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UAV remote sensing technologies for breeding and cultivation of *Camellia oleifera*: current progress, challenges, and future directions

Kunxi Wang[1], Hengchan Ye[1], Guangyuan Huang[1], Xinru Wang[1], Wei Long[2], Xiaohua Yao[2] and Chunlian Yu[1*]

[1] *Changshan Geopark Administration Center, Quzhou, Zhejiang 324200, China*
[2] *Research Institute of Subtropical Forestry, Chinese Academy of Forestry, Hangzhou, Zhejiang 311400, China*
* Correspondence: 15268088258@163.com (Yu C)

Abstract

Camellia oleifera (oil tea) is the most economically important woody oil crop in China, with a national planting area exceeding 5 million ha and annual tea oil production surpassing 1.1 million tonnes as of 2025. Despite massive government investment exceeding CNY 120 billion (approximately US$17.6 billion) during the 2023–2025 period, the breeding pipeline remains constrained by labor-intensive, destructive phenotyping methods that cannot efficiently evaluate the thousands of candidate genotypes across multisite breeding trials, whereas the subsequent deployment of improved varieties to millions of hectares under commercial cultivation demands equally scalable monitoring tools. Unmanned aerial vehicle (UAV)-based remote sensing has emerged as a transformative technology for high-throughput phenotyping in agriculture, yet its application to the breeding and cultivation of *C. oleifera* remains at an early stage. This review provides the first comprehensive synthesis of UAV-based remote sensing technologies applicable to *C. oleifera*, systematically examining five sensor modalities (red–green–blue, multispectral, hyperspectral, light detection and ranging, and thermal infrared), their associated data processing pipelines, and the analytical methods (including deep learning) that translate raw imagery into breeding-relevant phenotypic information. We evaluate the current state of *C. oleifera* UAV-based research (crown segmentation, tree detection, yield estimation, and fruit detection) against the substantially more advanced literature on olive (*Olea europaea*), tea (*Camellia sinensis*), oil palm (*Elaeis guineensis*), and *Citrus*, identifying critical gaps in multispectral field phenotyping, aerial disease detection, thermal stress assessment, multitemporal growth monitoring, and integration with genomic selection. Emerging technologies including multisensor fusion, foundation model transfer learning, edge computing, under-canopy autonomous navigation, and digital twin platforms are assessed for their potential to accelerate *C. oleifera* breeding. A prioritized technology roadmap aligned with China's national policy framework is proposed to guide the next decade of research. This review aims to serve as both a methodological reference and a strategic guide for integrating smart forestry technologies into woody oil crop breeding programs.

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Introduction

Camellia oleifera Abel, commonly known as oil tea or camellia oil, holds a singular position among the woody oil crops in the global agricultural landscape. Native to southern China and cultivated for more than two millennia, this evergreen species of the Theaceae family produces seeds with an oil content of 25%–35% that rivals olive (*Olea europaea*) oil in its fatty acid profile—rich in oleic acid (74%–87%) with a low saturated fat content—while offering additional bioactive compounds including squalene, polyphenols, and vitamin E[1−3]. Recent reviews have documented the broad range of nutritional constituents and biofunctional properties of camellia oil, underscoring its growing market value as a premium edible oil[4−6]. China dominates global production, accounting for approximately 90%–95% of the world's camellia oil output, and the industry has experienced remarkable expansion in recent years. By late 2025, the national planting area reached 75 million mu (approximately 5 million ha), with annual tea oil production surpassing 1.1 million tonnes, representing a 53% increase relative to 2020 levels. The total output value of the oil tea industry now exceeds CNY 100 billion (approximately US$14.7 billion).

The strategic significance of *C. oleifera* extends well beyond its direct economic value. China currently imports over 10 million tonnes of edible vegetable oil annually, with approximately 70% of its total edible oil supply dependent on foreign sources[7]. Against this backdrop, oil tea has been positioned as a cornerstone of the "Broad Food Concept" championed by the Chinese government, a policy framework that seeks to diversify domestic food and oil production from nonarable forestland. The joint Three-Year Action Plan for Accelerating Oil Tea Industry Development (2023–2025) issued by the National Forestry and Grassland Administration (NFGA), the National Development and Reform Commission (NDRC), and the Ministry of Finance established targets of 90 million mu in total area and 2 million tonnes of annual oil production capacity, backed by cumulative government investment exceeding CNY 120 billion (approximately US$17.6 billion).

A persistent bottleneck, however, constrains the realization of these ambitions: The pace and precision of breeding. Over 365 *C. oleifera* varieties have been developed to date, with 241 currently approved for commercial deployment, yet the coverage of improved varieties in existing forests remains below 20%—a primary cause of low national productivity[8,9]. The breeding cycle spans 15 to 20 years or more, driven in large part by the species' 5–6-year juvenile period before first flowering and the subsequent multiyear evaluation required to reliably assess yield performance[10]. Traditional phenotype evaluation relies on manual measurement of traits such as crown dimensions, fruit count, fruit weight, and oil content—methods that are destructive, labor-intensive, subjective, and fundamentally incapable of scaling to the millions of trees under evaluation across national breeding programs. This phenotyping bottleneck is well recognized across plant sciences[11] and is particularly acute in long-lived tree species where individual evaluation cycles span years rather than months[12,13]. The recent assembly of the *C. oleifera* reference genome[14] and emerging single nucleotide polymorphism (SNP) resources provide a genomic foundation, but their translation into accelerated breeding requires correspondingly high-throughput phenotyping capabilities.

Unmanned aerial vehicle (UAV)-based remote sensing has emerged over the past decade as a transformative technology for addressing precisely this kind of phenotyping bottleneck. In agricultural crops such as wheat (*Triticum aestivum*), maize (*Zea mays*), and soybean (*Glycine max*), UAV-based high-throughput phenotyping (HTP) platforms have emerged as a key solution. HTP refers to the automated, rapid, and nondestructive acquisition of quantitative trait data across large numbers of genotypes or experimental units, enabled by advanced sensor technologies and computational pipelines[11]. These platforms have demonstrated the capacity to measure canopy structure, vegetation vigor, biochemical composition, and stress responses across thousands of plots within hours, replacing weeks of manual work with quantitative, repeatable, and nondestructive measurements[15,16]. Comprehensive reviews have documented the rapid maturation of UAV sensor technology, data processing workflows, and analytical methods for agricultural applications[17−20]. For tree crops specifically, pioneering work on olive[21,22] (Díaz-Varela et al., 2015; Caruso et al., 2021), tea (*Camellia sinensis*)[23], oil palm (*Elaeis guineensis*), and *Citrus*[24] has established viable pipelines for UAV-based crown segmentation, canopy volume estimation, yield prediction, disease mapping, and cultivar discrimination—all traits that are directly relevant to breeding programs[25,26].

Despite this momentum, the application of UAV-based remote sensing to the breeding and cultivation of *C. oleifera* remains in an early exploratory phase. Existing studies have primarily addressed crown segmentation using red–green–blue (RGB) imagery and, to a limited extent, fruit detection for estimating yield. To the best of our knowledge, no published work has deployed multispectral or hyperspectral sensors for canopy-level physiological trait estimation in *C. oleifera*; no aerial disease detection has been attempted, despite anthracnose being a major yield-limiting factor[27]; and the integration of UAV-derived phenomic data with genomic selection frameworks—a frontier now emerging in conifer breeding[28,29]—remains entirely unexplored for oil tea.

This review addresses this gap by providing the first comprehensive synthesis of UAV-based remote sensing technologies applicable to the breeding and cultivation of *C. oleifera*. We systematically examine five sensor modalities (RGB, multispectral, hyperspectral, light detection and ranging [LiDAR], and thermal infrared) alongside their associated data processing pipelines and analytical methods, including deep learning approaches. The current state of UAV-based research into *C. oleifera* is critically evaluated against the substantially more advanced literature on comparable tree crops, enabling the identification of specific research gaps and technological opportunities. We also assess emerging technologies from foundation model transfer learning to under-canopy autonomous navigation, for their potential to accelerate the breeding of China's most strategically important woody oil crop. A prioritized technology roadmap aligned with national policy is proposed to guide the next decade of research in this rapidly evolving field.

UAV platforms, sensors, and data processing methods for tree crop phenotyping

The capacity of a UAV phenotyping system to generate breeding-relevant data depends on the interplay among three components: The aerial platform that determines the payload, flight endurance, and positional accuracy; the sensor payload that defines the spectral, spatial, and temporal resolution of the acquired data; and the processing pipeline that transforms the raw imagery into quantitative trait estimates[30]. Each component involves trade-offs that shape what can be measured, at what precision, and at what cost—considerations that become particularly acute when operating over the mountainous terrain characteristic of *C. oleifera* plantations.

UAV platforms

Multirotor platforms dominate tree crop phenotyping research, with the DJI Phantom 4 RTK and DJI Matrice 300 RTK accounting for the majority of published studies across olive, tea, oil palm, *Citrus*, and *C. oleifera*[17,25]. Multirotor systems offer vertical takeoff and landing (VTOL), hovering capability for close-range inspection, and terrain-following flight modes, which are essential for undulating terrain, though at the cost of limited flight endurance (typically 20–40 min) and restricted payload capacity (0.5–2.7 kg). Fixed-wing platforms such as the eBee X (senseFly) extend endurance to 60–90 min and survey coverage to 200+ ha per flight, making them suitable for plantation-scale mapping, but their higher ground speed and inability to hover reduce their spatial resolution for per-tree phenotyping. VTOL hybrids (e.g., Wingtra WingtraOne) combine the surveying efficiency of fixed-wing flight with multirotor precision during takeoff and landing, though their adoption in forestry phenotyping remains limited[18].

Positional accuracy represents a critical specification for breeding applications, where individual tree identity must be maintained across multiple flights and growing seasons. Real-time kinematic (RTK) and post-processed kinematic (PPK) global navigation satellite system (GNSS) corrections achieve horizontal accuracies of 1–3 cm and vertical accuracies of 2–5 cm under open-sky conditions[31,32]. Under the forest canopy, however, GNSS accuracy degrades substantially because of multipath and signal attenuation, necessitating ground control points (GCPs) for reliable georeferencing—a logistically demanding requirement in the mountainous, high-canopy-closure environments where *C. oleifera* is typically grown. Structure-from-motion (SfM) photogrammetric processing with 5–10 GCPs typically achieves root mean square error (RMSE) of 3–8 cm[33], which is sufficient for moitoring individual trees in breeding trials.

Sensor payloads

Five sensor modalities have been applied for phenotyping tree crops, each offering distinct information content (Fig. 1). RGB cameras remain the most accessible and widely deployed sensors, with consumer-grade models (20–45 megapixels) achieving ground sampling distances (GSD) of 1–3 cm at typical flight altitudes of 20–50 m. When processed through SfM pipelines[33], RGB imagery yields high-resolution orthomosaics, digital surface models (DSMs), and derived canopy height models (CHMs) that enable crown delineation, tree counting, canopy area and volume estimation, and—at sufficiently high resolution—fruit detection. For *C. oleifera* specifically, RGB-based approaches have achieved F1 scores of 0.85 for

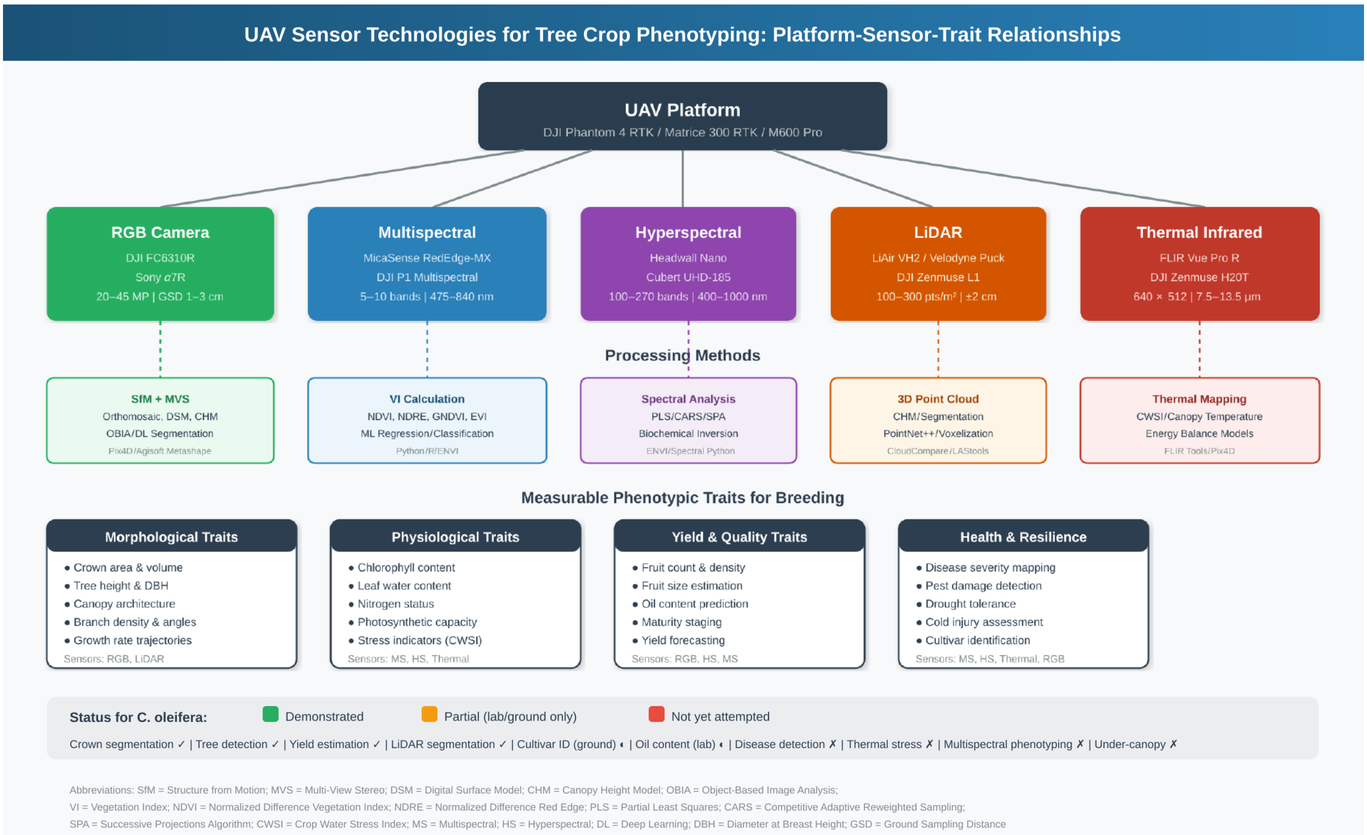


Fig. 1 Overview of UAV sensor technologies, processing methods, and measurable phenotypic traits for phenotyping in tree crop breeding. Status indicators reflect the current state of application specifically to *Camellia oleifera* as of early 2026.

crown detection[34], mean average precision (mAP) of 0.82 for tree counting[35], and fruit detection F1 scores of 0.90 for yield estimation[36].

Multispectral sensors capture reflectance in 4–10 discrete spectral bands spanning visible through near-infrared wavelengths (typically 475–840 nm), enabling the calculation of vegetation indices (VIs) that serve as proxies for physiological status[16]. The MicaSense RedEdge-MX (five bands, including a red edge at 717 nm) has become a standard in tree crop research, facilitating the estimation of chlorophyll content (via normalized difference vegetation index [NDVI], normalized difference red edge [NDRE]), leaf water status (via normalized difference water index [NDWI]), nitrogen concentration, and canopy vigor. In olive breeding trials, NDVI-derived vigor indices correlated with yield at $r = 0.63$ and with canopy area at $r = 0.87$[22]. For tea (*C. sinensis*), multispectral imaging combined with machine learning achieved R^2 values of 0.87 for chlorophyll estimation and 0.62[23]. Despite these proven capabilities, no published study has deployed multispectral UAV sensors for field phenotyping in *C. oleifera*, a striking gap, given the species' economic importance.

Hyperspectral sensors extend spectral coverage to 100–270 contiguous narrow bands spanning 400–2,500 nm (very near infrared [VNIR]: 400–1,000 nm; shortwave infrared [SWIR]: 1,000–2,500 nm), enabling detailed spectral signature analysis for biochemical trait estimation including oil content, moisture, and specific pigment concentrations[37,38]. Push-broom scanners (e.g., Headwall Nano-Hyperspec, Specim AFX10) offer high spectral resolution but require precise flight line planning, whereas snapshot sensors (e.g., Cubert UHD-185) provide area-based imaging at a reduced spectral resolution. For *C. oleifera*, laboratory-based hyperspectral imaging of seed kernels has achieved R^2 values of 0.94 for predicting oil content using competitive adaptive reweighted sampling (CARS) combined with partial least squares regression[39]. Translating these laboratory results to canopy-level aerial acquisition represents a major research opportunity, with the potential to enable the nondestructive screening of oil content across thousands of trees in breeding trials.

LiDAR sensors generate three-dimensional (3D) point clouds that directly measure the canopy structure independent of the illumination conditions[40]. UAV-borne LiDAR systems (e.g., LiAir VH2, DJI Zenmuse L1, and Velodyne Puck) typically achieve point densities of 100–300 points/m^2 with a vertical accuracy of ±2–3 cm, enabling precise measurement of tree height, crown dimensions, branch architecture, and under-canopy structure. For *C. oleifera*, Wang et al.[41] demonstrated individual tree canopy segmentation from LiDAR point clouds with an F-score of 0.93, whereas a multilevel LiDAR + RGB approach achieved an F-score of 0.975 for canopy area extraction in mountainous plantations with high canopy closure[42]. In olive breeding, UAV-based LiDAR has been deployed to compare canopy growth architecture across cultivars under rainfed conditions, directly supporting cultivar evaluation[43].

Thermal infrared cameras (e.g., FLIR Vue Pro R, DJI Zenmuse H20T) measure emitted radiation in the 7.5–13.5 μm waveband, providing surface temperature maps at resolutions of 5–15 cm from typical UAV altitudes. The crop water stress index (CWSI), derived from canopy temperature relative to air temperature and vapor pressure deficit, enables nondestructive assessment of plant water status—a trait of direct relevance to screening drought tolerance in breeding programs. Thermal imaging has been validated for assessing water stress in olive and citrus orchards[38,44], but remains entirely unexplored for *C. oleifera* despite the species' cultivation across drought-prone subtropical hillslopes (Table 1).

Data processing pipelines

The transformation of raw UAV imagery into breeding-relevant trait estimates follows a standardized multistage pipeline (Fig. 2), though specific implementations vary by sensor type and the research objective[20,30]. The initial stage involves radiometric calibration and geometric correction via SfM photogrammetric reconstruction, producing georeferenced orthomosaics, DSMs, and densified point clouds using software such as Agisoft Metashape, Pix4Dmapper, or DJI Terra[33]. The subsequent feature extraction stage transforms the raw geospatial products into trait-relevant variables: vegetation indices (NDVI, NDRE, enhanced vegetation index [EVI]) from multispectral data[45], canopy height models and structural metrics from LiDAR point clouds, and object-level features from RGB imagery via either classical object-based image analysis (OBIA) segmentation or deep learning networks[46]. The analytical stage applies statistical or machine learning models—ranging from Random Forest and support vector machine (SVM) regression for continuous trait estimation to convolutional neural networks (CNNs) for detection and classification[47]—to extracted features for predicting the target traits. The choice between traditional and deep learning approaches depends primarily on training samples' availability, a consideration discussed in detail in section "Deep learning and artificial intelligence methods for UAV-based phenotyping"[48].

UAV-based remote sensing applications for *Camellia oleifera*: current state of the art

The body of published research on UAV-based remote sensing for *C. oleifera*, though growing rapidly, remains concentrated in a narrow set of application domains. A systematic literature search identified approximately 25 directly relevant studies published between 2019 and early 2026, with the clear majority appearing in 2023–2025. These studies cluster into four primary categories: Canopy segmentation, individual tree detection and counting, yield estimation through fruit detection, and supporting work on cultivar identification and monitoring phenology. The following subsections evaluate each domain, with quantitative performance metrics compiled in Table 2.

Table 1. Comparison of UAV sensor modalities for tree crop phenotyping, with representative specifications and demonstrated applications.

Sensor	Spectral range	Typical GSD	Key outputs	Phenotypic traits	*C. oleifera* status
RGB	400–700 nm (3 bands)	1–3 cm	Orthomosaic, DSM, CHM, 3D model	Crown area, tree count, fruit detection, canopy volume	Active (F1 = 0.85 crown; mAP = 0.82 count)
Multispectral	475–840 nm (5–10 bands)	3–8 cm	VI maps (NDVI, NDRE), reflectance	Chlorophyll, vigor, N status, water content	Not attempted
Hyperspectral	400–2,500 nm (100–270 bands; VNIR: 400–1,000 nm; SWIR: 1,000–2,500 nm)	5–15 cm	Continuous spectral signatures, reflectance cubes	Oil content, pigments, moisture, disease markers	Lab only (R^2 = 0.94 oil content)
LiDAR	905/1,550 nm (single pulse)	2–5 cm vertical	3D point cloud, CHM, DTM	Height, DBH, crown architecture, branch density	Active (F-score = 0.93 segm.)
Thermal IR	7.5–13.5 μm	5–15 cm	Surface temperature map	CWSI, drought stress, stomatal conductance	Not attempted

GSD, ground sampling distance; CHM, canopy height model; DSM, digital surface model; DTM, digital terrain model; VI, vegetation index; NDVI, normalized difference vegetation index; NDRE, normalized difference red edge; CWSI, crop water stress index; DBH, diameter at breast height; 3D, three-dimensional. Biochemical trait maps (e.g., oil content, pigment concentrations) are derived products requiring chemometric modeling (e.g., partial least squares [PLS] regression), not direct sensor outputs. Both hyperspectral and multispectral data can serve as inputs for biochemical proxy estimation, with hyperspectral sensors offering a finer spectral resolution for resolving overlapping absorption features.

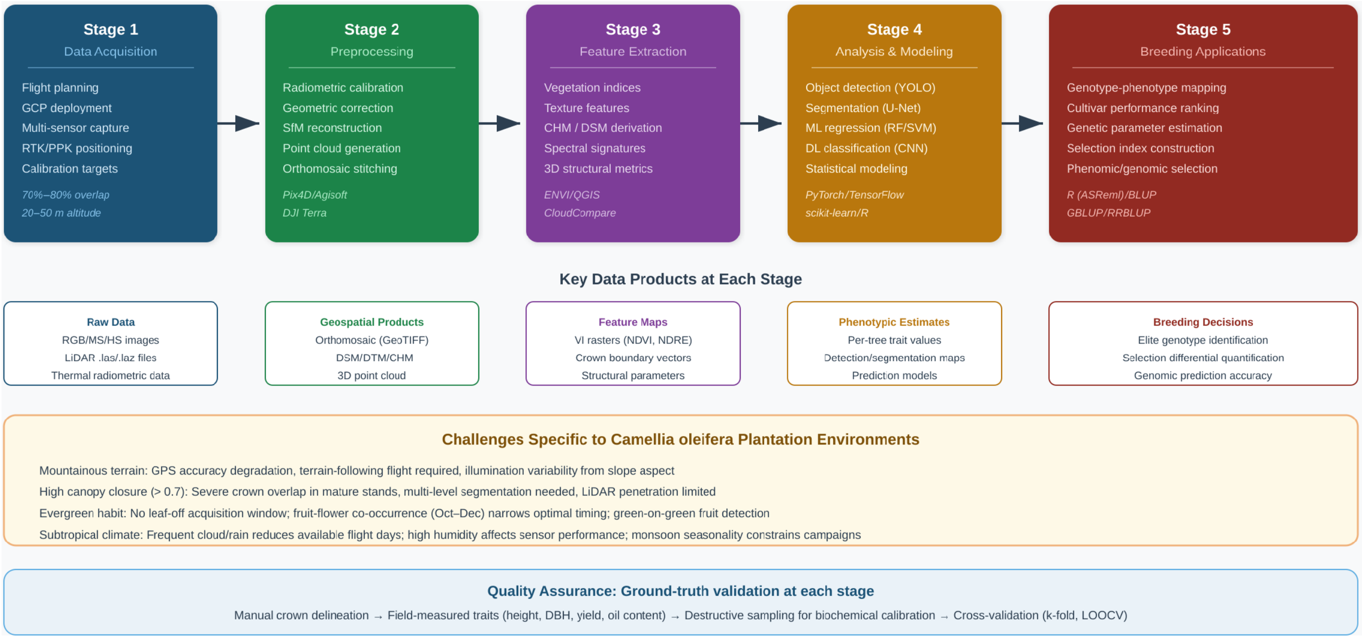


Fig. 2 Standard data processing pipeline for UAV-based tree crop phenotyping, illustrating the five processing stages from data acquisition through to breeding applications, with challenges specific to *C. oleifera* plantation environments.

Table 2. Summary of remote sensing and computer vision studies on *Camellia oleifera* phenotyping (2019–2026), ordered by application domain. Studies using ground-based platforms are included where the methodologies are directly transferable to UAV deployment.

Study	Year	Platform/sensor	Method	Target task	Key accuracy
[34]	2022	Phantom 4 RTK/RGB	ResU-Net + CHM	Crown segmentation	F1 = 84.68%; crown width R^2 = 0.93
[41]	2024	M300 RTK/LiAir VH2	Point cloud clustering	Individual tree segm.	F-score = 93%; fiameter RMSE = 0.42 m
[42]	2025	LiDAR + RGB fusion	Multi-level segmentation	Crown extraction	F-score = 97.5% (canopy); 91.7% (tree)
[35]	2024	Phantom 4 Pro/RGB	YOLOv8m	Tree detection/counting	mAP@0.5 = 82.3%; count R^2 = 0.94
[36]	2021	Mavic 2 PRO/RGB	Mask R-CNN	Fruit detection/yield	Fruit F1 = 89.91%; yield R^2 = 0.89–0.91
[50]	2022	Ground camera/RGB	YOLOv7 + augmentation	Fruit detection	Improved detection under occlusion
[51]	2024	Ground camera/RGB	YOLO-CFruit (YOLOv8)	Fruit detection	AP@0.5 = 98.2%
[49]	2022	Terrestrial LiDAR	Mean shift clustering	Yield estimation	Automated color-space detection
[53]	2024	Ground camera	RegNetY + CBAM	Cultivar identification	93.7% accuracy (118 varieties)
[39]	2024	Lab hyperspectral	CARS + PLS	Oil content prediction	R^2 = 0.94 (kernel samples)
[52]	2025	Smartphone/RGB video	YOLOv8 + RepViT + ByteTrack	Fruit detection/yield	mAP = 86.21%; yield R^2 = 0.905

Studies using ground-based sensors are included where they demonstrate methodological capabilities transferable to UAV platforms. YOLO, you only look once; PLS, partial least squares; CBAM, convolutional block attention module; AP, average precision; mAP@0.5, mean average precision at an intersection-over-union (IoU) threshold of 0.5.

Crown segmentation and canopy structure

Automated extraction of individual *C. oleifera* tree crowns from UAV imagery represents the most extensively studied problem, addressing a fundamental prerequisite for per-tree phenotyping in breeding trials. Ji et al.[34] established a foundational approach using the ResU-Net deep learning architecture applied to DJI Phantom 4 RTK RGB orthomosaics combined with CHM data derived from SfM point clouds. Operating over plantations in Hunan Province, the method achieved an F1 score of 84.68% for crown detection and an R^2 of 0.93 for crown width estimation relative to field measurements. The integration of CHM as an auxiliary input channel proved critical, as it distinguished overlapping tree crowns that appeared to be merged in RGB imagery alone—a pervasive challenge in mature *C. oleifera* stands, where canopy closure commonly exceeds 0.7.

Wang et al.[41] advanced the state of the art by deploying UAV-borne LiDAR (LiAir VH2 on DJI Matrice 300 RTK) for individual tree canopy segmentation. Their approach combined point cloud clustering with a local maximum detection algorithm for treetop identification, achieving an F-score of 93% and a crown diameter RMSE of 0.42 m. The LiDAR-based method demonstrated particular advantages under the conditions of high canopy closure that confound two-dimensional (2D) image-based approaches, as the 3D point cloud resolves vertical crown boundaries that are invisible in nadir imagery. Complementary work by Tang et al.[49] used terrestrial laser scanning (TLS) with mean shift clustering to identify *C. oleifera* fruit yield via color-space analysis, achieving automated yield estimation in ground-based point clouds.

A notable recent contribution by Lai et al.[42] specifically addressed the challenge of mountainous *C. oleifera* plantations with high canopy closure using a multilevel segmentation framework that fused LiDAR and RGB data. This approach decomposed the problem hierarchically by first extracting plantation boundaries from RGB orthomosaics, then performing coarse segmentation using CHM-based watershed analysis, and finally refining individual tree boundaries through marker-controlled segmentation of the original point cloud. The integrated pipeline achieved F-scores of 97.5% for canopy area extraction and 91.7% for individual tree isolation, the highest reported accuracy for *C. oleifera* crown segmentation under operationally realistic conditions. Despite these advances, current crown segmentation approaches face several operational limitations that constrain their deployment in breeding programs. Low flight altitudes (typically 20–50 m for RGB, lower for detailed crown delineation) restrict survey coverage to 5–20 ha per flight mission, making the phenotyping of large-scale breeding trials time-intensive. Canopy occlusion remains a persistent challenge: In mature plantations with canopy closure exceeding 0.7, overlapping crowns lead to undersegmentation errors that can misrepresent individual trees' performance. Model generalization across sites is also poorly characterized, as most studies validate their models within a single plantation; transferability across different terrains, planting densities, and cultivar mixtures—conditions typical of multisite breeding trials—has not been systematically evaluated.

Tree detection and counting

Accurate tree counting from UAV imagery provides essential management data, including stand density, planting survival rates, and missing tree identification, information that is relevant both to plantation management and to the design of breeding trials' layouts. Yang et al.[35] evaluated YOLOv8 variants (YOLOv8n, s, m, l, x) for detecting *C. oleifera* trees from DJI Phantom 4 Pro RGB imagery, with the medium-scale model (YOLOv8m) achieving the optimal balance of precision (86.2%), recall (80.1%), and mAP@0.5 (82.3%). The correlation between UAV-counted and field-counted trees reached R^2 = 0.94 across 50 validation plots, demonstrating operational reliability for stand inventory. Detection performance degraded predictably with increasing canopy closure and decreasing tree spacing, with mAP dropping below 0.70 in plots where the intertree spacing was less than 2 m.

Yield estimation through fruit detection

Fruit detection using UAV imagery offers a direct path to nondestructive yield estimation, a trait of paramount importance in breeding programs where fruit production is the primary selection criterion. Yan et al.[36] conducted a pioneering study using a DJI Mavic 2 PRO drone at low altitude (3–5 m above the canopy) to capture close-range canopy photographs, processed by Mask R-CNN for fruit instance segmentation. The method achieved a fruit detection F1 of 89.91%, with a R^2 of 0.89–0.91 for estimated yield when canopy-visible fruit counts were regressed against total harvested fruit weight.

Parallel advances in ground-level fruit detection provide methodological foundations that are readily transferable to UAV platforms. Wu et al.[50] applied YOLOv7 with data augmentation strategies (mosaic, mixup, and photometric distortions) to detecting *C. oleifera* fruit in complex orchard scenes, demonstrating that augmentation strategies substantially improved performance under variable illumination and occlusion conditions. Luo et al.[51] developed YOLO-CFruit, a customized YOLOv8 variant with enhanced multiscale feature fusion, achieving an AP@0.5 of 98.2% for fruit detection under challenging conditions including overlapping fruits, shadows, and partial occlusion. More recently, Dong et al.[52] extended the detection-tracking paradigm by combining an improved YOLOv8 (with a RepViT backbone and a P2 small-object detection layer) with ByteTrack multiobject tracking applied to smartphone-captured video sequences of *C. oleifera* canopies across three varieties, achieving a fruit detection mAP of 86.21% and R^2 = 0.905 for multi-variety yield estimation. These studies collectively highlight a fundamental constraint: Effective fruit detection requires imaging distances of 3–8 m from the canopy to resolve *C. oleifera* fruits, which are 2–4 cm in diameter, via low-altitude UAV flights or handheld devices, which limits survey coverage and increases operational complexity in dense canopy environments.

Supporting research: cultivar identification and phenology

Two additional research domains provide important context, though they have not yet been conducted with UAV platforms. Deep learning-based cultivar identification using ground-level leaf images achieved 93.7% accuracy across 118 *C. oleifera* varieties using a RegNetY-4.0GF architecture with convolutional block attention module (CBAM) attention[53], demonstrating that the intercultivar morphological variation captured in leaf features is sufficient for machine vision-based discrimination. Separately, monitoring phenology using field cameras and deep learning has tracked key developmental stages including bud formation, flowering, and fruit maturation[54]. Integrating both approaches—cultivar identification and phenological staging—into UAV-based aerial platforms represents a logical and technically feasible extension. Comprehensive germplasm evaluation studies, including trait analyses across 143+ accessions from diverse geographic origins[55,56], provide the ground-truth phenotypic datasets against which UAV-derived measurements can be calibrated and validated.

Deep learning and artificial intelligence methods for UAV-based phenotyping

The analytical methods applied to UAV imagery have undergone a paradigm shift over the past 5 years, moving from handcrafted feature extraction combined with classical machine learning toward end-to-end deep learning architectures that learn the relevant features directly from the data[46]. Although traditional approaches (Random Forest, SVM, object-based image analysis) remain appropriate for many tasks, particularly where training data are limited, deep learning has become the dominant framework for detection, segmentation, and classification problems in high-resolution UAV imagery.

Object detection: the YOLO family and beyond

Object detection in UAV imagery is dominated by the YOLO (you only look once) family of single-stage detectors, whose evolution from Version 1 to Version 8 and YOLO-NAS has been comprehensively reviewed by Terven et al[57]. YOLO's single-pass architecture yields real-time inference speeds (30–120 fps), making it well suited for processing the large image volumes generated in UAV phenotyping flights. For *C. oleifera*, YOLOv8m achieved the best balance of accuracy and speed for tree detection (mAP@0.5 = 82.3%)[35], whereas YOLO-CFruit (a customized YOLOv8 variant) achieved an AP@0.5 of 98.2% for ground-level fruit detection[51]. Transformer-based detectors, particularly DETR (detection transformer) and its derivatives real-time detection transformer (RT-DETR) and Roboflow detection transformer (RF-DETR), are emerging as alternatives that replace the hand-designed components of YOLO (anchor boxes, nonmaximum suppression) with learned attention mechanisms[58]. For *C. oleifera*, where crown overlap in dense plantations is a primary detection challenge, transformers merit investigation because of their global receptive field.

Semantic and instance segmentation

Segmentation—assigning class labels to every pixel (semantic) or delineating individual objects' boundaries (instance)—is essential for extracting precise crown shapes and areas from UAV imagery. The U-Net architecture and its variants form the backbone of most segmentation work in phenotyping tree crops. ResU-Net has been directly validated for *C. oleifera* crown extraction (F1 = 84.68%)[34]. Mask R-CNN extends the Faster R-CNN detection framework with a parallel segmentation branch and has been adapted for counting and sizing plants via UAV imagery[59].

The DeepForest Python package, based on RetinaNet with a ResNet-50 backbone, provides a particularly relevant pretrained model for tree crown delineation. Trained on over 30 million algorithmically generated tree crowns from the National Ecological Observatory Network (NEON), DeepForest achieves reasonable out-of-the-box performance on diverse forest types and can be fine-tuned with relatively small site-specific datasets[60,61]. Cross-site learning experiments also demonstrated that models trained on one forest type transfer to others with modest fine-tuning[62]. For *C. oleifera*, fine-tuning DeepForest with plantation-specific annotations represents a low-barrier entry point.

Point cloud deep learning

LiDAR point cloud processing has its own deep learning ecosystem that is distinct from 2D image analysis. PointNet and PointNet++ process unstructured 3D point sets directly, learning the per-point features through shared multilayer perceptrons and hierarchical grouping. These architectures have been applied to individual tree segmentation and species classification using UAV LiDAR data[63,64]. The SegmentAnyTree framework applies a PointGroup-inspired architecture for sensor-agnostic individual tree segmentation from diverse LiDAR platforms.

Foundation models and transfer learning

The emergence of vision-based foundation models—large-scale pretrained models that can be adapted to downstream tasks with minimal fine-tuning—offers a potential solution to the labeled data scarcity that constrains deep learning in specialized domains like phenotyping *C. oleifera*[48]. The Segment Anything Model (SAM) and its successor SAM2 demonstrate zero-shot and few-shot segmentation capabilities that are applicable to the task of tree crown delineation. Osco et al.[65] provided a comprehensive evaluation of SAM for remote sensing applications, demonstrating both its potential and its limitations for specialized vegetation analysis. Remote sensing foundation models including Prithvi[66] provide pretrained representations of multitemporal and multispectral satellite and aerial imagery that can be fine-tuned for domain-specific tasks[67]. Though these models have not yet been applied to *C. oleifera*, their adaptation through parameter-efficient fine-tuning methods, such as low-rank adaptation (LoRA) and adapters represents a high-priority research direction for rapidly bootstrapping phenotyping capabilities with limited labeled data. Chen et al.[68] demonstrated that adapting vision-based foundation models (MAE, DINO, DINOv2) with LoRA for plant phenotyping achieved near state-of-the-art performance.

Research gaps and challenges specific to oil tea

The preceding sections reveal a striking asymmetry: Although UAV-based phenotyping for olive, tea, oil palm, and *Citrus* has progressed from detection and counting toward multisensor physiological trait estimation and breeding integration, *C. oleifera* research remains concentrated in the initial phase of detection and counting (Fig. 3).

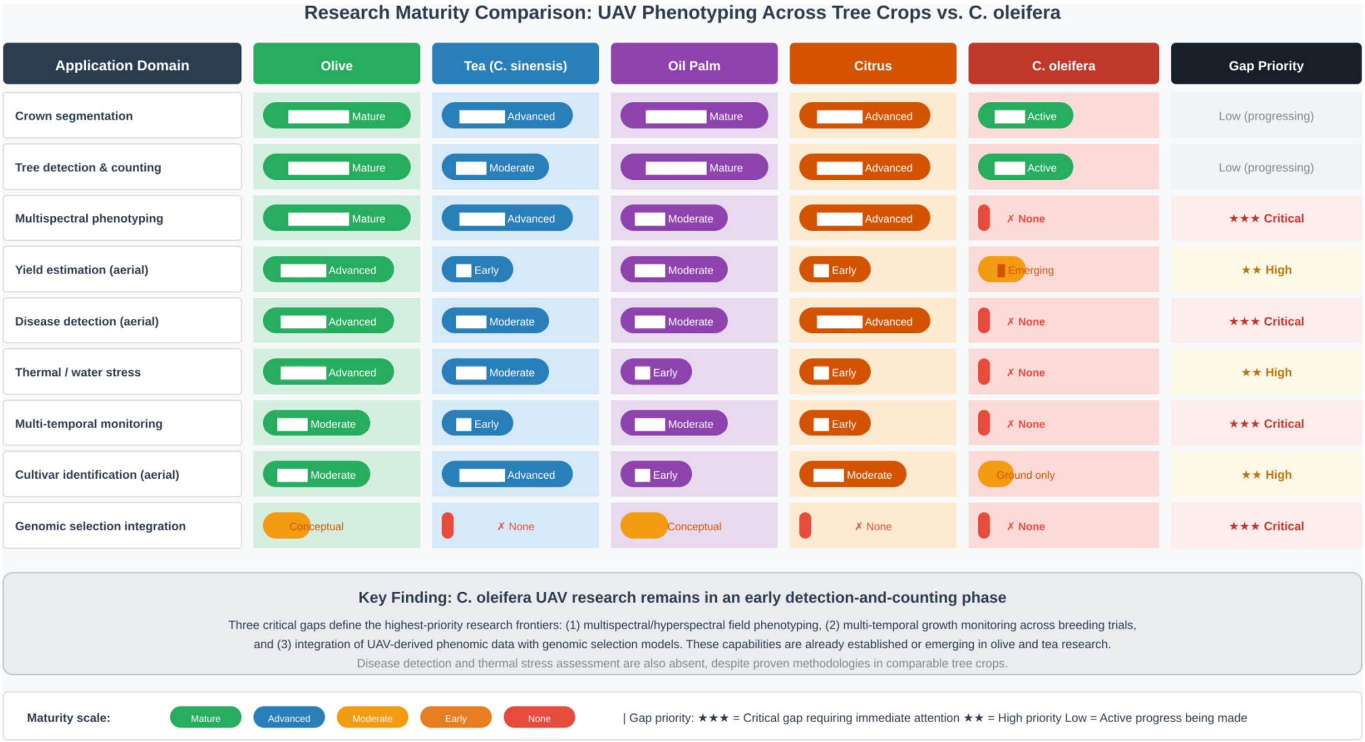
Critical technology gaps

The most consequential gap is the complete absence of UAV-mounted multispectral or hyperspectral sensing for *C. oleifera* in field conditions. Laboratory-based hyperspectral imaging has demonstrated that biochemical traits, including oil content, are spectrally predictable ($R^2 = 0.94$)[39], and multispectral NDVI-based vigor mapping is the established method for cultivar screening in olive breeding trials[22]. The failure to translate these demonstrated capabilities to aerial phenotyping of *C. oleifera* likely reflects a combination of factors: The relatively recent convergence of UAV technology costs with forestry research budgets, the technical challenges of operating multispectral sensors over mountainous terrain[69], and the disciplinary gap between the remote sensing and tree breeding research communities in China. More specifically, multispectral sensors (e.g., MicaSense RedEdge-MX) cost approximately US$5,000–6,000 per unit excluding the UAV platform, whereas hyperspectral payloads exceed US$50,000—investment levels that most forestry research groups in China have not historically allocated to phenotyping equipment. The mountainous terrain further compounds costs: Steep slopes (frequently > 15°) demand RTK-equipped multirotor platforms with terrain-following capability, which are more expensive and complex to operate than the consumer-grade RGB drones used in existing *C. oleifera* studies. Additionally, the evergreen phenology of *C. oleifera* eliminates the leaf-off window that simplifies radiometric calibration and atmospheric correction in deciduous tree systems, and the subtropical monsoon climate limits cloud-free flight opportunities to approximately 10–15 days per month during the growing season. These combined barriers of cost, terrain difficulty, and limited flight windows have collectively delayed the adoption of advanced sensor modalities, leaving breeding programs reliant on destructive sampling methods that cannot evaluate thousands of candidate genotypes within operationally feasible timeframes.

Aerial disease detection represents the second major gap. Anthracnose (*Colletotrichum gloeosporioides*) is the most destructive foliar disease of *C. oleifera*, causing yield losses of 10%–40% in severely affected plantations[27]. Disease resistance is a primary breeding objective, yet no published study has attempted UAV-based detection or severity mapping. Spectroscopic detection of anthracnose's severity has been demonstrated at the laboratory level using combined laser-induced breakdown spectroscopy (LIBS) and terahertz (THz) technology[70], providing spectral markers that could be translated to aerial platforms.

Multitemporal growth monitoring—repeated UAV flights tracking individual trees' growth trajectories across seasons and years—is absent from the *C. oleifera* literature. This capability is foundational for breeding applications because estimating genetic parameters (heritability, breeding values) requires measurements of the same genotypes across multiple time points and environments[12,13]. Rincón et al.[71] demonstrated a four-dimensional phenotyping model integrating LiDAR and multispectral imagery for tracking plants' growth over time, providing a methodological template for longitudinal *C. oleifera* monitoring.

The integration of UAV-derived phenomic data with genomic selection models represents the most transformative unfilled opportunity. Building on the phenomic selection concept first demonstrated in wheat and poplar (*Populus* spp.)[29] and genomic selection



Research Maturity Comparison: UAV Phenotyping Across Tree Crops vs. C. oleifera

Application Domain	Olive	Tea (C. sinensis)	Oil Palm	Citrus	C. oleifera	Gap Priority
Crown segmentation	Mature	Advanced	Mature	Advanced	Active	Low (progressing)
Tree detection & counting	Mature	Moderate	Mature	Advanced	Active	Low (progressing)
Multispectral phenotyping	Mature	Advanced	Moderate	Advanced	✗ None	★★★ Critical
Yield estimation (aerial)	Advanced	Early	Moderate	Early	Emerging	★★ High
Disease detection (aerial)	Advanced	Moderate	Moderate	Advanced	✗ None	★★★ Critical
Thermal / water stress	Advanced	Moderate	Early	Early	✗ None	★★ High
Multi-temporal monitoring	Moderate	Early	Moderate	Early	✗ None	★★★ Critical
Cultivar identification (aerial)	Moderate	Advanced	Early	Moderate	Ground only	★★ High
Genomic selection integration	Conceptual	✗ None	Conceptual	✗ None	✗ None	★★★ Critical

Key Finding: C. oleifera UAV research remains in an early detection-and-counting phase

Three critical gaps define the highest-priority research frontiers: (1) multispectral/hyperspectral field phenotyping, (2) multi-temporal growth monitoring across breeding trials, and (3) integration of UAV-derived phenomic data with genomic selection models. These capabilities are already established or emerging in olive and tea research.

Disease detection and thermal stress assessment are also absent, despite proven methodologies in comparable tree crops.

Maturity scale: Mature Advanced Moderate Early None | Gap priority: ★★★ = Critical gap requiring immediate attention ★★ = High priority Low = Active progress being made

Fig. 3 Comparison of the research maturity of UAV-based phenotyping across five tree crops, highlighting critical gaps for *C. oleifera*. This assessment is based on published literature through to early 2026.

frameworks established for forest trees[72–74], Li et al.[28] showed that UAV multispectral time-series data alone without molecular markers achieved prediction accuracies of 0.52–0.56 for the growth and wood quality traits of slash pine (*Pinus elliottii*) in genomic best linear unbiased prediction (GBLUP) models. Translating this approach to *C. oleifera* could dramatically accelerate breeding, but it requires the ability to acquire multitemporal and multisensor data, which does not yet exist for this species.

Environmental and operational challenges

The environments in which *C. oleifera* is cultivated present distinctive operational challenges that are substantially more demanding than the relatively flat, open orchard systems in which most UAV phenotyping research has been conducted (Table 3). The mountainous terrain across southern China's subtropical hill regions degrades the accuracy of the global positioning system (GPS) via multipath signals, requires terrain-following flight modes that reduce surveys' efficiency, and generates variable illumination across slope aspects that distorts vegetation indices[31,69]. The high canopy closure (frequently exceeding 0.7) in mature plantations causes severe crown overlap in 2D imagery, limiting the effectiveness of standard detection algorithms optimized for isolated tree crowns.

The phenological characteristics of *C. oleifera* add biological complexity. As an evergreen species, *C. oleifera* offers no leaf-off acquisition window for revealing the understory structure. The unusual simultaneous flowering and fruiting phenology—the flowers emerge October through December while the prior year's fruits mature—creates a narrow optimal window for fruit-specific imaging[54]. The small fruit size (2–4 cm in diameter) with green coloring against a green foliage background creates a green-on-green detection challenge that demands either very low flight altitudes (3–8 m), which limit coverage and increase the collision risk, or spectral information beyond the visible range. Compounding these biological constraints, the subtropical monsoon climate brings frequent cloud cover, mist, and precipitation that reduce the available flight days to an estimated 10–15 clear-sky days per month during the growing season, making multitemporal monitoring logistically challenging without flexible, rapid-deployment UAV capabilities.

Emerging technologies and future directions

Closing the gaps identified above will require not only the straightforward extension of established methods to *C. oleifera*, but also the adoption of emerging technologies that address the species' specific challenges. We evaluate six technology domains with the greatest potential to transform *C. oleifera* breeding phenotyping over the next decade (Fig. 4). Critically, these six technology domains are not independent pathways but form an interconnected capability stack. Multisensor fusion generates the high-dimensional data required by foundation models for effective transfer learning; edge computing enables the real-time processing needed for adaptive multisensor flights; under-canopy navigation extends the observable trait space that can feed into digital twin platforms; and phenomic selection provides the quantitative genetic framework for converting upstream sensing data into actionable breeding decisions (Table 4). The following subsections examine each domain individually while highlighting these synergistic linkages.

Multisensor fusion

The most immediately actionable advancement is the deployment of multisensor fusion campaigns that combine complementary data streams in a single flight or coordinated flight series. Li et al.[23] demonstrated this principle for phenotyping tea by simultaneously deploying five sensor types (multispectral, thermal, RGB, LiDAR, and tilt camera), showing that multisource fusion consistently outperformed individual sensors: Height estimation reached R^2 = 0.82, chlorophyll achieved R^2 = 0.87, and leaf water content achieved R^2 = 0.62. Rincón et al.[71] also demonstrated a four-dimensional phenotyping model integrating LiDAR and multispectral data for temporal plant growth monitoring. For *C. oleifera* breeding, a minimal effective configuration would combine LiDAR (canopy structure), multispectral (vigor/NDVI), and RGB (fruit detection) on a single platform. Thermal imaging could be added as a fourth modality for screening drought tolerance[44]. For *C. oleifera* specifically, multisensor fusion addresses two species-specific challenges that single-sensor approaches cannot resolve: The 'green-on-green' fruit detection problem, where green fruits measuring 2–4 cm are indistinguishable from the foliage in RGB imagery alone but exhibit distinct spectral signatures in the near infrared (NIR) and SWIR regions, and the severe crown overlap under high canopy closure (> 0.7), where LiDAR-derived 3D structures are essential for disambiguating individual tree boundaries that are irrecoverable from 2D multispectral imagery.

Foundation model transfer learning

The data scarcity problem—we have insufficient annotated *C. oleifera* UAV imagery to train deep learning models from scratch—can be addressed through transfer learning from foundation models.

As reviewed in section "Foundation models and transfer learning", foundation models including SAM/SAM2[65] and remote sensing-specific models such as Prithvi[66] offer pretrained representations that may be adaptable to C. oleifera with minimal labeled data. Chen et al.[68] demonstrated that adapting vision-based foundation models with LoRA for plant phenotyping achieved near state-of-the-art performance, suggesting a viable path for rapid capability development in *C. oleifera* without prohibitive data collection costs. The broader trend toward geospatial foundation models promises

Table 3. Summary of critical research gaps and priority tasks for UAV-based *C. oleifera* phenotyping.

Research gap	Current status	Impact on breeding	Priority
Multispectral field phenotyping	Not attempted for *C. oleifera*	Prevents nondestructive screening of vigor/chlorophyll across genotypes	High (1–2 yr)
Aerial disease detection	Not attempted; lab spectroscopy only	Cannot screen for anthracnose resistance at scale	High (1–2 yr)
Multitemporal growth monitoring	Absent; all studies used a single time point	Blocks genetic parameter estimation (heritability, breeding values)	High (2–3 yr)
Phenomic–genomic integration	Unexplored for *C. oleifera*	Cannot leverage UAV data for accelerating genomic selection	Transformative (3–5 yr)
Cross-site model generalization	Not evaluated	Limits deployment across multienvironment breeding trials	Medium (2–3 yr)
Under-canopy phenotyping	No capability exists	Invisible lower-branch fruit and trunk traits excluded from evaluations	Long-term (5–7 yr)

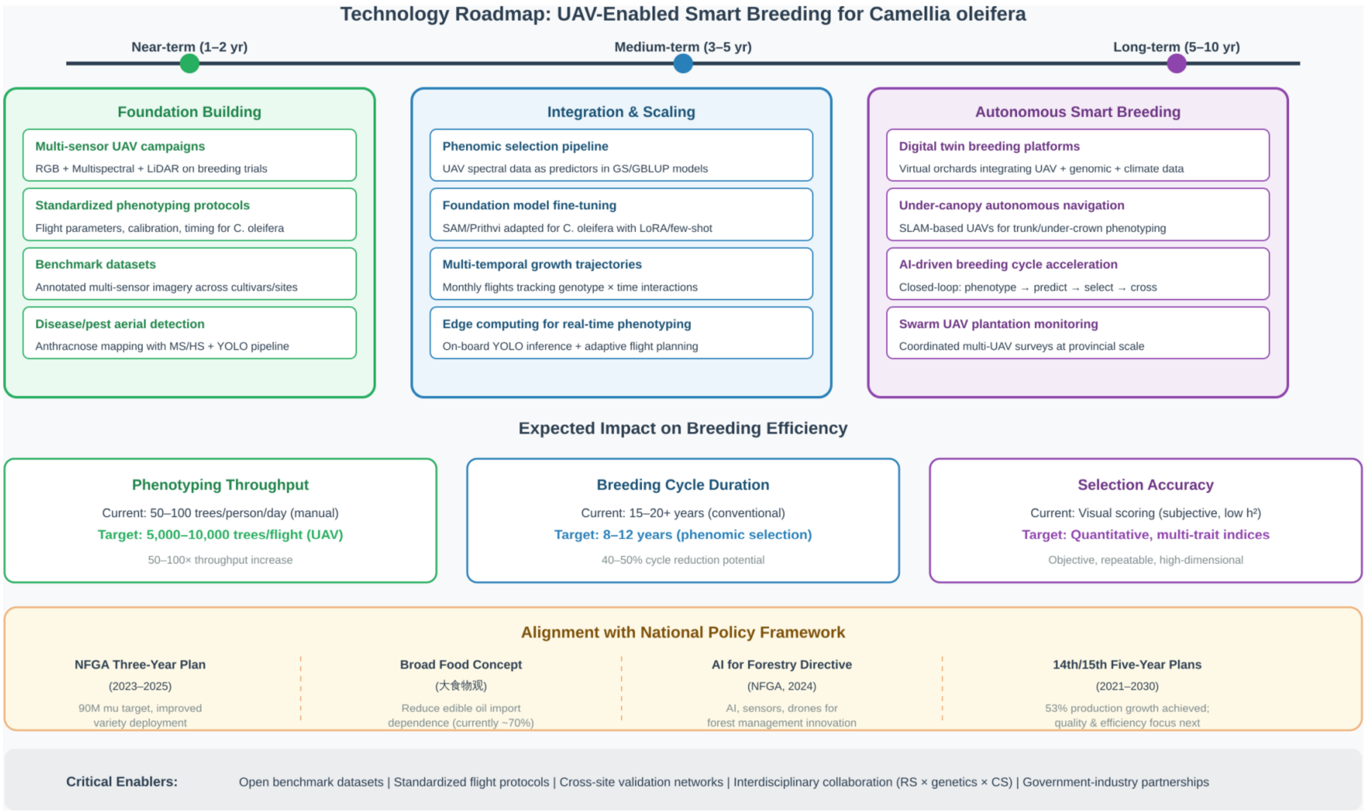


Fig. 4 Technology roadmap for UAV-enabled smart breeding of *C. oleifera*, showing near-, medium-, and long-term priorities aligned with China's national policy framework.

Table 4. Emerging technologies for *C. oleifera* UAV phenotyping: readiness, impact potential, and implementation requirements.

Technology	TRL	Timeline	Impact	Key barrier	Required infrastructure
Multisensor fusion	TRL 6–7	1–2 years	High	Cost (US$50–100 K)	Multipayload UAV, calibration protocols
Foundation model fine-tuning	TRL 4–5	2–3 years	High	GPU computer	Annotated benchmarks (500+ trees), GPU cluster
Edge computing phenotyping	TRL 5–6	2–4 years	Medium	Model compression	Jetson hardware, lightweight models
Under-canopy SLAM-UAV	TRL 3–4	5–7 years	High	Safety	Custom UAV, LiDAR-SLAM, obstacle avoidance
Digital twin platforms	TRL 3–4	5–10 years	Very high	System integration	Cloud platform, multisource data APIs
Phenomic selection	TRL 4–5	3–5 years	Transformative	Multiyear data	Multitemporal UAV, genotyping, quantitative genetics

TRL, Technology readiness level (1–9 scale). TRL 3–4 = experimental proof of concept; TRL 5–6 = validated in a relevant environment; TRL 7+ = demonstrated in an operational environment. SLAM, simultaneous localization and mapping; GPU, graphics processing unit; APIs, application programming interfaces.

increasingly powerful pretrained representations for domain-specific fine-tuning[48].

Edge computing for real-time phenotyping

Processing UAV imagery on board the aircraft, rather than downloading and processing after the flight, would enable real-time decision-making including adaptive flight path planning based on the initial detection results. Lightweight YOLO variants deployed on NVIDIA Jetson Nano or similar edge computing platforms achieved inference speeds of 3–5 ms per frame, which is sufficient for real-time fruit counting during flight. Hayajneh et al.[75] presented a TinyML framework for transfer learning on UAV edge devices specifically designed for agricultural monitoring, demonstrating that compressed models retain sufficient accuracy for operational decision-making. For *C. oleifera*, edge computing could enable the UAV to automatically adjust its altitude and flight path density according to the canopy complexity detected in real-time. Emerging 5G–UAV integration architectures[76] could enable low-latency offloading to cloud resources when the on-board computer is insufficient. In *C. oleifera* plantations on steep terraced slopes, real-time canopy complexity assessments could trigger automatic altitude reduction from the standard survey height (30–50 m) to close-range fruit detection mode (3–8 m) over high-priority genotypes, maximizing both coverage efficiency and phenotyping resolution within a single adaptive flight mission.

Under-canopy autonomous navigation

An entirely new phenotyping dimension opens with the development of SLAM-based (simultaneous localization and mapping) autonomous UAV navigation under the forest canopy. Conventional above-canopy UAV flights cannot observe trunk characteristics, under-crown fruit loads, or lower-canopy disease symptoms. Liu et al.[77] demonstrated large-scale autonomous flight with real-time semantic SLAM under a dense forest canopy. Multi-UAV search strategies for under-canopy operation have also been explored[78]. For breeding *C. oleifera*, under-canopy UAVs could enable measurements of trunk diameter, comprehensive counting of fruits on lower branches invisible from above, and close-range disease assessment throughout the canopy profile. The technological readiness is advancing rapidly. This capability is particularly relevant for *C.*

oleifera because the evergreen, high-density canopy makes a substantial proportion of the fruit load, especially on the lower branches, invisible to conventional above-canopy nadir imagery, and the mountainous terrain with narrow inter-row spacing (often 2–3 m) presents a navigation environment that is more challenging than the open-row orchards where most UAV phenotyping research has been conducted. However, operational deployment in *C. oleifera*'s densely planted, sloping terrain remains a medium- to long-term prospect.

Digital twin platforms

The integration of multitemporal UAV data, soil sensors, weather station data, genetic information, and management records into unified digital twin platforms represents the long-term vision for smart breeding systems[79,80]. A digital twin of a *C. oleifera* breeding trial would maintain a continuously updated virtual representation of every tree, enabling the simulation of management interventions, predictions of genotype performance under alternative climate scenarios, and optimization of crossing schemes based on comprehensive phenotypic and genetic data.

Phenomic selection integration

Perhaps the most transformative opportunity lies at the intersection of UAV phenotyping and quantitative genetics through phenomic selection, whose foundational proof of concept in wheat and poplar[29] and the extension to tree breeding[28] were discussed in section "Critical technology gaps".

For *C. oleifera*, where the reference genome has recently been assembled[14] and SNP resources are emerging, the combination of UAV-derived phenomic predictors with genomic data in multikernel GBLUP models could dramatically improve selection accuracy while reducing reliance on laborious field phenotyping. The genomic selection infrastructure developed for *Eucalyptus*[73] and reviewed across forest tree species[72,74] provides methodological templates that are directly applicable to *C. oleifera*. Generative adversarial network (GAN)-based data augmentation approaches, which have already been proven for remote sensing-based classification[81], could further expand the training datasets for phenomic models.

Conclusions and research roadmap

This review has provided the first comprehensive synthesis of UAV-based remote sensing technologies for the breeding and cultivation of *C. oleifera*, revealing a field poised for rapid advancement. The current state of research, concentrated on RGB-based crown segmentation, tree detection, and fruit-based yield estimation, has established the proof of concept for UAV-based phenotyping in oil tea environments, with accuracies that are already operationally useful (crown segmentation F-scores up to 0.975, tree counting R^2 values of 0.94, yield estimation R^2 values of 0.905). However, the comparison with olive, tea, oil palm, and *Citrus* research reveals that *C. oleifera* lags substantially behind in the deployment of multispectral, hyperspectral, thermal, and multitemporal sensing—the very capabilities required to transition from plantation inventory to breeding-oriented phenotypic evaluation.

On the basis of the evidence reviewed, we propose a prioritized research agenda organized around three time horizons. In the near term (1–2 years), the immediate priorities are (1) deploying multisensor UAV campaigns (LiDAR + multispectral + RGB) over structured breeding trials with known genotype identities; (2) establishing standardized flight protocols and calibration procedures adapted to *C. oleifera*'s mountainous terrain and phenological timing[30,69]; (3) creating open benchmark datasets with multisensor imagery and field-validated trait measurements to enable reproducible algorithm development; and (4) conducting the first aerial disease detection studies targeting anthracnose using multispectral and hyperspectral approaches proven in comparable tree crop systems.

In the medium term (3–5 years), the research focus should advance toward (1) multitemporal monitoring of growth trajectories through repeated flights across seasons and years, providing the longitudinal data essential for genetic parameter estimation; (2) integration of phenomic selection, using UAV-derived spectral features as predictors in genomic selection models following the methodology demonstrated by Rincent et al.[29] and Li et al.[28]; (3) foundation model adaptation (SAM, Prithvi) for *C. oleifera*-specific phenotyping tasks with minimal labeled data; and (4) deploying edge computing for real-time on-board phenotyping and adaptive flight planning.

In the long term (5–10 years), the vision encompasses (1) digital twin breeding platforms integrating UAV data, genomic information, climate data, and management records into continuously updated virtual representations of breeding trials; (2) under-canopy autonomous UAV navigation for trunk and lower-canopy phenotyping; (3) artificial intelligence (AI)-driven closed-loop breeding systems where phenotypic data acquisition, prediction, selection, and crossing recommendations are integrated into semiautomated pipelines; and (4) coordinated multi-UAV swarm monitoring at the provincial scale to support national variety deployment decisions.

Realizing this roadmap requires not only technological development but also institutional and interdisciplinary commitment. The gap between remote sensing engineering and tree breeding science must be bridged through collaborative teams that embed geneticists, physiologists, and breeders alongside computer vision and remote sensing specialists. Standardized protocols for the acquisition and processing of UAV data and phenotypic trait extraction must be developed and adopted across the *C. oleifera* research community to ensure reproducibility and comparability. Open data initiatives, including shared benchmark datasets and processing codes, will be essential for accelerating progress beyond isolated case studies.

The convergence of unprecedented government investment in the oil tea industry, rapidly maturing UAV sensor and AI technologies, and the demonstrated success of UAV phenotyping in comparable tree crops creates a unique window of opportunity. By strategically closing the identified research gaps, UAV-based remote sensing can evolve from a monitoring tool to a core engine of genetic improvement, contributing directly to China's food security objectives and the sustainable intensification of its most valuable woody oil crop.

Author contributions

The authors confirm their contributions to the paper as follows: wrote the manuscript: Wang K, Ye H; designed the idea: Huang G, Wang X; performed revisions of the manuscript: Long W, Yao X, Yu C. All authors reviewed the results and approved the final version of the manuscript.

Data availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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