

Applications of Remote Sensing in Agricultural Soil and Crop Mapping

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Agricultural soils and crops form the foundation of global food systems, and their sustainable management is essential for ensuring food security, mitigating climate change, and adapting to environmental pressures [1]. Recent advances in remote sensing and geospatial analytics provide powerful opportunities to monitor soils and crops across scales—from field-level UAV surveys to continental assessments using satellite constellations [2–5]. This Special Issue, “Applications of Remote Sensing in Agricultural Soil and Crop Mapping”, brings together 11 research contributions that advance methods and applications of optical, radar, and UAV-based sensing for yield estimation [6–9], cropland monitoring [10–13], soil property mapping [14,15], and land use change assessment [16], as summarized below and in Table 1.

Collectively, these papers demonstrate how multi-source data fusion, advanced machine learning (ML), deep learning (DL) models, and innovative sampling or adaptation strategies can push forward the frontier of agricultural monitoring. At the same time, they highlight ongoing challenges, such as class imbalance, cloud interference, computational scalability, and model transferability across regions. The papers in this Special Issue have been systematized into three coherent thematic blocks, presented below:

- **Advances in Crop Yield Estimation:** Several contributions in this Special Issue focus on improving yield prediction through remote sensing and ML (Contribution 1–4 [6–9]). Contribution 1, by Cunha et al. [6], integrated optical and synthetic aperture radar (SAR) data, testing different SAR variables, speckle filters, and soybean growth stages. The findings show that although SAR variables alone had weak correlations with yield, their combination with optical indices (EVI) significantly improved predictions, especially at the maturation stage, reducing the root mean square error (RMSE). Similarly, in Contribution 2, from Fan et al. [7], a model for rice yield estimation in hilly and mountainous Chongqing, China, was developed, demonstrating that vegetation indices integrated over growth stages, together with agro-meteorological data and Random Forest algorithms, can achieve a high predictive accuracy ($R^2 \approx 0.85$). At the UAV scale, in Contribution 3, Kešelj et al. [8] used multispectral UAV imagery and automated ML (AutoML) approaches to predict wheat yield across European varieties and management treatments. Their AutoML-driven framework identified support vector regression as a top-performing model, achieving an R^2 above 0.9 in the early growth stages, highlighting the potential of UAVs for precision agriculture and experimental crop research. In Brazil, in Contribution 4, Martins et al. [9] tested deep learning segmentation of UAV imagery for corn crop analysis, including detection of animal damage. Their results show that architectures such as SegFormer [17] and



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DeepLabV3+ [18] can reliably identify crop and non-crop areas, supporting field-scale management. Together, these studies highlight a strong trend toward phenology-aware modeling and data fusion (optical + SAR, UAV + field data), confirming that no single sensor is sufficient for robust yield estimation under all conditions.

- **Cropland Mapping and Classification Innovations:** Another set of papers tackles the challenge of accurate crop type and cropland boundary mapping, particularly in complex or fragmented landscapes (Contribution 5–9 [10–13,16]). In Contribution 5, by Lu et al. [10], a hybrid method combining edge detection and semantic segmentation with geographic stratification is proposed. Applied in mountainous Chongqing, their approach achieved ~95% accuracy across flat, terraced, and sloping farmland, outperforming traditional methods. Addressing class imbalance in UAV imagery, in Contribution 6, Cheng et al. [11] developed a Minority Enhanced Sampler (MES) that augments minority crop classes and improves segmentation models. Tested across datasets, MES significantly boosted the mean intersection-over-union (mIoU) for underrepresented crops. Similarly, in Contribution 7, Cao et al. [12] advanced weed detection in tea gardens using an improved U-Net with skeleton refinement for precise weed localization, achieving substantial improvements in the mean IoU and localization accuracy. At larger scales, in Contribution 8, Hu et al. [16] examined paddy field changes in Northeast China (2000–2020) using MODIS time-series and decision tree modeling. They found a marked northeastward expansion of paddy fields (~292 km), driven largely by climate warming, with climate scenarios (CMIP6) predicting continued expansion. This illustrates how remote sensing combined with climate modeling can support strategic planning for future food security. Finally, in Contribution 9, Guo et al. [13] explored cross-domain classification with compact polarimetric SAR (CP-SAR), proposing a Gini coefficient-based unsupervised domain adaptation framework. Their method improved classification accuracy by up to 12% compared to existing UDA approaches, showing potential for crop mapping in regions with scarce labeled data.
- **Soil Properties and Environmental Fluxes:** Beyond crop monitoring, two contributions extend remote sensing applications to soil and environmental variables (Contribution 10 and 11 [14,15]). In Contribution 10, Zhao et al. [14] reconstructed soil moisture over the contiguous United States by applying Empirical Orthogonal Functions interpolation (DINEOF) [19] to SMAP data, validated against in situ stations. Their approach effectively filled data gaps, achieving an $R^2 > 0.65$ and MAE of $0.01\text{--}0.04\text{ m}^3/\text{m}^3$, thus improving temporal continuity in soil moisture monitoring. In Contribution 11, Yu et al. [15] combined multi-source optical data, XGBoost, and SHAP interpretability analysis to map soil CO_2 fluxes in the Yellow River Delta. Their framework achieved an $R^2 \approx 0.73$ and identified key drivers such as vegetation indices and soil texture, providing insights into carbon dynamics in intensively cultivated farmland.

Table 1. Summary of research contributions.

#	Focus Area	First Author [REF]	Data/Methods	Key Contribution
1	Soybean yield prediction	Cunha et al. [6]	Sentinel-2 optical + Sentinel-1 SAR; Random Forest; growth-stage stratification	SAR + optical fusion reduced RMSE vs. optical-only, best performance at maturation stage.
2	Rice yield estimation	Fan et al. [7]	Sentinel-2 vegetation indices + agro-meteorological data; feature selection; ML models	Growth-stage integrated indices + RF achieved strong rice yield predictions ($R^2 \approx 0.85$).

Table 1. Cont.

#	Focus Area	First Author [REF]	Data/Methods	Key Contribution
3	Wheat yield prediction	Kešelj et al. [8]	UAV multispectral imagery; AutoML (PyCaret)	High-accuracy ($R^2 > 0.9$) wheat yield prediction across varieties and treatments.
4	Corn crop analysis	Martins et al. [9]	UAV imagery; DL architectures (DeepLabV3+, SegFormer)	Reliable corn segmentation (IoU~70–80%); useful for precision management and damage detection.
5	Cropland mapping	Lu et al. [10]	Geographic zoning + semantic segmentation + edge detection	High cropland mapping accuracy (~95%) in mountainous terrain with complex landforms.
6	Crop classification	Cheng et al. [11]	UAV imagery; Minority Enhanced Sampler (MES) + augmentation; tested with DL networks	Improved mIoU on minority crop classes under severe class imbalance.
7	Weed detection	Cao et al. [12]	UAV/ground imagery; improved U-Net + ASPP + skeleton refinement	Improved weed segmentation and precise center localization for targeted weeding.
8	Land use change	Hu et al. [16]	MODIS time series (2000–2020); decision tree classification; CMIP6 climate projections	Paddy fields expanded NE by ~292 km; main climate warming driver; future scenarios project continued expansion.
9	Cross-domain classification	Guo et al. [13]	Compact polarimetric SAR; Gini-based feature selection; UDA	Improved classification (2–12% gains) under domain shift; enables transfer across regions.
10	Soil moisture monitoring	Zhao et al. [14]	SMAP soil moisture; DINEOF (EOF interpolation); in situ validation	Filled SMAP gaps and improved temporal continuity ($R^2 > 0.65$ vs. in situ data).
11	Soil CO ₂ flux mapping	Yu et al. [15]	Multi-source optical indices + soil variables; XGBoost + SHAP	Spatial CO ₂ flux mapping ($R^2 \approx 0.73$); vegetation indices and soil texture identified as main drivers.

The 11 contributions in this Special Issue illustrate how remote sensing can bridge agronomy and climate science, monitoring soil–plant–atmosphere exchanges that underpin both productivity and sustainability.

The Special Issue showcases cutting-edge applications of remote sensing in soil and crop mapping, from UAV-based yield prediction to SAR-enhanced classification, soil moisture reconstruction, and climate-driven paddy expansion. Together, these contributions demonstrate the transformative potential of combining multi-source remote sensing with advanced ML/DL for sustainable agricultural monitoring. We hope that the insights presented here will inspire further cross-disciplinary research, bridge geospatial science, agronomy, and sustainability, and ultimately contribute to resilient global food systems.

Conflicts of Interest: The authors declare no conflicts of interest.

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