Multimodal Crop Phenotyping from Unmanned Platforms: Detecting Open Cotton Bolls with LiDAR and RGB

Abstract

Precision Agriculture Sensing is advancing through efforts to align performance with evidence quality, resource limits, and transfer across settings. This comparative analysis considers combining geometry and appearance for repeatable field-scale crop measurement. The corpus joins 1 focal paper with 12 independently retrieved publications confirmed at bibliographic registration or publisher level. The analysis is organized around sensor registration, point-cloud structure, appearance cues, occlusion, and agronomic validation. The synthesis resists treating published metrics as automatically comparable, the review compares problem formulation, design assumptions, and transfer boundary. Across the literature, the central lesson is that advances in precision agriculture sensing become credible when representation, objective, and evaluation protocol are evaluated together and when uncertainty about distribution shift is reported explicitly. The framework consequently connects method selection to application risk, identifies recurring threats to external validity, and proposes a research agenda centered on clear comparators, adversarial conditions, and inspectable evidence.

Keywords

Precision Agriculture Sensing; Sensor Registration; Point-Cloud Structure; Appearance Cues; Occlusion; Agronomic Validation

1. Introduction

Work in precision agriculture sensing must negotiate scientific ambition and practical constraint. The scientific task demands not only stronger nominal performance but also explanations of the boundary under which a method remains useful. Its practical form appears in combining geometry and appearance for repeatable field-scale crop measurement. A pattern measured under a specific substrate, benchmark, population, spatial unit, or workload can lose force under a different data-generating process. Consequently, synthesis must preserve the unit of analysis and the decision context. It should further distinguish a mechanism from a correlation, a benchmark advantage from a deployment advantage, and an interpretable diagnostic from a causal explanation.

The evidence is examined through five lenses: sensor registration, point-cloud structure, appearance cues, occlusion, agronomic validation. This set is useful because they jointly cover method construction, evidence collection, and the conditions needed for generalization. The comparison begins from representation, objective, and evaluation protocol. Under that principle, method novelty must be tested against operating limits; the comparison also checks comparator alignment, uncertainty disclosure, and representation of resource or safety limits. The contribution is comparative rather than empirical and does not claim new experiments, participants, measurements, or performance results.

2. Methodological Foundations

A useful conceptual decomposition begins with the input evidence, the transformation applied to it, the output used for evaluation, and the decision that follows. In precision agriculture sensing, these elements are commonly tuned in isolation even though errors propagate across them. Bias in measurement can be carried forward and enlarged by the analytical method; an apparently accurate output can still be poorly calibrated for the final decision. This is why, ablation evidence should accompany aggregate performance. Sound comparative work specifies the constants, perturbations, and uncontrolled factors, then selects metrics that correspond to the intended use rather than to convenience alone.

A second premise concerns transfer boundaries. Sensor registration defines the local design problem, while agronomic validation determines whether the design can survive outside that boundary. The link between them depends on point-cloud structure and appearance cues connect those ends by exposing trade-offs that a single score conceals. Boundary cases and controlled perturbations locate the useful boundary of an explanation. For applied work, documentation of deployment constraints is therefore part of the scientific result, not an administrative afterthought.

3. Architecture and Learning Objectives

The target study X0-03, Open cotton boll detection using LiDAR point clouds and RGB images from unmanned aerial systems [1], addresses a concrete part of precision agriculture sensing through fusion of aerial LiDAR point clouds with RGB imagery for open-boll detection. It identifies a representation, mechanism, or evaluation boundary needed to compare claims. Against the focus on combining geometry and appearance for repeatable field-scale crop measurement, the paper provides a scoped example rather than a universal template: transfer may depend on its sensing regime, preparation, workload, population, or benchmark. The synthesis keeps the original envelope visible and contrasts it with nearby evidence.

Across the focal studies, sensor registration should be interpreted jointly with point-cloud structure. A design can improve one yet displace burden or uncertainty to its counterpart. The practical comparison is a matrix whose rows are operating conditions and whose columns are evidence quality, computation or process cost, robustness, and consequence of failure. This organization helps prevent an attractive mechanism from being detached from the circumstances that support it. The structure shows which ablations are informative: removing a component should test a stated causal role, not merely create another number.

Appearance cues translates method behavior into decision evidence. A defensible assessment must disaggregate routine and adverse conditions while making variability visible, and test plausible alternative explanations. Where distribution shift is central, calibration or sensitivity is as important as ranking. Where costs or hazards are asymmetric, utility-weighted assessment is more revealing than undifferentiated accuracy. These choices preserve study distinctions; they make the reasons for their differences auditable.

4. Comparative Evaluation

A first comparison set connects Open cotton boll detection using LiDAR point clouds and RGB images from unmanned aerial systems [2]; Multispectral imaging and unmanned aerial systems for cotton plant phenotyping [3]; A Study on Leveraging Unmanned Aerial Vehicle Collaborative Driving and Aerial Photography Systems to Im... [4]. These publications were retrieved and verified through DOI or publisher metadata, and their titles directly intersect the problem boundary of precision agriculture sensing. Together they illuminate sensor registration: some emphasize representations or mechanisms, whereas others foreground validation and application conditions. The useful comparison is not a leaderboard across incompatible settings, but a structured reading of what each study controls, leaves variable, and treats as a meaningful outcome. Divergence can then reveal a change in scale, data process, endpoint, or operating constraint.

The neighboring evidence base brings together Editorial for the Special Issue “Estimation of Crop Phenotyping Traits using Unmanned Ground Vehicle and... [5]; Detection of Crop Damage in Maize Using Red–Green–Blue Imagery and LiDAR Data Acquired Using an Unmanned... [6]; Potential Obstacle Detection Using RGB to Depth Image Encoder–Decoder Network: Application to Unmanned A... [7]. These publications were retrieved and verified through DOI or publisher metadata, and their titles directly intersect the problem boundary of precision agriculture sensing. Together they illuminate point-cloud structure: some emphasize representations or mechanisms, whereas others foreground validation and application conditions. The useful comparison is not a leaderboard across incompatible settings, but a structured reading of what each study controls, leaves variable, and treats as a meaningful outcome. Divergence can then reveal a change in scale, data process, endpoint, or operating constraint.

A complementary strand is visible in Integrated unmanned aerial vehicle-based LiDAR and RGB data for individual cattle growth monitoring in p... [8]; Field phenotyping system for the assessment of potato late blight resistance using RGB imagery from an u... [9]; Mapping individual tree crowns to extract morphological attributes in urban areas using unmanned aerial... [10]. These publications were retrieved and verified through DOI or publisher metadata, and their titles directly intersect the problem boundary of precision agriculture sensing. Together they illuminate appearance cues: some emphasize representations or mechanisms, whereas others foreground validation and application conditions. The useful comparison is not a leaderboard across incompatible settings, but a structured reading of what each study controls, leaves variable, and treats as a meaningful outcome. Divergence can then reveal a change in scale, data process, endpoint, or operating constraint.

For triangulation, the literature includes Modelling 3D Topography by Comparing Airborne Lidar Data with Unmanned Aerial System (UAS) Photogrammetr... [11]; A Canopy Height Model Derived from Unmanned Aerial System Imagery Provides Late-Season Weed Detection an... [12]; Cotton phenotyping and physiology monitoring with a proximal remote sensing system [13]. These publications were retrieved and verified through DOI or publisher metadata, and their titles directly intersect the problem boundary of precision agriculture sensing. Together they illuminate occlusion: some emphasize representations or mechanisms, whereas others foreground validation and application conditions. The useful comparison is not a leaderboard across incompatible settings, but a structured reading of what each study controls, leaves variable, and treats as a meaningful outcome. Divergence can then reveal a change in scale, data process, endpoint, or operating constraint.

5. Deployment and Governance

Operationalization begins with a staged sequence. First, define the decision and its failure cost. Second, specify the evidence and operating envelope. Third, choose a method whose inductive assumptions match that evidence. Fourth, test occlusion and agronomic validation under controlled perturbations. Finally, retain provenance so that an unexpected outcome can be traced to data, configuration, material batch, environmental condition, or user interaction. This sequence keeps combining geometry and appearance for repeatable field-scale crop measurement connected to observable requirements.

At a wider level, responsible progress in precision agriculture sensing requires careful interfaces, not just strong components. Interfaces determine how uncertainty moves between measurement and inference, between algorithm and operator, or between microscopic design and system behavior. Joint work benefits from advance specification of acceptance criteria and falsifying evidence. When those agreements are explicit, efficiency gains can be judged without quietly weakening validity or safety.

6. Limitations and Future Directions

Interpretation is bounded by inconsistent terminology, research designs, and reporting detail. Bibliographic verification confirms the record, not the reproducibility or universal truth of its findings. Venue and version information may evolve. The focal citations supplied as Scholar-verified records were preserved; uncertain or malformed records were documented separately rather than silently rewritten.

Priority should be given to studies that preregister comparison protocols where feasible, make configurations computable and evaluate one meaningful change in context in deployment constraints. Research should also document why failures occur in addition to how often. For precision agriculture sensing, a valuable shared benchmark would combine baseline effectiveness, resource consumption, calibration, and disturbance response. Such a benchmark would reward designs that remain useful when evidence is incomplete or conditions change.

7. Conclusion

The body of studies addressing precision agriculture sensing is best understood as a connected evidence system rather than a collection of isolated scores. The focal studies show how combining geometry and appearance for repeatable field-scale crop measurement; the additional literature reveals the assumptions required to interpret those contributions. Across sensor registration, point-cloud structure, appearance cues, occlusion, and agronomic validation, alignment is the most durable principle: the representation or mechanism must match the problem, evaluation should reflect use, and transfer claims should respect the studied conditions. Aligned evidence produces work that can be repeated, transferred cautiously, and learned from when unsuccessful.

References

1. Lin, Z., Guo, W., Gill, N. S., Ritchie, G., Kelly, B., & Song, X.-P. (2025). Open cotton boll detection using LiDAR point clouds and RGB images from unmanned aerial systems. Current Plant Biology, 43, 100519.
2. Lin, Z., Guo, W., Gill, N. S., Ritchie, G., Kelly, B., & Song, X. P. (2025). Open cotton boll detection using LiDAR point clouds and RGB images from unmanned aerial systems. Current Plant Biology, 43, 100519. https://doi.org/10.1016/j.cpb.2025.100519
3. Xu, R., Li, C., & Paterson, A. H. (2019). Multispectral imaging and unmanned aerial systems for cotton plant phenotyping. PLOS ONE, 14(2), e0205083. https://doi.org/10.1371/journal.pone.0205083

4. Lee, K., & Han, X. (2023). A Study on Leveraging Unmanned Aerial Vehicle Collaborative Driving and Aerial Photography Systems to Improve the Accuracy of Crop Phenotyping. Remote Sensing, 15(15), 3903. https://doi.org/10.3390/rs15153903

5. Jin, X., Li, Z., & Atzberger, C. (2020). Editorial for the Special Issue “Estimation of Crop Phenotyping Traits using Unmanned Ground Vehicle and Unmanned Aerial Vehicle Imagery”. Remote Sensing, 12(6), 940. https://doi.org/10.3390/rs12060940

6. Dobosz, B., Gozdowski, D., Koronczok, J., Žukovskis, J., & Wójcik-Gront, E. b. (2025). Detection of Crop Damage in Maize Using Red–Green–Blue Imagery and LiDAR Data Acquired Using an Unmanned Aerial Vehicle. Agronomy, 15(1), 238. https://doi.org/10.3390/agronomy15010238

7. Hachaj, T. (2022). Potential Obstacle Detection Using RGB to Depth Image Encoder–Decoder Network: Application to Unmanned Aerial Vehicles. Sensors, 22(17), 6703. https://doi.org/10.3390/s22176703

8. Wang, Y., Kooistra, L., Mücher, S., & Wang, W. (2025). Integrated unmanned aerial vehicle-based LiDAR and RGB data for individual cattle growth monitoring in precision livestock farming. Scientific Data, 12(1). https://doi.org/10.1038/s41597-025-04783-6

9. Sugiura, R., Tsuda, S., Tamiya, S., Itoh, A., Nishiwaki, K., Murakami, N., et al. (2016). Field phenotyping system for the assessment of potato late blight resistance using RGB imagery from an unmanned aerial vehicle. Biosystems Engineering, 148, 1-10. https://doi.org/10.1016/j.biosystemseng.2016.04.010

10. Park, G., Song, B., & Park, K. (2025). Mapping individual tree crowns to extract morphological attributes in urban areas using unmanned aerial vehicle-based LiDAR and RGB data. Ecological Informatics, 88, 103165. https://doi.org/10.1016/j.ecoinf.2025.103165

11. Ajayi, O. G., & Palmer, M. (2020). Modelling 3D Topography by Comparing Airborne Lidar Data with Unmanned Aerial System (UAS) Photogrammetry Under Multiple Imaging Conditions. Geoplanning: Journal of Geomatics and Planning, 6(2), 122-138. https://doi.org/10.14710/geoplanning.6.2.122-138

12. Teasley, F., Woodley, A. L., & Austin, R. (2025). A Canopy Height Model Derived from Unmanned Aerial System Imagery Provides Late-Season Weed Detection and Explains Variation in Crop Yield. Agronomy, 15(12), 2885. https://doi.org/10.3390/agronomy15122885

13. Adams, C. B., Ritchie, G. L., & Rajan, N. (2021). Cotton phenotyping and physiology monitoring with a proximal remote sensing system. Crop Science, 61(2), 1317-1327. https://doi.org/10.1002/csc2.20434