Papers on Satellite Domain

Serial No	*Name of the Paper*	*Year of Publication*	*Models Used*	*Accuracy*	*Dataset*	*Number of Classes*	*Number of Images*	*Image Format & Resolution*	*Split*	*Limitations*
1.	Land Cover Classification Model Using Multispectral Satellite Images Based on a Deep Learning Synergistic Semantic Segmentation Network	2025	**Supervised** (DeepLab v3+ CNN with K-medoids clustering)	Overall Accuracy (**88.4%**), MCC improved by **5.7%**	Sentinel-2 Level-2A images. (Use coordinates for Lake Garda to filter). Images captured from all four seasons of 2024.	8 classes: Pastures, Other Built-Up Areas, Water Bodies, Urban Areas, Grasslands, Forest, Farmland, and Others.	49,439 patches (224×224×12) extracted	Multispectral imagery (.JP2), 12 bands from Sentinel-2 Level-2A Sentinel-2 bands at 10 m and 20 m resolutions,	60% train, 20% test, 20% validation	High computational complexity; assumes isolated errors; limited generalization beyond similar regions
2.	A comprehensive dataset of above-ground forest biomass over the Kashmir Himalaya	2025	**Supervised** learning (Random Forest)	Correlation coefficient of 0.9, a coefficient of determination of 0.7, and a root mean square error of 0.05	A comprehensive dataset of forest above-ground biomass from field observations, machine learning and topographically augmented allometric models over the Kashmir Himalaya	10 districts of Kashmir (6220 individual trees were sampled across 275 plots)	6220 individuals trees images	Satellite imagery:.tif and forest inventory: .shp Landsat imagery: **30 meters** spatial resolution **Sentinel-2** imagery: **10 meters** spatial resolution **SRTM DEM** (for topography): **90 meters** spatial resolution	80% train, 20% test	Low accuracy for certain classes (such as rainfed crop = 0%), highly fragmented landscape, cloud cover challenges
3.	Urban tree species benchmark dataset for time series classification	2025	**Supervised** learning (Inception Time, Dual-Inception Time)	1.InceptionTime-S2 (Sentinel-2 only) – 0.603 ± 0.003 accuracy 2. Inception Time-PS (Planet Scope only) – 0.615 ± 0.004 accuracy 3.Dual-InceptionTime0.656 ± 0.005	Sentinel-2 & PlanetScope time series (2022)	20 urban tree species (45,084 trees)	67 satellite images	. GPKG 10-20m	training (52.5%), validation (17.5%) and test sets (30%)	Limited to public trees in Strasbourg (France); generalization to other regions/sensors is untested

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4.	AgriPotential: A Novel Multi-Spectral and Multi-Temporal Remote Sensing Dataset for Agricultural Potentials	2025	**Supervised** (UNet with 2D CNN on 110-channel multi-temporal input) Baseline experiment: Single-class classification, Regression and Ordinal regression	ordinal labels consistently outperformed other representations (one-hot and scalars) in terms of both mean absolute error (MAE) and accuracy with tolerance of } 1 class, as these metrics reflect the practical significance of predictions.	AgriPotential on Zenodo (HDF5 format)	5 ordinal classes per crop (Very low, low, average, high, very high) × 3 crop types (Viticulture, Market Gardening, Field Crops)	8,890 images (128×128 px) from 11 timestamps, 10 channels Sentinel-2 months	HDF5 (.h5) 5 meters per pixel.	80% train, 10% test, 10% validation	Only covers Southern France (Mediterranean climate); some unlabeled pixels; seasonal cloud coverage; high storage size (28.4 GB .h5 file)
5.	reBEN: Refined Bigearthnet Dataset For Remote Sensing Image Analysis	2025	**Supervised** (ResNet-50, ResNet-101, MLPMixer Base, MobileViT S, MobileNet V4 Hybrid Medium [20], ConvNeXt V2 Base, InceptionNeXt Base, RDNet Base	**86.21%** micro-average precision (ResNet-101)	BigEarthNet v2	19 (CORINE Land Cover classes)	549,488 patches (1200 m × 1200 m)	GeoTIFF (multispectral Sentinel-2, radar Sentinel-1) 10 m (upsampled from 10–20 m)	Geographic-based: 50% train, 25% test, 25% validation (2:1:1)	Computationally intensive, relies heavily on Sentinel imagery quality
6.	A fine crop classification model based on multitemporal Sentinel-2 images	2024	**Supervised** (CTANet: convolutional attention architecture + temporal attention architecture (TAA) + forest-SHAP	Overall Accuracy (**93.9%**), Mean IoU (**87.5%**)	Custom field-verified Sentinel-2 dataset from Youyi County, China (2022)	4 (Rice, Maize, Soybean, Others)	268 labeled plots with sizes of 640 m × 640 m	Sentinel-2 imagery (.JP2/GeoTIFF), Level-1C processed to Level-2A 10 m (SNAP version 9.0.0,)	60% (162 plots) train, 20% (53 plots) validation, 20% (53 plots) test	Relatively small dataset; model complexity; limited geographic generalizability
7.	Sen-2 LULC: Land use land cover dataset for deep learning	2023	**Supervised** (U-Net with ResNet50/101/152)	Overall, **95%**	Sentinel-2 L2A imagery (RGB bands B4, B3, B2) from 4 tiles in India	7 distinct classes: Water bodies, Dense Forest, Sparse Forest, Barren land, Built-up, Agricultural land, Fallow land	2,13,750+ pre-processed images	.JPG with red, blue and green bands 64x64 pixels and 10m resolution.	70% train, 15% test, 15% validation	Limited geographic diversity (only 4 tile); ground truthing difficult in mountainous/forested areas; only 7 predefined classes supported

Papers using EuroSAT Dataset

Serial No	Name of the Paper	Year of Publication	Models Used	Accuracy	Dataset	Number of Classes	Number of Images	Image Format & Resolution	Split	Limitations
1.	Deep Ensembling of Multiband Images for Earth Remote Sensing and Foramnifera Data	2025	**Supervised** (ResNet50, DenseNet201, MobileNetV2, Custom ResNet-based, Attention-based CNN)	F1: 92.5 (Foraminifera), Acc: 99.41 (EuroSAT), Acc: 72.79 (LCZ42)	Foraminifera, EuroSAT, So2Sat LCZ42	7 (Foraminifera), 10 (EuroSAT), 17 (LCZ42)	1,437 (Foraminifera), 27,000 (EuroSAT), 400,000+ (LCZ42)	Grayscale (450×450), MS (64×64 or 10–20m GSD)	80/20 (EuroSAT), four-fold CV (Foraminifera), train/test/val (LCZ42)	High computation time; performance of scratch-trained models was unstable; not suited for on-device processing
2.	Extending global-local view alignment for self-supervised learning with remote sensing imagery	2024	**Self-Supervised** (DINO, DINO-TP, DINO-MC)	EuroSAT: 95.70% (DINO-MC WRN-50-2), BigEarthNet: 88.75 MAP (DINO-MC Swin), OSCD: F1 = 52.70 (DINO-MC WRN)	SeCo-100K (pretraining), EuroSAT, BigEarthNet, OSCD	EuroSAT: 10, BigEarthNet: 19 (multi-label), OSCD: 2 (binary change)	SeCo-100K: 100,000; EuroSAT: 27,000; BigEarthNet: 590,000+; OSCD: 24 image pairs	Sentinel-2 Multispectral; 64x64 to 224x224; 10–20m	EuroSAT: 21.6K/5.4K; BigEarthNet: 311K/104K; OSCD: 14/10 pairs	DINO-TP less suitable for change detection; Swin-Tiny underperforms; temporal contrast inconsistent
3.	Mapping of Land Use and Land Cover (LULC) Using EuroSAT and Transfer Learning	2024	**Supervised** (ViT, ResNet-50, VGG16 — all with Transfer Learning)	ViT (augmented): 99.19%; ResNet-50: 98.52%; VGG16: 98.06%	EuroSAT RGB (Sentinel-2)	10	27,000	RGB, 64×64 px, 10m resolution	80% train, 20% test	ViT training takes more time; non-augmented data reduces performance; only RGB bands used
4.	Kolmogorov-Arnold Network for Satellite Image Classification in Remote Sensing	2024	**Supervised** (ConvNeXt + KAN, VGG16, ResNet101, ViT, MobileNetV2, EfficientNet [pretrained])	ConvNeXt+KAN: 96%; ViT+KAN: 92%; VGG16: 88%; MobileNetV2: 75%; EfficientNet: 67%; ResNet101: 75%	EuroSAT (Sentinel-2)	10	27,000	RGB; 64×64 px resized to 224×224; 10m resolution	Train: 18,900; Validation: 4,050; Test: 4,050	KAN training is slower; interpretability still underdeveloped; no experiments on multi-sensor or multi-modal data
5.	Transformer-based Land Use and Land Cover Classification with Explainability	2024	**Supervised** (ViT-Base, ViT-Large, SwinT-Small, SwinT-Large, DeiT-Base — all with Transfer Learning)	ViT-Large: 99.11%, ViT-Base: 98.70%, SwinT-Small: 98.28%	EuroSAT (RGB, Sentinel-2), PatternNet	10 (EuroSAT), 38 (PatternNet)	27,000 (EuroSAT), 30,400 (PatternNet)	64×64 px (EuroSAT), 256×256 px (PatternNet)	80% train, 20% test	High compute cost; model complexity; class imbalance; need for high-resolution imagery; interpretability challenge

Papers using EuroSAT Dataset

	Using Satellite Imagery									
6.	Enhancing Active Learning for Sentinel 2 Imagery through Contrastive Learning and Uncertainty Estimation	2024	**Semi-Supervised** + **Self-Supervised** (ResNet50 + MoCo + MC Dropout)	Up to 95% with Semi-Supervised pretraining and 90% with just 2% labeled data	EuroSAT (Sentinel-2, 13 bands)	10 lands used	27,000 (64×64×13)	13-band Sentinel-2; 64×64 px; 10m resolution	80% training 20% testing; balanced and four class-unbalanced settings	Limited to EuroSAT; OSAL clustering unstable; hyperparameter tuning (e.g., dropout, neighbors) affects outcome
7.	Self-Supervised Learning for Invariant Representations from Multi-Spectral and SAR Images	2022	**Self-supervised** (RS-BYOL (BYOL-based distillation network))	F1: 0.92 (EuroSAT), mIoU: 59.6 (DFC2020)	EuroSAT, Sen12MS, RESISC45, DFC 2020	8 (DFC), 10 (EuroSAT), 45 (RESISC45)	90,000 (Sen12MS), 27,000 (EuroSAT), 31,500 (RESISC45), 900 (DFC used)	Multi-Spectral & SAR; 64x64 – 256x256 px; 10–20m	50% of Sen12MS for pretraining; DFC: 900 images used for eval-out eval	Limited resolution alignment; domain adaptation needed; segmentation performance bounded
8.	Semi-supervised Remote Sensing Image Scene Classification Based on GANs (SSGAN)	2022	**Semi-Supervised** (GAN + Dense Residual Blocks, Gating Units, PyConv, SN, Inception V3 [pretrained])	EuroSAT: up to 95.5%, UCM: up to 91.32%	EuroSAT, UCM Merced	10 (EuroSAT), 21 (UCM)	27,000 (EuroSAT), 2,100 (UCM)	64×64 (EuroSAT), 256×256 (UCM)	80% train, 10% test, 10% validation (variable labeled subset M)	High training time, GAN instability, performance varies with label count
9.	Self-Supervised Learning for Scene Classification in Remote Sensing: Current State of the Art and Perspectives	2022	**Self-Supervised** (SimCLR, MoCo-v2, BYOL, Barlow Twins, DINO, GAN, Tile2Vec, etc.)	Up to 95.59% (EuroSAT); 85.37% (Resisc-45)	Resisc-45, EuroSAT, BigEarthNet, SEN12MS, DFC2020, UC-Merced, etc.	2 to 45 (depending on dataset)	100 to 590,000+	RGB, Multispectral, SAR; 64x64 to 256x256 px; 0.2m–30m	Commonly 60% Train, 20% Validation, 20% Test	Needs large batch, augmentation sensitive, domain shift issues, high compute for some methods
10.	Land Cover and Land Use Detection using Semi-	2022	**Semi-Supervised** (FixMatch with custom augmentation + class rebalancing using Wide ResNet-28-2)	EuroSAT: 97.12%, UCM: 95.34%, WHU-RS19: 93.56%	EuroSAT, UCM, WHU-RS19	10 (EuroSAT), 21 (UCM), 19 (WHU-RS19)	27,000 (EuroSAT), 2,100 (UCM), 1,013 (WHU-RS19)	64×64 (EuroSAT), 256×256 (UCM), ~0.5m (WHU-RS19)	80% train, 10% validation, 10% test	Requires small amount of labeled data; not effective with fully unlabeled datasets; high

	Supervised Learning									training time; RGB only
11.	On Circuit-based Hybrid Quantum Neural Networks for Remote Sensing Imagery Classification	2021	**Supervised** (Hybrid QCNN (LeNet-5 + Quantum Circuits: Real Amplitude, Bellman, No Entanglement))	Up to **92%** with Real Amplitude Circuit	EuroSAT	10	27000	RGB (Sentinel-2), 64×64 pixels	80% train; 20% test	Requires quantum simulators; limited scalability to real quantum hardware
12.	Improving LULC Classification from Satellite Imagery Using Deep Learning	2021	**Supervised** (CNN – DenseNet201; RGB, 13 Bands, Bands + Indices)	RGB: 96.83%, 13 Bands: 98.78%, With Indices: 99.58%	EuroSAT (Sentinel-2, 13 bands)	10	27,000	64×64 px, 10m	70% train, 20% validation, 10% test	Class confusion on similar classes (e.g., Permanent Crop vs Pasture); limited to EuroSAT only
13.	MSMatch: Semi-Supervised Multispectral Scene Classification with Few Labels	2021	**Semi-Supervised** (EfficientNet + FixMatch)	EuroSAT-MS: **95.86%**, EuroSAT-RGB: **94.53%**, UCM: **90.71%** (with only 5 labels/class)	EuroSAT (RGB + MS), UCM	10 (EuroSAT), 21 (UCM)	27,000 (EuroSAT), 2,100 (UCM)	64×64 px, 10m (EuroSAT), 256×256 (UCM)	~5–300 labels/class used; remainder unlabeled	High training time (up to 131 hrs), class imbalance effects, weaker performance for some classes