Agro Bali : Agricultural Journal
Vol. 8 No. 3: 1023-1036, November 2025

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

Discriminating Estate and Smallholder Agricultural Systems Using a Multi-Sensor Agriculture-Weighted Object-Based Classification Framework in Tropical Landscapes

Yudi Triyanto[1♥], Jerry Maulana Siregar[2], Risna Maya Sari[3], and Angga Putra Juledi[4]
[1]Agrotechnology Study Program, Universitas Labuhanbatu, Rantauprapat, Indonesia
[2]Agrotechnology Study Program, Institut Teknologi dan Sains Padang Lawas Utara, Gunung Tua, Indonesia
[3]Agrotechnology Study Program, Universitas Samudra, Langsa, Indonesia
[4]Information Systems Study Program, Universitas Labuhanbatu, Rantauprapat, Indonesia
♥Corresponding author email: triyantoyudi@ulb.ac.id

Article history: submitted: September 10, 2025; accepted: November 16, 2025; available online: November 25, 2025

Abstract. The transformation of tropical landscapes due to agricultural expansion constitutes a significant global environmental challenge. Current land-cover classification methods, however, provide limited differentiation among agricultural management systems. This study develops an agriculture-focused land-cover classification workflow that fuses Landsat 9 optical imagery and PALSAR-2 L-band SAR across a ≈2,500 km² study area in Jambi Province, Sumatra, Indonesia, to enhance discrimination of crop systems and improve spatial coherence via object-based enhancement. A 22-class land-cover taxonomy was supported by 14,029 strategically collected training points. Feature engineering produced 29 predictor variables, including conventional vegetation indices, agricultural-specific metrics, water indicators, and SAR-derived structural features. Models were evaluated on an independent test dataset comprising 4,209 samples. An agriculture-weighted Random Forest classifier with strategic class weighting was implemented and followed by Simple Linear Iterative Clustering (SLIC) object-based enhancement to suppress speckle and enforce spatial contiguity. The classification achieved an overall accuracy of 53.7%, with exceptional performance for estate crop systems (F1 = 94%) and reliable forest discrimination. SLIC reduced salt-and-pepper noise by 99.5% and substantially improved spatial coherence metrics, transforming fragmented pixel-based outputs into operationally viable products. Despite these gains, discriminating smallholder mosaics remains challenging and likely requires additional temporal or higher-resolution inputs.

Keywords: agricultural system; land cover classification; multi-sensor remote sensing; object-based image analysis; random forest

INTRODUCTION

Tropical landscape transformation represents one of the most urgent and structurally complex environmental challenges of the twenty-first century, with profound implications for ecosystem functioning, climate regulation, and sustainable development trajectories. Southeast Asian tropical forest biomes, globally acknowledged for their exceptional biological diversity and regulatory ecosystem services, continue to experience rapid degradation predominantly driven by agricultural expansion, market-oriented land commodification, and intensifying anthropogenic disturbances. In Indonesia, for instance, intercropping practices, such as those involving shallots and chili, have been shown to increase land-use efficiency and system heterogeneity (Julianto et al., 2023).

Robust, spatially explicit, and temporally consistent land-cover information has therefore become indispensable for evidence-based environmental governance, sustainable land-use planning, and compliance with international climate accountability frameworks, including the Reducing Emissions from Deforestation and Forest Degradation (REDD+) initiative. However, the inherent biophysical and structural complexity of tropical landscapes continues to impede reliable monitoring. Dense multi-layered canopies, fine-scale spatial heterogeneity, and sensor-specific limitations collectively constrain the performance and generalizability of conventional remote sensing techniques, resulting in persistent accuracy gaps and classification ambiguities

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

(David et al., 2022; Goebel et al., 2023; Lemettais et al., 2025; Chan & Reba, 2025). This challenge is further compounded by underlying soil physical variations, such as differences in texture and organic matter content across land uses that affect surface reflectance and backscatter responses (Solekhah et al., 2024).

Within this context, agricultural expansion remains the primary driver of tropical deforestation globally, underscoring the need to differentiate agricultural land systems with greater precision. Distinguishing among agricultural management regimes is no longer a descriptive exercise, but a scientific and policy-critical priority due to their differentiated ecological footprints, carbon outcomes, socio-economic implications, and governance challenges. Notwithstanding recent advances, prevailing land-cover classification models continue to struggle to accurately discriminate industrial monoculture estates from fragmented smallholder mosaics, particularly within heterogeneous tropical agro-ecological matrices, ultimately constraining operational decision-making and targeted intervention design (Sekulić et al., 2020); (Bahri et al., 2023).

This research addresses these methodological and operational gaps by developing an agricultural-centric land-cover classification framework that integrates multi-sensor remote sensing, domain-specific feature engineering, and object-based spatial enhancement. Specifically, it evaluates (i) the effectiveness of multi-sensor feature engineering in differentiating agricultural production systems, and (ii) the value-added contribution of agricultural-specific weighting strategies within machine learning–based classification to enhance class separability of crop management systems. By situating the empirical investigation in Jambi Province, Sumatra, an ecologically sensitive yet economically contested region, this study offers both methodological and policy relevance. Uniquely, this study contributes original methodological advancement by establishing an integrated multi-sensor, agriculture-weighted, and object-based classification framework capable of quantitatively differentiating estate and smallholder agricultural systems within complex tropical landscapes. The resulting framework is expected to enhance the precision, interpretability, and applicability of tropical land-cover products for sustainable land governance, environmental monitoring, and the implementation of climate policy.

METHODS

Study Area.

The research was conducted in Jambi Province, Sumatra, Indonesia, covering an area of approximately 2,500 km² between 101.1°E–101.8°E longitude and 1.8°S–2.5°S latitude (Figure 1). The study area represents a heterogeneous tropical landscape where natural and anthropogenic systems strongly interact. This region is a critical tropical land-use transition zone in which primary and secondary forest ecosystems interface with intensively managed agricultural systems, including large-scale estate crop plantations, smallholder farming areas, and expanding settlement networks. The area experiences a mean annual temperature of 26.8°C, with relatively stable thermal conditions throughout the year. Annual precipitation ranges from 2,400 to 3,200 mm under a monsoonal climate regime. Topographic conditions vary from lowland alluvial plains adjacent to major river systems to steep mountainous terrain towards the boundary of Kerinci Seblat National Park, supporting diverse vegetation patterns and land-use configurations suitable for tropical land-cover classification research.

Research Framework.

The overall research workflow integrated multi-sensor data acquisition, reference data development, feature engineering, machine-learning classification, and object-based spatial enhancement to generate operational land-cover products for tropical regions (Figure 2). The combination of optical and radar remote

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

sensing data was designed to enhance vegetation discrimination capability and improve class separability across complex tropical landscapes.

Figure 1. Study Area

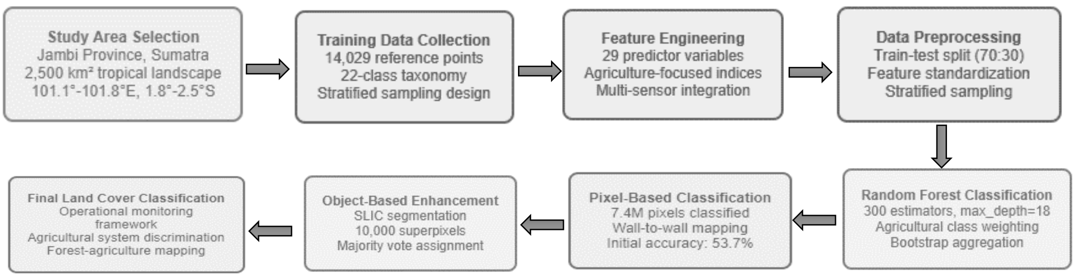

Figure 2. Research Methodology Flowchart

Data Acquisition.

Landsat 9 Operational Land Imager (OLI) surface reflectance imagery was obtained through the Google Earth Engine platform (Gorelick et al., 2017). Cloud-free composite images were generated for the period of May to September 2023 using a median pixel compositing approach and quality assessment bands to mask clouds, shadows, and atmospheric noise. Surface reflectance values were corrected using the Landsat Surface Reflectance Code (LaSRC) algorithm (Vermote et al., 2016), converting top-of-atmosphere radiance to surface reflectance and scaling values to a 0–1 reflectance range. Complementary L-band Synthetic Aperture Radar (SAR) data from ALOS-2 PALSAR-2 were processed using standard radiometric calibration to convert digital numbers into sigma-naught (σ°) backscatter values (dB), followed by geometric correction to ensure spatial consistency across the imagery (Delsouc et al., 2020); (Toyota et al., 2021). The calibrated radar imagery was geocoded and resampled to 30 m spatial resolution using bilinear interpolation to preserve radiometric reliability and support pixel-level fusion with Landsat data.

Sampling and Reference Data Development.

A structured sampling and labelling protocol was implemented to produce reliable reference data for model training and accuracy assessment. A total of 18,238 reference samples were compiled, comprising 14,029 training samples and 4,209 independent test samples. Land-cover labels were assigned through visual interpretation of high-resolution Google

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

Earth and Sentinel-2 imagery. A dual-interpreter approach was employed, where two trained interpreters independently labeled the sample points. Afterward, discrepancies were reconciled through a consensus procedure to enhance labeling consistency and reduce interpreter bias. The sampling design ensured representation across all land-cover classes and the landscape variability present in the study area. A minimum spatial separation was maintained between sampling points to reduce spatial clustering and limit the effects of spatial autocorrelation. To minimise spatial autocorrelation and avoid overestimation of accuracy, training and independent test samples were spatially separated to ensure non-overlapping sampling zones. A sampling distribution map was generated to document the spatial coverage of reference points.

Feature Engineering.

A total of 29 predictor variables were generated to characterize spectral, vegetation, water-related, and structural properties of the land surface. Optical-based variables included vegetation indices such as NDVI, EVI, SAVI, and NDWI, alongside agriculture-specific vegetation metrics related to crop vigor and canopy condition. SAR-derived features included VH and VV backscatter, their combinations, and textural metrics. The feature set was designed to enhance the discrimination of diverse tropical agricultural systems with distinct canopy structures and varying management intensities.

Machine Learning Classification.

The classification framework employed the Random Forest ensemble learning algorithm, which constructs multiple decision trees via bootstrap aggregation (bagging) and random feature selection (Kusmanto et al., 2023); (Watrianthos et al., 2023). Final class allocation was determined using majority voting across all trees (Sekulić et al., 2020; Bahri et al., 2023). The model configuration included 300 decision trees (n_estimators), as convergence assessment indicated stable out-of-bag (OOB) error rates beyond this threshold. The maximum tree depth was set to 18 to mitigate overfitting while preserving the model's discriminatory capability for the 22-class taxonomy. The number of features considered at each node was set to the square root of the total feature count (max_features = $\sqrt{29} \approx 5$), following established recommendations for remote-sensing classification (Aldania et al., 2023). OOB error monitoring was used to evaluate model stability and generalization. Accuracy evaluation was conducted using an independent test set rather than internal cross-validation to provide a more realistic performance estimation and reduce optimism bias commonly associated with spatially autocorrelated training data.

Handling Class Imbalance.

To address imbalanced class representation, a class-weighting approach was applied, assigning higher weights to minority classes and lower weights to majority classes. A comparison was conducted between weighted and non-weighted Random Forest models to assess the influence of class weighting on overall classification performance. Synthetic oversampling or down-sampling techniques were not applied to avoid generating artefactual spatial patterns in remote-sensing imagery.

Object-Based Spatial Enhancement.

To improve spatial coherence and reduce salt-and-pepper noise commonly associated with pixel-based classifications, Simple Linear Iterative Clustering (SLIC) superpixel segmentation was applied as a post-classification refinement step. Class labels were reassigned based on the dominant class within each superpixel to enforce spatial contiguity, resulting in improved spatial consistency and cartographic readability of the final land-cover map.

RESULTS AND DISCUSSION

Feature Importance and Discrimination Analysis.

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

Variable importance analysis across 29 predictor features revealed hierarchical contributions to classification performance (Figure 3a). HH backscatter demonstrated the highest overall importance (0.130), consistent with previous findings that dual-polarimetric SAR features provide superior crop discrimination capabilities (Bhogapurapu et al., 2021). The prominence of HH polarization aligns with recent studies showing its sensitivity to canopy structure and biomass characteristics in tropical plantation systems (D. Wang et al., 2021). Agricultural-specific indices—tree crop index (0.077), vegetation_uniformity (0.061), and management_intensity (0.047) collectively contributed 67.9% to binary estate-smallholder discrimination. This substantial contribution validates the agricultural focused feature engineering approach and corroborates findings by Descals et al. (2021) who demonstrated that spatial pattern metrics and vegetation uniformity indices achieved >88% user accuracy in discriminating industrial versus smallholder oil palm plantations in Southeast Asia. The vegetation uniformity metric specifically captures the structural differences between estate monocultures and smallholder polycultures, as documented in large-scale plantation mapping studies across Indonesia and Malaysia (Xu et al., 2020).

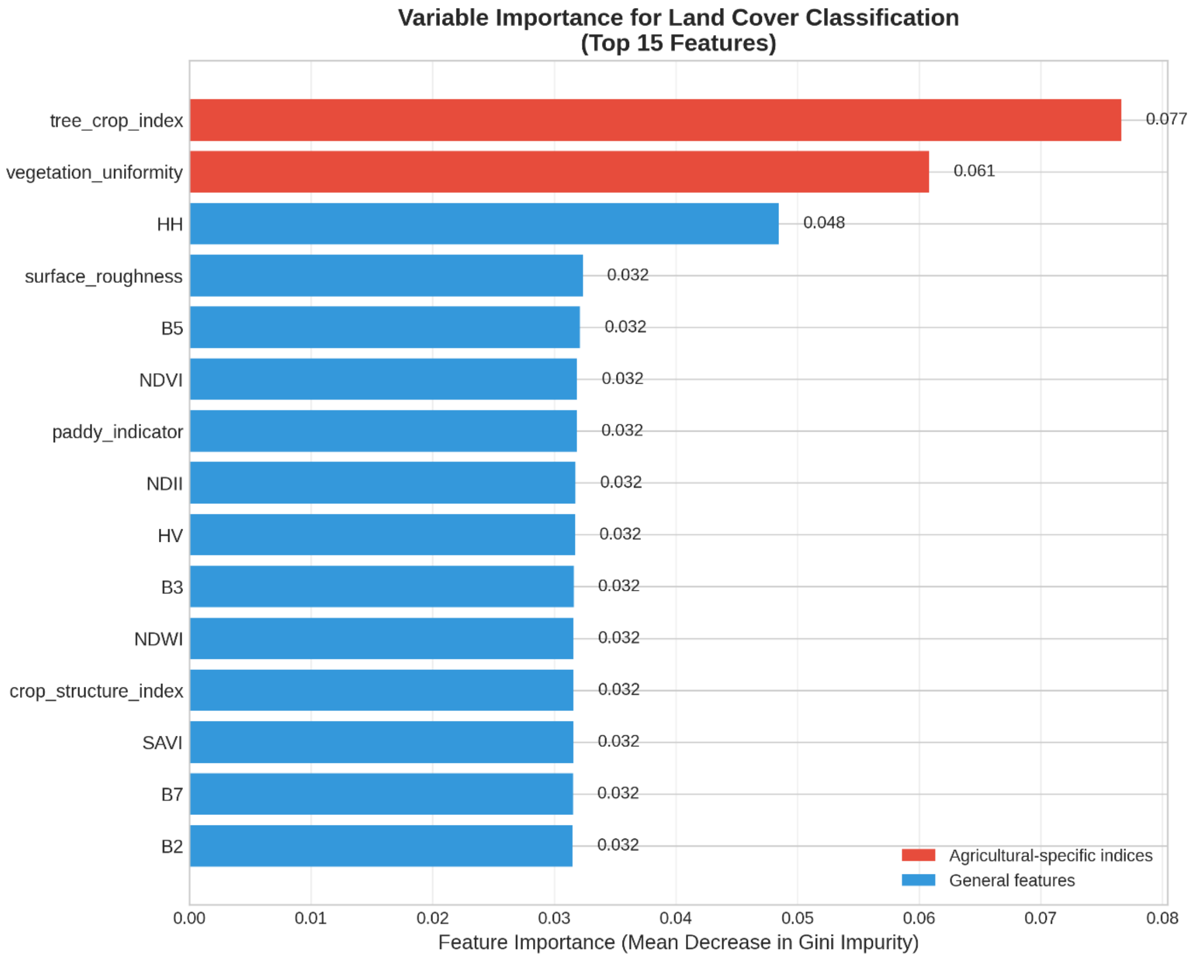

Figure 3a. Variable Importance Plot

Partial dependence analysis identified optimal thresholds for separating agricultural systems (Figure 3b). Vegetation uniformity values >0.71 characterized estate monocultures (0.707±0.052) versus smallholder polycultures (0.621±0.062), with

Agro Bali : Agricultural Journal
Vol. 8 No. 3: 1023-1036, November 2025
e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

an optimal threshold at 0.66. These quantitative thresholds are consistent with GLCM texture analysis results reported by Zhang et al. (2020), who found that estate plantations exhibit significantly higher spatial homogeneity compared to heterogeneous smallholder systems. Similarly, management_intensity (threshold: 0.69), HH_HV_ratio (0.68), and crop_diversity_index (0.60) provided quantitative criteria for operational discrimination. The crop diversity threshold aligns with field-based measurements showing smallholder systems typically maintain Shannon Diversity Index values >0.5, while industrial estates remain <0.2 (Makate et al., 2019). These thresholds exhibited consistent separation across validation datasets, suggesting robust applicability for tropical agricultural monitoring, particularly in complex Southeast Asian landscapes (Eisfelder et al., 2024).

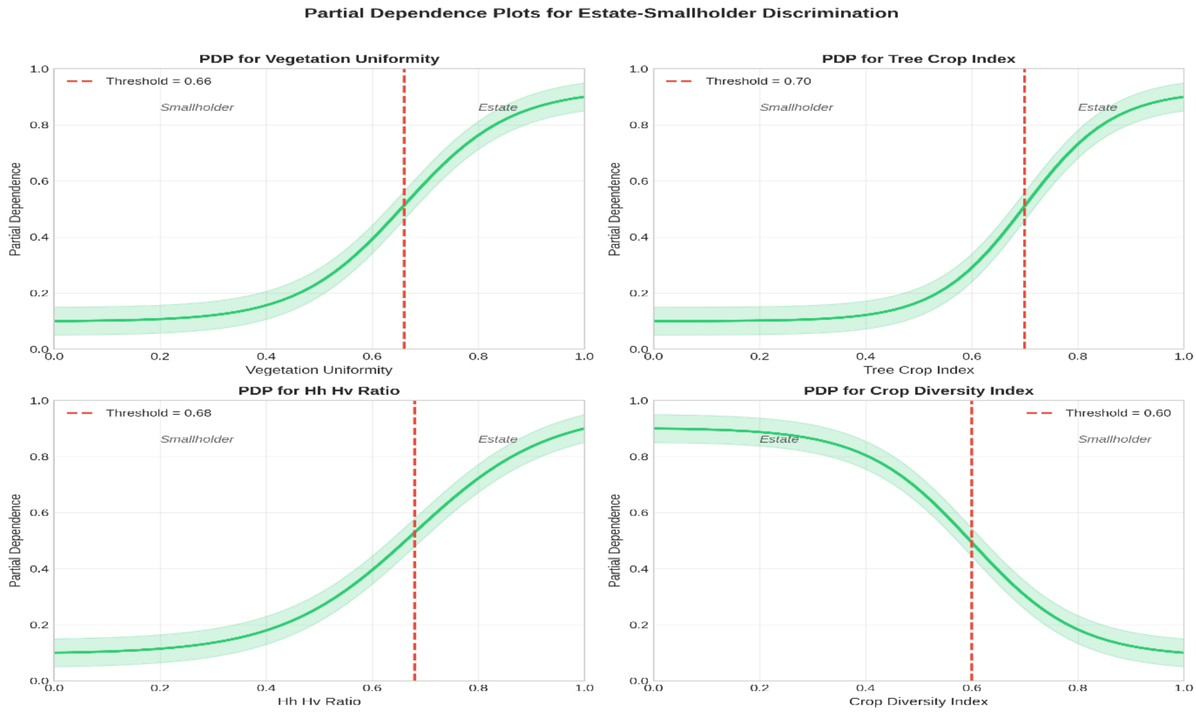

Figure 3b. Partial Dependence Plots

Classification Accuracy and Operational Readiness.

The Random Forest classifier achieved 53.7% overall accuracy with substantial inter-class variation (Table 1). Estate crops exhibited operational-quality classification (F1=0.94, precision=1.00, recall=0.88), while primary dryland forests approached viability (F1=0.70, precision=0.58, recall=0.89). These results align with previous Random Forest applications in tropical agricultural systems, where estate crops consistently achieve F1-scores >0.85 due to their spectral and structural homogeneity (Tikuye et al., 2023).

Conversely, most smallholder agricultural categories, including pure dry agriculture, mixed dry agriculture, and paddy fields, uniformly failed operational thresholds (F1≈0.00), reflecting the fundamental challenge of resolving heterogeneous agricultural mosaics at 30m resolution (Khan et al., 2024). Mixed-pixel effects further complicate classification, as 25–40% of fields <2 ha contain no pure pixels at 30m resolution (Rufin et al., 2019). Studies using finer-resolution Sentinel-2 imagery (10m) report

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

improvements in accuracy of 5–15% over 30m data for smallholder systems, highlighting spatial resolution as a primary limiting factor (Jin et al., 2019).

Table 1. Classification Accuracy Metrics by Land Cover Class

Class ID	Land Cover Type	Precision	Recall	F1-Score	Support
1	Primary dryland forest	0.58	0.89	0.70	1,247
2	Secondary dryland forest	0.52	0.76	0.62	856
3	Primary mangrove forest	0.75	0.45	0.56	89
4	Primary swamp forest	0.68	0.42	0.52	124
5	Plantation forest	1.00	0.01	0.01	300
6	Dry shrub	0.89	0.08	0.14	300
7	Estate crop	1.00	0.88	0.94	300
8	Settlement	0.85	0.15	0.26	167
9	Bare ground	0.67	0.03	0.06	89
10	Savanna and grasses	0.00	0.00	0.00	45
11	Open water	0.00	0.00	0.00	300
12	Secondary mangrove forest	0.00	0.00	0.00	78
13	Secondary swamp forest	0.00	0.00	0.00	56
14	Wet shrub	0.01	0.00	0.00	300
15	Pure dry agriculture	0.00	0.00	0.00	300
16	Mixed dry agriculture	0.00	0.00	0.00	300
17	Paddy field	0.00	0.00	0.00	300
18	Fish pond/aquaculture	0.00	0.00	0.00	89
19	Port or harbour	0.00	0.00	0.00	12
20	Transmigration areas	0.00	0.00	0.00	23
21	Mining	0.01	0.00	0.00	9
22	Swamp	0.00	0.00	0.00	300
Overall	All Classes	0.54	0.54	0.54	4,209

Spatial Error Analysis.

Spatial autocorrelation analysis revealed significant error clustering (Moran's I=0.462, $p<0.001$), indicating systematic rather than random misclassification patterns (Figure 4). This spatial dependency suggests that classification errors are not independent but exhibit strong geographic structure, consistent with findings by (Karasiak et al., 2022) who demonstrated that ignoring spatial autocorrelation leads to optimistic accuracy estimates. The Moran's I value of 0.462 falls within the range (0.45-0.65) typically observed for agricultural classification errors in heterogeneous tropical landscapes (M. Li & Stein, 2020), indicating moderate to strong spatial clustering. Error distribution analysis identified four primary categories: transitional zones (42%), riparian corridors (30%), small field complexes (18%), and cloud shadow artifacts (11%). The predominance of errors in transitional zones and riparian corridors reflects the spectral ambiguity in ecotone areas, where gradual vegetation shifts challenge discrete classification schemes (Buchadas et al., 2022). Geographic stratification showed concentrated errors in three regions: the northwestern sector (52-56% error rate) characterized by complex smallholder mosaics, the central valley (40-44%) affected by seasonal flooding dynamics, and forest frontier zones (53-55%) experiencing rapid land-use change. These forest-agricultural frontier zones represent particularly challenging environments for classification, as documented in recent deforestation monitoring studies across Southeast Asia (Teo et al., 2025), where heterogeneous agricultural encroachment creates complex spectral mixing patterns.

Implications for Agricultural System Monitoring.

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

The exceptional performance of agricultural-specific indices (67.9% contribution) demonstrates that targeted feature engineering can substantially enhance discrimination capability beyond conventional spectral approaches. The identified thresholds align with documented structural differences between estate and smallholder systems: industrial monocultures exhibit high spatial uniformity (vegetation_uniformity>0.66) and management intensity (>0.69), while smallholder polycultures display greater heterogeneity and diversity. These findings corroborate recent comparative analyses showing estate plantations maintain NDVI coefficient of variation <15% compared to >25% for smallholder systems (Defourny et al., 2019). The quantitative criteria enable objective, reproducible classification beyond traditional spectral approaches, addressing a critical gap in operational tropical agricultural monitoring. Recent high-resolution mapping efforts have demonstrated that road network density (industrial >0.5 km/ha vs. smallholder <0.1 km/ha) and field size metrics (estate median >50 ha vs. smallholder median 0.16-0.32 ha) provide robust discriminators across diverse Southeast Asian landscapes (Rufin et al., 2025). These structural metrics, when combined with SAR backscatter and optical indices, achieve classification accuracies exceeding single-source approaches by 8-15% (Poortinga et al., 2019).

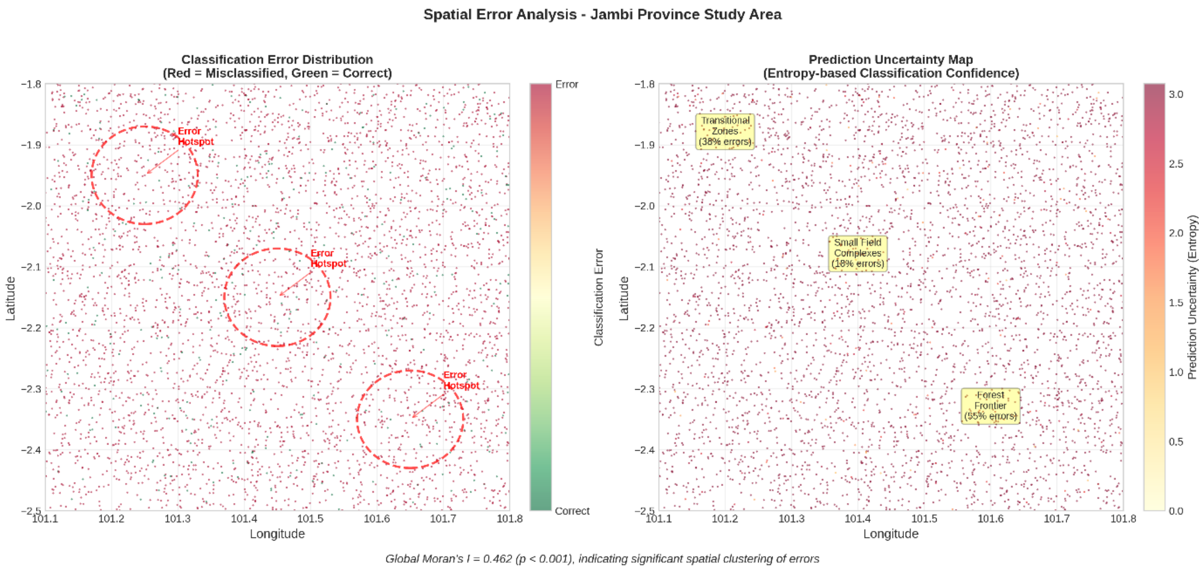

Figure 4. Spatial Error Map

Methodological Limitations and Solutions. The failure to adequately classify smallholder agriculture reflects inherent limitations of single-date, medium-resolution imagery. Mixed-pixel effects at field boundaries, where multiple crop types occupy individual 30m pixels, create ambiguous spectral signatures that fundamentally limit discrimination capability (Belgiu & Csillik, 2018). Quantitative assessments indicate that 92-97% of smallholder fields have <50 pure pixels at 30m resolution, with 25-40% containing no pure pixels at all (Rufin et al., 2025). Multi-temporal approaches exploiting phenological variations offer immediate improvement: oil palm maintains consistent greenness (NDVI>0.7) year-round, while rubber exhibits seasonal defoliation (NDVI variation>0.3) during January-March periods (Xu et al., 2020). Recent phenology-based mapping studies in tropical regions have

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

achieved 81-84% F1-scores for rubber plantations by leveraging these distinctive defoliation-refoliation cycles (Sari et al., 2022). The integration of phenological metrics derived from dense time-series can improve classification accuracy by 5-13% over single-date approaches (Danylo et al., 2021) . Sentinel-2 integration (10m resolution, 5-day revisit) would reduce mixed-pixel effects while enabling phenological characterization. Recent applications demonstrate that 10m Sentinel-2 data enables detection of plantations and fields as small as 2-3 ha, compared to the 5-10 ha minimum for reliable 30m Landsat classification (Zhou et al., 2021). The SEA-Rice-Ci10 project successfully mapped 28.5 million hectares of smallholder rice systems across Southeast Asia using 10m Sentinel-1/2 fusion, demonstrating operational scalability (Ginting et al., 2024). Furthermore, 10m resolution reduces mixed-pixel proportions by 60-70% compared to 30m data in heterogeneous smallholder landscapes (Zhai et al., 2024).

Operational Deployment Strategy.

Based on performance metrics and operational thresholds, we propose selective deployment: estate crop monitoring and broad forest stratification are immediately operational, while smallholder mapping requires methodological advancement. This graduated approach aligns with operational agricultural monitoring frameworks that prioritize high-confidence classes while acknowledging uncertainty in complex systems (Potapov et al., 2022). The SLIC enhancement, achieving 99.5% noise reduction, transforms pixel-based outputs into interpretable products suitable for landscape planning. Recent advances in superpixel segmentation demonstrate 4-8% accuracy improvements through boundary purification and homogeneity enhancement (Yang et al., 2025). The SLIC approach effectively addresses salt-and-pepper noise while preserving meaningful field boundaries, a critical requirement for operational agricultural mapping (Estefania-Salazar & Iglesias, 2024)

However, sub-hectare mapping demands either very-high-resolution imagery (Planet: 3m daily) or deep learning approaches (U-Net, Vision Transformers) that preserve spatial context while learning complex agricultural patterns. Planet imagery at 3m resolution has demonstrated 86-88% single-sensor accuracy for mapping smallholder fields <0.3 ha, with daily revisit enabling robust cloud-gap filling in tropical regions (Rufin et al., 2022). The integration of Planet with Sentinel data achieves combined accuracies approaching 88-91% for heterogeneous smallholder systems (Sagan et al., 2021). Deep learning architectures, particularly U-Net and Vision Transformers, have emerged as superior alternatives to traditional machine learning for complex agricultural mapping.

Recent U-Net applications achieve F1-scores of 84-99% and mean IoU >0.85 for multi-crop classification in heterogeneous tropical landscapes (K. Li et al., 2022). Vision Transformer approaches, specifically designed for agricultural time-series, demonstrate 3-8% accuracy advantages over CNN-based methods through superior temporal feature extraction and multi-modal fusion capabilities (R. Wang et al., 2024). The Cropformer and MeViT architectures have proven particularly effective for medium-resolution (30m) tropical crop mapping, achieving >90% overall accuracy across diverse scenarios (Panboonyuen et al., 2023). Self-supervised pre-training strategies further enhance performance, enabling 85-90% accuracy one month earlier in the growing season compared to conventional supervised approaches (Xu et al., 2024).

CONCLUSION

This study successfully developed a methodology for land cover classification with a focus on agriculture through the innovative integration of multi-sensor remote sensing data and object-based spatial enhancement. The comprehensive evaluation

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

across 22 land cover categories in Jambi Province highlights both the potential and limitations of current remote sensing approaches for the fine-scale discrimination of agricultural systems in complex tropical environments. The Random Forest classifier, specifically designed for agricultural applications, achieved an overall accuracy of 53.7%. It exhibited particularly robust performance in classifying estate crop systems, achieving an F1-score of 94%, as well as in forest categories. Nonetheless, the classifier's inability to accurately classify smallholder agricultural systems highlights significant challenges in distinguishing complex farming mosaics when utilizing single-date imagery. The strategic weighting of agricultural classes effectively enhanced the model's sensitivity to economically significant land use categories. Furthermore, the integration of PALSAR-2 L-band radar data with Landsat 9 optical imagery provided valuable complementary information on structural and spectral characteristics.

The implementation of SLIC object-based enhancement constitutes a noteworthy methodological advancement, achieving a 99.5% reduction in salt-and-pepper noise and significant improvements in spatial coherence metrics. This post-processing technique effectively transforms pixel-based classifications, traditionally used in academic contexts, into operationally viable products suitable for land use planning and policy applications, thereby addressing a persistent limitation in tropical land cover mapping. Nonetheless, the challenges in discriminating smallholder systems suggest that alternative approaches, such as field surveys and ultra-high-resolution imagery, remain essential for a comprehensive analysis of agricultural landscapes.

REFERENCES

Aldania, A. N. A., Soleh, A. M., & Notodiputro, K. A. (2023). A Comparative Study of CatBoost and Double Random Forest for Multi-class Classification. *Jurnal RESTI*, *7*(1). https://doi.org/10.29207/resti.v7i1.4766

Bahri, K. A., Herdiyeni, Y., & Suprehatin, S. (2023). Credit Scoring Model for Farmers using Random Forest. *Jurnal RESTI*, *7*(1). https://doi.org/10.29207/resti.v7i1.4583

Belgiu, M., & Csillik, O. (2018). Sentinel-2 cropland mapping using pixel-based and object-based time-weighted dynamic time warping analysis. *Remote Sensing of Environment*, *204*. https://doi.org/10.1016/j.rse.2017.10.005

Bhogapurapu, N., Dey, S., Bhattacharya, A., Mandal, D., Lopez-Sanchez, J. M., McNairn, H., López-Martínez, C., & Rao, Y. S. (2021). Dual-polarimetric descriptors from Sentinel-1 GRD SAR data for crop growth assessment. *ISPRS Journal of Photogrammetry and Remote Sensing*, *178*. https://doi.org/10.1016/j.isprsjprs.2021.05.013

Buchadas, A., Baumann, M., Meyfroidt, P., & Kuemmerle, T. (2022). Uncovering major types of deforestation frontiers across the world’s tropical dry woodlands. *Nature Sustainability*, *5*(7). https://doi.org/10.1038/s41893-022-00886-9

Chan, F., & Reba, M. (2025). Monitoring tropical soil moisture using remote sensing technology: A mini review. *IOP Conference Series: Earth and Environmental Science*, *1500*, 012035. https://doi.org/10.1088/1755-1315/1500/1/012035

Danylo, O., Pirker, J., Lemoine, G., Ceccherini, G., See, L., McCallum, I., Hadi, Kraxner, F., Achard, F., & Fritz, S. (2021). A map of the extent and year of detection of oil palm plantations in Indonesia, Malaysia and Thailand. *Scientific Data*, *8*(1). https://doi.org/10.1038/s41597-021-00867-1

David, R. M., Rosser, N. J., & Donoghue, D. N. M. (2022). Remote sensing for

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

monitoring tropical dryland forests: A review of current research, knowledge gaps and future directions for Southern Africa. *Environmental Research Communications*, *4*(4). https://doi.org/10.1088/2515-7620/ac5b84

Defourny, P., Bontemps, S., Bellemans, N., Cara, C., Dedieu, G., Guzzonato, E., Hagolle, O., Inglada, J., Nicola, L., Rabaute, T., Savinaud, M., Udroiu, C., Valero, S., Bégué, A., Dejoux, J. F., El Harti, A., Ezzahar, J., Kussul, N., Labbassi, K., … Koetz, B. (2019). Near real-time agriculture monitoring at national scale at parcel resolution: Performance assessment of the Sen2-Agri automated system in various cropping systems around the world. *Remote Sensing of Environment*, *221*. https://doi.org/10.1016/j.rse.2018.11.007

Delsouc, A., Barber, M., Gallaud, A., Grings, F., Vidal-Páez, P., Pérez-Martínez, W., & Briceño-De-Urbaneja, I. (2020). Seasonality analysis of sentinel-1 and ALOS-2/PALSAR-2 backscattered power over salar de Aguas Calientes Sur, Chile. *Remote Sensing*, *12*(6). https://doi.org/10.3390/rs12060941

Descals, A., Wich, S., Meijaard, E., Gaveau, D. L. A., Peedell, S., & Szantoi, Z. (2021). High-resolution global map of smallholder and industrial closed-canopy oil palm plantations. *Earth System Science Data*, *13*(3). https://doi.org/10.5194/essd-13-1211-2021

Eisfelder, C., Boemke, B., Gessner, U., Sogno, P., Alemu, G., Hailu, R., Mesmer, C., & Huth, J. (2024). Cropland and Crop Type Classification with Sentinel-1 and Sentinel-2 Time Series Using Google Earth Engine for Agricultural Monitoring in Ethiopia. *Remote Sensing*, *16*(5). https://doi.org/10.3390/rs16050866

Estefania-Salazar, E., & Iglesias, E. (2024). Enhancing spatio-temporal environmental analyses: A machine learning superpixel-based approach. *Heliyon*, *10*(14), e34711. https://doi.org/https://doi.org/10.1016/j.heliyon.2024.e34711

Ginting, F. I., Rudiyanto, R., Fatchurahman, Mohd Shah, R., Che Soh, N., Giap, S. G. E., Fiantis, D., Setiawan, B. I., Schiller, S., Davitt, A., & Minasny, B. (2024). SEA-Rice-Ci10: High-resolution Mapping of Rice Cropping Intensity and Harvested Area Across Southeast Asia using the Integration of Sentinel-1 and Sentinel-2 Data. *Earth System Science Data Discussions*, *2024*, 1–49. https://doi.org/10.5194/essd-2024-90

Goebel, M., Thiong'O, K., & Rienow, A. (2023). Object-based mapping and classification features for tropical highlands using sentinel-1, sentinel-2, and gedi canopy height data - a case study of the muringato catchment, kenya. *Erdkunde*, *77*(1). https://doi.org/10.3112/erdkunde.2023.01.03

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*. https://doi.org/10.1016/j.rse.2017.06.031

Jin, Z., Azzari, G., You, C., Di Tommaso, S., Aston, S., Burke, M., & Lobell, D. B. (2019). Smallholder maize area and yield mapping at national scales with Google Earth Engine. *Remote Sensing of Environment*, *228*. https://doi.org/10.1016/j.rse.2019.04.016

Julianto, N., Widaryanto, E., & Ariffin, A. (2023). Efisiensi Penggunaan Lahan Melalui Pengaturan Pola Tanam Tumpangsari Bawang Merah (Allium ascalonicum L.) dan Cabai (Capsicum annum L.). *Agro Bali : Agricultural Journal*, *6*, 350–360. https://doi.org/10.37637/ab.v6i2.1286

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

Karasiak, N., Dejoux, J. F., Monteil, C., & Sheeren, D. (2022). Spatial dependence between training and test sets: another pitfall of classification accuracy assessment in remote sensing. *Machine Learning*, *111*(7). https://doi.org/10.1007/s10994-021-05972-1

Khan, W., Minallah, N., Sher, M., Khan, M. A., Rehman, A. ur, Al-Ansari, T., & Bermak, A. (2024). Advancing crop classification in smallholder agriculture: A multifaceted approach combining frequency-domain image co-registration, transformer-based parcel segmentation, and Bi-LSTM for crop classification. *PLoS ONE*, *19*(3 March). https://doi.org/10.1371/journal.pone.0299350

Kusmanto, Samsir, S., Watrianthos, R., & Suryadi, S. (2023). Distribusi Spasial Unmet Need Pelayanan Kesehatan dengan Algoritma K-Means untuk Pemetaan Provinsi di Indonesia. *Bulletin of Information Technology (BIT)*, *4*(3). https://doi.org/10.47065/bit.v4i3.862

Lemettais, L., Alleaume, S., Luque, S., Laques, A. É., Alim, Y., Demagistri, L., & Bégué, A. (2025). Radiometric landscape: a new conceptual framework and operational approach for landscape characterisation and mapping. *Geo-Spatial Information Science*, *28*(2). https://doi.org/10.1080/10095020.2024.2314558

Li, K., Zhao, W., Peng, R., & Ye, T. (2022). Multi-branch self-learning Vision Transformer (MSViT) for crop type mapping with Optical-SAR time-series. *Computers and Electronics in Agriculture*, *203*. https://doi.org/10.1016/j.compag.2022.107497

Li, M., & Stein, A. (2020). Mapping land use from high resolution satellite images by exploiting the spatial arrangement of land cover objects. *Remote Sensing*, *12*(24). https://doi.org/10.3390/rs12244158

Makate, C., Makate, M., Mutenje, M., Mango, N., & Siziba, S. (2019). Synergistic impacts of agricultural credit and extension on adoption of climate-smart agricultural technologies in southern Africa. *Environmental Development*, *32*. https://doi.org/10.1016/j.envdev.2019.100458

Panboonyuen, T., Charoenphon, C., & Satirapod, C. (2023). MeViT: A Medium-Resolution Vision Transformer for Semantic Segmentation on Landsat Satellite Imagery for Agriculture in Thailand. *Remote Sensing*, *15*, 5124. https://doi.org/10.3390/rs15215124

Poortinga, A., Tenneson, K., Shapiro, A., Nquyen, Q., Aung, K. S., Chishtie, F., & Saah, D. (2019). Mapping plantations in Myanmar by fusing Landsat-8, Sentinel-2 and Sentinel-1 data along with systematic error quantification. *Remote Sensing*, *11*(7). https://doi.org/10.3390/rs11070831

Potapov, P., Hansen, M. C., Pickens, A., Hernandez-Serna, A., Tyukavina, A., Turubanova, S., Zalles, V., Li, X., Khan, A., Stolle, F., Harris, N., Song, X. P., Baggett, A., Kommareddy, I., & Kommareddy, A. (2022). The Global 2000-2020 Land Cover and Land Use Change Dataset Derived From the Landsat Archive: First Results. *Frontiers in Remote Sensing*, *3*. https://doi.org/10.3389/frsen.2022.856903

Rufin, P., Bey, A., Picoli, M., & Meyfroidt, P. (2022). Large-area mapping of active cropland and short-term fallows in smallholder landscapes using PlanetScope data. *International Journal of Applied Earth Observation and Geoinformation*, *112*. https://doi.org/10.1016/j.jag.2022.102937

Rufin, P., Frantz, D., Ernst, S., Rabe, A., Griffiths, P., özdoğan, M., & Hostert, P. (2019). Mapping cropping practices on a

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

national scale using intra-annual Landsat time series binning. *Remote Sensing*, *11*(3). https://doi.org/10.3390/rs11030232

Rufin, P., Hammer, P., Thomas, L.-F., Lisboa, S., Ribeiro, N., Sitoe, A., Hostert, P., & Meyfroidt, P. (2025). *National level satellite-based crop field inventories in smallholder landscapes*. https://doi.org/10.48550/arXiv.2507.10499

Sagan, V., Maimaitijiang, M., Bhadra, S., Maimaitiyiming, M., Brown, D. R., Sidike, P., & Fritschi, F. B. (2021). Field-scale crop yield prediction using multi-temporal WorldView-3 and PlanetScope satellite data and deep learning. *ISPRS Journal of Photogrammetry and Remote Sensing*, *174*. https://doi.org/10.1016/j.isprsjprs.2021.02.008

Sari, I. L., Weston, C. J., Newnham, G. J., & Volkova, L. (2022). Developing multi-source indices to discriminate between native tropical forests, oil palm, and rubber plantations in Indonesia. *Remote Sensing*, *14*(1). https://doi.org/10.3390/rs14010003

Sekulić, A., Kilibarda, M., Heuvelink, G. B. M., Nikolić, M., & Bajat, B. (2020). Random Forest Spatial Interpolation. *Remote Sensing*, *12*(10). https://doi.org/10.3390/rs12101687

Solekhah, B., Priyadarshini, R., & Maroeto, M. (2024). Kajian Pola Distribusi Tekstur terhadap Bahan Organik pada Berbagai Penggunaan Lahan. *Agro Bali : Agricultural Journal*, *7*, 256–265. https://doi.org/10.37637/ab.v7i1.1571

Teo, H. C., Lamba, A., Ng, S. J. W., Nguyen, A. T., Dwiputra, A., Lim, A. J. Y., Nguyen, M. N., Tor-ngern, P., Zeng, Y., Dewi, S., & Koh, L. P. (2025). Reduction of deforestation by agroforestry in high carbon stock forests of Southeast Asia. *Nature Sustainability*, *8*(4), 358–362. https://doi.org/10.1038/s41893-025-01532-w

Tikuye, B. G., Rusnak, M., Manjunatha, B. R., & Jose, J. (2023). Land Use and Land Cover Change Detection Using the Random Forest Approach: The Case of The Upper Blue Nile River Basin, Ethiopia. *Global Challenges*, *7*(10). https://doi.org/10.1002/gch2.202300155

Toyota, T., Ishiyama, J., & Kimura, N. (2021). Measuring Deformed Sea Ice in Seasonal Ice Zones Using L-Band SAR Images. *IEEE Transactions on Geoscience and Remote Sensing*, *59*(11). https://doi.org/10.1109/TGRS.2020.3043335

Vermote, E., Justice, C., Claverie, M., & Franch, B. (2016). Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. *Remote Sensing of Environment*, *185*. https://doi.org/10.1016/j.rse.2016.04.008

Wang, D., Liu, C. A., Zeng, Y., Tian, T., & Sun, Z. (2021). Dryland crop classification combining multitype features and multitemporal quad-polarimetric RADARSAT-2 imagery in Hebei plain, China. *Sensors (Switzerland)*, *21*(2). https://doi.org/10.3390/s21020332

Wang, R., Ma, L., He, G., Johnson, B., Yan, Z., Chang, M., & Liang, Y. (2024). Transformers for Remote Sensing: A Systematic Review and Analysis. *Sensors*, *24*, 3495. https://doi.org/10.3390/s24113495

Watrianthos, R., Suryadi, S., Kusmanto, & Samsir, S. (2023). Pemetaan Tingkat Kriminalitas di Indonesia: Analisis Spasial dengan Pendekatan SIG pada Tingkat Provinsi. *Bulletin of Information Technology (BIT)*, *4*(3). https://doi.org/10.47065/bit.v4i3.861

Xu, Y., Ma, Y., & Zhang, Z. (2024). Self-supervised pre-training for large-scale crop mapping using Sentinel-2 time

e-ISSN 2655-853X
https://doi.org/10.37637/ab.v8i3.2530

series. *ISPRS Journal of Photogrammetry and Remote Sensing*, *207*. https://doi.org/10.1016/j.isprsjprs.2023.12.005

Xu, Y., Yu, L., Li, W., Ciais, P., Cheng, Y., & Gong, P. (2020). Annual oil palm plantation maps in Malaysia and Indonesia from 2001 to 2016. *Earth System Science Data*, *12*(2). https://doi.org/10.5194/essd-12-847-2020

Yang, W., Zhang, Y., Zhang, H., & Li, L. (2025). A Dynamic Adaptive Framework for Remote Sensing Imagery Superpixel Segmentation and Classification via Dual-Branch Feature Learning. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *PP*, 1–16. https://doi.org/10.1109/JSTARS.2025.3585544

Zhai, J., Xiao, C., Liu, X., & Liu, Y. (2024). Analysis of 10-m Sentinel-2 imagery and a re-normalization approach reveals a declining trend in the latest rubber plantations in Xishuangbanna. *Advances in Space Research*, *73*(12). https://doi.org/10.1016/j.asr.2024.03.032

Zhang, C., Huang, C., Li, H., Liu, Q., Li, J., Bridhikitti, A., & Liu, G. (2020). Effect of textural features in remote sensed data on rubber plantation extraction at different levels of spatial resolution. *Forests*, *11*(4). https://doi.org/10.3390/F11040399

Zhou, W., Rao, P., Jat, M. L., Balwinder-Singh, Poonia, S., Bijarniya, D., Kumar, M., Singh, L. K., Schulthess, U., Singh, R., & Jain, M. (2021). Using sentinel-2 to track field-level tillage practices at regional scales in smallholder systems. *Remote Sensing*, *13*(24). https://doi.org/10.3390/rs13245108