Estimation of Leaf Area in Hydroponic Microgreenhouses by Digital Image Processing and Color-Based Segmentation

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Abstract.

Nutrient-film technique (NFT) lettuce production needs timely canopy information for irrigation and fertilizer decisions, yet routine destructive sampling is burdensome for small automated horticulture platforms and conflicts with frequent dashboard updates. Operational trials used the same GreenSe instrumentation stack described by Andrade (2024). Under artificial lighting and reflective NFT conditions, the pipeline had to isolate plant pixels despite glare, overlapping leaves, and color changes as the crop developed. The objectives were (i) to implement a non-destructive pipeline for projected leaf area of greenhouse lettuce (Lactuca sativa L., cv. BRS Leila) on NFT tables inside the GreenSe prototype at the University of Brasília (UnB) Gama campus, (ii) to compare nine automatic segmentation recipes against operator polygons on radially undistorted nadir frames from an ESP32-linked wide-angle camera with Raspberry Pi backend processing, and (iii) to select the variant that best tracked canopy expansion for this fixed viewpoint. Undistorted images were segmented in HSV; mask pixel counts then yielded projected area via $Acalc = Kp\ Np$ *with planar factor* Kp $(m^2 \cdot pixel^{-1})$*. Distortion correction follows Gonzalez and Woods (2009); VARI scores (Gitelson et al. 2002) defined the index comparator; microcontroller NFT work (Abu Sneineh and Shabaneh 2023) motivated the fixed daily capture window on the edge node. The evaluated pipelines included chromatic thresholding, filtering, local minima suppression, contrast reinforcement, temporal HSV updates (with or without reinforcement), and VARI mapping. Methods were judged against manual gold-standard masks across three independent 18-day cycles (six, ten, and seven plants) with captures in the same 3-hour lighting window each day. Temporal adaptive HSV segmentation (Algorithm 07) delivered the lowest pooled mean absolute percentage error, approximately 3.82%, with cycle means of 4.27%, 3.53%, and 3.65%. A supplementary weighing campaign showed an approximately linear relationship between projected area and fresh biomass, supporting area as a vigor proxy. These error levels are already suitable for fertigation monitoring in compact NFT systems when daily masks drive dashboard alerts instead of one-off checks. Periodically retuned color thresholds on inexpensive edge hardware thus provide NFT leaf-area traces suitable for routine monitoring and for coupling with fertigation and climate telemetry toward a closed-loop decision support system in urban protected horticulture.*

Keywords.* *Precision horticulture, image segmentation, hydroponics, smart farming, leaf area, HSV color space

Introduction

NFT lettuce dashboards need repeatable canopy surrogates; embedded hydroponic pilots often pair ESP32-class nodes with proximal sensing (Abu Sneineh and Shabaneh 2023). Leaf area links intercepted radiation and transpiration in soilless production, so tracking it over 18-day cycles supports irrigation and supplemental-light decisions when manual planimetry is impractical. Proximal imaging can provide those proxies if segmentation remains stable under plastic glare, film reflections, and color drift from the lamps. Using the GreenSe prototype described by Andrade (2024), this summary documents nine segmentation pipelines for cv. BRS Leila on NFT tables, explains why periodic retuning of color rules beat static thresholds and index-only masks under our LEDs, and reports the Algorithm 07 setup that gave the lowest error against manual polygons.

Materials and methods

Fig. 2 shows the auxiliary HSV-parameter GUI (Portuguese labels) used to preview OpenCV inRange bounds before Algorithm 07 temporal resets. Nine automatic variants—including chromatic thresholds, filtering, local-minima suppression, reinforcement, temporal HSV resets, and VARI indices (Gitelson et al. 2002)—were compared to operator-drawn polygons on undistorted frames; those polygons were the gold standard for percent error along the cultivation curve. Temporal adaptive thresholds (Algorithm 07) gave the lowest mean absolute percentage error for this lighting by classifying juvenile, intermediate, and dense canopies and switching HSV ranges accordingly without extra manual labeling after deployment.

Hardware matched the GreenSe stack (Andrade 2024): an ESP32 with a 120° wide-angle nadir camera sent frames to a Raspberry Pi that performed radial undistortion and mask operations following Gonzalez and Woods (2009); Fig. 1 shows the undistortion step. Each daily image reused a mechanically fixed viewpoint inside a repeatable 3-hour window so sun and azimuth effects stayed negligible under the lamps. Across three 18-day cycles (six, ten, and seven plants), binary vegetation masks came from HSV thresholding with Acalc = Kp Np and planar scale Kp ($m^2 \cdot pixel^{-1}$). Kp was set from planar references printed on rigid substrates aligned during calibration.

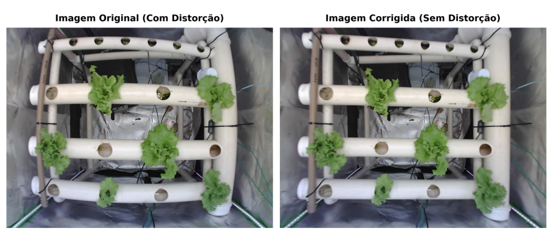

Fig. 1 Radial distortion correction of a representative top-down canopy frame (undistorted output used in segmentation)

Fig. 2 Auxiliary GUI for choosing HSV inRange segmentation parameters (segmented canopy, slider controls, binary mask preview; workflow from thesis Fig. 4.9; Cheng et al., 2001)

Results and discussion

Algorithm 07 tracked the gold-standard area series with pooled error near 3.82% and cycle means of 4.27%, 3.53%, and 3.65%. Errors stayed in the single-digit percent envelope targeted for supervisory NFT growth dashboards rather than archival mapping alone. Fig. 3 and Fig. 4 juxtapose daily percent error for Algorithm 07 across three independent cultivation cycles with the projected canopy area–fresh biomass scatter from the weighing study. Disagreement mainly tracks specular highlights and fused crowns—cases where fixed saturation limits the mask and where Algorithm 07 later widened saturation gates for denser canopies.

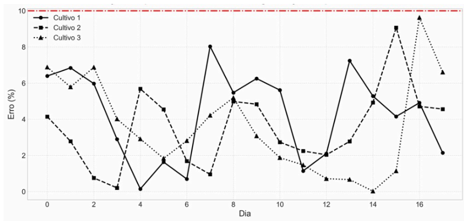

Fig. 3 Daily percent error versus manual gold-standard masks for Algorithm 07 across three cultivation cycles (Portuguese axis labels as exported from the thesis; dashed line at the 10% supervisory band)

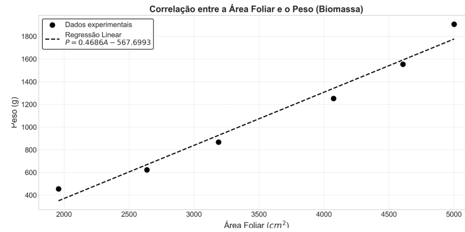

Fig. 4 Correlation between projected leaf area and fresh biomass (Crop 1)

Conclusions

Adaptive HSV on embedded hardware delivers an economical leaf-area signal for NFT smart greenhouses with artifacts shared through the public GreenSe repository (Andrade 2024). Next engineering steps include streaming masks into UnB Gama telemetry together with nutrient-conductivity and vapor-pressure-deficit channels (Khan et al., 2018; Rofiansyah et al., 2025) so fertigation rules can close the loop automatically. Testing other cultivars will show whether the adaptive threshold logic scales without full recalibration for each genotype. Tying area estimates to live telemetry is the next step for agronomic advisory in protected urban horticulture.

Acknowledgments

This summary derives from an undergraduate thesis supervised at UnB Gama and from the GreenSe smart-greenhouse platform (Andrade 2024).

Transparency on generative AI (CNPq policy)

In keeping with the scientific-integrity policy of the Brazilian National Council for Scientific and Technological Development (CNPq) on generative artificial intelligence, the authors declare that a large language model accessed through the Cursor environment assisted with language editing, layout checks, and aligning this summary with ISPAG manuscript guidance. Experimental protocols, numerical results, figure selection, and agronomic interpretation come from the supervised undergraduate thesis and GreenSe deployments (Andrade 2024); all authors critically reviewed every statement and accept full responsibility for the final text.

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