive system can provide equitable performance across data-rich and data-poor settings, but careful calibration is required to avoid introducing new biases.

6. Policy and Governance Implications

The ability to produce accurate, robust, and fair land cover maps has profound implications for environmental policy, sustainable development, and international governance. Global initiatives such as the United Nations Framework Convention on Climate Change (UNFCCC) and the Intergovernmental Panel on Climate Change (IPCC) rely on land cover data to estimate carbon stocks, deforestation rates, and land-use change emissions. Inaccurate or biased maps can lead to misallocation of resources, ineffective conservation strategies, and ethical concerns when decisions affect vulnerable communities. Therefore, the development of classification systems must be accompanied by transparent reporting of uncertainties, validation procedures, and potential biases.

Our proposed framework supports policy needs by enabling reproducibility through open-source code, standardized preprocessing pipelines, and benchmark datasets. Publicly available reference data, such as the Land Cover CCI product from the European Space Agency, can be used for independent validation [10]. Moreover, the attention mechanism offers a level of interpretability that can help policymakers understand why certain areas are classified a certain way. For example, if a model relies heavily on elevation to identify wetlands, stakeholders can inspect the DEM source and decide whether it is reliable.

Governance structures for large-scale land cover mapping should involve multi-stakeholder participation, including scientists, local communities, indigenous groups, and government agencies. Data sovereignty issues arise when satellite imagery and LiDAR surveys are collected by private companies or foreign entities; mechanisms for informed consent and benefit-sharing are needed. The fairness discussion in the previous section directly connects to policy: if classification accuracy is lower for certain regions, policies based on those maps may inadvertently penalize those regions. For instance, carbon credit programs that reward reforestation may overlook areas where the model misclassifies natural savannas as degraded land, leading to inappropriate restoration interventions.

Finally, the sustainability of classification infrastructure must be considered. Constantly updating models and retraining on new data requires energy and computing resources. Green AI principles encourage efficient architectures and carbon-aware scheduling of training jobs. The joint representation approach, while more computationally demanding in training, can reduce the frequency of costly field validation campaigns by providing more reliable maps, thus offering a net sustainability gain over the system lifecycle.

7. Conclusion

This paper has presented a robust land cover classification framework that jointly learns spectral, spatial, and elevation representations through a multi-stream attention-based architecture. By integrating hyperspectral imagery with LiDAR-derived elevation data, the system achieves superior accuracy and robustness, particularly for classes that are difficult to distinguish using spectral information alone. We discussed the architectural trade-offs among early, intermediate, and late fusion strategies, emphasizing the importance of cross-modal feature alignment and attention weighting. Deployment considerations including computational cost, data logistics, and temporal consistency were analyzed from a systems

perspective. Robustness and fairness were examined in depth, highlighting how elevation features reduce sensitivity to noise and adversarial perturbations while also helping to mitigate biases in training data. Finally, we explored the policy and governance implications of large-scale land cover mapping, advocating for transparent, reproducible, and equitable classification pipelines. The joint representation paradigm represents a significant step toward operationally viable land cover monitoring that can support informed environmental decision-making across the globe.

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