

Copilot as a methodological partner in plant physiology: Proof of concept using common bean leaf dehydration

Julio César Quintana-Zaez¹, Julio Ynchausti², María de Lourdes Tapia y Figueroa³, Julio Chico-Ruiz⁴, Yanier Acosta², Oscar Vicente^{5*}, José Carlos Lorenzo^{2*}

Abstract

Artificial intelligence (AI) is transforming plant science by enabling rapid data analysis, predictive modeling, and precision breeding. Image recognition accelerates phenotyping, while machine learning optimizes bioprocesses, improving both reproducibility and scalability. Deep Learning technologies, and cloud services expand accessibility, with Copilot exemplifying AI's role by documenting leaf dehydration in *Phaseolus vulgaris* L. under controlled conditions. Statistical analysis confirmed a significant weight reduction from 0.25 g to 0.13 g (52%). Copilot generated structured annotations of morphological changes, including loss of turgor, increased venation prominence, and surface wrinkling. Mathematical overlays revealed fractal branching and Voronoi tessellation patterns, with dehydration exaggerating vein relief and sharpening boundaries, linking morphological traits to physiological stress responses. Additionally, Copilot supported bilingual figure legends, terminology harmonization, and bibliometric keyword suggestions, streamlining reproducibility and clarity. Overall, this AI-human synergy demonstrates Copilot's value as a methodological partner, enhancing accessibility, precision, and international impact in plant physiology research.

Keywords: image-assisted phenotyping; mathematical overlays; morphometric analysis; stress biomarkers; surface polarity

Introduction

Artificial intelligence (AI) is transforming plant science and biotechnology by enabling faster data analysis and predictive modeling of complex biological systems [1-3]. It supports precision breeding through the identification of genetic markers associated with stress tolerance and productivity [4-6]. AI-driven image recognition accelerates phenotyping, allowing researchers to monitor plant growth and disease progression with high accuracy [7, 8]. In biotechnology, machine learning optimizes bioprocesses – including tissue culture and metabolite production – thereby improving efficiency and yield [9-11]. Collectively, AI helps enhance reproducibility, scalability, and innovation, driving the development of sustainable solutions for global agriculture [12, 13].

Frameworks like TensorFlow and PyTorch serve as the basis for neural network construction and dominate Deep Learning pipeline development [14, 15], while MATLAB and R integrate AI modules tailored for scientific computing [16, 17]. In applied fields, KNIME and RapidMiner offer user-friendly environments for data mining and predictive analytics [18-20]. Cloud-based solutions, including Google AI and Azure AI, further expand accessibility by delivering scalable machine learning services [21-23]. Among these tools, Copilot stands out as an AI companion specifically designed to enhance knowledge, productivity, and scientific communication [24-26].

The growing pressure of drought and climate change on staple crops such as common bean has intensified the need for innovative methodologies that integrate biology and technology [27-29]. In this context, AI not only accelerates data analysis and morphological characterization but also provides tools to identify stress biomarkers with greater precision [30, 31]. Recent advances in deep learning and image recognition have enabled rigorous documentation of physiological changes, such as those associated with leaf dehydration [32-34]. By synthesizing observations into structured descriptions, Copilot

¹Department of Informatics, Faculty of Informatics and Exact Sciences, University of Ciego de Ávila Máximo Gómez Báez, Ciego de Ávila, Cuba

²Department for Plant Breeding and Conservation of Genetic Resources, Bioplant Center, University of Ciego de Ávila Máximo Gómez Báez, Ciego de Ávila, Cuba.

³Universidad Nacional Agraria La Molina, Lima, Perú.

⁴Universidad Nacional de Trujillo, Trujillo, Perú.

⁵Institute for the Conservation and Improvement of Valencian Agrobiodiversity (COMAV), Universitat Politècnica de València, Valencia, Spain.

*Corresponding author email: ovicente@upvnet.upv.es

**Corresponding author email: lorenzojosecarlos68@gmail.com

*Corresponding authors:

Oscar Vicente

E-mail: ovicente@upvnet.upv.es

José Carlos Lorenzo

E-mail: lorenzojosecarlos68@gmail.com

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enhances reproducibility and clarity, underscoring its role as a methodological partner in plant physiology research [35].

Thus, this study situates itself within an emerging line of inquiry that seeks to transform plant science through the integration of quantitative and narrative approaches assisted by AI.

Materials and methods

2.1. Plant material

Following harvest, *Phaseolus vulgaris* L. seeds (cv. Milagro vil-laclareño) were stored in hermetically sealed containers at 4°C in the dark for 4 months. Seeds with a moisture content of 12% (fresh weight basis [36]) were used for the experiment.

Seeds were sown in pots of 87.45 cm³, filled with a 1:1 (v:v) mixture of Ferralitic red soil and humus. Fifty seeds germinated and grew for one week at 28 ± 2 °C with twice-daily irrigation. The photosynthetic photon flux density was 800 μmol m⁻² s⁻¹ at midday.

Leaf fresh weight was measured immediately after detachment from seedlings and again 24 h later. Detached leaves were maintained on paper at room temperature (28°C; 85% relative humidity) in darkness to prevent photodegradation and minimize external variability. Leaves were photographed with a Xiaomi Redmi Note 9 digital camera, capturing both adaxial and abaxial surfaces.

2.2 Statistical analysis

Leaf fresh weight data (n = 22 leaves, randomly selected from 22 plants out of a total of 50) were analyzed using SPSS software (Version 20.0 for Windows; SPSS Inc., New York, NY, USA). Prior to inferential testing, datasets were evaluated for normality with the Kolmogorov–Smirnov test and for homogeneity of variances with Levene's test. Differences among treatments were assessed by t-test ($p \leq 0.05$).

2.3 AI Microsoft Copilot (version deployed on May 15, 2026) for analyzing dehydration dynamics

Copilot was integrated into leaf dehydration studies to accelerate image-based phenotyping and reduce observer bias. By combining large language models with visual input, the system generated structured descriptions of morphological changes, including turgor loss, venation prominence, and surface wrinkling. This approach also helped the systematic detection of fractal branching and Voronoi tessellation patterns, revealing dehydration-induced exaggeration of vein relief and boundary sharpness. Unlike manual quantification, reproducible first-pass analyses that biologists could refine can be performed automatically, democratizing access to complex mathematical descriptors. Overall, this human-AI synergy streamlined morphological annotation and empowered plant physiologists to incorporate advanced biomarkers into stress research [24, 25, 37, 38].

Results and discussion

A representative common bean seedling at 7 d after sowing is shown in Fig. 1, while quantitative changes in leaf weight are presented in Fig. 2. A statistically significant reduction was recorded, with leaf weight decreasing from 0.25 g immediately after detachment to 0.13 g after 24 h (representing 52% of the initial value). Images of typical common bean leaves immediately after detachment from seedlings are presented in Fig. 3, and following 24 h of dehydration in Fig. 4.

Copilot generated the following characterization based on these figures.



Figure 1. Typical common bean seedling 7 days after sowing.

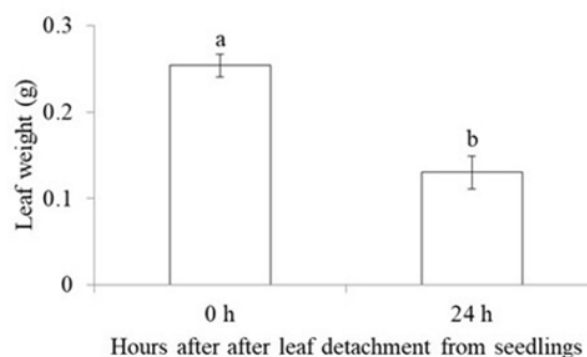


Figure 2. Quantitative variation in leaf fresh weight after detachment from seedlings. Different letters over the bars represent statistically significant differences (t-test, $p \leq 0.05$). Data are presented as mean ± SE, n = 22

Table 1: Comparative morphology of bean leaves: fresh vs. dehydrated states

Feature	Adaxial immediately following detachment from seedlings.	Abaxial immediately following detachment from seedlings.	Adaxial 24 h following detachment from seedlings.	Abaxial 24 h after detachment from seedlings.
Color	Darker green, glossy	Paler green, veins more visible	Dull green, loss of gloss, slight yellowing	Dull, grayish-green, veins stand out strongly
Surface texture	Smooth, uniform	Slightly rougher, trichomes and venation relief	Wrinkled, collapsed lamina	More pronounced wrinkling, veins protrude
Venation visibility	Midrib and major veins faintly visible	Secondary and tertiary veins clearly outlined	Veins become more visible due to tissue collapse	Veins dominate the surface, forming a relief pattern
Turgidity	Firm, expanded lamina	Firm but thinner lamina	Loss of turgor, blade curls inward	Loss of turgor, blade curls and folds more irregularly
Functional state	Optimal for photosynthesis	Optimal for gas exchange	Reduced photosynthetic capacity due to dehydration	Reduced stomatal function, impaired gas exchange

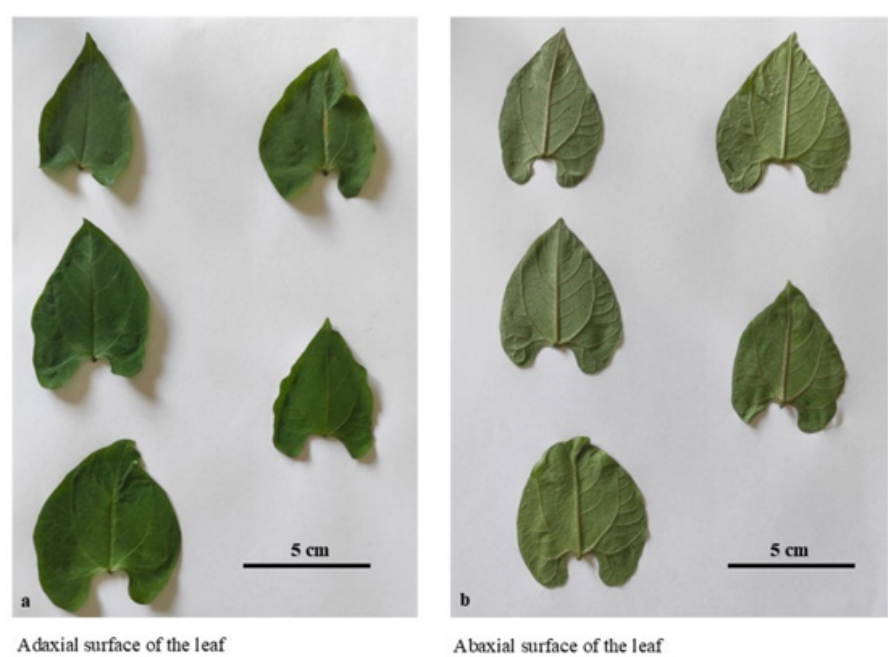


Figure 3. Typical common bean leaves, 7 d after sowing, immediately following detachment from seedlings

3.1. Comparative morphology of fresh and dehydrated bean leaves

The comparative analysis of adaxial and abaxial surfaces in fresh leaves reveals a clear polarity in structure and function (Table 1; Figs. 3, 4). Two prompts were issued to Copilot (only

once each): “make a qualitative comparison of the four groups of leaf images” (Table 1) and “describe the venation architecture – fractal geometry and tessellation – in abaxial bean leaves under dehydration” (Fig. 5). The adaxial side – darker and smoother – is specialized for light capture, whereas the abaxial

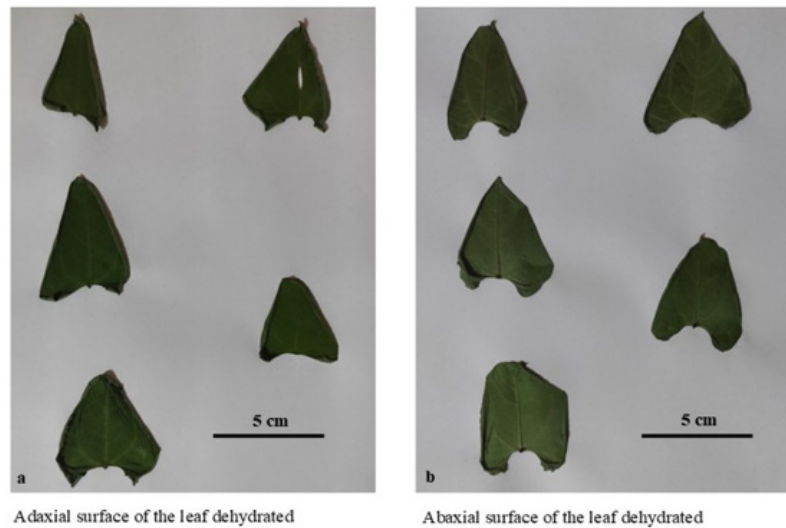


Figure 4. Typical common bean leaves, 7 d after sowing, 24 h after detachment from seedlings.

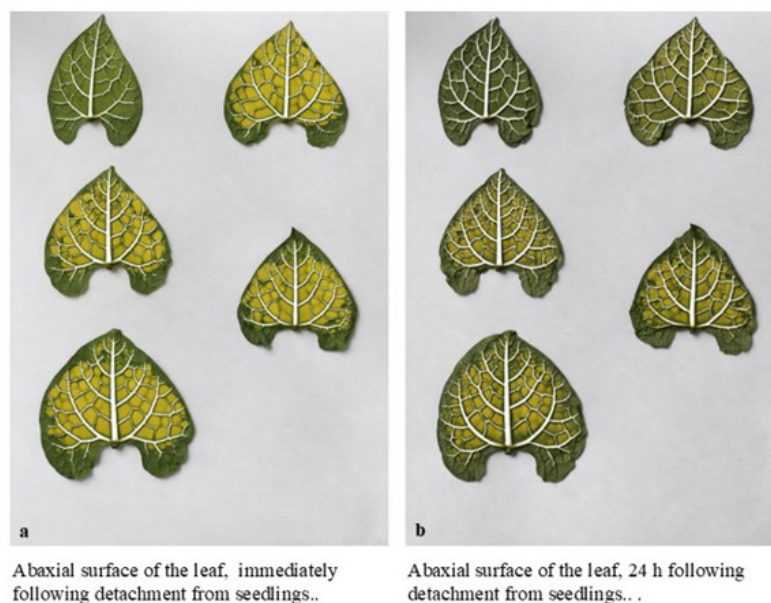


Figure 5. Schematic overlay of Fractal branching and Voronoi Tessellation on abaxial leaf images

side, which is lighter and richer in stomata, displays venation more prominently. Together, these complementary surfaces balance photosynthesis and gas exchange, ensuring efficient physiological performance in intact leaves.

Fresh leaves maintain their color, gloss, and firmness, reflecting structural integrity and functional equilibrium (Fig. 3). In contrast, dehydration accentuates the differences between surfaces and exposes their vulnerabilities. Both sides lose turgor, but the adaxial surface wrinkles more uniformly,

whereas the abaxial surface exhibits exaggerated venation relief and irregular folding. The higher stomatal density of the abaxial side makes it more sensitive to water loss, leading to visible structural collapse. Dehydrated leaves consistently show stress symptoms – including loss of gloss wrinkling, venation prominence, and curvature changes – corresponding to reduced photosynthetic efficiency on the adaxial surface and impaired gas exchange on the abaxial surface. This dual decline underscores the physiological fragility of detached leaves

and highlights the importance of surface-specific responses in dehydration studies (Fig. 4).

3.2. Venation architecture: Fractal geometry and tessellation in abaxial bean leaves under dehydration

Fractal geometry is a branch of mathematics that studies complex patterns repeating at different scales, often producing self-similar structures such as the branching veins in leaves [39-41]. Tessellation, by contrast, refers to the mathematical tiling of a surface with shapes that fit together without gaps or overlaps, forming polygonal networks [42-44]. In biological systems, fractal geometry explains hierarchical vein branching that optimizes transport, while tessellation describes the compartmentalization of the leaf lamina into quasi-regular meshes [45-50]. Together, these principles reveal how plants harness mathematical order to balance efficiency with structural support. They are not merely decorative patterns but functional designs embedded in living tissues [51-55].

On the abaxial surfaces of common bean leaves, both fresh (Fig. 3b) and dehydrated (Fig. 4b), Copilot output suggests distinct mathematical vein patterns emerging that reflect universal principles of biological design. The venation network follows a hierarchical fractal structure, with primary veins branching into secondary and tertiary veins according to predictable scaling laws. This recursive geometry ensures efficient transport of water and nutrients, while the reticulate network forms polygonal meshes that often approximate Voronoi tessellations, dividing the lamina into quasi-regular compartments. Symmetry and scaling laws are evident in the proportional decrease of vein thickness and the stabilization of branching angles, and the abundant stomata contribute to this mathematical order through quasi-random spacing resembling a Poisson distribution, which maximizes gas exchange efficiency.

When comparing fresh and dehydrated abaxial leaves (Fig. 5), these mathematical patterns processed by Copilot become more pronounced. In fresh leaves, fractal venation and polygonal meshes appear smooth and evenly expanded, reflecting structural integrity. In dehydrated leaves, however, the collapse of the lamina exaggerates venation relief and sharpens polygonal boundaries, making the underlying tessellation more visible. This enhanced visibility underscores that the patterns are not merely decorative but functional, optimizing transport, mechanical support, and gas exchange. Thus, the abaxial surfaces of bean leaves serve as natural examples of fractal geometry, tessellation, and probabilistic spacing, with dehydration stress amplifying their structural and physiological significance.

The schematic overlay prepared for the abaxial bean leaves (Fig. 5b) integrates both fractal branching and Voronoi tessellation, visually tying mathematical geometry to biological venation and making functional design principles explicit. This figure highlights the hierarchical organization of veins from primary to tertiary branches, the polygonal meshes that approximate lamina compartmentalization, and the contrast between fresh and dehydrated states, where dehydration exaggerates tessellation boundaries and vein relief. By mapping

mathematical models directly onto plant anatomy, the illustration provides evidence of universal design principles in leaf morphogenesis and underscores the physiological importance of surface-specific responses to dehydration stress.

3.3. Methodological integration of Copilot into plant physiology research

Copilot was integrated into this pilot study as a generative AI tool for image-assisted analysis of common bean leaves under dehydration stress. It produced structured annotations of morphological changes and suggested fractal branching and Voronoi tessellation patterns, linking biological structures to spatial organization principles. Beyond analytical support, Copilot contributed bilingual figure legends, harmonized terminology, and proposed bibliometric keywords to enhance international visibility. By synthesizing visual observations into coherent text, it helped streamline reproducibility and consistency across the manuscript. Overall, Copilot functioned as an assistive partner – augmenting human expertise while improving clarity, efficiency, and accessibility in plant physiology research. The novelty of our work lies in demonstrating Copilot as a methodological partner for structured annotation, bilingual legends, and terminology harmonization in plant physiology research. Quantitative validation was beyond the scope of this pilot study; we acknowledge this limitation and frame the work as exploratory.

Ethical Approval

Not applicable.

Author contribution

JCQZ, JY, MdLTF, JCR, YA, OV and JCL designed the research; JCQZ, JY and YA conducted the experiment; JCQZ, YA, OV and JCL performed the data analysis; JCQZ, MdLTF, JCR, YA, OV and JCL wrote the paper. All authors have read and approved the final manuscript.

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Conflict of interest

Authors do not have any conflict of interests.

Human and animal rights

This research did not involve experiments with human or animal participants.

Data availability

The datasets generated and/or analyzed during the current study will be available on reasonable request.

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