RESEARCH PAPER

A Comprehensive study of Land Use Land Cover (LULC) Change Dynamics and Crop Classification Testing

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Abstract

Systematic monitoring and predictive assessment of Land Use/Land Cover (LULC) dynamics, especially changes in agricultural land and crop-type distribution, are vital for food security, environmental management and sustainable land-use planning. Continuous changes in agricultural landscapes are occurring due to population pressure, rapid urbanization, agricultural intensification and climate variability over space and time. This review summarizes recent developments in spatiotemporal land use land cover (LULC) change detection with a focus on crop type classification, method assessment, and validation strategies. Recent developments in cloud-based geospatial platforms (e.g., Google Earth Engine) and high-frequency Earth observation systems (e.g., Sentinel, Landsat, and PlanetScope) have greatly enhanced the capacity for large-scale and time-series-based agricultural monitoring. The review discusses the progress of classification methods from the classical parametric methods to the modern machine learning and algorithms used in deep learning. Special emphasis is given to accuracy assessment for crop-type mapping including confusion matrices, class-specific performance indicators, spectral separability, mixed-pixel effects, class imbalance and spatially independent validation. Ongoing methodological challenges such as ground-reference data limitations, regional data imbalance, spectral similarity between crop classes and limited model transferability across agroecological regions are also discussed. Future directions include multi-sensor data fusion, spatially robust validation, transfer learning, domain adaptation, and physicsinformed machine learning. Overall, the review presents an in-depth review of the technological and methodological advancements needed to improve the accuracy, scalability, and transferability of agricultural LULC and crop-type mapping.

Keywords: Land Use/Land Cover, Crop-Type Mapping, Agriculture Remote Sensing, Machine Learning, Deep Learning, Accuracy Assessment, Spatial Validation, Geospatial Modeling.

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1. **Introduction**

The dynamics of Land Use/Land Cover (LULC) are important indicators of the interactions between human activities and terrestrial ecosystems. Changes in land use affect ecosystem functioning, biogeochemical processes, hydrological regimes, biodiversity, and the long-term availability of natural resources (Lambin et al., 2001). Agricultural land is particularly dynamic and socioeconomically important among the major land-cover categories because it is used for food production and it impacts regional environmental processes (Foley et al., 2005). Agricultural landscapes have been rapidly transformed in recent decades due to population growth, industrialization, economic development and urban expansion. Increasing amounts of productive agricultural land have been converted to urban and built-up land, and agriculture has expanded into some regions, leading to the conversion of forests, wetlands, and other environmentally sensitive ecosystems (Seto et al., 2011; Liu et al., 2020). These countervailing processes have increased the need for continuous and spatially explicit monitoring of agricultural land systems.

Earth observation (EO) technologies and Geographic Information Systems (GIS) have become essential instruments for monitoring, quantifying and analyzing such transformations across multiple spatial and temporal scales (Thenkabail et al., 2012). However, the traditional LULC mapping, which usually represents broad categories such as agriculture, forest, water, and built-up land, might not be adequate to meet the contemporary agricultural monitoring needs. The need to differentiate individual crop types, describe seasonal cropping practices, track phenological progression, and assess agricultural dynamics at regional to global scales is growing (Kussul et al., 2017).

2. Methodology

The methodological framework was designed to integrate multi-source remote sensing data with sophisticated classification and validation methods for crop-type mapping and spatiotemporal LULC assessment. We used multi-temporal satellite datasets (Landsat and Sentinel-2) with ancillary information (Sentinel-1 SAR data, digital elevation data, climatic variables and field-based reference samples). All datasets were systematically pre-processed to generate a consistent analytical dataset including radiometric and atmospheric correction, cloud and shadow removal, temporal compositing, spatial registration and resampling. Spectral bands and derived vegetation indices (e.g. NDVI, EVI) were used to characterize the crop conditions and seasonal phenological changes. Also, spectral, temporal, textural and ancillary variables were extracted and integrated into a comprehensive multi-source feature dataset.

The features prepared were then used for the classification of the crop type and LULC with the application of machine learning and deep learning approaches. We employed representative machine learning algorithms: Random Forest, Support Vector Machine, and XGBoost, and considered Convolutional Neural Networks and Long Short-Term Memory networks to capture the spatial patterns and temporal crop dynamics. Parameter optimization and cross-validation improved model performance. The reliability of the classification was evaluated against independent reference data using a confusion matrix and related performance indicators including producer's accuracy, user's accuracy, overall accuracy, Kappa coefficient, and F1-score. spatial block cross-validation was also incorporated to diminish the spatial autocorrelation effect and provide a more trustworthy estimate of a model's generalization. The validated classification outputs were utilized for generating crop-specific LULC maps and assessing spatiotemporal changes, thus providing support for agricultural monitoring, sustainable land management and informed environmental planning.

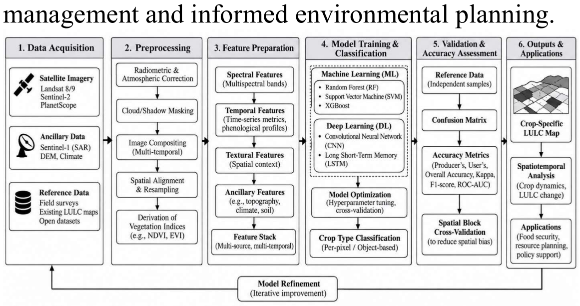

Fig. Methodology for the study

2.1 Theoretical framework and methodological evolution of LULC mapping

The first remote sensing applications in agricultural monitoring had major constraints such as limited temporal coverage, relatively coarse spatial resolution and limited computational capacity. Therefore, many early studies used single-date imagery and were more concerned with broad land-cover discrimination than with detailed characterization of crop types and seasonal agricultural dynamics (Foody, 2002).

The ongoing development of Earth observation missions, particularly the Landsat program and the Sentinel missions, has transformed the ability to monitor agriculture. Recent progress in multi-temporal satellite observations allows the repeated characterization of vegetation conditions and land-surface changes at medium spatial resolution. This shift has allowed for the transition from static inventories of the land-cover to dynamic monitoring of agricultural systems.
The advent of geospatial computing in the cloud has further accelerated this transition. Platforms like Google Earth Engine provide storage, processing, and analysis of large amounts of multi-source satellite data, without requiring substantial local computational infrastructure (Gorelick et al., 2017). These capabilities have enabled the analysis of dense satellite time series and the extraction of crop specific phenological signatures. Temporal vegetation indices such as Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) can be used to monitor seasonal crop development. Differences in temporal trajectories can be used to differentiate crops based on differences in planting dates, growth stages, peak vegetation conditions and senescence patterns. Therefore, analysis of time series is becoming more and more important part of modern crop type classification.

2.2 Space and Time Drivers of Agricultural LULC Transitions

Agricultural LULC change results from interactions between demographic, economic, technological, climatic and environmental processes. One of the main reasons for converting agricultural land is urban expansion. Urban expansion often takes place on productive and accessible agricultural land that is near existing settlements, infrastructure, transportation networks and water resources. Urban expansion has significant impacts on global cropland resources, as shown by Seto et al. (2011), and subsequent studies have underlined the potential consequences of unchecked urban growth for agricultural sustainability (Aburas et al., 2019; Liu et al., 2020).

Agricultural landscapes are also altered by opposing processes of intensification and extensification. Intensification is defined as the increase in agricultural output per area of land already under cultivation through irrigation, improved crop varieties, fertilizers, mechanization and multiple cropping cycles. Extensification, however, refers to the expansion of agricultural activity into previously uncultivated land, which may result in the conversion of forests, wetlands, and other natural ecosystems (Gibbs et al., 2010). These processes lead to complex spatial and temporal patterns which demand frequent and reliable Earth observations.

2.3 Role of Multiresolution Satellite Constellations

The capacity for agricultural LULC monitoring and crop-type mapping has been greatly improved by multi-resolution satellite systems. Coarse-resolution sensors such as MODIS have provided frequent observations in the past but were limited in fragmented agricultural landscapes because individual pixels often contained multiple land-cover types. There are also medium-resolution missions, such as Landsat 8/9 and Sentinel-2A/2B, that provide higher spatial detail and higher-frequency repeat observations. Their open data policies have spurred even more their use in agricultural remote sensing. Sentinel-2 provides multispectral observations at spatial resolution suitable for field scale analysis with spectral bands of interest for vegetation and crop monitoring.

Commercial satellite constellations, like PlanetScope, offer much higher resolution and revisit rates. Such datasets can be used to monitor smaller agricultural parcels and rapid changes in crop conditions. The complementary use of coarse-, medium-, and high-resolution observations therefore offers important opportunities for improved crop mapping across the different field sizes and management systems of the landscape.

3. Crop-Type Classification Algorithmic Methods

3.1 Standard Parametric Classifiers

Early remote sensing classification was done using parametric approaches like Maximum Likelihood Classifier (MLC). These techniques make class membership predictions based on statistical assumptions about the spectral distribution of training data (Foody, 2002). These factors can degrade the performance of classifiers based on simplified assumptions about class distributions.

3.2 Machine Learning Methods

Among the major advances in agricultural remote sensing were the development of non-parametric machine learning algorithms. Random Forest (RF), Support Vector Machines (SVM) and gradient-boosting algorithms are widely used due to their capability to model complex and non-linear relationships between spectral, spatial and temporal variables (Belgiu and Drăguț, 2016).

RandomForest

Random Forest creates an ensemble of decision tree models from random samples of training observations and predictor variables. The final classification is obtained by aggregating the individual trees predictions (Breiman, 2001). The main advantages are that it is robust to over-fitting, can handle large numbers of predictor variables and can estimate variable importance.

These features make RF a particularly suitable approach for multi-temporal agricultural datasets with spectral bands, vegetation indices, texture variables, topography and phenological features. They can be particularly effective when training datasets are small and class boundaries are complex or non-linear (Mountrakis et al., 2011). The computational requirements may increase when SVM is used for very large multi-temporal datasets. They are especially helpful when detailed feature engineering and the integration of predictors from several sources is necessary.

3.3 Deep Learning and Spatio-Temporal Phenology Modeling

Standard machine learning algorithms work well on structured feature vectors, but can be limited in automatically extracting spatial patterns and long term temporal dependencies. Deep learning methods address these limitations by learning hierarchical representations directly from complex spatial-temporal datasets. This allows the classification process to incorporate field texture, shape, spatial context and local structural information. This spatial information can improve the discrimination of agricultural fields and reduce the classification uncertainty at field boundaries (Kussul et al., 2017). Recurrent Neural Networks (RNNs), in particular Long Short-Term Memory (LSTM) networks, are designed for modeling sequential data. This makes LSTMs well suited to multi-temporal satellite observations and vegetation index time series. Such models learn temporal relationships over a growing season and can differentiate crop types by their characteristic phenological trajectories (Rußwurm and Körner, 2018).

4. Validation Frameworks and Accuracy Assessment

The reliability of a crop type classification is not only a function of the classification algorithm, but also of the quality and independence of the validation procedure. The confusion matrix, also known as the error matrix, is the foundation for evaluating the accuracy of thematic classification. It compares predicted class labels with independently collected reference observations and is the basis for deriving class-specific and overall performance measures (Congalton, 1991).
This rigorous validation framework is particularly relevant to agriculture mapping as individual crop classes may vary significantly in terms of sample size, spectral separability and spatial distribution.

4.1 Total Accuracy

Overall accuracy is the percentage of all validation observations that are correctly classified. It is well known that classes that are highly imbalanced may not be sufficient since dominant classes might have a disproportionate influence on the outcome.

4.2 Coefficient Kappa

The Kappa coefficient was historically employed to measure agreement beyond chance. However, its interpretation has been increasingly debated since its value can be influenced by class prevalence and marginal distributions. Kappa should thus not be considered a replacement for detailed class-specific accuracy assessment. Precision, recall and F1-score give us some extra information, especially when we have imbalanced classes in the dataset. The F1-score combines precision and recall and can give a more balanced evaluation of minority crop classes than overall accuracy.

4.3 Spatial Autocorrelation and Spatial Cross-Validation

Spatial autocorrelation is one of the key methodological issues in geospatial machine learning. Typically, adjacent observations share similar environmental and spectral properties. This implies that the usual random partitioning of training and testing data can put neighboring observations in the same and in different data sets. This may lead to spatial data leakage and artificially optimistic accuracy estimates because the test observations are not fully independent of the training data. Spatial block cross-validation, which separates training and testing samples geographically, overcomes this limitation. Independent spatial blocks are a common method to assess whether a model can generalize beyond the specific locations used during training (Ploton et al., 2020).
Spatially explicit validation should therefore be included in a rigorous model evaluation of agricultural LULC and crop-type mapping.

5. Contemporary Challenges in Agricultural LULC and Crop-Type Mapping

In spite of great technological and methodological progress, some challenges still plague the reliability of agricultural classification.
Supervised classification needs reliable reference information for model training and independent validation . However, collecting field data across large areas can be expensive, time consuming and logistically challenging. Ground observations need to be temporally consistent with satellite acquisitions and representative of crop diversity.

5.1 Transferability of Models

A model trained in one geographical or agroecological region may not perform equally well in other regions. Differences in climate, soils, types of crops, management, cropping calendars and sensor conditions may alter the spectral and phenological relationships.
Therefore, how to improve the cross-region generalization remains a key challenge for operational large-scale crop-type mapping.

5.2 Directions for Future Research and Emerging Frontiers

One of the most promising directions for agricultural remote sensing is the integration of complementary satellite sensors. The optical observations from Sentinel-2, Landsat and high-resolution commercial sensors can provide detailed spectral information, whereas Synthetic Aperture Radar (SAR) data from systems like Sentinel-1 can provide structural information and maintain observational capability under cloudy conditions. The fusion of optical and SAR observations may improve temporal continuity and crop discrimination in cloud-prone regions.

5.3 Transfer Learning and Domain Adaptation

Transfer learning and domain adaptation are possible ways to address the shortage of training data in many areas. Models trained on large, well-characterized data sets can be adapted to new locations with relatively small amounts of additional reference information. More effort should be devoted to developing robust domain adaptation strategies in the future to address the variations in climate, crop calendars, management practices, and satellite observation conditions.

6 RESULTS AND DISCUSSION

Table 1. Comparative performance of conventional, machine learning, and deep learning approaches for crop classification

Table 1 presents a comparative synthesis of commonly applied classification approaches for agricultural crop mapping using remote sensing data. The reported performance ranges represent generalized benchmarks synthesized from previous studies and are intended to illustrate the relative capabilities of different algorithmic approaches rather than establish universally applicable accuracy thresholds.

Classifier	**Algorithmic approach**	**Typical overall accuracy (%)**	**Typical F1-score range**	**Major advantages**	**Major limitations**
Maximum Likelihood Classification (MLC)	Parametric statistical classifier	68–74	0.60–0.68	Computationally efficient, easy to implement, and suitable for baseline classification where training data are limited.	Relies on assumptions regarding data distribution and is sensitive to spectral variability, mixed pixels, and noise.
Support Vector Machine (SVM)	Non-parametric kernel-based classifier	82–89	0.75–0.84	Performs effectively with relatively limited training samples and can model complex and non-linear class boundaries.	Performance depends strongly on kernel and hyperparameter selection and computational requirements may increase for large multi-temporal datasets.
Random Forest (RF)	Ensemble tree-based machine learning classifier	85–92	0.80–0.88	Robust to overfitting, capable of handling high-dimensional and multi-source datasets, and provides estimates of feature importance.	May exhibit bias toward dominant classes when the training dataset is highly imbalanced.
Deep Learning (CNN/LSTM)	Neural network-based spatia	**93–97**	**0.89–0.95**	Highly effective in extracting comple	Requires substantial training data,

	l and temporal learning			x spatial patterns, spectral features, and seasonal or phenological dynamics from multi-temporal data.	greater computational resources, and careful model optimization to avoid overfitting.

The accuracy and F1-score ranges represent generalized performance intervals synthesized from published agricultural remote sensing studies. Actual classification performance may vary according to crop diversity, field size, spatial resolution, training sample quality, sensor characteristics, and local environmental conditions.

Table 2. Influence of feature input strategy on the accuracy of satellite-based crop classification

The selection of input features plays a critical role in determining crop classification performance. Table 2 compares the expected performance of single-date imagery, multi-temporal vegetation-index time series, and multi-sensor optical–SAR data fusion. The comparison highlights the increasing value of temporal and complementary sensor information for discriminating crops with similar spectral characteristics.

Feature input strategy	**Sensor/ data source**	**Typical producer's accuracy for major crops (%)**	**Typical user's accuracy for major crops (%)**	**Key limitation**
Single-date multispectral imagery	Landsat-8 or Sentinel-2 acquired during a representative growing period	70–78	65–72	Spectral similarity among crops at a single phenological stage can result in substantial commission and omission errors.
Multi-temporal vegetation-index time series	Sentinel-2 or Landsat-8 seasonal NDVI/EVI observations	**88–94**	**85–91**	Cloud contamination and missing observations can disrupt seasonal trajectories and may require gap filling, interpolation, or temporal smoothing.
Multi-sensor data fusion	Sentinel-2 optical data integrated with Sentinel-1 C-band SAR observations	**92–96**	**90–94**	Requires more complex preprocessing, including radiometric calibration, geometric co-registration,

				temporal matching, and sensor-data harmonization.

Multi-temporal and multi-sensor approaches generally improve crop discrimination because they capture phenological variations and complementary optical and radar responses. However, the magnitude of improvement depends on crop calendars, revisit frequency, cloud conditions, field fragmentation, spatial resolution, and the availability of reliable reference data.

Comparative interpretation of classification performance

The comparative analysis indicates a progressive improvement in crop classification capability from conventional parametric approaches to advanced machine learning and deep learning frameworks. Maximum Likelihood Classification generally provides a useful baseline because of its simplicity and low computational requirements; however, its performance is constrained by distributional assumptions and spectral overlap among crop classes. Machine learning approaches, particularly SVM and Random Forest, substantially improve classification performance by accommodating complex and non-linear relationships within multispectral datasets. Among the evaluated approaches, deep learning architectures, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, demonstrate the greatest potential for high-accuracy crop mapping. CNN models are particularly effective for extracting spatial and textural characteristics, whereas LSTM-based architectures can exploit temporal dependencies within crop phenological sequences. Consequently, deep learning approaches are especially advantageous when dense multi-temporal satellite observations and sufficiently large reference datasets are available.

The feature-input comparison further demonstrates that classification accuracy is strongly influenced by the temporal and spectral richness of the input data. Single-date imagery may be inadequate for distinguishing crops exhibiting similar spectral responses during a particular growth stage. The integration of multi-temporal NDVI or EVI observations improves discrimination by incorporating crop-specific seasonal trajectories. Further improvements can be achieved through optical–SAR fusion, as Sentinel-1 radar observations provide complementary information on crop structure and moisture conditions and remain available under cloudy atmospheric conditions.The evidence suggests that multi-temporal and multi-sensor feature strategies combined with advanced machine learning or deep learning algorithms provide the most effective framework for operational crop classification. Nevertheless, the reported performance ranges should be interpreted as literature-based comparative benchmarks, since actual accuracy is influenced by local cropping patterns, field parcel size, crop heterogeneity, atmospheric conditions, spatial resolution, temporal sampling frequency, and the quality and representativeness of ground-reference data.

Conclusion

Changes in land use/land cover are constantly changing agricultural landscapes, resulting in an increasing demand for accurate, timely, and spatially explicit information on crop types. Recent advances in Earth observation, geospatial computing in the cloud and computational intelligence have transitioned agricultural remote sensing from static broad-scale land-cover mapping to dynamic spatiotemporal monitoring of crop systems. Classical parametric classifiers have evolved into machine learning and deep learning techniques, greatly improving the capability to handle complex spectral, spatial, and temporal information. Algorithms such as Random Forest, Support Vector Machines, gradient-boosting methods, CNNs and LSTMs provide complementary capabilities for agricultural classification. But the classification performance should be assessed by rigorous and spatially independent validation, rather than just aggregate accuracy measures. Ongoing difficulties include spectral similarity among crop classes, mixed-pixel effects, lack of ground-reference data, class imbalance, spatial autocorrelation, and limited cross-regional model transferability. Overcoming these limitations will require greater integration of multi-temporal and multi-sensor observations, improved field-reference databases, spatially robust validation frameworks, and methods that can transfer knowledge across various agroecological environments. Future progress is anticipated from multi-sensor data fusion, physics-informed machine learning, transfer learning, domain adaptation, and advanced spatiotemporal deep learning architectures. The development of such integrated approaches can improve not only the accuracy of classification but also the scalability, interpretability and operational applicability of agricultural LULC and crop-type mapping. Thus, the future of agricultural remote sensing research must be geared toward robust validation, cross-regional generalization, and scientifically informed predictive modeling for sustainable land management, agricultural planning, and long-term food security.

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