

BiodiverseNet: Multitask Learning on Fused Multispectral and Radar Data for Scalable Ecosystem Monitoring

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Abstract

*Monitoring global biodiversity is a pressing challenge given the accelerating rates of ecosystem degradation and loss. Earth observation (EO) offers a scalable solution, but existing methods struggle with heterogeneity in ecosystems, label sparsity, and modality limitations. We propose **BiodiverseNet**¹, a multitask learning framework that leverages fused multispectral (Sentinel-2) and radar (Sentinel-1) imagery to jointly predict key biodiversity metrics: canopy cover, habitat fragmentation, and landscape connectivity. Our model employs a Vision Transformer (ViT) backbone with DINOv2 pre-training, combined with task-specific heads and auxiliary objectives including land cover classification and NDVI prediction. Evaluated on a global benchmark spanning 15 ecoregions across five continents, BiodiverseNet achieves competitive performance with R^2 scores of 0.76 for canopy cover, 0.62 for fragmentation, and 0.67 for connectivity, showing modest but consistent improvements of 2-2.5% over transformer baselines. The model demonstrates reasonable robustness across diverse biomes, though performance varies with ecosystem complexity and data availability.*

1. Introduction

Biodiversity loss represents one of the most critical environmental challenges of our time, with species extinction rates estimated to be 100 to 1,000 times higher than natural background rates [15]. The rapid degradation of ecosystems due to anthropogenic activities—including deforestation, urbanization, agricultural expansion, and climate change—necessitates urgent and comprehensive monitoring strategies. Traditional ground-based biodiversity assessments, while accurate, are labor-intensive, spatially limited, and temporally sparse, making them inadequate for

global-scale monitoring requirements.

Remote sensing presents a transformative opportunity for biodiversity monitoring by providing consistent, repeatable, and spatially comprehensive observations of Earth’s surface. The European Space Agency’s Copernicus program, particularly the Sentinel-1 (Synthetic Aperture Radar) and Sentinel-2 (multispectral optical) missions, offers unprecedented temporal resolution (5-6 day revisit time) and global coverage at moderate spatial resolution (10-20m). However, translating raw satellite observations into meaningful biodiversity indicators remains a significant computational and methodological challenge.

Current approaches to EO-based biodiversity monitoring suffer from several limitations: (1) reliance on single modalities that are vulnerable to atmospheric conditions or seasonal variations, (2) focus on individual metrics rather than holistic ecosystem assessment, (3) limited generalization across diverse biomes and ecological contexts, and (4) inadequate handling of the complex spatial relationships inherent in ecological processes.

In this work, we introduce **BiodiverseNet**, a comprehensive multitask learning framework that addresses these limitations through several key innovations:

- **Multimodal Architecture:** We design a novel fusion architecture that combines Sentinel-1 SAR and Sentinel-2 optical data using cross-modal attention mechanisms, leveraging the complementary strengths of each modality.
- **Advanced Backbone:** Our model employs a Vision Transformer (ViT) architecture with DINOv2 pre-training, enabling effective capture of long-range spatial dependencies crucial for biodiversity pattern recognition.
- **Multitask Learning:** We jointly predict multiple interconnected biodiversity metrics (canopy cover, habitat fragmentation, landscape connectivity) along with auxiliary tasks (land cover classification, NDVI estimation) to improve representation learning and reduce overfitting.
- **Global Evaluation:** We compile and evaluate on the most comprehensive global biodiversity monitoring dataset to

¹<https://github.com/TransformerTitan/BiodiverseNet>

date, spanning 15 distinct ecoregions across five continents with over 3 million annotated image tiles.

- **Open Science:** We commit to full reproducibility by releasing our dataset, pre-trained models, and evaluation framework to accelerate community research.

Our experimental results demonstrate that BiodiverseNet achieves state-of-the-art performance across all target metrics, with particularly strong improvements in challenging scenarios such as cloud-covered regions, seasonal transitions, and structurally complex ecosystems. The model’s robust generalization across diverse biomes suggests its potential for operational deployment in global biodiversity monitoring systems.

2. Related Work

Remote Sensing for Biodiversity Assessment. Remote sensing has long supported biodiversity monitoring, beginning with vegetation indices like NDVI [21] and EVI [6]. While useful, these indices offer limited insight into the spatial complexity of biodiversity. Later work, such as that by Skole and Tucker [18] and Hansen et al. [5], advanced forest change monitoring via satellite data, but often focused on binary outcomes rather than continuous biodiversity indicators. Recent efforts have emphasized ecological relevance, with reviews like Pettorelli et al. [14] highlighting key challenges such as spatial scale mismatches and limited ground-truth validation. Machine learning has further enabled biodiversity modeling, including species distribution modeling using satellite-derived variables [3, 11].

Deep Learning in Earth Observation. Deep learning has transformed remote sensing, with CNNs excelling at tasks like land cover classification [24], crop monitoring [9], and poverty mapping [7]. More recently, Vision Transformers (ViTs) [4] have shown strong performance in EO, including hyperspectral image classification [2] and segmentation [22]. Self-supervised learning methods such as DINOv2 [13] offer promising avenues for learning from unlabeled remote sensing data, which our work builds upon for biodiversity applications.

Multimodal Fusion in Remote Sensing. Integrating multiple sensing modalities, especially SAR and optical imagery, has proven effective due to their complementary properties. Fusion methods span early (input-level) [17], late (prediction-level) [10], and intermediate (feature-level) [1] strategies. Attention-based fusion has gained traction for capturing complex inter-modality relationships [23], and our work extends this with biodiversity-specific cross-modal attention mechanisms.

Multitask Learning for Earth Observation. Multitask learning (MTL) improves efficiency by exploiting relationships between tasks [16]. Both hard and soft parameter sharing approaches have been explored in EO, with applications in land cover classification and change detection [20].

Despite its potential, MTL remains underused in biodiversity monitoring—a gap our work aims to fill.

3. Dataset and Target Metrics

3.1. Satellite Data Sources and Preprocessing

Our dataset integrates multiple Earth observation data sources to provide comprehensive coverage of biodiversity-relevant information:

Sentinel-1 SAR Data: We utilize Sentinel-1 Ground Range Detected (GRD) products in Interferometric Wide (IW) swath mode, providing dual-polarization (VV and VH) backscatter measurements at 10m spatial resolution. SAR data preprocessing includes: (1) thermal noise removal using ESA’s Sentinel-1 Toolbox, (2) radiometric calibration to sigma-naught backscatter coefficients, (3) terrain correction using the SRTM 30m digital elevation model, and (4) speckle reduction using a 7×7 refined Lee filter. We compute additional SAR-derived features including the VV/VH ratio and radar vegetation index (RVI).

Sentinel-2 Multispectral Data: We use Sentinel-2 Level-2A (bottom-of-atmosphere reflectance) products, incorporating all 13 spectral bands resampled to 10m resolution. Preprocessing steps include: (1) cloud and cloud shadow masking using the Scene Classification Layer (SCL), (2) temporal compositing using median values over cloud-free observations within 30-day windows, (3) atmospheric correction validation using ground-based sun photometer measurements where available, and (4) calculation of spectral indices including NDVI, EVI, NDWI, and SAVI.

Temporal Integration: For each location, we construct multi-temporal feature vectors spanning one full year with monthly composites, resulting in 12 temporal observations per location. This temporal dimension enables the model to capture seasonal dynamics crucial for biodiversity assessment.

3.2. Ground Truth Biodiversity Metrics

We target three key biodiversity indicators that are both ecologically meaningful and amenable to remote sensing estimation:

Canopy Cover Percentage: Canopy cover represents the proportion of ground area covered by tree canopy when viewed from above. We derive reference data from multiple sources: (1) GEDI lidar observations providing precise canopy height and cover measurements at 25m footprints, (2) high-resolution PlanetScope imagery (3m) for spatial upsampling using regression kriging, and (3) field measurements from permanent forest plots in tropical regions. The final canopy cover dataset achieves 95% spatial coverage.

Habitat Fragmentation Index: We quantify habitat fragmentation using a modified version of the Morphological Spatial Pattern Analysis (MSPA) approach [19]. The

fragmentation index considers: (1) patch size distribution, (2) edge-to-interior ratio, (3) connectivity between patches, and (4) shape complexity. Values range from 0 (highly fragmented) to 1 (continuous habitat). Reference data is derived from high-resolution land cover maps (WorldView-2/3 at 2m resolution) manually validated by expert ecologists.

Landscape Connectivity Score: We assess landscape connectivity using circuit theory-based resistance modeling implemented through Circuitscape software [12]. The connectivity score integrates: (1) habitat quality maps derived from field surveys, (2) species-specific movement models for indicator taxa, (3) landscape resistance surfaces incorporating topography and land use, and (4) corridor identification using least-cost path analysis. Validation against radio-tracking data from 15 mammal species shows strong correlation ($r = 0.78$) between predicted and observed movement patterns.

3.3. Geographic Coverage and Sampling Strategy

Our dataset encompasses 15 distinct ecoregions selected to represent global biodiversity patterns and major biome types:

Tropical Regions:

- Amazon Basin (Brazil, Peru, Colombia): 450,000 tiles
- Congo Basin (DRC, Cameroon, CAR): 380,000 tiles
- Southeast Asian Lowlands (Indonesia, Malaysia): 290,000 tiles
- Atlantic Forest (Brazil): 180,000 tiles

Temperate Regions:

- North American Boreal (Canada): 320,000 tiles
- Eurasian Taiga (Russia, Finland): 280,000 tiles
- Mediterranean Basin (Spain, Greece, Turkey): 210,000 tiles
- Eastern Deciduous Forest (USA): 190,000 tiles

Arid and Semi-Arid Regions:

- East African Savannas (Kenya, Tanzania): 160,000 tiles
- Australian Outback (Australia): 140,000 tiles
- Patagonian Steppe (Argentina, Chile): 110,000 tiles

Mountain and Arctic Regions:

- Himalayan Foothills (Nepal, Bhutan): 95,000 tiles
- Rocky Mountains (USA, Canada): 85,000 tiles
- Scandinavian Mountains (Norway, Sweden): 75,000 tiles
- Arctic Tundra (Alaska, Siberia): 65,000 tiles

Each tile covers $1\text{km} \times 1\text{km}$ (100×100 pixels at 10m resolution) and includes complete multimodal and multi-temporal data. The dataset is split geographically with 70% for training, 15% for validation, and 15% for testing, ensuring no spatial overlap between splits.

4. Methodology

4.1. Model Architecture Overview

BiodiverseNet employs a hierarchical architecture designed to effectively process multimodal, multi-temporal satellite imagery for biodiversity assessment. The model consists of four primary components: (1) modality-specific feature extractors, (2) a shared Vision Transformer backbone with DINOv2 initialization, (3) cross-modal attention fusion modules, and (4) task-specific prediction heads.

4.2. Vision Transformer Backbone with DINOv2 Pre-training

We adopt a Vision Transformer (ViT) architecture as our primary backbone, specifically the ViT-Base variant with 12 transformer layers, 768 hidden dimensions, and 12 attention heads. The choice of ViT over traditional CNNs is motivated by several factors relevant to biodiversity monitoring:

Long-range Spatial Dependencies: Biodiversity patterns often exhibit complex spatial relationships across multiple scales. The self-attention mechanism in transformers naturally captures long-range dependencies that are crucial for understanding landscape-level ecological processes such as habitat connectivity and fragmentation patterns.

Multi-scale Feature Learning: The hierarchical attention patterns learned by ViT enable effective multi-scale feature extraction, from fine-grained texture patterns indicative of species composition to broad landscape patterns reflecting ecosystem structure.

DINOv2 Initialization: We initialize our ViT backbone with weights from DINOv2 [13], a state-of-the-art self-supervised learning approach. DINOv2 pre-training on large-scale natural image datasets provides robust visual representations that transfer effectively to remote sensing applications, particularly for tasks requiring fine-grained visual understanding.

The DINOv2 pre-trained weights are adapted to our multi-channel input through channel expansion techniques. Specifically, we replicate the RGB channel weights across our multi-band input channels and apply a learned linear transformation to adapt the feature dimensions.

4.3. Modality-Specific Feature Extraction

To handle the distinct characteristics of SAR and optical data, we implement modality-specific adapters that project each input modality to a unified feature space while preserving modality-specific semantics:

SAR Feature Extractor: For Sentinel-1 data, we design a specialized adapter that accounts for the multiplicative nature of SAR backscatter and its sensitivity to surface

geometry. The SAR adapter consists of:

$$F_{\text{SAR}} = \text{LayerNorm}(\text{Conv2D}(\log(\sigma^0 + \epsilon))) + \text{Conv2D}(\text{ReLU}(\text{Conv2D}(F_{\text{SAR}}))) \quad (1)$$

where σ^0 represents the backscatter coefficient and $\epsilon = 10^{-6}$ prevents numerical instability in logarithmic transformation.

Optical Feature Extractor: For Sentinel-2 multispectral data, we apply spectral normalization and band-specific scaling:

$$F_{\text{Opt}} = \text{LayerNorm}(\mathbf{W}_{\text{spectral}} \cdot \mathbf{X}_{\text{optical}} + \mathbf{b}_{\text{spectral}}) \quad (2)$$

where $\mathbf{W}_{\text{spectral}}$ and $\mathbf{b}_{\text{spectral}}$ are learned parameters that adapt spectral bands to optimal ranges for transformer processing.

4.4. Cross-Modal Attention Fusion

To effectively integrate SAR and optical information, we develop a cross-modal attention mechanism that dynamically weights contributions from each modality based on local image content and task requirements. Unlike simple concatenation or averaging approaches, our fusion strategy maintains the integrity of modality-specific features while enabling rich cross-modal interactions.

The cross-modal attention operates at multiple scales within the transformer backbone:

Early Fusion (Layer 1-4): Low-level features from both modalities are fused using cross-attention:

$$\begin{aligned} \mathbf{Q}_{\text{opt}} &= \mathbf{W}_q^{(1)} F_{\text{opt}}, & \mathbf{K}_{\text{sar}} &= \mathbf{W}_k^{(1)} F_{\text{sar}}, \\ \mathbf{V}_{\text{sar}} &= \mathbf{W}_v^{(1)} F_{\text{sar}} \\ \mathbf{A}_1 &= \text{softmax} \left(\frac{\mathbf{Q}_{\text{opt}} \mathbf{K}_{\text{sar}}^T}{\sqrt{d_k}} \right) \\ F_{\text{fused}}^{(1)} &= \mathbf{A}_1 \mathbf{V}_{\text{sar}} + F_{\text{opt}} \end{aligned} \quad (3)$$

Mid-level Fusion (Layer 5-8): Feature maps are fused using bidirectional attention:

$$\begin{aligned} F_{\text{fused}}^{(2)} &= \text{CrossAttn}(F_{\text{opt}}^{(1)}, F_{\text{sar}}^{(1)}) \\ &+ \text{CrossAttn}(F_{\text{sar}}^{(1)}, F_{\text{opt}}^{(1)}) \end{aligned} \quad (4)$$

Late Fusion (Layer 9-12): High-level semantic features are combined using learned gating mechanisms:

$$\begin{aligned} \mathbf{g} &= \sigma(\mathbf{W}_g[F_{\text{opt}}^{(2)}; F_{\text{sar}}^{(2)}] + \mathbf{b}_g) \\ F_{\text{final}} &= \mathbf{g} \odot F_{\text{opt}}^{(2)} + (1 - \mathbf{g}) \odot F_{\text{sar}}^{(2)} \end{aligned} \quad (5)$$

where σ represents the sigmoid activation and \odot denotes element-wise multiplication.

4.5. Task-Specific Prediction Heads

Each biodiversity metric and auxiliary task is predicted using dedicated neural network heads that process the shared representation from the transformer backbone:

Regression Heads (Canopy Cover, Connectivity, NDVI): Implemented as 3-layer MLPs with residual connections:

$$\begin{aligned} h_1 &= \text{ReLU}(\text{Linear}(F_{\text{final}})) + F_{\text{final}} \\ h_2 &= \text{ReLU}(\text{Linear}(h_1)) + h_1 \\ \hat{y} &= \text{Linear}(h_2) \end{aligned} \quad (6)$$

Classification Head (Land Cover): Multi-class classification using softmax output:

$$\hat{y}_{\text{class}} = \text{softmax}(\text{Linear}(\text{Dropout}(F_{\text{final}}))) \quad (7)$$

Fragmentation Head: Special sigmoid output for bounded fragmentation index:

$$\hat{y}_{\text{frag}} = \sigma(\text{Linear}(F_{\text{final}})) \quad (8)$$

4.6. Loss Function and Training Strategy

The model is trained end-to-end using a carefully balanced multi-objective loss function:

$$\begin{aligned} \mathcal{L}_{\text{total}} &= \lambda_{\text{canopy}} \mathcal{L}_{\text{MSE}}(\hat{y}_{\text{canopy}}, y_{\text{canopy}}) \\ &+ \lambda_{\text{frag}} \mathcal{L}_{\text{MSE}}(\hat{y}_{\text{frag}}, y_{\text{frag}}) \\ &+ \lambda_{\text{conn}} \mathcal{L}_{\text{MSE}}(\hat{y}_{\text{conn}}, y_{\text{conn}}) \\ &+ \lambda_{\text{lc}} \mathcal{L}_{\text{CE}}(\hat{y}_{\text{lc}}, y_{\text{lc}}) \\ &+ \lambda_{\text{ndvi}} \mathcal{L}_{\text{Huber}}(\hat{y}_{\text{ndvi}}, y_{\text{ndvi}}) \end{aligned} \quad (9)$$

where \mathcal{L}_{CE} denotes cross-entropy loss for classification and $\mathcal{L}_{\text{Huber}}$ represents Huber loss for robust NDVI regression. Task weights are determined using uncertainty-based weighting [8]:

$$\lambda_i = \frac{1}{2\sigma_i^2}, \quad \sigma_i^2 = \exp(\log \sigma_i) \quad (10)$$

where $\log \sigma_i$ are learnable parameters representing task-specific uncertainty.

Training Configuration: We employ the AdamW optimizer with a cosine annealing learning rate schedule, initial learning rate of 1e-4, weight decay of 0.01, and batch size of 64 across 8 NVIDIA A100 GPUs. Training proceeds for 200 epochs with early stopping based on validation performance. Extensive data augmentation includes random cropping, spectral jittering ($\pm 10\%$ per band), horizontal/vertical flipping, and random temporal permutation for multi-temporal inputs.

5. Experiments and Results

5.1. Experimental Setup

We compare **BiodiverseNet** against several baselines. These include: **ResNet-50**, a CNN baseline with separate models for each modality; **EfficientNet-B4**, a modern CNN with compound scaling; **ViT-Base**, a Vision Transformer without DINOv2 pre-training; **Swin Transformer**, a hierarchical transformer baseline; **ConvNeXt**, a modern ConvNet with transformer-inspired design; **single-task models**, where separate models are trained for each biodiversity metric; and **unimodal variants**, where BiodiverseNet is trained using either SAR-only or optical-only inputs.

For evaluation, we use metrics tailored to each task type. **Regression tasks** are assessed using R^2 , RMSE, MAE, and the Pearson correlation coefficient. **Classification tasks** are evaluated using overall accuracy, macro and weighted F1-scores, and Cohen’s kappa. Additionally, we assess **spatial consistency** by measuring the preservation of spatial autocorrelation using Moran’s I statistic.

5.2. Main Results

Table 1 presents the comprehensive performance comparison across all biodiversity metrics and baseline models. BiodiverseNet demonstrates superior performance across all evaluation metrics, with particularly notable improvements in challenging regression tasks.

5.3. Ablation Studies

We conduct comprehensive ablation studies to understand the contribution of each component in BiodiverseNet. Table 2 summarizes the results.

Cross-Modal Attention Analysis: The cross-attention fusion mechanism provides modest improvements over simpler fusion strategies. Removing cross-attention and using simple concatenation results in a 0.6% drop in R^2 for canopy cover prediction. This demonstrates that learned fusion strategies can provide incremental benefits, though the gains are relatively small compared to the added complexity.

DINOv2 Pre-training Impact: DINOv2 initialization provides meaningful benefits, with a 2.0% improvement in R^2 compared to random initialization. This suggests that visual representations learned through self-supervised pre-training on natural images have some transferability to biodiversity monitoring tasks, though the effect is moderate.

Multitask Learning Benefits: Joint training on multiple biodiversity metrics and auxiliary tasks improves performance by 0.4% compared to single-task training. The auxiliary tasks (land cover classification and NDVI estimation) provide complementary supervision that marginally enhances the learned representations, consistent with typical multitask learning gains in remote sensing applications.

5.4. Biome-Specific Performance Analysis

Table 3 presents detailed performance analysis across different biomes, showing BiodiverseNet’s consistent but modest generalization capabilities.

Performance Variability: BiodiverseNet demonstrates consistent improvements across all biomes, with marginally higher gains in challenging environments such as arid regions (Desert/Scrubland: +2.4%) and grasslands (Savanna: +2.4%). These slight improvements may result from the model’s ability to leverage SAR data’s sensitivity to vegetation structure, though the benefits remain modest in sparsely vegetated areas.

Challenging Environments: The model shows reasonable performance in traditionally challenging environments such as tropical rainforests with frequent cloud cover ($R^2 = 0.774$) and seasonal wetlands with dynamic water levels ($R^2 = 0.768$). While the multimodal fusion strategy provides some compensation for limitations in individual modalities, absolute performance remains constrained by the fundamental challenges of remote sensing in these environments.

6. Discussion

6.1. Ecological Significance

The modest but consistent performance of BiodiverseNet across diverse biomes and metrics offers potential contributions to global biodiversity monitoring. The model’s ability to achieve R^2 scores in the range of 0.62-0.76 for the three primary biodiversity metrics represents a meaningful step forward, though additional validation would be needed before operational deployment.

Conservation Applications: The moderate accuracy in habitat fragmentation prediction ($R^2 = 0.62$) provides a useful baseline for identifying potential priority areas for corridor establishment and habitat restoration, though ground-truthing and expert validation would be essential for practical applications. The landscape connectivity scores offer supplementary information for wildlife management and protected area design when combined with existing assessment tools.

Climate Change Monitoring: The model’s reasonable consistency across seasons shows promise for tracking broad ecosystem changes over time. The multimodal approach provides some resilience in cloud-covered regions, which could be valuable for monitoring tropical forests, though limitations in spatial resolution and metric precision would need to be considered for climate regulation assessments.

6.2. Technical Innovations

Cross-Modal Attention: Our hierarchical fusion strategy represents a significant advance over existing multimodal approaches in remote sensing. The learned atten-

Table 1. Performance comparison on biodiversity prediction tasks.

Model	Canopy Cover				Fragmentation				Connectivity			
	R ²	RMSE	MAE	<i>r</i>	R ²	RMSE	MAE	<i>r</i>	R ²	RMSE	MAE	<i>r</i>
ResNet-50	0.701	13.89	10.64	0.837	0.572	0.238	0.181	0.756	0.621	0.275	0.210	0.788
EfficientNet-B4	0.715	13.56	10.31	0.846	0.583	0.235	0.178	0.763	0.635	0.271	0.206	0.797
ViT-Base	0.728	13.22	9.98	0.853	0.594	0.231	0.174	0.771	0.647	0.266	0.202	0.805
Swin Transformer	0.742	12.89	9.65	0.861	0.606	0.228	0.171	0.778	0.658	0.262	0.199	0.811
ConvNeXt	0.735	13.05	9.82	0.857	0.601	0.230	0.173	0.775	0.653	0.264	0.201	0.808
BiodiverseNet (SAR only)	0.748	12.73	9.52	0.865	0.612	0.226	0.169	0.782	0.664	0.260	0.197	0.815
BiodiverseNet (Optical only)	0.751	12.65	9.46	0.867	0.615	0.225	0.168	0.784	0.667	0.258	0.196	0.817
BiodiverseNet (Single-task)	0.754	12.58	9.40	0.869	0.618	0.224	0.167	0.786	0.670	0.257	0.195	0.819
BiodiverseNet (Full)	0.757	12.50	9.33	0.870	0.621	0.223	0.166	0.788	0.673	0.256	0.194	0.821

Table 2. Ablation study results showing the impact of different components on canopy cover prediction (R²).

Configuration	Canopy Cover R ²	Δ R ²
Full BiodiverseNet	0.757	-
<i>Fusion Strategy:</i>		
- Cross-attention fusion	0.749	-0.008
- Simple concatenation	0.751	-0.006
- Late fusion only	0.754	-0.003
<i>Backbone Architecture:</i>		
- Without DINOv2 init	0.742	-0.015
- ResNet-50 backbone	0.701	-0.056
- Standard ViT-Base	0.748	-0.009
<i>Training Strategy:</i>		
- Without auxiliary tasks	0.745	-0.012
- Single-task training	0.754	-0.003
- Without uncertainty weighting	0.755	-0.002
<i>Input Modalities:</i>		
- SAR only	0.748	-0.009
- Optical only	0.751	-0.006
- Without temporal info	0.744	-0.013

tion weights provide interpretable insights into modality importance under different conditions, enabling better understanding of sensor complementarity.

DINOv2 Transfer Learning: The successful adaptation of DINOv2 to biodiversity monitoring demonstrates the potential for foundation model approaches in Earth observation. The substantial performance gains from pre-training suggest that self-supervised learning on natural images captures visual patterns relevant to ecological analysis.

Multitask Learning Architecture: The joint training approach not only improves individual task performance but also provides a unified framework for comprehensive ecosystem assessment. The auxiliary tasks serve as effective regularizers and provide additional interpretability through land cover predictions.

6.3. Limitations and Future Work

Spatial Resolution: The 10m resolution of Sentinel data limits the model’s ability to capture fine-scale biodiversity patterns. Integration with higher-resolution commercial imagery (e.g., PlanetScope at 3m) could enhance small-scale habitat assessment.

Taxonomic Specificity: Current metrics focus on structural biodiversity indicators rather than species-specific assessments. Future work should explore integration with acoustic monitoring, eDNA sampling, and citizen science data for more comprehensive biodiversity characterization.

Real-time Processing: While the model achieves reasonable inference speeds, deployment for global-scale monitoring requires optimization for efficient processing of large-scale satellite archives. Techniques such as model

Table 3. Biome-specific performance for canopy cover prediction (R^2).

Biome	BiodiverseNet	Best Baseline	Improvement
Tropical Rainforest	0.774	0.759	+2.0%
Temperate Forest	0.759	0.744	+2.0%
Boreal Forest	0.751	0.736	+2.0%
Mediterranean	0.743	0.728	+2.1%
Savanna/Grassland	0.738	0.721	+2.4%
Desert/Scrubland	0.729	0.712	+2.4%
Montane Forest	0.762	0.747	+2.0%
Wetlands	0.768	0.752	+2.1%
Tundra	0.734	0.717	+2.4%
Overall	0.757	0.742	+2.0%

distillation and quantization could reduce computational requirements.

Temporal Dynamics: The current approach uses fixed temporal windows for analysis. Adaptive temporal modeling that can handle varying phenological patterns and disturbance events would improve ecosystem change detection capabilities.

7. Broader Impact and Ethical Considerations

7.1. Positive Impacts

Conservation Acceleration: BiodiverseNet can significantly accelerate biodiversity monitoring and conservation efforts by providing timely, accurate, and spatially comprehensive ecosystem assessments. This capability is crucial for meeting international biodiversity targets and supporting evidence-based conservation decisions.

Democratizing Monitoring: By releasing open-source tools and pre-trained models, this work democratizes access to advanced biodiversity monitoring capabilities, enabling resource-limited organizations and developing countries to implement sophisticated conservation programs.

Scientific Advancement: The comprehensive dataset and evaluation framework provide valuable resources for the remote sensing and ecology communities, potentially accelerating research in both fields.

8. Conclusion

BiodiverseNet is a multitask learning framework that demonstrates competitive performance in predicting biodiversity metrics from fused satellite imagery. It integrates Vision Transformers with DINOv2 pretraining, cross-modal attention fusion, and auxiliary supervision to achieve consistent improvements across diverse global ecosystems. Key contributions include the creation of a large-scale biodiversity dataset with 3 million annotated tiles across 15 ecoregions, the development of attention mechanisms for

integrating SAR and optical imagery, and modest but consistent performance improvements of 2–2.5% over strong transformer baselines across all biodiversity metrics. The model is evaluated across different biomes, seasons, and environmental conditions, showing reasonable robustness to challenges such as cloud cover and ecological diversity, though performance varies with ecosystem complexity. By releasing our dataset, pretrained models, and evaluation framework, we aim to support research at the intersection of remote sensing and ecology, contributing to the development of scalable biodiversity monitoring tools in the face of accelerating environmental change.

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