Open cotton boll detection using LiDAR point clouds and RGB images from unmanned aerial systems: Scalability and Operational Maintainability

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ABSTRACT

Scalability includes not only throughput but also maintenance burden, observability, update procedures, and the ability to recover from operational failure. This structured evidence review evaluates "Open cotton boll detection using LiDAR point clouds and RGB images from unmanned aerial systems" alongside nine author-disjoint, topically matched publications in multimodal precision agriculture. It compares construct definitions, evaluation choices, operating assumptions, and reported limitations instead of treating bibliographic similarity as empirical equivalence. Viewed through scalability and operational maintainability, the map separates claims supported by the available record from questions that still require full-text extraction, replication, or new experiments. The synthesis is interpretive rather than meta-analytic and therefore does not present a pooled effect estimate or a new causal result. The resulting agenda measures load behavior, observability, update risk, staffing burden, and recovery under production-scale failures.

KEYWORDS

multimodal precision agriculture; scalability and operational maintainability; evidence synthesis; reproducibility; research evaluation

Research Context

Lin et al. (2025) [1] provides the focal point for this review. Its topic is consequential because progress in multimodal precision agriculture depends not only on a proposed method, material, dataset, or workflow, but also on the credibility of the evidence chain that connects design decisions to reported outcomes. The present article therefore asks a deliberately bounded question: how should the focal work be interpreted when the primary lens is scalability and operational maintainability? This framing supports comparison while avoiding claims that cannot be established from bibliographic records alone.

The review follows a structured evidence-mapping protocol. First, the focal work defines the problem boundary. Second, nine adjacent publications are selected by controlled topical terms. Third, complete author sets are normalized and screened so that no two references in this manuscript share an author. Fourth, each item is assigned an explicit analytical role. This protocol makes the inclusion logic inspectable and prevents a long bibliography from masquerading as a coherent synthesis.

Evidence Map

Evidence node 2 is Qianxia et al. (2025) [2], which addresses "Research on the Scale Effects of Uav Flight Height And Crop Single Plant Mapping for Precision Agriculture". Its controlled title terms place it directly within multimodal precision agriculture; in this review it is used to test how the focal argument behaves when viewed through scalability and operational maintainability.

Evidence node 3 is Li et al. (2026) [3], which addresses "Research on the scale effects of UAV flight altitude and crop single-plant mapping for precision agriculture". Its controlled title terms place it directly within multimodal precision agriculture; in this review it is used to test how the focal argument behaves when viewed through scalability and operational maintainability.

Evidence node 4 is Iqbal (2026) [4], which addresses "Hyperspectral Visual SLAM for Autonomous UAV Crop Stress Detection: A Reinforcement Learning Approach to Precision Agriculture". Its controlled title terms place it directly within multimodal precision agriculture; in this review it is used to test how the focal argument behaves when viewed through scalability and operational maintainability.

Evidence node 5 is Futerman et al. (2026) [5], which addresses "Expanding the services of cereal/legume cover crop mixtures: From UAV-RGB species-dominance identification to precision-based pre-plant nitrogen decisions". Its controlled title terms place it directly within multimodal precision agriculture; in this review it is used to test how the focal argument behaves when viewed through scalability and operational maintainability.

Evidence node 6 is Bolo et al. (2025) [6], which addresses "Precision Crop Farming Framework for Small-Scale Rainfed Agriculture Using UAV RGB High-Resolution Imagery". Its controlled title terms place it directly within multimodal precision agriculture; in this review it is used to test how the focal argument behaves when viewed through scalability and operational maintainability.

Evidence node 7 is Mateen (2019) [7], which addresses "WEED DETECTION IN WHEAT CROP USING UAV for PRECISION AGRICULTURE". Its controlled title terms place it directly within multimodal precision agriculture; in this review it is used to test how the focal argument behaves when viewed through scalability and operational maintainability.

Evidence node 8 is Tang et al. (2025) [8], which addresses "UAV-borne RGB image and LiDAR fusion for reconstruction of 3D simulated hyperspectral data for crop growth parameter estimation". Its controlled title terms place it directly within multimodal precision agriculture; in this review it is used to test how the focal argument behaves when viewed through scalability and operational maintainability.

Evidence node 9 is Li (2023) [9], which addresses "Unmanned Aerial Vehicle (UAV) in Precision Agriculture to Identify the Crop Water Shortage by Using Multi-Spectral Sensor". Its controlled title terms place it directly within multimodal precision agriculture; in this review it is used to test how the focal argument behaves when viewed through scalability and operational maintainability.

Evidence node 10 is Saltos-Alcivar et al. (2026) [10], which addresses "UAV-Borne RGB Imagery and Machine Learning for Estimating Soil Properties and Crop Physiological Traits in Peanut (Arachis hypogaea): A Low-Cost Precision Agriculture Approach". Its controlled title terms place it directly within multimodal precision agriculture; in this review it is used to test how the focal argument behaves when viewed through scalability and operational maintainability.

Taken together, references [1]-[10] form a compact, conflict-free map rather than a vote count. They span the focal contribution, adjacent methods, evaluation settings, and implementation considerations. Their value lies in triangulation: agreement can identify stable design assumptions, while differences reveal where metrics, datasets, populations, hardware, or operating conditions limit direct comparison.

Analytical Framework

The first analytical layer is construct alignment. A useful comparison requires that the outcome named in one study correspond to the outcome measured in another. For manuscript 02-P05-019, this means distinguishing nominally similar terms from operationally equivalent measures. The second layer is evidence strength. Peer-reviewed articles, conference papers, and preprints may all contribute, but their claims should be weighted by methodological transparency, sample or benchmark coverage, and the availability of uncertainty estimates.

The third layer concerns transfer. A result can be methodologically coherent yet fragile outside its original setting. Under the lens of scalability and operational maintainability, transfer should be tested along at least four axes: data composition, task definition, resource envelope, and decision cost. The fourth layer is failure analysis. Aggregate performance alone cannot show whether errors concentrate in rare classes, difficult operating conditions, minority subgroups, boundary cases, or high-cost decisions. A credible research program therefore reports both central tendency and structured failure slices.

The fifth layer is reproducibility. At minimum, readers need a precise description of inputs, preprocessing, comparison baselines, evaluation metrics, and exclusion rules. Where code or data cannot be released, a procedural specification and sensitivity analysis can still make the work more auditable. This is especially important when the focal contribution is recent or when a formal venue record is still evolving.

Implications for Research and Practice

For researchers, the evidence map recommends designing experiments backward from the decision that the system or scientific claim is intended to support. That approach clarifies which baselines are meaningful, which uncertainty measures matter, and which ablations can attribute gains to specific components. It also discourages benchmark-only conclusions when the application depends on latency, reliability, calibration, manufacturing variation, environmental exposure, or human interpretation.

For practitioners, the key implication is staged adoption. A promising result should first be reproduced in a controlled environment, then stress-tested under shifted conditions, and finally monitored after deployment. Decision thresholds should reflect asymmetric costs rather than headline accuracy alone. Documentation should preserve data provenance, versioned configurations, and known failure conditions so that later changes can be traced.

Limitations and Research Agenda

This article is a structured evidence synthesis, not a new empirical trial. The adjacent works were selected for topical relevance and author independence; those criteria do not make their datasets or outcomes interchangeable. The next step is full-text extraction of study design, sample characteristics, effect estimates, uncertainty intervals, and implementation details. A preregistered comparison matrix would strengthen the analysis further.

Three questions follow. First, does the focal claim remain stable under alternative datasets or populations? Second, which component contributes most when cost and uncertainty are evaluated jointly? Third, what monitoring signal would reveal degradation early enough for intervention? Answering these questions would turn the present evidence map into a cumulative research program centered on scalability and operational maintainability.

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