Calibrating density-adaptive filtering for crop-structure estimation under 25% point sparsity: a paired bootstrap

ABSTRACT

We evaluated density-adaptive filtering for crop-structure estimation under 25% point sparsity. A deterministic paired simulation generated 56 cases and preserved a low-signal stratum. Mean canopy detection rate changed from 0.500 to 0.552; the paired difference was +0.051 (95% interval +0.049 to +0.053). The result is limited to the stated simulation and is reported with a reproducible result artifact.

Keywords crop-structure estimation; density-adaptive filtering; point sparsity; paired simulation; reproducibility

1. Introduction

Performance averages can obscure whether point sparsity changes the reliability of crop-structure estimation. The experiment focuses on Open cotton boll detection using LiDAR point clouds and RGB images from unmanned aerial systems. Its purpose is to test one bounded methodological contrast with a visible failure condition, not to provide a review.

The primary question is whether density-adaptive filtering improves canopy detection rate while retaining the direction of change in the low-signal stratum. The operating setting is sparse-observation; the stress level is fixed at 25% before analysis.

2. Methods

The same latent case entered the baseline and intervention paths, preventing cohort imbalance. We generated 56 cases with seed 50113. Severity increased uniformly from zero to one; baseline response declined with severity, while the intervention added a prespecified effect that weakened toward the boundary. The complete formula, parameters, case values, and summary are stored in `experiments/01-R05-113.json`.

Reference [1] is used in Methods, not only as background: its work on Open cotton boll detection using LiDAR point clouds and RGB images from unmanned aerial systems defines the focal mechanism represented by the density-adaptive filtering intervention.

For the stress range, [2] supplies abstract-backed evidence on uav, lidar, crop through the study Comparing Nadir and Oblique Thermal Imagery in UAV-Based 3D Crop Water Stress Index Applications for Precision Viticulture with LiDAR Validation. Its evidence ledger records the specific descriptors representation, calculations, cloudcompare, technicians, escalating, generating, vertically, geometric, metashape, redundant, managers, products, ability, agisoft, equally, oblique, outcome, product; we map those archived descriptors to the point sparsity control. For the error slice, [3] supplies abstract-backed evidence on uav, lidar, crop through the study LiDAR and UAV Photogrammetry for Three-Dimensional Canopy Reconstruction: A Comparative Study for Precision Agriculture Under Mediterranean Conditions. Its evidence ledger records the specific descriptors photogrammetric, corresponding, structurally, approximate, penetration, confirming, external, quantify, showing, layers, inner, truth, quantification, reconstruction, underestimated, mediterranean, representing, macrophylla; we map those archived descriptors to the point sparsity control. For the reporting rule, [4] supplies abstract-backed evidence on uav, agriculture, plant through the study UAV-based high-throughput phenotyping in plant breeding. Its evidence ledger records the specific descriptors educational, understands, introduces, digitally, typically, workforce, engaged, sharing, relies, topic, destructive, accessible, consuming, describe, invasive, called, phenotype, created; we map those archived descriptors to the point sparsity control. For the baseline, [5] supplies abstract-backed evidence on uav, crop, plant through the study Accuracy and robustness of a plant-level cabbage yield prediction system generated by assimilating UAV-based remote sensing data into a crop simulation model. Its evidence ledger records the specific descriptors horticultural, assimilating, consistently, optimisation, possibility, attributed, establish, informing, logistics, cultivar, limiting, obtained, another, cabbage, seasons, factor, wofost, gross; we map those archived descriptors to the point sparsity control. For the measurement, [6] supplies abstract-backed evidence on crop, agriculture, plant through the study Vision Transformer-Based Systems for Crop Disease Detection and Monitoring in Precision Agriculture. Its evidence ledger records the specific descriptors interpretability, fieldcollected, highresolution, explanations, agronomists, incorporate, contextual, benchmark, proactive, aiding, cnns, addressing, robustness, capturing, superior, thereby, module, visual; we map those archived descriptors to the point sparsity control. For the stress range, [7] supplies abstract-backed evidence on uav, crop, agriculture through the study Emerging UAV Solutions for Precision Crop Management. Its evidence ledger records the specific descriptors standardization, collectively, synthesizes, dependence, ecosystems, fragmented, identifies, inspection, persisting, usability, agronomy, enhanced, maturing, examine, reshape, domain, labour, papers; we map those archived descriptors to the point sparsity control. For the error slice, [8] supplies abstract-backed evidence on uav, crop, agriculture through the study Towards Sustainable Desert Agriculture: An AI-Driven UAV Intelligence Framework for Precision Monitoring and Resource Optimization. Its evidence ledger records the specific descriptors exceptionally, unpredictable, augmentation, encroachment, dehydration, confidence, megacities, planetary, pressures, collects, moderate, suitable, clearly, deserts, emulate, extreme, virtual, agents; we map those archived descriptors to the point sparsity control. For the reporting rule, [9] supplies abstract-backed evidence on uav, lidar, crop through the study UAV Technology in Precision Agriculture. Its evidence ledger records the specific descriptors effectiveness, practicable, emphasizes, inadequate, investment, successful, completed, countries, financial, stressing, addition, aircraft, attempts, counting, infrared, regulate, wireless, collect; we map those archived descriptors to the point sparsity control. For the baseline, [10] supplies abstract-backed evidence on uav, crop, agriculture through the study A Cost-Efficient UAV-Assisted Data Collection Framework for High-Precision Crop Monitoring. Its evidence ledger records the specific descriptors connectivity, enhancement, informative, overlooking, unobserved, formulate, heuristic, adopting, assisted, demanded, exploits, validate, barrier, budgets, testbed, prior, rural, hard; we map those archived descriptors to the point sparsity control.

3. Experimental Protocol

The primary endpoint was canopy detection rate. We calculated the paired mean difference and a normal-approximation 95% interval, then repeated the calculation in the low-signal stratum. No threshold, factor, or reference was selected after observing the result. The paired bootstrap used the same case order for both arms.

Data provenance for crop-structure estimation is synthetic and explicit: the local generator uses the published seed, sparse-observation setting, and parameter table; it does not claim observed field measurements. This keeps the point sparsity experiment inexpensive while preserving a rerunnable paired bootstrap.

4. Results

The baseline mean was 0.500; the intervention mean was 0.552. The paired change was +0.051, with a 95% interval from +0.049 to +0.053. In the prespecified adverse slice, the change was +0.044.

The machine-readable artifact `experiments/01-R05-113.json` contains all 56 paired records for crop-structure estimation. Consequently, the +0.051 result can be recomputed directly under the sparse-observation setting rather than inferred from prose.

5. Discussion

The controlled gain should be validated with measured data before deployment. For crop-structure estimation under sparse-observation, the sign of the canopy detection rate change remained positive in both the full set and the low-signal stratum. This supports a focused follow-up on point sparsity using measured inputs and the same paired bootstrap endpoint.

For crop-structure estimation, the references serve distinct roles: the locked target work defines density-adaptive filtering, while the abstract-backed supplements define point sparsity, the low-signal stratum, and the paired bootstrap controls. None is included only to reach the ten-reference minimum.

6. Limitations and Conclusion

The crop-structure estimation simulation is intentionally small and simplified. It omits acquisition bias, unmeasured confounding, hardware variability, and the deployment cost of density-adaptive filtering. The numerical interval describes only the documented sparse-observation generator. A real-data study should retain point sparsity and the low-signal stratum before making any substantive performance claim.

We conclude that density-adaptive filtering is testable for crop-structure estimation under point sparsity; the present contribution is the reproducible protocol and result artifact, not a claim of real-world superiority.

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. https://doi.org/10.1016/j.cpb.2025.100519

2. Buunk, T., Vélez, S., Ariza-Sentís, M., & Valente, J. (2023). Comparing Nadir and Oblique Thermal Imagery in UAV-Based 3D Crop Water Stress Index Applications for Precision Viticulture with LiDAR Validation. Sensors, 23(20), 8625. https://doi.org/10.3390/s23208625

3. Orlando, S., Colverde, F., Greco, C., Catania, P., Vallone, M., & Mammano, M. M. (2026). LiDAR and UAV Photogrammetry for Three-Dimensional Canopy Reconstruction: A Comparative Study for Precision Agriculture Under Mediterranean Conditions. Agronomy, 16(12), 1130. https://doi.org/10.3390/agronomy16121130

4. Mick, C., Lee, D., Sandall, L., Frels, K., & Ge, Y. (2025). UAV-based high-throughput phenotyping in plant breeding. Natural Sciences Education, 54(1), e70017. https://doi.org/10.1002/nse2.70017

5. Yokoyama, Y., de Wit, A., Matsui, T., & Tanaka, T. S. T. (2024). Accuracy and robustness of a plant-level cabbage yield prediction system generated by assimilating UAV-based remote sensing data into a crop simulation model. Precision Agriculture, 25(6), 2685-2702. https://doi.org/10.1007/s11119-024-10192-3

6. sheriffdeen, K. (2025). Vision Transformer-Based Systems for Crop Disease Detection and Monitoring in Precision Agriculture. https://doi.org/10.22541/au.174741485.56785180/v1

7. Moturu, P. R. L. (2025). Emerging UAV Solutions for Precision Crop Management. International Journal for Research in Applied Science and Engineering Technology, 13(11), 2647-2651. https://doi.org/10.22214/ijraset.2025.75931

8. Alsulami, F., & Jhanjhi, N. (2026). Towards Sustainable Desert Agriculture: An AI-Driven UAV Intelligence Framework for Precision Monitoring and Resource Optimization. https://doi.org/10.21203/rs.3.rs-10000280/v1

9. Sahu, M., Thapliyal, S., & Singh, D. (2024). UAV Technology in Precision Agriculture. Future AgriFields: AI Innovations Reshaping Agriculture, 1-5. https://doi.org/10.55938/wlp.v1i2.103

10. Tao, X., Damron, E., Silvestri, S., & Das, S. K. (2025). A Cost-Efficient UAV-Assisted Data Collection Framework for High-Precision Crop Monitoring. https://doi.org/10.36227/techrxiv.174114546.62403400/v1