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Review

Advancements in Tobacco Crop Monitoring: A Survey of Deep Learning Technologies

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Abstract

The challenge of tobacco monitoring is a technical and political issue, given that tobacco production is a cross-cutting issue that involves agricultural management, regulatory compliance and illegal harvesting. Tobacco acreage estimation and tobacco classification have been expanded through the use of remote sensing and deep learning has enhanced the capacity to extract spatial, spectral, and temporal patterns from the timeseries data. This survey summarizes the literature on tobacco monitoring and tobacco-relevant crops in a new format, a critical comparison between the various sensing platforms and learning paradigms. It reviews the multispectral, Synthetic Aperture Radar (SAR), unmanned aerial vehicles (UAV) and hyperspectral data sources, as well as traditional machine learning, convolutional, recurrent, attention-based and hybrid models, and points out the experimental conditions in which several studies have achieved high accuracy. The most significant advances have been made in multi-temporal optical classification and UAV-based field-scale mapping, while operational deployment remains hindered by the lack of benchmark datasets, cross region validation, and few SAR–optical fusion studies, as well as the lack of mature decision support pipelines. Future progress will be possible with open tobacco-specific benchmarks, multi-sensor fusion, transferable models, explainable AI and scalable monitoring systems, which will facilitate agricultural and policy decision-making.

Keywords: tobacco monitoring; remote sensing; machine learning; deep learning; SAR; UAV; hyperspectral imaging; multi-sensor fusion

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Academic Editor: Belen Gallego-Elvira

Received: 26 July 2026
Revised: 29 September 2026
Accepted: 13 October 2026
Published: 8 November 2026

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1. Introduction

Despite being closely associated with public health regulation issues, concerns about illicit harvesting, and broader sustainable land use considerations, tobacco continues to be a high-value agricultural commodity in several producing countries [1–5]. This combination creates a unique importance for tobacco monitoring. Governments must estimate acreage, monitor production trends, identify unauthorized cultivation, and evaluate crop

substitution policies. There is also a need to provide timely information to agricultural agencies and growers on the extent, growth stage, stress, and likely yield of the crop. The relevance of remote sensing to agronomic management is, therefore, not only in terms of policy compliance but also for agricultural governance.

Monitoring tobacco is challenging both agronomically and technically. Tobacco production is often in smallholder and fragmented fields that are difficult to delineate at medium spatial resolution in many producing regions. It can grow between other broadleaf crops and so cannot always be reliably identified from a single date, particularly at early growth stages. Tobacco phenology is also cultivar-dependent, depends on management practices, and is sensitive to agroecological zone, so models are sensitive to season and location. In many tobacco growing areas, there is persistent cloud cover that limits the use of optical observations, and ground truth data is expensive, limited, and may not be available for independent validation. These challenges are the reason for the apparent success of experiments not always being reflected in reliable operational monitoring systems [6–11].

While there is a developing body of literature on agricultural remote sensing and deep learning as a whole [12,13], the specific case of tobacco is dispersed among satellite mapping applications, unmanned aerial vehicle (UAV) segmentation research, hyperspectral disease detection research, and a handful of policy oriented applications. Current discussions also focus on reported performance with little attention given to the comparison of model assumptions, data constraints, model validation and readiness for operations. A focused survey is thus necessary to collate what is known specifically about tobacco monitoring, to compare the key methodological options critically, and to identify gaps in the literature and areas of literature.

This survey has three principal contributions:

- It analyzes the capabilities, weaknesses, and tobacco-monitoring appropriateness of optical, Synthetic Aperture Radar (SAR), UAV, and hyperspectral data sources.
- It critically examines traditional machine learning models, Convolutional Neural Network (CNN)-based models, recurrent models, attention-based models, and hybrid models, highlighting their strengths and limitations.
- It brings together the issues that remain unsolved in the field, research gaps, and future directions, such as benchmark datasets and multi-sensor fusion studies.

2. Review Methodology and Literature Selection

A structured literature review was conducted using Scopus, Web of Science, Google Scholar, IEEE Xplore, and ScienceDirect. The final literature search was conducted on 26 July 2026 and covered publications from 2009 to 2026.

The literature search was conducted using Scopus, Web of Science, Google Scholar, IEEE Xplore, and ScienceDirect. Searches were performed using combinations of keywords relevant to tobacco monitoring, including “tobacco crop classification”, “remote sensing tobacco monitoring”, “tobacco AND deep learning”, “tobacco AND UAV”, “tobacco AND hyperspectral”, “tobacco AND SAR”, “Sentinel-2 crop classification”, “deep learning crop mapping”, and related terms. The original literature search did not use a single standardized Boolean search string across all databases; instead, combinations of these keywords were adapted according to the search functionality of each database. Additional method-specific searches were used where necessary to identify studies related to UAV monitoring, time-series classification, sensor fusion, semantic segmentation, disease detection, and biochemical retrieval.

The original search was conducted iteratively, and the saved screening record did not preserve verifiable aggregate totals for initial database hits or duplicate removals. These values are therefore not reconstructed retrospectively. The reproducible information that

can be verified from the review record is the search date, search logic, title/abstract followed by full-text screening procedure, and the final search-derived corpus of 71 retained sources.

Records were screened first by title and abstract and then by full-text assessment. Duplicate records, studies unrelated to crop or remote-sensing monitoring, and studies concerned exclusively with tobacco consumption, public-health impacts, economics, or epidemiology were excluded. Purely agronomic studies without a remote-sensing or data-driven monitoring component were also excluded. A final set of 71 sources was retained for the review and contextual synthesis, including tobacco-specific studies and methodologically relevant agricultural remote-sensing studies.

The two additional methodological references suggested during peer review were added as contextual sources after the original search and are therefore not counted within the 71-source search-derived corpus or the thematic counts in Table 1.

Because tobacco-specific literature remains limited and geographically clustered, neighbouring crop-monitoring studies were retained only when they provided methods directly transferable to tobacco monitoring, such as time-series classification, sensor fusion, semantic segmentation, or biophysical retrieval.

To avoid implying that all reviewed methods have been validated directly for tobacco, the evidence was classified into four categories: (i) tobacco-specific studies, (ii) studies in which tobacco was included among ultiple crops, (iii) generic agricultural methodologies with direct relevance to tobacco monitoring, and (iv) proposed or emerging research directions. These categories are used in the comparative discussion to distinguish established tobacco-specific evidence from transferable or prospective approaches.

The thematic categories in Table 1 were assigned during the literature synthesis based on each study's primary data source and methodological focus; because the categories were non-mutually exclusive, individual studies could be assigned to more than one category.

Table 1. Non-exclusive thematic distribution of the 71 search-derived sources retained in the review.

Dimension	Sub-Category	Number of Studies
Review corpus		
	Total search-derived sources retained	71
Paper category		
	UAV-based studies	8
	SAR-based studies	3
	Hyperspectral studies	8
Technology focus		
	Transformer/attention-based methods	6
	Hybrid/fusion models	10
	Remote sensing platform studies	8

Note: the thematic categories are non-mutually exclusive. A single study may contribute to more than one category (for example, a UAV study may also use a hybrid model), so category totals are not expected to sum to 71. The previous database/publisher grouping was removed because indexing databases and publisher platforms are not equivalent counting units. The two methodological references added during peer review are contextual additions and are not included in these counts.

This literature base is interdisciplinary, covering tobacco-specific crop monitoring, studies on remote sensing platforms, machine learning and deep learning techniques, UAV mapping, SAR time series analysis, hyperspectral disease and quality assessment, and methodological reviews. This diversity is essential due to the need for both the agronomic specificity and the technical integration of sensors, models, validation practices and policy-oriented use cases.

Evolution of Tobacco Crop Monitoring Technologies

The path of technological development of tobacco crop monitoring has not been straightforward. Tobacco is a hard crop to monitor with any one source of information, and it has shifted from labor-intensive field reporting to multi-sensor, multi-temporal, and increasingly automatic reporting processes. The key forces behind this change were the separation of tobacco from similar crops in the spectrum; the precision of monitoring smallholder systems; and support earlier in the season for regulatory and procurement decisions.

These developments have had a direct impact on the development of tobacco monitoring systems, as shown in Figure 1. The evolution from basic decision trees to recent deep-learning methods reflects the increasing complexity of agricultural data, while foundation models and self-supervised learning represent emerging directions whose tobacco-specific validation remains limited.

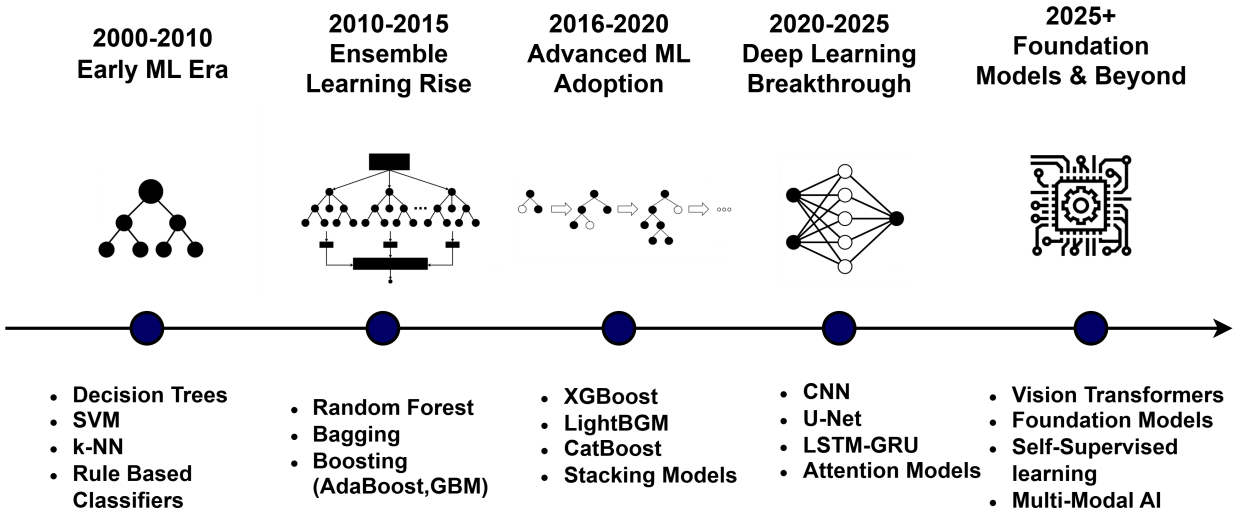


Figure 1. Conceptual evolution of AI methods relevant to tobacco monitoring; foundation models and self-supervised learning are shown as emerging research directions rather than established tobacco-specific methods.

2009–2015. The initial period was characterized by a predominance of ground surveys, digitization with the aid of GIS, and fairly basic spectral interpretation. In many tobacco growing regions, acreage counts were largely based on field inspection, farmer declaration, or manual mapping processes using GPS and GIS tools [14]. Cloud-based mobile surveying tools, such as GeoSurvey, also provide a means of collecting and managing georeferenced field observations [15]. In the remote sensing literature, Krezhova et al. presented disease-oriented hyperspectral research, which indicated that tobacco leaf diseases, such as Potato Virus Y and Tomato Spotted Wilt Virus, could be identified in the leaf area before the first symptoms were visually noticeable [16–18]. Meanwhile, agricultural change detection in the era of the 1990s was primarily based on analytical frameworks that involved NDVI and GIS-driven techniques like the use of threshold logic and engineering features instead of learned end to end models [19]. In the case of tobacco, this initial phase concluded that remote sensing was a scientifically relevant tool, but was not scalable, relied heavily on local knowledge, and was not well adapted to regular regional monitoring.

2016–2020. The second phase started with the actual use of Sentinel-2 and the wider availability of dense time series of multispectral data. Open optical data reduced barriers to entry and enabled more efficient monitoring of tobacco acreage for some areas, particularly those where multiple field campaigns were costly [20]. Support Vector Machines (SVM) and Random Forest (RF) were still appealing options during this time as the training datasets were still comparatively small and the labels were typically collected locally and

not from public archives of large datasets [11,21,22]. Meanwhile, the tobacco monitoring was expanded from one date classification. Multi-temporal optical stacks, PlanetScope Sentinel fusion, UAV mapping, and early CNN-style classification emerged due to the fact that tobacco separability is often more related to the crop calendar and canopy development than to the instantaneous spectra [10,23,24]. Tobacco monitoring is, in effect, moving from "spectral tobacco detection" to "phenology aware tobacco monitoring" during this period.

Figure 2 illustrates an Inception-inspired convolutional architecture used in tobacco-relevant crop classification, providing an example of the deep-learning approaches discussed in this review.

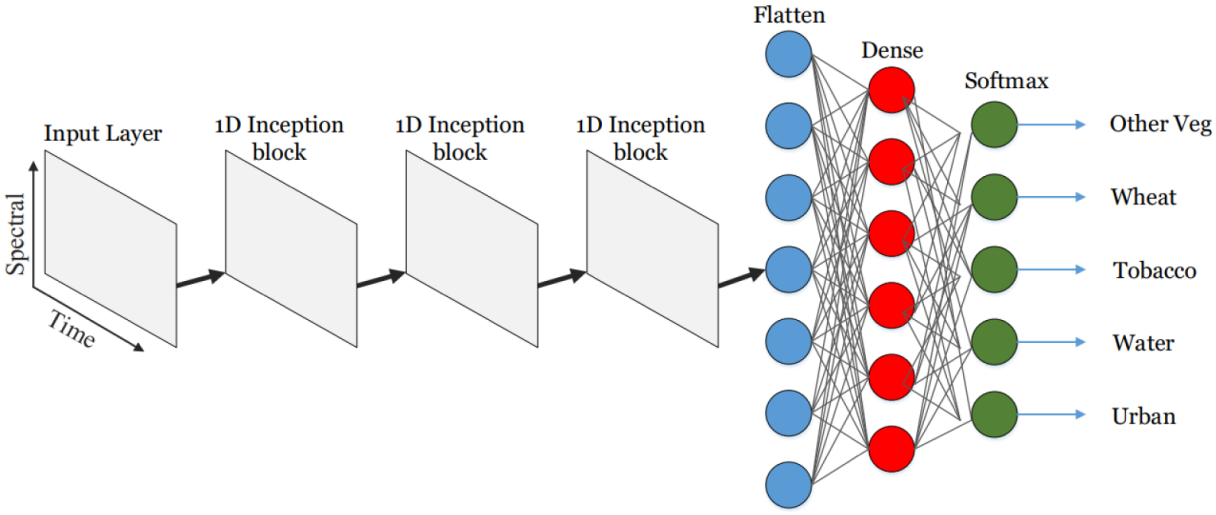


Figure 2. Inception- inspired deep convolutional neural network (adopted from [24]).

2021–present. The current phase is defined by temporal deep learning, task-specific UAV analytics, SAR integration, and multi-sensor fusion. Multi-annual tobacco monitoring for subsidy control in Spain, UAV segmentation in mountainous tobacco areas of China, smallholder mapping with Sentinel-1, Sentinel-2, and PlanetScope in India, and early tobacco identification from Sentinel-1 SAR in Fujian show how the field has diversified in both sensors and objectives [9,11,25–27]. More recent models such as Convolutional Long Short-Term Memory (ConvLSTM), Temporal CNN (TempCNN), attention enhanced networks, and Conv1D-LSTM emerged because the operational questions have become harder: agencies increasingly need early-season identification, growers need field-level precision, and researchers need models that can fuse spatial detail with temporal context [24,28–30]. The 2025–2026 literature indicates a further acceleration toward tobacco-specific UAV plant detection, high-resolution images, hyperspectral disease and nicotine retrieval, early-season mapping, and multimodal semantic segmentation [31–37]. The field is therefore no longer asking whether tobacco can be detected remotely; it is asking how reliably, how early, at what cost, and under what regulatory constraints that monitoring can be sustained.

Figure 3 illustrates the combination of convolutional and long short-term memory components used to integrate feature extraction with temporal modeling.

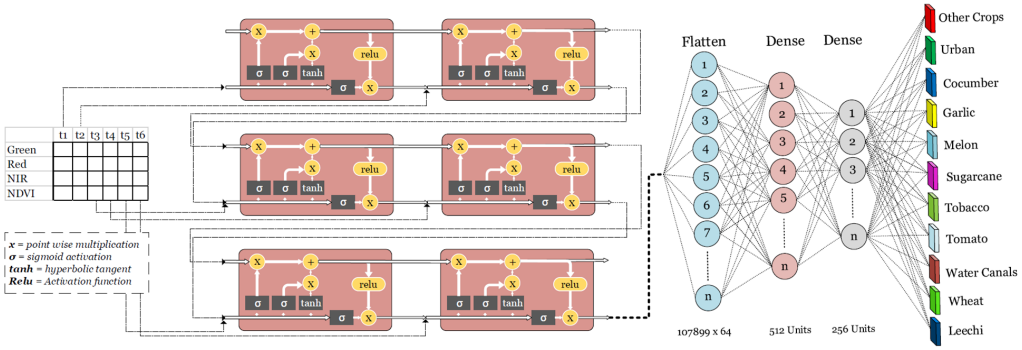


Figure 3. A visual representation of long short-term memory concatenated with convolutional neural networks (adopted from [29]). The input comprises green, red, near-infrared (NIR), and normalized difference vegetation index (NDVI) observations across six temporal steps (t1–t6). The LSTM blocks capture temporal dependencies, followed by flattening and fully connected layers for crop classification. Numbers (1, 2, 3, ..., n) indicate illustrative neuron positions, whereas 512 and 256 denote the numbers of units in the respective dense layers. The annotation 107,899 × 64 represents the input-sample count and an indicated feature dimension, respectively. The output layer represents the crop and non-crop classes.

3. Remote Sensing Data Sources for Tobacco Monitoring

The selection of the remote sensing platform has a significant impact on the aspects of tobacco that can be reliably monitored. The fundamental compromise is between spatial detail, temporal frequency, spectral richness, operational scalability, and acquisition cost. The monitoring of tobacco is especially challenging as it frequently requires seasonality and fine spatial discrimination.

Figure 4 summarizes how sensing data, learning methods, and monitoring applications can be linked within a conceptual decision-support framework for tobacco monitoring.

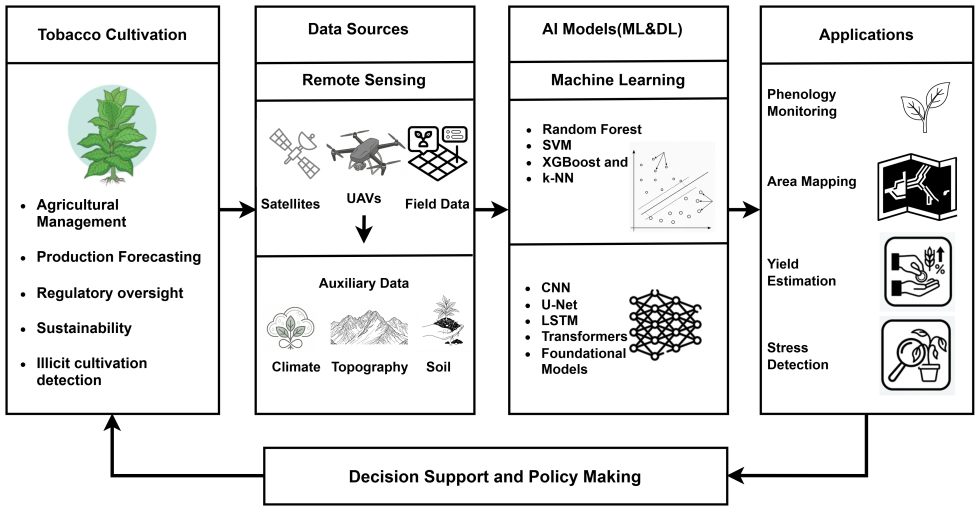


Figure 4. Integrated framework for tobacco crop monitoring, linking multi-source data, AI models, agricultural applications, and decision support.

3.1. Satellite Imagery

Optical satellite imagery is the most developed data source for tobacco mapping, as it provides regular regional coverage and a cost-scalable solution. Optical monitoring is ideal for tobacco because of the seasonal dynamics of the crop that change the reflectance of the crop during the season, canopy closure, leaf growth and maturity, and harvest time.

The use of optical imagery is therefore crucial for acreage estimation, crop classification, condition assessment for the season.

Sentinel-2. The suite of bands at 10 m resolution in visible and near-infrared, 20 m resolution red-edge and shortwave-infrared, and the five-day revisit cycle of Sentinel-2 has proven to be a great compromise in spatial detail and phenological coverage, making it an ideal free source for remote-sensing-based monitoring [10,20,25,27]. The red-edge bands are especially valuable for tobacco because they can be used to monitor canopy vigor, changes in chlorophyll content, and crop development differences. This is one of the reasons why Sentinel-2 has proven effective in tobacco detection in Pakistan and policy oriented monitoring in Spain [10,25]. The most valuable asset of its operational scalability is that imagery is open access, systematically archived and available globally, making it suitable for annual acreage mapping by national or provincial agencies. Its primary drawback is its lack of spatial resolution. A 10 m pixel could also contain tobacco and soil, trees, or crops, particularly in the early season, in smallholder systems with narrow, terraced or irregular tobacco fields. While the data are free, the operational costs for purchasing images are not as high as for preprocessing, cloud masking, temporal compositing and field-label acquisition.

Recent early-season efforts also demonstrate the need for ensemble learning and transitioning to cloud platforms over single-image classification for sentinel monitoring. Liu et al. mapped tobacco cultivation using multi-source remote sensing data and stacked generalization in Google Earth Engine, with an overall accuracy of 87.17% and a high correlation between the mapped tobacco area at the township level and the purchase volume data [37]. This type of evidence is valuable because it establishes a connection between the remote-sensing classification and administrative tobacco workflows, but also shows that early-season accuracy is less robust and less reliable than in full-season mapping with appropriate phenological separation.

Landsat. Landsat is still significant because of its long time series which can be used for retrospective studies of tobacco cultivation and decline, land use change, and policy reaction over multiple years or decades [7]. Deep convolutional neural networks have also been investigated for large-area land-cover classification using Landsat time-series imagery [38]. Compared to Sentinel-2, Landsat has a lower level of competitiveness for current-season classification for tobacco applications, due to its 30 m spatial resolution, which is too coarse for small, fragmented tobacco farms in some regions, e.g., eastern India or parts of Pakistan, where several tobacco plots can be captured within a single pixel. However, Landsat is still valuable for contextual questions such as identifying where tobacco production zones have shifted over time or where alternative crops have replaced tobacco after policy changes. Its cost and scalability profile is excellent because the archive is free and globally standardized, but the platform is better suited to historical or regional analysis than to parcel-level operational monitoring.

PlanetScope. PlanetScope is particularly valuable for tobacco because it directly addresses one of the field's hardest problems: fragmented smallholder agriculture. In many tobacco-growing regions, individual fields are too small for Sentinel-2 to resolve cleanly, and their edges are confounded by intercropping, road margins, and heterogeneous backgrounds. PlanetScope's approximately 3 m spatial resolution and near-daily revisit reduce mixed pixels and preserve field geometry far better than medium-resolution systems [11,24,39,40]. This is why PlanetScope has been applied to numerous tobacco-focused classification projects across South Asia as well as to smallholder crop mapping projects more generally. It has the main advantage of being parcel separable and has dense seasonal coverage, while its main drawbacks are that it is radiometrically inconsistent across constellations, and requires harmonization when combined with Sentinel-2 [39]. PlanetScope is very well suited for targeted programmes in provinces or contract farming areas where tobacco is

economically or politically significant, particularly for operations. Unless there is a licensing agreement or institutional access, it is less easy in open, national public monitoring.

Commercial very-high-resolution optical data and MODIS. Very-high-resolution commercial imagery such as systems like GeoEye, Jilin-1 and others, and associated platforms, can be used to support fine scale tobacco boundary delineation, audit sampling and localized compliance checks [32,41,42]. These data are best suited for high-confidence verification of areas of dispute or concern rather than national mapping. Huang et al. extracted film-mulched tobacco fields with a 0.5 m Jilin-1 imagery using the Skip_Segformer model, achieving an extraction accuracy of 97% and a relative error in estimating the planting area of 1.6% in the study conditions [32]. This is of operational significance because the mulching practice can be observed before the tobacco canopy, provided that high resolution imagery is available, local annotation is available, and the tobacco crop has a unique mulching practice. In contrast, MODIS has good temporal resolution but is typically not fine enough to be used directly for tobacco field mapping, but rather as a background source of information for regional vegetation dynamics and/or anomaly screening. Optical satellite imagery is still vital to tobacco monitoring, although it is highly dependent on field size, cloud regime, and the type of monitoring target (production zone, a farm) parcel, or an individual field edge.

3.2. SAR Data

Synthetic Aperture Radar (SAR) is a complementary observation stream since it is not affected by the cloud cover and it is sensitive to canopy structure, surface roughness and moisture conditions. Therefore, these characteristics are of particular importance for tobacco, when cloud contamination is likely to be at the highest point of the season when agencies and growers are most interested in early classification. The primary SAR source mentioned in the tobacco literature is Sentinel-1 which provides a spatial resolution of 10 m and revisit cycles of 6–12 days depending on the orbital configuration [43]. This translates to the ability of SAR to maintain a usable seasonal record when optical platforms miss important dates.

The use of tobacco-specific SARs is still fairly limited, and the evidence available is technically significant. Liu et al. demonstrated that the time series from Sentinel-1 can be used with the Attention LSTM Fully CNN to assist with early detection of tobacco crops, especially with dual-polarization observations [9]. This is important because early-season classification is more challenging than late-season mapping, the canopy is not fully developed, the contrast between canopy and ground is lower, and windows to the ground for enforcement and/or management may be limited. SAR's advantage is that it can detect changes in structure and moisture even in the absence of optical contrast and in the presence of clouds. Sentinel-1 is cost-attractive from a cost point of view since the data are open access.

There are also restrictions on SAR. Backscattering response is not as easy to interpret agronomically as optical reflectance, and SAR-based discrimination of crops may be inconsistent in small fields and in the presence of similar crop structure. For smallholder tobacco systems, the 10 m SAR still contains mixed-pixel issues and the association between backscatter and tobacco state is subject to variation with soil background, rainfall, incidence angle and management practices. Thus, SAR can be best thought of as a resilience-enabling sensor for tobacco monitoring. It is well adaptable for cloudy areas, early warning, and temporal gap filling, but it becomes most powerful when integrated with optical data rather than used alone.

Practical SAR–optical fusion also introduces engineering requirements that are often hidden by final accuracy values. The data must be geometrically co-registered on a common grid, Sentinel-1 backscatter must be radiometrically calibrated and terrain corrected, and optical and SAR observations should be matched as closely as possible in time or by pheno-

logical stage. Differences in acquisition date and spatial resolution can otherwise combine different crop-growth stages or increase mixed-pixel effects. In operational workflows, these issues can be reduced through consistent preprocessing, common-grid resampling, temporally matched composites, and explicit handling of missing observations rather than simple image stacking.

3.3. UAV Imagery

The literature cited above shows that unmanned aerial vehicles (UAVs) provide the greatest spatial detail, particularly when monitoring goals call for the plant-level or row-level information. This is particularly important with tobacco since many tobacco production systems are intensively managed at the field level; plant spacing, row spacing, canopy gaps, localized disease stress, and field-edge irregularities are all important to the crop and post-harvest planning. UAV RGB imagery has been used to map tobacco fields, segment field boundaries, and extract plant spacing, row spacing, and field area, including under mountainous terrain conditions [9,23,44]. The temporal resolution is generally mission-specific and can be coordinated with other agronomic activities like disease scouting, transplanting, canopy closure, etc., and is usually at the centimeter scale. Operationally, UAV monitoring is best treated as a targeted field-scale verification and data-collection tool rather than a routine large-area monitoring system because flight logistics, coverage, and annotation effort increase rapidly with area.

3.4. Hyperspectral Imagery

The advantage of hyperspectral sensing for tobacco is that it can be used to measure the narrow-band spectral response that is linked to biochemical variation, disease, and quality-related traits. This is particularly true of tobacco compared to many staple crops since tobacco value is also strongly linked to field survival or total biomass as well as leaf chemistry, quality, stress exposure and disease status. In the literature, hyperspectral data are primarily used for disease or stress detection, or for estimation of the quality parameters, and only rarely for routine regional acreage mapping [16–18,45]. This is a sensible pattern, because hyperspectral sensing is best suited to detect a subtle, physiological target variable that is not just physical rather than purely geometric.

The strongest tobacco-specific examples come from viral disease detection and biochemical retrieval. Krezhova and colleagues showed that hyperspectral reflectance in the green, red, red-edge, and near-infrared regions could differentiate infected tobacco leaves from healthy leaves before symptoms became obvious to the eye [16–18]. More recently, Mao et al. used UAV hyperspectral imagery from 400–1000 nm to identify Tomato Spotted Wilt Virus in tobacco, comparing SVM, k-NN, and XGBoost and reporting the best performance for an SVM-Relief workflow, with overall accuracy of 97.3%, AUC of 0.994, and Kappa of 0.947 under the study conditions [35]. The same study emphasized red-edge bands and showed that feature reduction can retain key diagnostic wavelengths, which is important if future systems need to move from full hyperspectral cameras toward cheaper multispectral payloads.

Hyperspectral sensing is also beginning to move beyond binary disease detection. Chen et al. combined hyperspectral reflectance with LAI and chlorophyll-content information, used continuous wavelet transform (CWT) feature extraction, and applied Random Forest to classify tobacco leaf diseases, reporting an overall accuracy of 88.7% and Kappa of 0.83 [31]. Tian et al. used UAV hyperspectral data to estimate nicotine content in cigar leaves, comparing preprocessing and band-selection combinations such as MSC, SG, SNV, CARS, SPA, and UVE with PLS, BP, RF, and SVM models; their best MSC-SNV-SG-CARS-BP model reported R^2 = 0.797, RMSE = 0.078, and RPD = 2.182 [33]. These studies are

important because tobacco commercial value depends strongly on leaf chemistry and quality, not only on mapped acreage. The relevance of hyperspectral sensing to quality estimation, stress detection, trait retrieval, commercial grading, and yield-quality assessment is further emphasized by Zhang et al. [45]. From an operational perspective, hyperspectral sensing has demonstrated its best performance in targeted monitoring within high-value plots, breeding trials, disease studies, and/or calibration campaigns, as opposed to when it is used for routine national acreage estimation.

The restrictions are very significant. Hyperspectral systems tend to be expensive, plot-scale or greenhouse-based, or deployed by unmanned aerial vehicles (UAV), and are typically used during campaigns. The amount of data is significant, calibration is complex, and the spectral signatures of interest may vary as a function of illumination, view geometry, cultivar, and disease stage. Publicly accessible tobacco hyperspectral data are also limited, and this restricts model development and cross-study reproducibility. Hyperspectral sensing is typically not cost-effective or technically feasible for routine use in smallholder tobacco systems, but can be used strategically to contribute to the development of higher-value calibration knowledge that can be used to inform simpler multispectral and/or broadband monitoring pipelines. Accordingly, airborne and UAV hyperspectral sensing should currently be viewed mainly as a local experimental, diagnostic, or calibration technology rather than a platform for routine large-area tobacco surveillance.

Methodological work beyond tobacco also shows that lower-cost plant-derived indicators can complement high-end sensing for crop stress and water-status monitoring. Atanasov reviewed remote-sensing approaches across spatial scales for assessing crop water and nutrient status [46]. A later study used leaf-colour information from RGB/HSL imagery together with soil temperature and piecewise linear regression to estimate soil moisture and support automated irrigation management [47]. These studies are not tobacco-specific and are included only as methodological context, but they illustrate how low-cost visual sensing and plant-derived indicators can complement satellite or UAV systems when operational crop-health and water-status information is required.

Figure 5 summarizes the spatial, temporal, and operational trade-offs among the sensing platforms discussed above and their relevance to tobacco-monitoring applications.

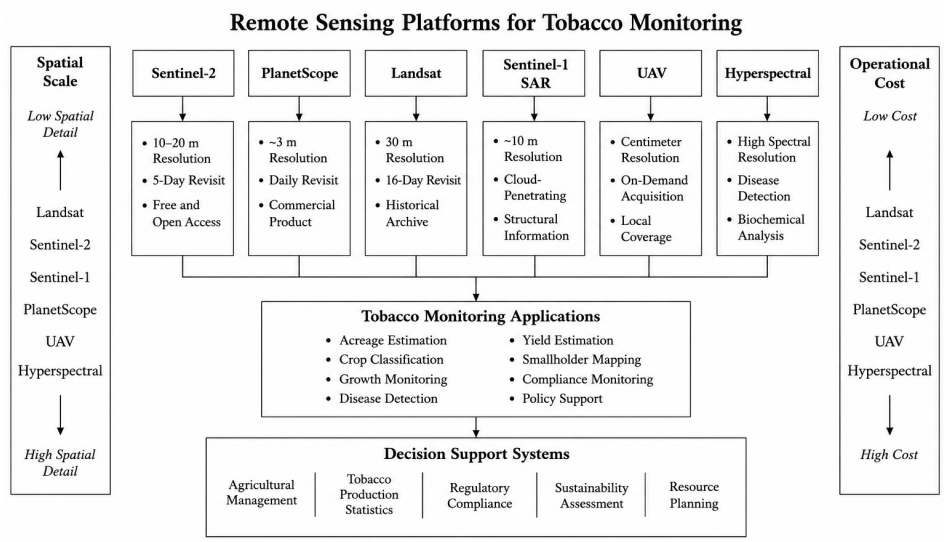


Figure 5. Comparison of remote sensing platforms for tobacco monitoring in terms of spatial resolution, temporal density, operational cost, scalability, and suitability for tobacco-specific applications.

4. Machine Learning and Deep Learning Approaches

The structure of the input data will determine model selection for tobacco monitoring. Some methods are suitable for tabular spectral features and limited labels, while others take advantage of image texture, seasonal trajectories and cross-sensor fusion. Rather than as a universal ranking, it is recommended that reported performance be interpreted in the context of the data type, task definition and validation protocol.

To maintain a consistent taxonomy, the methods in this section are organized primarily according to model architecture. Classification, segmentation, detection, and regression are treated as monitoring tasks and are discussed separately in Section 5, while sensor and multimodal fusion are treated as data-integration strategies rather than independent architecture families.

4.1. Traditional Machine Learning

However, traditional machine learning is still relevant as tobacco studies may have small or moderate datasets, and hand-crafted spectral features. The most prominent baselines that are found in the reviewed literature are SVM and RF [11,21,22,28]. These models are appropriate for multispectral bands, vegetation indices, hyperspectral wavelengths and small sets of physiological features. They are relatively data-efficient, can be tuned much more easily than deep models in low data regimes, and are helpful for determining if there is a genuine improvement from a new deep architecture. This is significant for tobacco monitoring as it is often sampled from a small set of villages, farms, or seasons rather than from a large benchmark set. This is further confirmed by the recent tobacco hyperspectral literature: when the disease and biochemical retrieval datasets are too small to support very deep models, without careful validation, the RF, SVM, k-NN, XGBoost, PLS, and BP neural networks are still widely compared [31,33,35].

SVM. SVM is also appealing for tobacco classification if the analyst has a relatively small, but well-chosen, subset of features, such as vegetation indices, spectral bands, hyperspectral wavelengths, or summary phenology descriptors. It is particularly well suited for high dimensional feature spaces and limited training data, and this is why it is still used in some of the smallholder crop mapping studies that include tobacco [11]. A good example of this is the UAV-hyperspectral Tomato Spotted Wilt Virus study by Mao et al. [35] that reported the best results with SVM and feature selection using Relief, which indicates that the red-edge features can be very competitive for disease detection in the context of tobacco. SVM is a computationally feasible approach for small numbers of pixels or time series, and is less convenient when millions of pixels or long time series are involved. Its main drawback is that it cannot learn spatial texture and temporal evolution independently; these need to be programmed in by hand. Therefore, transferability is often low as the selected features can be due to the particularities of a region's crop calendar, disease stage or sensor calibration and not to tobacco strong features.

Random Forest. It is useful for tabular inputs, including spectral bands and vegetation indices, physiological variables, and ancillary features, and is less sensitive to certain hyperparameter selections than SVM [22]. Random Forest has also demonstrated effectiveness in remote-sensing-based land-cover classification [48]. Despite the fact that the data set was not as large as it is for end-to-end deep learning, Chen et al. demonstrated the continued relevance of RF for the classification of tobacco leaf disease using hyperspectral reflectance, Leaf Area Index (LAI), and features derived from the CWT [31]. The computational cost is typically not high, making RF more popular for rapid testing or for operational prototypes. Nevertheless, RF shares the same limitation as SVM: it requires feature engineering. RF frequently performs better than temporal deep models when there is little difference between the behavior of tobacco and its similar crops, except for subtle differences in space and time.

XGBoost and k-NN. Both XGBoost and k-NN are less commonly seen in the regional tobacco mapping, but are seen in tobacco disease and hyperspectral benchmarking, where the feature space is controlled and the intent is to compare models for operational mapping. XGBoost is appealing when the monitoring system is based on well-structured tabular inputs like temporal summary statistics, phenological metrics, selected wavelengths or fused remote-sensing and survey features. It can efficiently model the interactions between the features that are not linear; however, like RF, it relies on the quality of engineered descriptors. k-NN is simple and interpretable, but it scales poorly with large image archives, is sensitive to feature normalization, and is usually too local in behavior to be reliable across heterogeneous tobacco production environments. Mao et al. compared both k-NN and XGBoost with SVM for UAV-hyperspectral TSWV detection, while Tian et al. compared RF and SVM with PLS and BP models for nicotine retrieval [33,35]. In practical terms, traditional machine learning remains useful for pilot studies, small datasets, biochemical retrieval, and interpretable baselines, but it is less suitable than deep learning when tobacco monitoring requires joint reasoning over spectral, spatial, and temporal dimensions.

As a practical selection rule, SVM and RF remain cost-effective choices for small or moderately sized datasets with engineered spectral or biochemical features, including many hyperspectral disease and quality studies. Their main limitation is their dependence on expert-designed features, which may encode local crop calendars, cultivars, or sensor conditions and therefore transfer poorly to new regions. Deep learning becomes more appropriate when larger image or time-series datasets are available and the task requires automatic learning of spatial texture, temporal phenology, or multimodal interactions.

4.2. Convolutional Architectures

Convolutional Neural Networks (CNNs) are effective when tobacco monitoring depends on spatial texture, local spectral-spatial patterns, or dense image labeling [49]. In satellite workflows, CNNs can exploit stacked temporal inputs or patch-based imagery for crop identification [10,24,25,50–52]. Fully convolutional deep learning architectures have also been evaluated for land-cover classification using high-spatial-resolution Gaofen-2 satellite imagery [53]. In UAV and high-resolution workflows, encoder–decoder CNNs such as U-Net, DeepLabV3+, PSPNet, SegNet, and SegFormer-family architectures have shown strong performance for tobacco area segmentation and boundary extraction [26,32,36,54–57]. Object-detection pipelines such as RetinaNet and YOLO-based models have also been used to recover field geometry, planting structure, and individual transplant-stage plants from high-resolution UAV imagery [34,44]. For tobacco, CNNs are particularly useful because field shape, canopy texture, plastic-mulch patterns, row arrangement, and local neighborhood context often matter in addition to spectral values.

Standard CNNs While conventional CNNs work well for image patches or stacked raster inputs that provide useful contextual information to the neighboring pixels, they are unsuitable for other types of inputs. They have greater data requirements than SVM or RF as they do not need to select features, but learn filters instead. Computation is also higher, particularly for training over large scenes or high resolution UAV orthomosaics. Standard CNNs work well for tobacco monitoring tasks such as field-edge delineation, patch-based crop identification, and compliance mapping in regions where local texture is informative. The drawbacks to them are that they can overfit the spatial context. One CNN in one area of tobacco could be trained to recognize local background artifacts, soil tone, or surrounding landscape geometry, not tobacco characteristics.

TempCNN Temporal CNNs like TempCNN are also important, and deserve separate attention, as they are among the most significant advances in the deep-learning field for tobacco classification. In contrast, TempCNN employs 1-D convolutions over the temporal

dimension of a satellite image time series to capture local phenological motifs [24,58]. More broadly, deep learning approaches have demonstrated the value of multi-temporal satellite observations for crop classification [59]. This is especially applicable to tobacco since the crop has a seasonal reflectance profile that can be measured with short temporal kernels for transplanting, vegetative growth, topping and harvest. From the point of view of training, LSTM models are generally more difficult to train than TempCNN, and in terms of memory usage, LSTM models are also more memory-intensive than TempCNN, especially if acquisition frequencies are relatively regular. But, its transferability remains to be determined if there is any congruence in the tobacco calendars in different regions. The model may not directly be applicable to a production area with different cultivars or sowing dates without adapting the model specifically to that area.

Segmentation and detection CNNs. UAV-based and very-high-resolution tobacco monitoring is particularly relevant for networks that operate directly on fine-scale geometry, such as U-Net, DeepLabV3+, PSPNet, SegNet, RetinaNet, YOLO and SegFormer [26,32,34,36,44,55–57]. These models can retrieve plot boundaries, plant rows, film-mulched tobacco beds and object-level spacing metrics that cannot be measured from medium-resolution satellite imagery. Huang et al.'s Skip_Segformer study is notable because it targets pre-transplanting film-mulched tobacco fields using 0.5 m Jilin-1 imagery, which shifts acreage estimation earlier than canopy-based detection [32]. Chen et al.'s YOLO–NTD study addresses the even finer problem of detecting individual transplant-stage tobacco plants under small-object, weed, soil, and plastic-mulch interference [34]. Their computational requirements range from moderate to high depending on backbone depth and scene size, but they are operationally justified when the task is field management, plot auditing, or calibration. Their major limitation is annotation cost: dense masks or object boxes for tobacco plants require substantial manual effort, and results are rarely validated outside the original study area. For tobacco, CNNs are therefore mature for local spatial analysis, but less mature as geographically transferable national classifiers.

4.3. Recurrent Architectures

Recurrent models are designed for sequence data and are therefore particularly relevant for tobacco phenology. LSTM-based approaches can learn how reflectance or backscatter changes through transplanting, canopy development, and harvest, which is often more discriminative than any single observation [60,61]. In tobacco-related studies, recurrent or recurrence-enhanced models have been used for early SAR-based identification, seasonal crop classification, and ConvLSTM-based feature learning [9,29]. This model family is important because tobacco often becomes separable not through a single image, but through the order and timing of its seasonal trajectory.

LSTM. LSTM is an appropriate method for multi-temporal monitoring of tobacco, as it has the ability to store information from previous time steps and still incorporate new data. This is useful in situations where the tobacco is similar to other crops in color and/or texture at one stage and different at a later stage. It has a moderate to high data requirement: repeated observations throughout a season, and consistent temporal sampling, are useful for a good LSTM. It requires more computational resources compared to tabular methods, but fewer than some transformer models. LSTM can be used for seasonal classification, early warning and time-series fusion in tobacco applications, but it may be prone to missing observations and regions misaligned in the sequence.

BiLSTM and GRU. There is limited literature on the use of BiLSTM or Gated Recurrent Units (GRU) in tobacco monitoring, but they warrant mention. When the entire seasonal sequence is available, and the objective is to classify acreage or crop-type after the season, it is desirable that BiLSTM can use forward and backward temporal context. The downside is

that it is less natural for a true early warning since observations need to be made in the future to fully take advantage of the reverse direction. GRU provides a less complex and less gated (fewer gates) alternative to recurrent networks. This will reduce the amount of computing required and could be appealing for tobacco data sets where a more complicated recurrence is not warranted. If researchers can start benchmarking both the accuracy and the speed of inference, as well as the robustness to missing dates and the performance on short seasonal windows, both architectures may prove to be useful in operational tobacco monitoring.

Recurrent models are one of the best models to use when the tobacco needs to be distinguished by seasonality and not just texture. The biggest problems with them are the lack of transferability and data regularity. A model trained in one region's crop calendar can be incorrect in another region if there are variations in the timing of planting, rainfall, or harvesting. In the case of tobacco, that is not a limiting factor—it is a key obstacle to deployment.

Accordingly, BiLSTM and GRU are discussed here as relevant recurrent architectures with limited tobacco-specific validation rather than as established tobacco-monitoring methods.

4.4. Convolutional–Recurrent Hybrid Architectures

ConvLSTM. ConvLSTM is a hybrid model that incorporates spatial filtering with temporal memory. This is important in situations where the analyst desires to capture both the field texture and the neighborhood context while modeling crop evolution. When multi-date image patches instead of image sequences are available, ConvLSTM may prove to be more informative than a simple LSTM in practice [29]. The price is the computation. ConvLSTM is more memory-intensive, tuning is more critical and more training data is needed than simpler temporal models. It is thus more suitable for research environments with multi-sensor time series and curated labels, while it is not as simple to deploy in low-resource environments.

Conv1D-LSTM and related hybrids Conv1D–LSTM is an example of a suitable hybrid that is suitable for a tobacco because it uses both local spectral–temporal feature extraction and recurrent sequence modeling [28]. This architecture is suitable if the analyst has a regular multispectral time series and is interested in learning the temporal motifs in the short term and crop-season dependencies in the longer term. It is claimed that Conv1D preprocessing can improve the insensitivity to noise and local fluctuation, compared to a standalone LSTM. The recurrent layer maintains more general phenological context than a pure CNN. The central challenge is complexity: fusion models need to be trained on harmonized inputs, carefully resampled, and trained with more complicated pipelines.

4.5. Attention and Transformer Architectures

Attention networks Tobacco-specific relevance of attention is best demonstrated in early identification and multimodal segmentation tasks. If only a partial season can be sampled, an attention module may pay more attention to dates with transplanting or establishment of canopy or dates with a sudden change in structure, rather than paying the same amount of attention to all dates [62]. This could enhance both the performance and interpretability of models like ALSTM-FCN, as the analyst can examine which time steps the model highlight [9]. Zheng et al. further extend this idea to the spatial dimension by applying channel-spatial attention and adaptive convolution in tobacco distribution mapping over complex mountainous areas, where ground and shadow effects and the heterogeneous backgrounds of different areas can compromise traditional segmentation backbones [36]. These requirements are still high, but sometimes attention modules can be more efficient with regard to the number of samples required as compared to deeper

architectures of a more generic nature by concentrating learning on the most informative dates, channels, or spatial neighbourhoods.

Transformers Transformer models are appealing for tobacco monitoring due to its ability of representing multi-date, multi-band, multi-sensor inputs as tokens and learning the cross-time or cross-sensor relationship between them without recurrence [63]. That is potentially valuable for tobacco because the decisive evidence may lie in the interaction between red-edge behavior, SAR backscatter changes, high-resolution mulch texture, and field geometry rather than in any single modality. SegFormer-derived segmentation, as used in the film-mulched tobacco extraction study, illustrates how transformer-style encoders can become operationally useful when high-resolution imagery provides clear spatial cues [32]. The challenge is that transformers are data-hungry and computationally demanding. In literature that still lacks open tobacco benchmarks, this is a serious constraint. Without large multi-region training corpora, transformer performance may be unstable or difficult to interpret. For now, transformers are best viewed as an emerging direction for multimodal tobacco monitoring rather than a settled operational choice.

In transferability terms, attention and transformers may ultimately help more than current local models if paired with large pretraining corpora or self-supervised objectives. However, that potential has not yet been demonstrated convincingly for tobacco-specific monitoring. At present, the main contribution of this model family is to signal where the field is heading: toward date-aware, modality-aware, and more interpretable sequence modeling.

They are therefore treated as an emerging architecture family for tobacco monitoring rather than a universally validated operational choice.

4.6. Multi-Sensor and Multimodal Fusion Strategies

Sensor fusion. Sensor fusion is not only a modeling choice but a deployment choice. The combination of Sentinel-2 and PlanetScope can enhance the accuracy of tobacco classification, but it also makes the process dependent on the commercial availability of the data, as well as further processing [24,39,40]. The association of Sentinel-1 with optical imagery increases the resilience against cloud cover; however, there are also data distribution issues with heterogeneity and more complex calibration [9,11]. Labels can be improved with UAV imagery and individual plants can be detected using UAV imagery or can be assisted with local segmentation in mountainous terrain; adding hyperspectral or physiological variables changes the task from acreage mapping to disease, nicotine, chlorophyll, and quality assessment [31,33–36]. But in smallholder tobacco systems, these additional steps may be justified because single-sensor performance can drop off dramatically with small fields, an absence of key optical dates, and/or pre-canvas detection compared to mature-field classification.

These models are appropriate for phenology, spatial texture and spectral detail. Their drawbacks include complexity of pre-processing, cross-sensor harmonization, cost, and lack of reproducibility. If fusion is poorly aligned, or only measured in a single area, the gain could be a local calibration, and not a generalization. Despite this, hybrid solutions are the most promising solution to strong tobacco monitoring in complex, dispersed and cloudy production systems as they do not rely on a single sensor or architecture to solve all problems.

Model suitability is therefore task-dependent. U-Net, DeepLab-style, and related encoder–decoder architectures are effective for tobacco plot segmentation because they preserve spatial texture and boundary information; object detectors are appropriate for individual plants or planting structures; and TempCNN or LSTM-type models are better suited to crop-type classification when tobacco is distinguished mainly by its seasonal growth trajectory. For disease or biochemical retrieval from smaller structured hyperspectral

datasets, SVM and RF can remain competitive because the informative spectral features can be explicitly selected.

Figure 6 provides a schematic overview of learning architectures and their relationships to agricultural remote-sensing tasks; the evidence and maturity of their tobacco-specific applications vary, as discussed above.

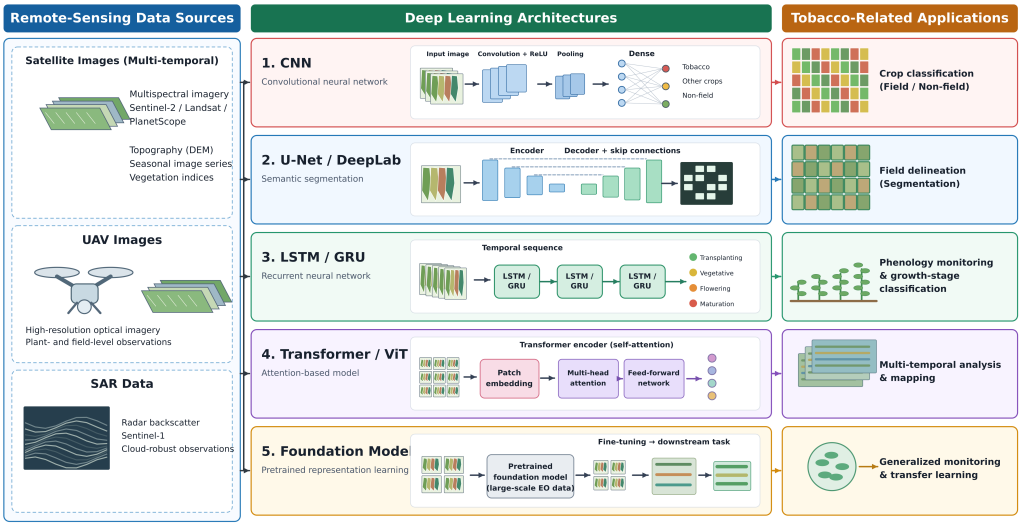


Figure 6. Overview of deep learning architectures used in agricultural remote sensing.

5. Tobacco Monitoring Tasks

When organizing the literature by monitoring task, rather than sensor or model, the literature becomes much clearer. Tobacco is not tracked for any one purpose. Imagery can be applied in a variety of ways depending on the goal of the application, for acreage estimation, crop-type classification, disease detection, yield-related assessment, or compliance verification. This section reviews the main tobacco monitoring tasks explicitly.

5.1. Tobacco Acreage Estimation

Tobacco acreage estimation is one of the most operationally important tasks because it underpins production forecasting, procurement planning, subsidy verification, and policy oversight. In practice, acreage estimation usually combines field delineation with crop-type confirmation. Medium-resolution optical data such as Sentinel-2 are attractive because they can be deployed over wide areas at low cost and updated repeatedly across the season [10,25,27]. When parcels are large enough, time-series classification outputs can be aggregated to estimated tobacco area at village, district, or provincial scale. In fragmented smallholder systems, however, acreage estimation improves substantially when higher-resolution imagery such as PlanetScope or UAV data is introduced [11,24,44].

From a modeling perspective, acreage estimation has used both classical and deep-learning approaches. SVM and related classifiers remain useful when the task is field-wise classification from fused multisensor features [11]. CNN- and TempCNN-style models become more attractive when dense time series are available and tobacco must be separated from other crops with similar spectral appearance [10,24,25]. UAV-based methods such as the work of Liao et al. push acreage estimation further by recovering field area directly from detected planting geometry rather than only from class labels [44]. Recent high-resolution satellite work extends this idea to the pre-transplanting stage: Huang et al. extracted film-mulched tobacco fields from 0.5 m Jilin-1 imagery and reported a 1.6% relative error in planting-area estimation, showing that mulch patterns can serve as an early proxy for tobacco acreage where film mulch is consistently used [32]. Liu et al.'s

early-season stacked generalization workflow similarly connects mapped tobacco area to purchase-volume records, which is useful for district-level planning and administrative monitoring [37]. The main limitation is that reported acreage accuracy is often local and conditioned on a carefully labeled study area. Operationally, acreage estimation is central for tobacco because it is the task most directly linked to administrative decision-making, yet it is also the task most vulnerable to mixed pixels, field-boundary uncertainty, and local management practices such as plastic-film use.

5.2. Tobacco Crop Classification

Tobacco crop classification is the dominant task in the current literature because many downstream uses depend on first identifying where tobacco is located. This task has been addressed with Sentinel-2 temporal stacking, Sentinel-2 and PlanetScope fusion, Sentinel-1 SAR time series, high-resolution satellite imagery, UAV imagery, and multimodal satellite-UAV datasets depending on the scale and purpose of the study [9–11,24,28,29,32,36,37]. The central technical challenge is that tobacco is often confusable with other broadleaf crops when classification relies on single-date imagery alone. As a result, temporal models such as LSTM, TempCNN, ConvLSTM, and Conv1D–LSTM have become especially relevant because they exploit phenological differences across the season.

Tobacco classification also reveals the gap between research accuracy and operational robustness. Several studies report very high accuracies, especially in Pakistan and Spain, but most of those results are still based on region-specific datasets, limited crop sets, or same-season validation [10,24,25,27,28]. In contrast, more difficult scenarios such as small-holder mapping in India, early SAR-based detection under cloud pressure, or early-season classification before canopy maturity show lower but more operationally realistic performance [9,11,37]. At finer spatial scales, Chen et al.'s YOLO–NTD plant detector shows that transplanting-stage monitoring is closer to small-object detection than ordinary crop classification, especially when tobacco seedlings are mixed with weeds, bare soil, and plastic mulch [34]. This task is therefore technically mature in terms of model development, but not yet mature in terms of transferability or benchmarked reproducibility.

5.3. Tobacco Disease Detection

Disease detection is one of the most tobacco-specific monitoring tasks because disease pressure affects both yield and leaf quality, and small delays in intervention can have large economic consequences. The best supporting evidence is from hyperspectral data that were used to detect signatures of viral infection on tobacco leaves using ground-based measurements [16–18]. It is important that these studies demonstrate that hyperspectral remote sensing is able to detect physiological stress prior to the development of visual stress symptoms, which is the type of capability growers and extension services desire in precision monitoring.

But, the way tobacco diseases are detected is still narrow in method. Most previous published work has been conducted in greenhouse or controlled environments, and most have been at the leaf level instead of field-level monitoring on a parcel [16–18]. Recent studies are starting to fill this void. Tobacco leaf disease was mapped using multi-source disease features such as hyperspectral reflectance, LAI, chlorophyll content, and descriptors derived from CWT using RF classification [31]. Mao et al. evaluated Tomato Spotted Wilt Virus detection in a UAV-hyperspectral field setting and reported strong separability using red-edge-sensitive features and SVM-Relief modelling [35]. Although these studies add to the tobacco-specific evidence base, the general challenge is still to be addressed: disease labels are costly to gather, and the stage of infection has a significant impact on spectra, while a leaf- or plot-level disease signature is not yet being scaled to routine farm-level

warning systems. The operational relevance is high, but multi-season field evidence is still required.

5.4. Tobacco Yield Estimation

In the case of tobacco, yield estimation is an important strategic issue since growers, buyers, and regulators require early estimates of the amount of tobacco that will be available, but the literature is sparser on this topic than on crop classification. One of the main reasons is that tobacco yield is not only dependent on field area but also on leaf count, canopy development, stress history, topping, and post-harvest quality processes. Therefore, direct yield prediction models are not as prevalent as proxy variable estimation.

The most relevant current trend is biophysical and biochemical retrieval. Liu et al. have shown that attention-based neural networks can estimate Leaf Area Index (LAI) that is closely related to the development of the canopy and hence related to potential yield [30]. Leaf Area Index (LAI) is an established biophysical indicator of vegetation canopy development, with widely documented remote sensing retrieval methods, products, and validation approaches [64]. The authors also demonstrate the potential of hyperspectral remote sensing in the estimation of tobacco quality, stress detection and retrieval of tobacco traits, such as nitrogen and chlorophyll content, which affects the commercial value of tobacco [45]. Tian et al. present another tobacco-related biochemical example, estimating the amount of nicotine in cigar leaves by applying UAV hyperspectral data and preprocessing and band-selection pipelines in conjunction with machine learning, achieving a best reported R of $R^2 = 0.797$ under the study conditions [33]. This is important because the value of cured leaves cannot be assessed just by biomass or by acreage mapped.

The problem is that a proxy, like LAI, chlorophyll, nitrogen or nicotine is not a final yield of cured leaves, and many studies do not tie remote-sensing outputs to farm-level harvested tobacco data. Biochemical retrieval also is affected by cultivar, sampling stage, curing practices, and sensor calibration, making it difficult to transfer. Yield and quality estimation are still important but not well developed operational tasks that need to be better integrated with remote sensing, agronomic measurements, chemical assays and post-harvest production records.

5.5. Tobacco Compliance and Regulatory Monitoring

Tobacco compliance and regulatory monitoring differs from agronomic monitoring because the objective is not only to identify the crop but also to verify where and how much tobacco has been cultivated. Remote sensing can support declared-area verification, subsidy monitoring, identification of potentially unauthorized cultivation, and comparison of mapped tobacco acreage with administrative or procurement records. Such applications require repeatable observations, spatial traceability, timely information, and sufficient transparency to support administrative decision-making.

The most obvious application is the use of multi-annual Sentinel-2 imagery and neural network classification to verify declared tobacco plots under the European Common Agricultural Policy (EUCAP) framework [25,27]. In this case, monitoring is not about the accuracy of science, it is about the trustworthiness of administration on a large scale.

Technically, compliance monitoring requires multiple characteristics: coverage over a broad spatial area, regular updates (seasonal), cost-effectiveness, and interpretability sufficient to warrant intervention. Open satellite data (Sentinel-2) are thus appealing, and very-high-resolution images and UAVs are useful as secondary verification tools in areas of dispute or of high value. This is particularly applicable to Huang et al.'s study on the extraction of tobacco using a film mulch, which can detect the intended planting of tobacco before the crop becomes spectrally mature, potentially aiding earlier area verification where

film mulch is used in tobacco planting [32]. Liu et al.'s use of early-season mapped area in relation to tobacco purchase volumes also points toward operational cross-checking between remote-sensing outputs and administrative datasets [37]. The main limitation is that most research pipelines are still optimized for academic performance metrics rather than for audit trails, explainability, uncertainty reporting, or integration with administrative databases. For tobacco, this is a central gap because the crop's regulatory context means that operational monitoring requirements are stricter than those for generic crop mapping.

6. Comparative Analysis

Reported accuracies are influenced by field size, season, region, class composition, label quality, and whether evaluation is pixel-based, field-based, or temporally independent. Table 2 compares sensing platforms in terms of their practical suitability and limitations, while Table 3 summarizes representative studies, their evaluation metrics, strengths, and limitations.

Table 2 shows that no single platform dominates every tobacco monitoring objective. Open optical systems are the most mature for scalable mapping, SAR is the most valuable hedge against missing observations, UAVs are strongest for local management and validation, and hyperspectral sensing is most valuable where the target is stress or quality rather than field extent. The main operational question is therefore not which sensor is best in isolation, but which sensor combination matches the spatial, seasonal, and policy requirements of a given tobacco-producing region.

Table 3 reinforces three patterns. First, strong tobacco results are concentrated in a small number of regions and should not be over-generalized. Second, where studies directly compared temporal or fused inputs with simpler alternatives under the same dataset and experimental setting, the added temporal or complementary sensor information generally improved tobacco discrimination; headline metrics from independent studies are not treated as direct evidence of superiority. Third, model quality and deployment readiness are not the same: the most accurate experimental models are not automatically the easiest to scale, explain, or transfer. The newer 2025–2026 studies broaden the evidence base substantially by adding plant-level detection, film-mulched field extraction, UAV-hyperspectral disease detection, nicotine retrieval, early-season mapping, and multimodal segmentation, but they also increase metric heterogeneity because accuracy, mIoU, AUC, mAP, and R^2 answer different monitoring questions [31–37].

Several high-performing studies operate within a single region, use carefully collected labels from the same season as testing, and evaluate a fixed set of classes under locally consistent agronomic conditions [10,24,25,27,28]. In those settings, tobacco may have a stable phenological signature relative to the chosen comparison crops, and dense time-series coverage can make the class highly separable. Similarly, high reported performance in film-mulch extraction or UAV-hyperspectral disease detection reflects tasks with strong local cues, such as plastic mulch or red-edge disease response, not necessarily a universally portable tobacco signature [32,35]. These are important achievements, but they do not imply that the same trained model would maintain that performance in a different tobacco-growing zone with different planting dates, field geometry, cultivar choice, disease pressure, management practice, or competing crops.

Table 2. Remote sensing platforms relevant to tobacco and tobacco-related crop monitoring.

Platform	Resolution	Revisit Time	Data Cost	Annotation/ Field Effort	Compute Need	Scalability	Advantages	Limitations	Tobacco Monitoring Relevance
Sentinel-2 optical	10–20 m	5 days	Free/open	Moderate	Moderate	High	Open access, red-edge bands, and a strong balance between coverage and detail	Cloud sensitivity and mixed pixels in fragmented fields	Mature option for acreage estimation, seasonal mapping, and phenology-aware classification; useful in cloud-platform early-season workflows [10,20,25,27,37]
Landsat optical	30 m	16 days	Free/open	Low–moderate	Low–moderate	High	Long historical archive, useful for trend analysis	Coarser spatial detail and slower revisit time than Sentinel-2	Better for multi-year context than for fragmented field delineation [7]
PlanetScope optical	About 3 m	Near-daily	Commercial	Moderate	Moderate	Medium	Strong smallholder separability and dense time series	Commercial access and radiometric harmonization burden	Highly relevant where tobacco plots are smaller than medium-resolution pixels [11,24,39,40]
MODIS optical	250 m–1 km	1–2 days	Free/open	Low	Low	High	Very high temporal density and regional coverage	Far too coarse for plot-level mapping	Useful mainly for broad production-zone dynamics rather than direct tobacco-field mapping
Commercial very-high-resolution optical	Sub-meter to a few meters	Variable or tasking-dependent	Commercial/ high	Moderate–high	Moderate–high	Low–medium	Fine boundary extraction, film-mulch detection, and local compliance checks	Cost, restricted archive access, and preprocessing complexity	Useful for local verification, pre-transplanting film-mulched tobacco extraction, and detailed mapping, but difficult to scale [32,41,42]
Sentinel-1 SAR	About 10 m	6–12 days	Free/open	Moderate	Moderate	High	Cloud-robust and sensitive to vegetation structure and moisture	More difficult feature interpretation and lower separability when used alone	Important for early-season and cloud-prone tobacco monitoring [9,11,43]
UAV imagery	Centimeter level	On demand	Mission-specific	High	Moderate–high	Low	Plant-level detail, flexible timing, and effectiveness in complex terrain	Limited coverage, annotation cost, and operational logistics	Best suited to field-scale management, validation, plant detection, and satellite-label support [23,26,34,36,44]
Hyperspectral imagery	Plot scale to centimeter level	Campaign-based	High/ specialized	High	High	Low	Sensitive to biochemical stress, disease, nicotine, and quality variation	Expensive, data-heavy, and limited in operational coverage	Best suited to disease, stress, nicotine, and quality assessment rather than routine acreage mapping [16–18,31,33,35,45]

Operational-feasibility entries are qualitative because commercial imagery prices, UAV field effort, annotation time, and computing requirements vary strongly with study area, provider, hardware, and survey design and are not reported consistently across the reviewed studies.

Table 3. Representative machine learning and deep learning studies relevant to tobacco monitoring.

Study	Evidence	Crop/Context	Data Source	Model	Evaluation Metric/Reported Value	Strengths	Limitations
Lozano-Tello et al. [25]	Tobacco-specific	Tobacco identification for CAP subsidy control	Multi-annual Sentinel-2	CNN-based neural network	Overall accuracy 99.21%	Operationally oriented, multi-year optical archive, and policy relevance	Temporal validation within the same geographic region; no cross-region validation was reported.
Fernandez-Sellers et al. [27]	Tobacco-specific	Tobacco detection with optimized sensing windows	Sentinel-2 time series	Hill climbing plus neural network	F-score 0.97	Reduces storage and processing burden while preserving strong discrimination	Temporal validation within the same geographic region; no cross-region validation was reported
Khan et al. [10]	Tobacco-specific	Tobacco detection in Pakistan	Sentinel-2 temporal stacking	Neural network using stacked imagery	Overall accuracy 95.81%	Shows the value of multi-date phenology over single-date inputs	Medium-resolution optical workflow remains cloud-sensitive and locally trained
Qazi et al. [28]	Tobacco-specific	Tobacco classification	Multi-sensor satellite time series	Conv1D–LSTM	Validation accuracy 98.4%	Combines convolutional feature extraction with temporal learning	Performance was reported under study-specific conditions; the data description in the available manuscript record is limited
Liu et al. [9]	Tobacco-specific	Early tobacco identification in cloud-prone conditions	Sentinel-1 SAR time series	ALSTM-FCN	Overall accuracy 90.76%	Cloud-robust and explicitly temporal; useful early in the season	Lower separability than strong optical-fusion studies; SAR interpretation is more difficult
Rao et al. [11]	Tobacco among multiple crops	Smallholder crop mapping including tobacco	Sentinel-1, Sentinel-2, and PlanetScope	SVM	Overall accuracy 85%	Demonstrates the importance of sensor fusion in fragmented fields	Traditional model depends on hand-crafted features and does not learn deep temporal structure
Minallah et al. [24]	Tobacco among multiple crops	Tobacco-focused crop classification	Sentinel-2 plus PlanetScope	Inception-inspired TempCNN	Overall accuracy 98.1%; tobacco accuracy 99%	Effective spectral–temporal fusion for smallholder-like conditions	Access to dense high-resolution imagery may limit reproducibility at scale
Durrani et al. [29]	Tobacco among multiple crops	Crop classification including tobacco	Multi-temporal satellite imagery	ConvLSTM	Overall accuracy 98.1%	Captures temporal dynamics and spatial context jointly	Hyperparameter sensitivity and local random-split validation limit broader conclusions; no cross-region validation was reported.
Huang et al. [26]	Tobacco-specific	Tobacco planting-area segmentation in mountainous terrain	UAV imagery	U-Net, DeepLabV3+, PSPNet, and SegNet	mIoU about 0.91–0.95	Strong field-scale delineation in complex terrain	Limited geographic extent and UAV deployment burden
Liao et al. [44]	Tobacco-specific	Tobacco field geometry extraction	UAV high-resolution imagery	RetinaNet-based detection	Task-specific reported values 94.48–99.98%	Practical retrieval of area and spacing metrics	Designed for detailed local monitoring rather than repeated regional mapping

Table 3. *Cont.*

Study	Evidence	Crop/Context	Data Source	Model	Evaluation Metric/Reported Value	Strengths	Limitations
Liu et al. [30]	Tobacco among multiple crops	LAI prediction including tobacco	Image-based crop dataset	Attention-based pyramid network	$R^2 = 0.941$	Useful for biophysical estimation and downstream yield modelling	Performance is not directly comparable with classification metrics
Krezhova et al. [16,18]	Tobacco-specific	Tobacco disease detection	Ground hyperspectral measurements	Statistical and derivative analysis	Significant spectral separability reported	Sensitive to pre-visual stress and infection signals	Small-scale experimental settings and limited scalability
Chen et al. [31]	Tobacco-specific	Tobacco leaf disease classification	Hyperspectral reflectance, LAI, and chlorophyll content	CWT plus Random Forest	OA 88.7%; Kappa 0.83	Uses multi-source physiological and spectral features for tobacco disease discrimination	Local disease dataset; operational canopy-scale transfer remains uncertain
Huang et al. [32]	Tobacco-specific	Film-mulched tobacco field extraction and area estimation	0.5 m Jilin-1 high-resolution imagery	Skip_Segformer	97% extraction accuracy; 1.6% relative area error	Enables pre-transplanting acreage estimation where plastic mulch identifies tobacco fields	Depends on high-resolution imagery and region-specific mulch practices
Tian et al. [33]	Tobacco-specific	Nicotine-content retrieval in cigar tobacco leaves	UAV hyperspectral imagery	MSC-SNV-SG-CARS-BP	$R^2 = 0.797$; RMSE = 0.078; RPD = 2.182	Connects remote sensing to tobacco biochemical quality rather than only acreage	Quality retrieval is cultivar- and sampling-stage-sensitive; it is not directly comparable with classification metrics
Chen et al. [34]	Tobacco-specific	Transplanting-stage tobacco plant detection	UAV imagery plus NDVI	YOLO–NTD	69.9% mAP@50–95; 54.6% AP_{tiny}	Targets early small-object detection under soil, weed, and plastic-mulch interference	Lower headline metrics reflect a more difficult plant-level task; transferability still requires testing
Mao et al. [35]	Tobacco-specific	Tomato Spotted Wilt Virus detection in tobacco	UAV hyperspectral imagery, 400–1000 nm	SVM-Relief with RPR feature reduction	OA 97.3%; AUC 0.994; Kappa 0.947	Shows strong red-edge disease sensitivity and compact wavelength selection	Disease-stage- and site-specific validation may limit broader operational use
Zheng et al. [36]	Tobacco-specific	Tobacco spatial-distribution mapping in mountainous regions	UAV imagery and multi-temporal satellite data	Attention and adaptive-convolution segmentation	About 5% mIoU improvement over U-Net and DeepLabV3+	Demonstrates multimodal segmentation and dataset construction for complex terrain	Conference abstract evidence; full validation details should be assessed when available
Liu et al. [37]	Tobacco-specific	Early-season tobacco cultivation mapping	Multi-source remote sensing in Google Earth Engine	Stacked generalization ensemble	OA 87.17%; PA 85.97%; UA 92.28%	Links early-season mapped area with administrative purchase-volume patterns	Early-season results remain region-specific and lower than full-season favourable-condition studies

Note: the metrics in Table 3 are task- and study-specific. Overall accuracy, validation accuracy, F-score, mIoU, mAP, AUC, and Kappa, together with R^2, measure different outcomes and should not be interpreted on a common numerical scale.

Dataset comparability is therefore a central issue. The studies in Table 3 do not solve the same problem at the same scale. Lozano-Tello et al. and Fernandez-Sellers et al. conduct multi-annual monitoring for subsidy control in Spain using Sentinel-2 data [25,27]; the Pakistan studies are based on multi-temporal optical classification with tobacco-specific labels [10,24,28,29]; Rao et al. study fragmented smallholder fields in India, not regional classification, using optical and SAR data [11]; Liu et al. study early-season SAR classification under cloud pressure in Fujian [9]; Huang et al., and Liao et al., analyze UAV imagery for segmentation and geometric extraction, rather than regional classification [26,44]; recent studies from 2025–2026 include Jilin-1 film-mulch extraction, UAV plant detection, UAV-hyperspectral disease and nicotine retrieval, early-season GEE mapping, and UAV-satellite segmentation [31–37]; and Krezhova et al. operate at leaf level under controlled disease-detection conditions [16–18]. The accuracy, F-score, mIoU, average precision, AUC, Kappa, and R^2 presented in these studies cannot be directly compared as the tasks, labels, spatial units and deployment constraints are different.

There is also a wide range of variation in validation practice. The majority of tobacco studies are based on local validation of the data, typically by dividing the data for a particular region into training and testing sets. This is helpful in comparing models within a study, but is not independent validation. Monitoring that is multi-annual in Spain is slightly more robust in terms of temporal robustness as it covers several years, but the geography is unchanged [25,27]. Smallholder mapping in India is more challenging because parcel size variation is explicitly considered, but validation is still regional [11]. UAV and hyperspectral studies are even more localized by design, including the newest plant-detection, disease-detection, and nicotine-retrieval studies [26,33–35,44]. As a result, there is still very little evidence for genuine cross-region transferability in tobacco monitoring. Accordingly, very high accuracy obtained from a local or same-region split should be interpreted as evidence of local performance, not as evidence that the trained model will work unchanged across new cultivars, crop calendars, or tobacco-growing regions.

For consistency, validation evidence in this review is interpreted using four levels: (1) local random-split validation, where training and testing samples come from the same region and season; (2) temporal validation, where testing uses a different year or season within the same geographic setting; (3) cross-region validation, where the model is evaluated in a geographically distinct tobacco-growing area; and (4) independent external validation, where the evaluation data are collected independently in a new geographic and/or seasonal setting. Most reported tobacco studies fall within the first category; the multi-annual Spanish studies provide stronger temporal evidence, whereas explicit cross-region validation is uncommon and truly independent external validation remains largely absent.

The results that appear most likely to transfer are therefore not the raw accuracy values, but the methodological lessons. Dense temporal coverage matters. High-resolution optical imagery helps fragmented tobacco farms. Film-mulch cues can support pre-transplanting acreage estimation where that management practice is widespread. SAR becomes valuable when cloud cover removes critical optical dates. UAV segmentation and object detection are strong when the task is field geometry or plant counting rather than regional scale. Hyperspectral red-edge features are highly informative for disease and biochemical assessment. And hybrid temporal or multimodal models are usually more suitable than single-date classifiers when tobacco must be separated from confusable crops. Those lessons are robust. What remains unproven is whether the exact trained models behind the strongest reported numbers can generalize across the diverse agroecological environments in which tobacco is grown.

7. Key Challenges in Tobacco Crop Monitoring

Table 4 summarizes the challenges discussed in this section, their impacts on tobacco monitoring, and possible response strategies and research directions.

Smallholder and fragmented fields. Tobacco may be grown in small parcels that are not regular in shape. This leads to mixed-pixel issues in medium resolution images, and to higher boundary uncertainty in areas where field sizes are close to or smaller than a Sentinel-2 pixel [10,11]. Recent UAV and multimodal studies have proved that plant-level or sub-field information can aid, but that weeds, mulch, shadows, terrain and annotation burden are both operational and solution challenges in fragmented tobacco mapping [34,36].

Similar spectral behavior with other crops. Tobacco can resemble other broadleaf crops in visible and near-infrared space, particularly during early growth. As a result, single-date optical classification is often insufficient unless temporal trajectories or higher-resolution context are included [9,10,24].

Cloud cover and missing observations. Optical monitoring pipelines degrade quickly when critical phenological dates are obscured by cloud. This is a significant concern at the humid and monsoon influenced tobacco growing areas and is the reason for the increasing interest in Sentinel-1 and fusion workflows [9,11,43].

Limited ground-truth data. The majority of studies are based on custom field surveys or locally annotated UAV scenes. These datasets are expensive to generate, are not always publicly available, and are often divided into training and test sets just once, reducing the likelihood of the true generalization of the results [26,44]. Recent multimodal work building a tobacco segmentation dataset is encouraging, but is also illustrative of the rarity of shared tobacco-specific datasets [36].

Regional transferability problems. There is no evidence in the field that models developed in Pakistan, China, Spain or India are generalizable across cultivars, climates, or management systems. This is one of the most obvious impediments to operational scaling [9–11,25].

Lack of benchmark datasets. If there are no tobacco-specific benchmarks, the differences in the level of accuracy reported may be due to differences in the difficulty of the data sets, not to differences in the superiority of the methods. This also complicates and slows cumulative progress with replication.

Computational cost of large-scale monitoring. The amount of storage, harmonization and inference required is increased with dense multi-temporal archives, cross-sensor fusion, and deep models, particularly for national scale monitoring programs [27,39].

Difficulty in early-season classification. Early identification is crucial for planning and policy, and is also the point where tobacco is most similar to other crops in terms of canopy structure and less distinct in terms of optical signatures [9]. However, recent research on film-mulch extraction, transplanting stage plant detection, and early-season stacked ensembles has demonstrated some promising alternatives, but these alternatives require local management cues or high resolution imagery and/or partial-season feature stability [32,34,37].

Table 4. Research challenges, their impact, and possible response strategies for tobacco monitoring.

Challenge	Impact on Tobacco Monitoring	Possible Solution	Future Research Direction
Fragmented smallholder fields	Mixed pixels and inaccurate field boundaries	Use higher-resolution optical data and UAV validation	Develop scalable small-parcel mapping pipelines that combine open-access and commercial imagery
Spectral confusion with other crops	False positives and unstable single-date classification	Emphasize phenology-aware time series and spatial context	Explicitly benchmark early-stage discrimination between tobacco and spectrally similar crops

Table 4. *Cont.*

Challenge	Impact on Tobacco Monitoring	Possible Solution	Future Research Direction
Cloud cover and missing observations	Temporal gaps during key growth stages	Integrate SAR with optical imagery	Develop tobacco-specific SAR–optical fusion workflows for monsoon-affected and humid regions
Sparse ground-truth data	Overfitting and weak external validity	Standardize field-data collection protocols and release shared reference labels	Create open, multi-region tobacco benchmark datasets
Poor regional transferability	Models perform poorly outside their original training domains	Use transfer learning and domain-adaptation methods	Directly evaluate cross-country, cross-region, and cross-season generalization
Lack of benchmark datasets	Reported accuracy values remain difficult to compare	Define common tasks, evaluation metrics, and independent test splits	Establish community benchmark datasets for classification, segmentation, and stress detection
High computational cost	Limits national-scale and recurring operational deployment	Use optimized sensing windows and cloud-computing workflows	Investigate edge- and cloud-computing trade-offs for recurring tobacco monitoring
Early-season ambiguity	Delays intervention, acreage estimation, and policy response	Fuse temporal, structural, and prior phenological information	Develop models specifically optimized for pre-canopy and transplanting-stage tobacco detection

8. Research Gaps

To avoid repeating the challenges listed in Section 7, the remaining research gaps are grouped into four areas:

- **Data and benchmark gaps:** There is no common open tobacco benchmark with standardized labels, tasks, evaluation metrics, and independent test splits across regions and seasons.
- **Sensor-integration gaps:** Tobacco-specific SAR–optical fusion, early-season monitoring, and UAV–satellite integration remain limited compared with single-sensor studies.
- **Generalization gaps:** Cross-region and cross-season validation, transfer learning, domain adaptation, and explicit interpretability remain underdeveloped.
- **Operational gaps:** Reproducible preprocessing, open code, uncertainty reporting, and integration with policy or administrative decision systems are still uncommon.

In terms of priority, near-to-medium-term work should focus on shared datasets and evaluation protocols, practical SAR–optical fusion, cross-season and cross-region validation, and reproducible operational workflows. Longer-term frontier research includes large-scale self-supervised or foundation-model pretraining, broader multimodal learning across UAV and satellite scales, and general-purpose transfer across agroecological zones.

9. Future Directions

Further studies are required to enhance the robustness, transferability and operational deployment of the models, and not only the accuracy of classification.

Foundation Models and Self-Supervised Learning. Foundation models and self-supervised learning are treated here as proposed or emerging research directions rather than established tobacco-monitoring approaches. With the rise of foundation models and self-supervised learning, there is a great opportunity to develop tobacco monitoring solutions, especially in areas where labeled data sets are scarce. Future models could learn generalized spectral–temporal representations from the vast archive of unlabeled Sentinel-1, Sentinel-2, Landsat and PlanetScope imagery that can be readily adapted to specific applications like acreage estimation, crop classification, and disease monitoring for tobacco. For tobacco specifically, pretraining on large volumes of unlabeled satellite imagery could

directly address the shortage and geographic concentration of field-verified tobacco labels, after which the pretrained representations could be fine-tuned using much smaller local tobacco datasets.

SAR–Optical Fusion. The integration of SAR and optical remote sensing data remains one of the most important research directions for operational tobacco monitoring. Optical imagery provides rich spectral information, while SAR observations offer cloud-independent monitoring capabilities. Future studies should investigate advanced fusion architectures capable of maintaining stable monitoring performance under variable weather conditions and incomplete image sequences [9,11,43].

Multimodal Learning and UAV–Satellite Integration. The newest tobacco literature suggests that the most useful future models will not be purely satellite-based or purely UAV-based. UAV imagery can provide high-confidence labels, plant-level evidence, and fine-scale segmentation masks, while satellite time series provide the regional repetition needed for acreage and policy monitoring [34,36]. Multimodal models should therefore be designed to transfer information across scale: UAV data can train or validate satellite segmentation, very high-resolution imagery can detect film-mulched fields before transplanting, and satellite products can identify priority zones for UAV inspection [32,36]. For tobacco, this integration is especially valuable in mountainous and smallholder areas where medium-resolution pixels often mix tobacco with soil, trees, roads, and neighboring crops.

Quality, Disease, and Biochemical Monitoring. Future tobacco monitoring should move beyond crop presence and area toward leaf quality, disease risk, nicotine content, chlorophyll, LAI, and other variables that influence commercial value and management decisions. Recent hyperspectral and UAV-hyperspectral studies show that disease and biochemical traits can be retrieved under specific experimental conditions, but operational use will require cheaper sensors, calibration transfer, and validation across cultivars, disease stages, and seasons [31,33,35]. A promising direction is to use hyperspectral campaigns to identify diagnostic bands and then translate those bands into lower-cost multispectral UAV or satellite payloads.

Transfer Learning Across Agroecological Zones. Most existing tobacco monitoring studies are developed and validated within limited geographic regions. Future research should prioritize transfer learning and domain adaptation approaches that enable models trained in one region to be effectively adapted to other tobacco-growing areas with minimal additional field data [65]. Such approaches would significantly improve scalability and reduce the cost of model deployment.

Explainable Artificial Intelligence. With the growing role of tobacco monitoring in policy and regulatory decision making, transparency of the models will gain importance. Future systems should have explainable AI capabilities that allow them to detect the spectral, temporal and spatial influences on model predictions, ensuring greater user confidence and ease of adoption by agronomists, policy makers and regulators. This is particularly important in compliance applications, where a mapped tobacco prediction may trigger field inspection or administrative verification; users should be able to examine the phenological, spectral, or spatial evidence and associated uncertainty behind such predictions.

Cloud-Native and Operational Monitoring Systems. The transition to cloud-native geospatial infrastructures for data processing, automated model deployment, and near real-time analysis is needed in future tobacco monitoring frameworks. This would allow for repeated monitoring in the same seasons and lessen the computational hurdles at agricultural institutions and government agencies.

Integrated Decision-Support Systems. Finally, tobacco monitoring needs to move from the basic crop classification to a comprehensive decision support system that integrates acreage estimation, crop health assessment, disease detection, yield and quality predictions

and compliance monitoring into a single platform. Such systems would provide actionable information for growers, researchers, industry stakeholders, and policymakers, supporting more efficient and sustainable tobacco production systems. The strongest near-term systems are likely to combine early-season satellite screening, targeted UAV verification, hyperspectral or multispectral stress diagnosis, and administrative cross-checks such as purchase records or declared planting area [32–34,37].

10. Discussion

The reviewed evidence indicates that multi-temporal optical satellite monitoring is the most mature option for recurring regional tobacco classification, while UAV and very-high-resolution imagery are strongest for local field delineation, plant detection, and verification. These established applications are supported by tobacco-specific studies in several regions, but their reported performance remains strongly dependent on local field size, crop calendar, class composition, and validation design [10,24–27,32,34,44].

By contrast, SAR-led early detection, hyperspectral disease or biochemical retrieval, transformer-based models, and richer multimodal approaches remain less mature for operational tobacco monitoring. Their main value is clear for cloud-prone conditions, physiological assessment, or complex spatial environments, but evidence is still concentrated in local or task-specific experiments and does not yet demonstrate broad cross-region transferability [9,16–18,33,35,36,45].

The literature supports a tiered monitoring strategy rather than a single best sensor or model: open satellite time series for regional surveillance, higher-resolution commercial or UAV data for targeted refinement and verification, and specialized hyperspectral observations for disease or quality assessment. The main requirement for the next stage of tobacco monitoring is therefore not simply higher local accuracy, but reproducible validation, transferable models, transparent uncertainty, and operational integration with agricultural and regulatory decision systems.

The limitation of this review is that the original literature search was conducted iteratively, and verifiable totals for the initial database records and duplicate removals were not retained. Therefore, although the review followed a structured process for literature searching, screening, and evidence classification, it should not be considered a fully reproducible systematic review. The search date, search terms, screening procedure, and final set of retained studies constitute the reproducible elements available from the review record.

11. Conclusions

Remote sensing has substantially improved the ability to monitor tobacco cultivation, especially for crop mapping, acreage estimation, disease detection, biochemical assessment, and field-scale assessment. Recent 2025–2026 studies show rapid growth in tobacco-specific UAV, hyperspectral, high-resolution satellite, and multimodal deep-learning research. Although classification and feature extraction have also benefited from deep learning, its best performance is still limited to specific datasets and experimental conditions, and not to common benchmarks.

The literature suggests that future steps will not be solely based on accuracy improvements, but rather on benchmark datasets, multi-sensor fusion, scalable and transferable models, and operational decision-support systems. Now, the main question is not if remote sensing and deep learning will work, but how to ensure reliability, comparability and usability of remote sensing and deep learning across regions, seasons and policy environments.

Author Contributions: W.K.: Data curation; formal analysis; writing—original Draft. H.K.: Visualization; writing—original draft; writing—review & editing. M.Z.: Methodology; investigation;

writing—review & editing. A.G.: Writing—review & editing; investigation; formal analysis; funding acquisition; methodology. S.D.: Methodology; writing—original draft; formal analysis. M.N.S.: Methodology; investigation; writing—review & editing. All authors have read and agreed to the published version of the manuscript.

Funding: A.G. was funded by the postgraduate course "Environmental Engineering and Science" of Democritus University of Thrace (project code 82211).

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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

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