

Article

Galvanic Cell Enables Copper Reuse and Energy Harvesting for Sustainable Plant Micronutrient Delivery with Potential Wireless Sensor Network Applications

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Abstract

Recent advances in circular economy strategies have accelerated the development of low-cost electrochemical systems for energy harvesting, and resource reutilization in intelligent Wireless Sensor Networks (WSNs). This study proposes a zinc–copper (Zn–Cu) galvanic cell platform for copper reuse and evaluates the residual solution as a potential sustainable plant micronutrient source within a conceptual framework for edge-enabled precision agriculture. A five-cell Zn–Cu galvanic assembly was electrochemically characterized, producing a cumulative open-circuit voltage of 5.286 V (~1.10 V per cell), consistent with theoretical redox behavior. The system (180.6 g total mass) exhibited a specific power and specific energy of 0.0114 W kg^{−1} and 0.0114 Wh kg^{−1}, respectively, indicating its potential as a low-power energy source for future WSN and edge-computing applications. The residual copper solution was diluted and applied to *Rosmarinus officinalis* at graded concentrations. Image-based phenotyping revealed a concentration-dependent response, with the 50 mg L^{−1} treatment producing the strongest improvement in vegetation indices, including excess green index, vegetative index difference, normalized green-red difference index, triangular greenness index, and color index of vegetation extraction. Multivariate analysis confirmed clear treatment separation driven primarily by spectral traits. Overall, the results demonstrate that the residual copper-containing electrolyte solution left after galvanic cell operation might serve as a potential micronutrient source, while highlighting the prospective integration of galvanic energy harvesting into future intelligent WSN-based precision agriculture systems.

Keywords: galvanic cell; copper recovery; circular economy; micronutrients; plant phenotyping; *Rosmarinus officinalis*; vegetation indices; sustainable agriculture



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1. Introduction

Recent advances in circular economy and sustainable resource management have accelerated the development of innovative technologies for recovering valuable metals from industrial waste streams and electronic residues. Among these technologies, electrochemical and galvanic systems have emerged as promising alternatives for the recycling of critical metals such as copper, offering environmentally friendly pathways that reduce waste generation, greenhouse gas emissions, and dependency on primary mining resources [1–3]. Copper is an essential micronutrient for plant growth and development because it participates in several physiological and biochemical processes. It acts as a structural and

catalytic component of numerous enzymes involved in photosynthesis, respiration, lignin synthesis, antioxidant defense, and electron transport chains [4]. Adequate copper availability is therefore critical for maintaining plant metabolism, reproductive development, and stress tolerance. However, copper deficiency in agricultural soils has become increasingly common due to intensive cultivation practices, soil degradation, and nutrient depletion [5]. Deficient copper levels can negatively affect chlorophyll synthesis, enzyme activity, and crop productivity, ultimately compromising agricultural sustainability and food security [4,6]. Despite its essential role in plant nutrition, excessive copper accumulation in soils can generate severe environmental and toxicological consequences. Elevated copper concentrations may induce oxidative stress, disrupt cellular metabolism, inhibit root elongation, and reduce nutrient uptake efficiency in plants [7]. Moreover, copper toxicity can alter soil microbial communities and negatively affect ecosystem functioning [8]. The increasing contamination of agricultural soils by heavy metals derived from industrial activities, mining, and excessive agrochemical applications has raised global concerns regarding soil quality and long-term agricultural productivity [9]. Therefore, sustainable copper management strategies are urgently required to balance agricultural micronutrient demands with environmental protection objectives.

In the context of the circular economy and sustainable resource management, recent years have seen a rapid expansion in the development of innovative hydrometallurgical and physicochemical technologies for recovering valuable metals from industrial waste streams and electronic residues. These include well-established processes such as chemical precipitation, adsorption, solvent extraction, ion exchange, and electrochemical methods, which are widely reported in recent literature for the recovery of critical metals such as Co, Ni, Cu, and rare earth elements from complex waste matrices [10–13]. For instance, adsorption-based approaches have been successfully applied for the removal and recovery of metal ions from industrial and mining effluents, demonstrating high efficiency and environmental compatibility [10]. Similarly, ion exchange has been extensively investigated as a highly selective and scalable technique for the separation and recovery of valuable metals from secondary resources, particularly rare earth elements from sulfate-based and complex leach solutions [11]. Solvent extraction and electrochemical processes remain industrially relevant due to their robustness, selectivity, and adaptability in large-scale metal recovery flowsheets [10–13].

The increasing global demand for copper in electronics, renewable energy systems, and agriculture has intensified concerns regarding the depletion of natural reserves and the environmental impacts associated with conventional extraction and refining practices [14,15]. Copper recovery from electronic waste (e-waste) has gained considerable attention due to the high concentration of recoverable metals present in discarded electrical and electronic equipment. Recent studies have demonstrated that electrochemical recovery processes can efficiently extract copper from waste streams while minimizing secondary pollution and reducing energy consumption compared to traditional pyrometallurgical approaches [1,16]. Conventional copper extraction technologies are often associated with high CO₂ emissions, toxic gaseous by-products, and substantial energy requirements, which contribute significantly to environmental degradation and climate change [2,17]. In contrast, galvanic-cell-assisted recycling systems operate under milder conditions and can facilitate selective copper recovery through spontaneous redox reactions, thereby improving sustainability and economic feasibility [5].

Galvanic cells have recently attracted scientific interest as eco-efficient systems capable of coupling metal recovery with energy generation and nutrient reutilization. These systems exploit electrochemical potential differences between dissimilar metals to drive redox reactions without requiring external energy inputs [18]. Recent investigations have reported

that galvanic technologies can effectively recover copper ions from industrial solutions, electronic residues, and wastewater streams while reducing chemical reagent consumption and operational costs [19,20]. Furthermore, the integration of galvanic processes into waste valorization strategies supports the transition toward low-carbon and resource-efficient industrial systems [6].

In this context, nutrient recycling approaches have gained increasing importance within circular bioeconomy models. The reuse of residual metals and nutrients from industrial residues and waste streams can contribute to reducing dependence on virgin raw materials while simultaneously minimizing waste disposal problems [21]. Recent studies have demonstrated that recycled nutrients can be successfully incorporated into agricultural systems as fertilizers, soil amendments, or plant growth stimulants, promoting more sustainable nutrient management practices [22–24]. The agricultural reutilization of residual copper derived from galvanic cell systems represents a particularly attractive strategy because it combines waste valorization with micronutrient delivery in crop production systems.

The application of galvanic-cell-derived copper solutions for agricultural purposes offers several environmental and economic advantages. First, it supports the recovery and reutilization of copper that would otherwise be discarded as waste, thereby reducing the environmental burden associated with e-waste accumulation and industrial effluents [3,22]. Second, it decreases the demand for primary copper mining, which is commonly associated with habitat destruction, water pollution, soil degradation, and high energy consumption [15,23]. Third, the reutilization of recycled copper as a micronutrient source contributes to the development of closed-loop agricultural systems in which waste-derived nutrients are reintroduced into productive cycles [24].

Recent research has also emphasized the importance of integrating sustainable metal recovery technologies with agricultural innovation to achieve the goals established by global sustainability agendas. The United Nations Sustainable Development Goals (SDGs), particularly those related to responsible consumption and production, climate action, and sustainable agriculture, encourage the development of circular technologies capable of reducing waste generation while improving resource efficiency [24]. Within this framework, galvanic-cell-assisted copper recycling represents a multidisciplinary approach that combines electrochemistry, environmental engineering, waste management, and plant science to promote sustainable agricultural practices [5].

Additionally, electrochemical and galvanic systems provide opportunities for decentralized and low-cost nutrient recovery processes suitable for implementation in both industrialized and developing regions [25]. Their relatively simple operational design, low energy requirements, and reduced chemical consumption make them promising technologies for sustainable micronutrient production [26]. Recent advances in material science and electrochemical engineering have further improved the efficiency, selectivity, and scalability of galvanic systems for metal recovery applications [27]. Such technological developments may facilitate the future integration of residual micronutrients into precision agriculture and smart fertilization strategies aimed at optimizing nutrient use efficiency while minimizing environmental risks [28].

Recent advances in low-power energy harvesting technologies have significantly accelerated the development of self-powered wireless sensor networks (WSNs) for autonomous environmental monitoring applications [29–31]. Energy harvesting techniques based on solar, thermal, vibrational, radio-frequency, and bioelectrochemical sources have been extensively investigated as sustainable alternatives to conventional batteries, enabling long-term operation of sensor nodes while reducing maintenance requirements [29,30]. Among these approaches, microbial fuel cells (MFCs) have attracted increasing attention

because they can simultaneously generate electrical energy from organic substrates and provide power for low-energy sensing and wireless communication systems, making them attractive for remote environmental monitoring applications [32]. Nevertheless, the low and intermittent power output of these harvesting systems requires efficient energy management strategies, including duty cycling, adaptive sampling, ultra-low-power hardware design, and optimized wireless communication protocols to ensure reliable operation under constrained energy conditions [30,33]. Recent studies have also highlighted the growing integration of energy harvesting technologies with Internet of Things (IoT)-enabled WSNs, demonstrating their potential for applications such as soil monitoring, water quality assessment, precision agriculture, and environmental sensing [29,30,34]. Nevertheless, despite these advances, existing research has primarily focused on optimizing energy harvesting devices or WSN architectures independently.

Image based phenotyping has emerged as an indispensable methodology for non-destructive monitoring of plant growth and stress responses in controlled environment agriculture. This approach offers distinct advantages over traditional destructive sampling, including high measurement precision, exceptional repeatability across temporal replicates, capability for continuous automated data acquisition, and complete elimination of external environmental confounders that typically compromise field-based assessments. In the present study, we employed this established framework to evaluate morphological and physiological alterations in *Rosmarinus officinalis* subjected to three copper concentrations residual from a laboratory scale galvanic cell system: a control condition (0 mg Cu), a moderate treatment (10 mg Cu), and an elevated treatment (50 mg Cu). To achieve comprehensive three-dimensional characterization of plant architecture, we implemented a dual angle image acquisition protocol incorporating both top-down nadir viewing and lateral perspective imaging at 180 degrees relative to the plant axis, thereby capturing complementary aspects of canopy structure that would remain obscured from a single vantage point.

The scientific literature provides substantial precedent for the utility of image-based phenotyping across diverse botanical contexts and sensor modalities. For example, Hobart et al. [35] demonstrated the efficacy of unmanned aerial vehicle based oblique photogrammetry coupled with structure from motion algorithms to derive three dimensional point clouds for tree wall height estimation, achieving strong concordance with light detection and ranging reference measurements (coefficient of determination ranging from 0.83 to 0.88), although systematic underestimation of 0.11 to 0.18 m was observed due to inherent limitations in capturing fine canopy architectural details. Likewise, Kim [36] employed unmanned aerial vehicle acquired red-green-blue imagery with Excess Green index based segmentation, structure from motion-derived plant height metrics, and multiple linear regression modeling incorporating vegetation fraction, plant height, and their interaction term to estimate crop biophysical traits, yielding robust predictive performance with coefficients of determination between 0.66 and 0.90 and validation R^2 values exceeding 0.76. Gang et al. [37] developed a two-stage convolutional neural network architecture based on ResNet50V2 using red-green-blue depth imagery to estimate lettuce growth indices, achieving remarkable accuracy with R^2 values from 0.88 to 0.95 and normalized root mean square errors ranging from 5.62 to 7.92 percent, while maintaining rapid inference times of approximately 0.83 s per image, thereby demonstrating suitability for real time monitoring applications.

Furthermore, Wasonga et al. [38] applied both red-green-blue and multispectral imaging with a suite of vegetation indices including the Normalized Difference Vegetation Index, Greenness Above, and Simple Ratio to estimate cassava growth and nutritional traits, reporting strong predictive performance for biomass accumulation, chlorophyll con-

tent, and photosynthetic capacity (R^2 approximately 0.90), moderate performance for leaf area estimation ($R^2 = 0.76$), acceptable performance for several quality traits (R^2 exceeding 0.80), but notably weak associations for mineral nutrient content (R^2 ranging from 0.14 to 0.48), highlighting the differential sensitivity of spectral approaches to various plant physiological parameters. Collectively, these investigations on image-based plant growth monitoring establish the methodological foundation upon which the current study builds, confirming that multi angle image acquisition combined with appropriate feature extraction and multivariate statistical analysis constitutes a rigorous framework for quantifying plant responses to metal stress under controlled environment conditions.

Therefore, the aim of this study was to develop and evaluate a green galvanic cell-based system for circular copper recovery and to assess its potential for residual copper as a micronutrient source for plant supplementation. The main contributions of this work are as follows:

- Development of a low-cost zinc–copper galvanic cell system for copper recovery;
- Experimental characterization of voltage, current, specific power, and specific energy;
- Benchmarking of the system using Ragone analysis;
- Evaluation of residual Cu as a possible micronutrient source for *Rosmarinus officinalis*;
- Use of image-based phenotyping and vegetation indices to quantify plant response.

The rest of this paper is structured as follows. Section 2 presents the related work. Section 3 describes the materials and methods, including galvanic cell configuration, copper application protocol, electrochemical operation, and image-based monitoring. Section 4 presents the results. Section 5 discusses the findings in the context of circular copper recovery and plant micronutrient reuse, along the limitations of present study. Finally, Section 6 provides conclusions and future work.

2. Related Work

Recent advancements in the evaluation of metal-bearing waste streams and the concurrent provision of crop micronutrients have focused on electrochemical methodologies and circular-economy strategies. These approaches are highly pertinent to the development of a sustainable galvanic-cell platform, thus enabling circular copper reutilization.

In 2023, Kowalik-Klimczak et al. [39] demonstrated that membrane-based treatment and reuse strategies for galvanic wastewaters enable the effective recovery and reutilization of metal-rich retentates within industrial process loops, thereby establishing a circular-economy precedent for the sustainable reuse of metal-bearing solutions. In the same year, complementary reviews and experimental studies demonstrated that coupling electrochemical and bio-electrochemical processes effectively concentrates, recovers, and electrodeposits copper from dilute waste streams [40]. These integrated approaches can simultaneously produce energy or generate value-added products. Collectively, these results indicate that low-energy galvanic and electrochemical configurations represent a viable strategy for sustainable metal recovery. On the agronomic side, recent reviews, such as the work conducted by Xu et al. [41], highlighted the narrow margin between copper deficiency and toxicity in plants, emphasizing the need for precise control of copper speciation, dosage, and bioavailability when recycled copper is intended for agricultural supplementation.

Recent investigations have further strengthened the role of electrochemical systems in sustainable copper recycling. Hernández and Tapia [42] developed a reactive electrodialysis configuration capable of recovering copper directly from pregnant leaching solutions with high current efficiency and low energy consumption. The principal benefit of this approach lies in its high selectivity and industrial applicability; however, the system still requires external electrical input and relatively complex membrane arrangements, which may limit scalability for decentralized agricultural applications. In contrast, the objective of the

present study is to exploit a self-sustaining galvanic-cell configuration that minimizes external energy demand while simultaneously enabling copper reutilization as a plant micronutrient source.

Similarly, paired electrochemical recovery systems applied to E-waste leachates demonstrated efficient simultaneous deposition of copper and other metals [43]. These systems achieved high metal recovery efficiencies and demonstrated the versatility of electrochemical reactors for multi-metal waste valorization. Nevertheless, the experiments mainly focused on metallurgical recovery and did not evaluate the biological or agronomic suitability of the residual copper products. Our proposed approach extends beyond recovery efficiency by specifically assessing the possibility of remodeling the residual copper into bioavailable forms suitable for plant supplementation.

Additional studies have explored integrated electrochemical treatment systems for industrial wastewater. For instance, environmentally friendly electrodeposition–precipitation–electrooxidation processes achieved copper recovery efficiencies exceeding 99% while simultaneously reducing organic pollutants [44]. The main advantage of these coupled systems is their high purification performance and ability to recover multiple resources from complex effluents. However, the requirement for chemical additives, strict pH control, and multiple treatment stages increases operational complexity and cost. By comparison, the galvanic-cell platform investigated in this study aims to simplify the recovery process through spontaneous electrochemical reactions under mild operating conditions.

Bio-electrochemical systems have also emerged as promising alternatives for sustainable copper recovery. Recent studies on microbial fuel cells demonstrated simultaneous copper removal and electricity generation through cathodic reduction in Cu(II) species [45]. These systems offer significant environmental advantages because they operate under low-energy conditions and may generate renewable electricity during treatment. However, microbial systems often suffer from long operational times, microbial instability, and difficulties in controlling the final oxidation state and morphology of the residual copper. In contrast, the present study seeks to employ a green galvanic-cell strategy capable of providing controlled copper recovery while maintaining operational simplicity and compatibility with agricultural reuse objectives.

Further progress was reported in 2026 through the development of self-driven electrochemical separation-recovery systems for electroless plating wastewater [5]. These spontaneous galvanic systems enabled simultaneous recovery of copper, phosphate, and EDTA without external energy input, achieving high copper recovery efficiencies and producing reusable metal products. The major benefit of this methodology is its self-powered nature, which aligns strongly with circular-economy principles. Nevertheless, the study primarily focused on wastewater remediation and resource separation rather than evaluating the residual copper for agronomic applications. Our work addresses this research gap by evaluating whether the residual copper-containing electrolyte obtained after galvanic operation can be directly reused as a potential micronutrient source for plant growth.

On another note, recent reviews addressing copper removal technologies from industrial wastewater emphasized that conventional physicochemical methods frequently generate secondary sludge and require substantial chemical and energy consumption [46]. Electrochemical and membrane-based alternatives were therefore identified as more sustainable pathways for copper reutilization. However, despite the technological progress in copper recovery, only limited studies have connected residual copper streams with agricultural micronutrient delivery systems. Therefore, this study was aimed to develop and evaluate a green galvanic cell-based system for circular copper recovery and to assess its potential for reusing the residual copper as a micronutrient source for plant supplementation.

3. Materials and Methods

This section describes the proposed galvanic cell system, the copper dilution protocol for plant supplementation, the galvanic operation principle, and the image-based phenotyping method used to evaluate plant growth (Figure 1). The experimental workflow integrated electrochemical characterization with image-based plant phenotyping to quantify treatment-induced physiological and morphological responses.

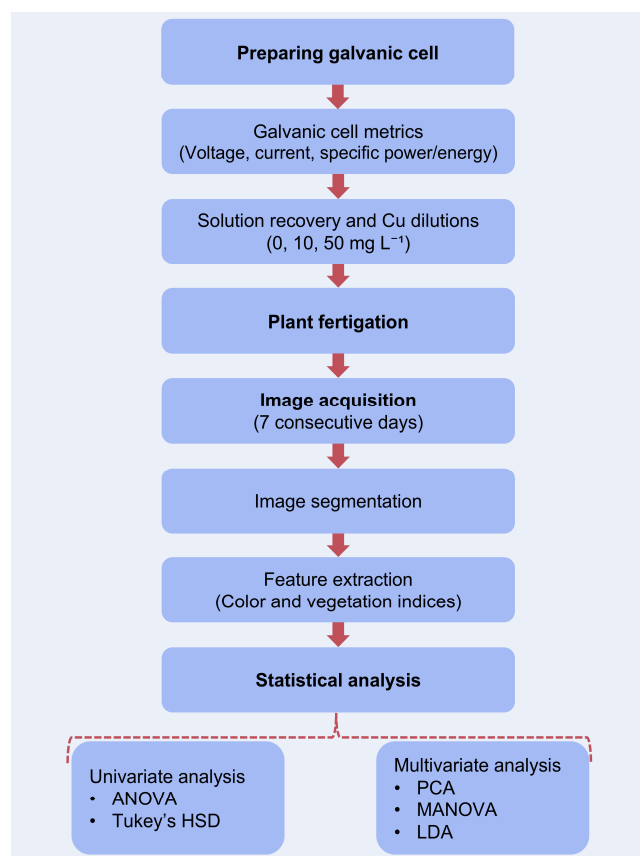


Figure 1. Summary of methodological workflow adopted in this study.

3.1. Galvanic Cell Configuration

The experimental galvanic cell was assembled using two metal electrodes: zinc as the anode and copper as the cathode. Each electrode was immersed in its corresponding electrolyte. The copper compartment contained copper sulfate (CuSO_4), whereas the zinc-side electrolyte was prepared using a vinegar–sodium chloride solution as a substitute in the absence of zinc sulfate (ZnSO_4). The cell compartments were connected through a salt bridge constructed from filter paper saturated with NaCl solution, enabling ionic exchange while limiting direct mixing of the electrolytes.

The CuSO_4 solution was prepared by dissolving 15 g of CuSO_4 in 125 mL of distilled water. The zinc-side electrolyte was prepared by mixing 125 mL of cleaning-grade vinegar, approximately 8–10% acetic acid, with 12 g of NaCl to enhance ionic conductivity. Before each experiment, the electrodes were polished to ensure clean surfaces and improve electrical contact with the electrolyte.

Voltage measurements were acquired using a digital multimeter under open-circuit conditions and during external loading tests. Measurements were recorded immediately after assembly and subsequently at regular intervals to evaluate voltage stability. Cells were connected in series to investigate cumulative voltage generation. Electrical performance

was further assessed using low-resistance external circuitry coupled to resistive loads and LED configurations.

The objective of the present work was to demonstrate the feasibility of integrating copper recovery, energy harvesting, and agricultural reutilization within a single galvanic-cell platform. Therefore, the electrochemical recovery process was evaluated as a proof-of-concept, and a detailed quantitative assessment of recovery metrics such as recovery efficiency, Faradaic efficiency, residual copper mass, and copper concentration before and after treatment was beyond the scope of this study. These parameters will be investigated in future work to enable a comprehensive comparison with conventional electrochemical copper recovery technologies. Consequently, the electrochemical characterization focused on demonstrating the feasibility of simultaneous copper recovery and energy harvesting rather than providing a complete quantitative evaluation of the recovery process.

3.2. Copper Application to Plants

The residual copper-containing solution remaining after galvanic operation was subsequently collected and evaluated as a potential micronutrient source for *Rosmarinus officinalis*. The residual solution contained dissolved copper species remaining after partial electrochemical reduction during galvanic operation. Rosemary, *Rosmarinus officinalis*, plants were selected due to their ecological relevance in Mediterranean and coastal environments, rapid vegetative growth, and documented sensitivity to trace metal imbalance, which collectively make it suitable for phenotypic response assessment.

Residual Cu containing solution was diluted to obtain three copper nominal concentrations: 0 mg L⁻¹ (control), 10 mg L⁻¹, and 50 mg L⁻¹ Cu (total dissolved copper). These concentrations represent the intended preparation concentrations and were not analytically verified by direct chemical determination. Throughout the manuscript, Cu concentrations are therefore referred to as nominal mg L⁻¹ Cu rather than measured dissolved copper concentrations. Expressing treatments in terms of elemental Cu, rather than CuSO₄ mass, follows standard practice in plant nutrition and environmental studies, which could facilitate comparison with previous literature. The initial CuSO₄ solution served as the electrolyte in the galvanic system, whereas the plant treatments were prepared by diluting the recovered solution remaining after galvanic operation, which contained dissolved copper species. Expressing treatment concentrations as mg L⁻¹ Cu follows standard practice in plant nutrition and environmental studies and provides a consistent basis for comparing copper availability across treatments. Copper supplementation was applied through a soil drenching approach designed to simulate practical fertigation conditions. Each plant received three independent applications during the experimental period on days 1, 3, and 5 after treatment initiation.

The experiment consisted of three copper treatments (0, 10, and 50 mg L⁻¹ Cu), each comprising four independent biological replicates (n = 4 plants per treatment). Multiple RGB images were acquired from each plant throughout the experimental period to monitor temporal changes in phenotypic traits. These repeated observations were used to characterize plant responses over time and were not considered independent biological replicates. Instead, image-derived features obtained from the same plant were treated as repeated measurements and aggregated at the individual plant level before statistical analyses, thereby preserving the plant as the experimental unit and avoiding pseudoreplication. This approach is consistent with established image-based plant phenotyping methodologies, in which multiple observations are acquired from the same biological replicate to improve temporal characterization while maintaining appropriate statistical independence [47,48]. Accordingly, all univariate and multivariate analyses, including PCA, MANOVA, LDA, permutation testing, and five-fold cross validation, were performed using plant level obser-

uations. During cross validation, data were partitioned according to biological replicate, ensuring that observations from the same plant were assigned exclusively to either the training or validation subset.

3.3. Electrochemical Operation of the Galvanic System

The initial phase involves the activation of the galvanic cell, which is based on a spontaneous redox reaction between zinc and copper electrodes in separate electrolyte solutions. In this system, zinc (Zn) acts as the anode and undergoes oxidation, releasing electrons according to the half-reaction; see (Equation (1)).



Simultaneously, copper ions (Cu^{2+}) in the CuSO_4 solution accept electrons at the copper cathode and are reduced; see (Equation (2)).



These reactions establish a potential difference between the electrodes, enabling electron flow through an external circuit and ionic migration through a salt bridge or porous membrane (Figure 2). The salt bridge maintains charge neutrality by allowing anions and cations to move between compartments, preventing local charge accumulation and sustaining the electrochemical reaction.

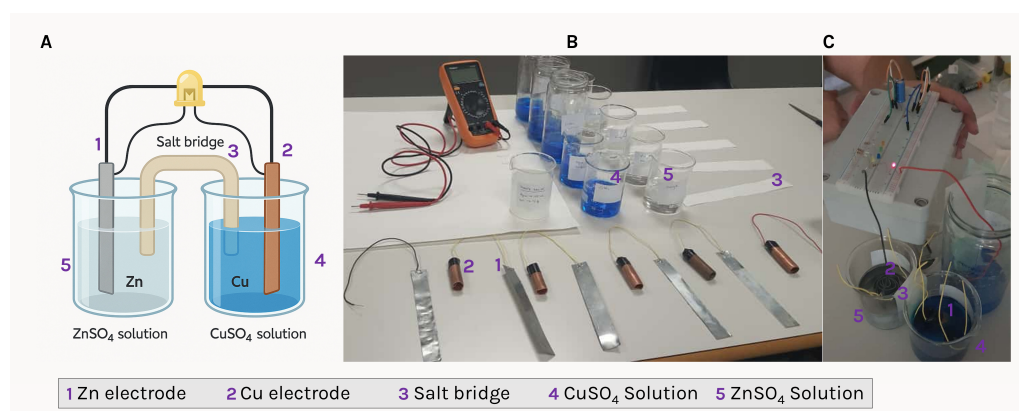


Figure 2. Schematic illustration (A) of experimental galvanic cells. (B) Materials used in the lab and (C) functioning galvanic cells with lighted LED.

The observed open-circuit voltage (OCV) corresponds to the standard electrode potential difference between zinc and copper, theoretically approximated at 1.10 V under standard conditions. Variations in electrode surface area, electrolyte concentration, and temperature may influence the cell's performance as shown in Figure 2. This phase serves as the foundation for subsequent electrochemical measurements, energy output analysis, and efficiency assessment under controlled experimental conditions.

3.4. Image-Based Plant Phenotyping

Plant responses were monitored for seven days using a non-destructive image-based phenotyping framework (Figure 3). Images were acquired from both lateral and nadir perspectives under controlled lighting conditions and at a fixed acquisition time to minimize variability associated with illumination and circadian effects.



Figure 3. Schematic illustration of experimental galvanic cell.

All images were processed in Python using a standardized computer vision workflow. Red, green, and blue (RGB) images were transformed into hue, saturation and value (HSV) color space to improve discrimination between vegetative tissue and background elements. Binary segmentation masks were generated using predefined threshold ranges (Hue: 35–85, Saturation: 40–255, Value: 40–255). Morphological closing operations employing a 5×5 kernel were subsequently applied to reduce segmentation noise and eliminate minor discontinuities in plant regions.

Morphological descriptors and spectral indices were extracted from the segmented plant regions to quantify treatment-induced phenotypic variation. The extracted features included geometric parameters, RGB and HSV color descriptors, Commission Internationale de l'Éclairage 1976 L^*a^*b (CIELAB) coordinates (ISO/CIE 11664-4:2019) [49], and vegetation indices associated with greenness, reflectance behavior, and pigment dynamics. The vegetation indices [35,36,38] used in this study are summarized in Table 1 (Equations (3)–(11)).

Table 1. Summary of vegetation indexes calculated from image features.

Parameter	Equation	
Excess Green Index (ExG)	$ExG = 2G - R - B$	(3)
Excess Red Index (ExR)	$ExR = 1.4R - G$	(4)
Triangular Greenness Index (TGI)	$TGI = -0.5[190(R - G) - 120(R - B)]$	(5)
Green–Red Vegetation Index (GRVI)	$GRVI = (G - R)/(G + R)$	(6)
Vegetative Index Difference (VID)	$VID = G - R$	(7)
Color Index of Vegetation Extraction (CIVE)	$CIVE = 0.441R - 0.811G + 0.385B + 18.787$	(8)
Normalized Green Red Difference Index (NGRDI)	$NGRDI = (G - R)/(G + R)$	(9)
Visible Atmospherically Resistant Index (VARI)	$VARI = (G - R)/(G + R - B)$	(10)
Green Leaf Index (GLI)	$GLI = \frac{2G - R - B}{2G + R + B}$	(11)

where G , B , and R denote the green, blue, and red spectral components, respectively.

3.5. Data Preprocessing and Feature Standardization

Prior to statistical analysis, all extracted phenotypic variables were standardized using z-score normalization to ensure comparability among heterogeneous feature scales [50]. The dataset included spectral descriptors, vegetation indices, and morphological traits derived from both lateral and nadir images. Standardization transformed each variable to zero mean and unit variance, thereby preventing variables with larger numerical ranges from disproportionately influencing subsequent multivariate analyses.

Following preprocessing, univariate analysis of variance (ANOVA) was conducted to evaluate treatment effects on individual image-derived features. When significant differences were detected ($\alpha = 0.05$), mean separation was performed using Tukey's Honestly Significant Difference (HSD) post hoc test [51]. All values are reported as mean $\pm$ stan-

standard error ($n = 4$), and means followed by different letters indicate statistically significant differences at $p < 0.05$.

This univariate framework provided an initial assessment of treatment-specific responses and established the basis for the subsequent multivariate analysis pipeline, including Principal Component Analysis (PCA), Multivariate Analysis of Variance (MANOVA), and Linear Discriminant Analysis (LDA), enabling a comprehensive evaluation of combined spectral and morphological variation.

3.6. Principal Component Analysis

PCA was performed to characterize the covariance structure of the phenotypic dataset and reduce dimensionality while preserving the dominant sources of variation. PCA transforms the original feature space into orthogonal linear combinations that maximize explained variance [52]. The standardized data matrix (X) was decomposed according to Equation (12).

$$T = XP \quad (12)$$

where (X) represents the standardized feature matrix, (P) contains the eigenvectors (loadings), and (T) represents the principal component scores.

The covariance matrix decomposition was defined as (Equation (13)):

$$\Sigma = V\Lambda V^T \quad (13)$$

where Λ contains the eigenvalues and V the associated eigenvectors.

Component retention followed Kaiser's criterion, whereby only components with eigenvalues greater than unity were retained. This criterion was selected because components with eigenvalues below 1 explain less variance than an individual standardized variable and therefore contribute limited explanatory power.

3.7. Multivariate Analysis of Variance

One-way MANOVA was conducted to evaluate the global effect of Cu treatments across the multidimensional phenotypic feature space. The null hypothesis assumed equality among treatment mean vectors (Equations (14) and (15)) [53]:

$$H_0 : \mu_1 = \mu_2 = \mu_3 \quad (14)$$

Wilks' lambda (Λ) was used as the primary multivariate test statistic and was calculated as

$$\Lambda = \frac{|E|}{|E + H|} \quad (15)$$

where (E) represents the error (within-group) sum of squares and cross-products (SSCP) matrix and (H) represents the hypothesis (between-groups) SSCP matrix. Smaller values of (Λ) indicate stronger multivariate separation among treatments. Statistical significance was determined using Rao's approximation to the F distribution.

3.8. Linear Discriminant Analysis

LDA was applied to evaluate treatment classification performance and identify the phenotypic variables contributing most strongly to treatment discrimination. LDA seeks linear combinations of variables that maximize the ratio of between-group variance to within-group variance.

The generalized f in Equations (16) and (17) [54].

$$S_B^v = \lambda S_w^v \quad (16)$$

where S_B^v and S_w^v correspond to the between-class and within-class scatter matrices, respectively. Discriminant scores were computed as

$$z = v^T x \quad (17)$$

Classification was performed under the assumption of multivariate normality and homogeneous covariance matrices among treatment groups. Model performance was evaluated using stratified five-fold cross-validation to preserve class proportions within each fold. For the multi-class case (0, 10, 50 mg L⁻¹), accuracy was computed as the overall proportion of correctly classified samples across all classes (Equation (18)) [50].

$$Accuracy = \frac{\sum_{i=1}^k n_{ii}}{N} \quad (18)$$

where n_{ii} represents the correctly classified samples in class i , k shows number of classes ($n = 3$), and N represents the total number of samples.

Similarly, to assess whether classification performance exceeded random expectation, permutation testing was conducted using 1000 iterations. Treatment labels were randomly shuffled during each iteration and the LDA model was refitted to generate a null distribution of classification accuracies. Permutation probability was calculated as present in Equation (19) [50].

$$p = \frac{1 + \sum_{i=1}^N I(acc_i^* \geq acc_{obs})}{N + 1} \quad (19)$$

Feature importance within discriminant space was evaluated using standardized discriminant coefficients, where larger absolute coefficient values indicated stronger contributions to treatment separation.

All analyses were conducted in Python (v3.9). PCA and LDA were implemented using the *scikit-learn* library, whereas MANOVA computations were performed using *statsmodels*. Permutation testing and additional statistical procedures were implemented using SciPy.

3.9. Conceptual WSN Architecture

The proposed galvanic-cell platform can be extended beyond copper recovery and micronutrient reutilization toward the development of sustainable intelligent WSN architectures for precision agriculture applications [55]. In this context, the galvanic system not only acts as a copper recovery mechanism but also operates as a low-power energy harvesting source capable of supporting ultra-low-power sensing and edge-computing tasks within distributed agricultural monitoring systems [56].

Figure 4 presents a conceptual architecture illustrating how the proposed galvanic-cell platform could be integrated into an intelligent wireless sensor network for precision agriculture. The framework is intended to demonstrate a possible system-level implementation and does not represent an experimentally validated deployment.

The architecture comprises four interconnected layers: (i) a galvanic energy harvesting subsystem, (ii) an edge sensing and processing node, (iii) a wireless communication layer, and (iv) a cloud monitoring infrastructure.

The galvanic subsystem serves as the primary energy harvesting unit, while simultaneously enabling copper recovery from the electrolyte. The harvested electrical energy may be regulated and temporarily stored using appropriate power management circuitry before supplying low-power electronic components.

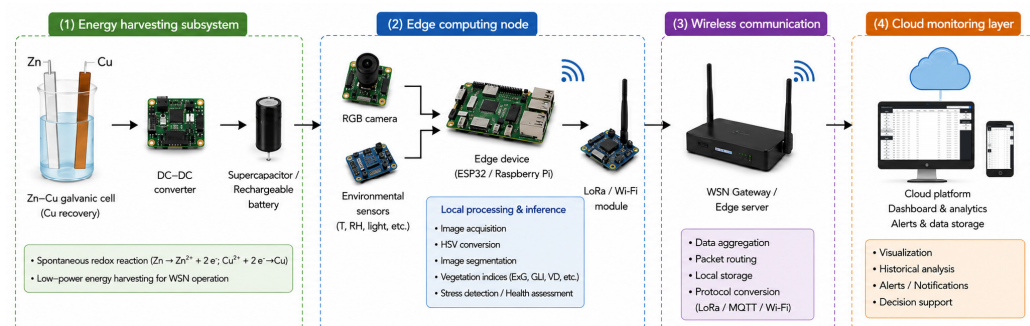


Figure 4. Proposed intelligent agricultural WSN architecture integrating galvanic-cell energy harvesting, edge-computing nodes, RGB image acquisition, local computer vision inference, wireless communication, gateway infrastructure, and cloud-based monitoring.

The edge node may incorporate embedded platforms such as ESP32, Raspberry Pi, or similar microcontroller-based systems equipped with RGB cameras and environmental sensors. These devices acquire plant images and environmental information directly within the cultivation area. Local processing may include vegetation index calculation, image segmentation, feature extraction, and lightweight machine learning inference before transmitting summarized information to higher network layers.

Communication between edge nodes and the gateway may be implemented using low-power communication technologies such as LoRa, ZigBee, Wi-Fi, or MQTT based Internet of Things protocols according to deployment requirements. The gateway aggregates information from multiple nodes and forwards processed data to cloud servers for storage, visualization, and decision support.

This conceptual architecture illustrates a potential pathway for integrating galvanic energy harvesting, edge intelligence, computer vision, and wireless sensing within future precision agriculture platforms.

The galvanic cell subsystem may provide electrical energy generated through spontaneous electrochemical reactions between Zn and Cu electrodes. Although the generated power remains limited compared to conventional battery systems, The harvested energy could potentially support low-duty-cycle sensing operations, sensor standby modes, intermittent wireless transmissions, and lightweight edge-computing processes, which are common strategies adopted in energy-harvesting wireless sensor networks for precision agriculture [57]. The harvested energy may be temporarily stored using rechargeable batteries or supercapacitors coupled with DC–DC regulation modules to stabilize voltage delivery to the electronic subsystem.

4. Results

This section includes the results of experimental galvanic cells and the effect of reused Cu on plants.

4.1. Galvanic Cell Performance

The experimental voltage measured across a five-cell zinc–copper galvanic system reached a cumulative total of 5.286 V, with each cell contributing a voltage increment closely aligned with the theoretical potential difference of approximately 1.10 V per cell (Figure 5). The slight deviations observed between segments can be attributed to factors such as electrode surface conditions, electrolyte concentration differences, and contact resistance within the series configuration. These results confirm the additive behavior expected in serially connected galvanic cells and are summarized in Figure 5A.

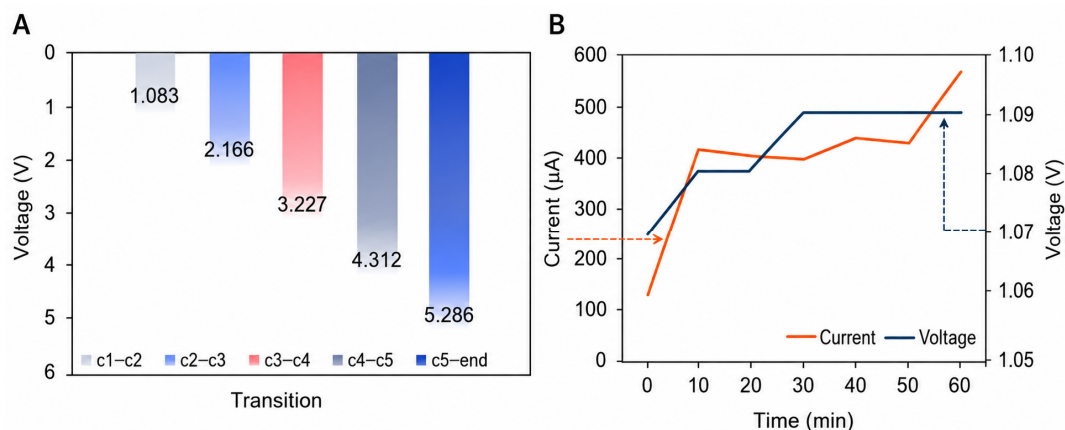


Figure 5. Voltage by cell segment in a five-cell Zn-Cu galvanic battery (A). Voltage and current variation over time of single galvanic cells (B). Orange and blue colored arrows indicate the curves for current and voltage, respectively.

Figure 5B shows the evolution of both current and voltage over a 60 min interval during continuous operation of a single zinc–copper galvanic cell. The voltage remained relatively stable throughout the test, fluctuating slightly around 1.09 V, with an initial increase observed between 0 and 30 min, possibly due to improved ion mobility as the system stabilized. The current followed a similar trend, increasing from approximately 120 μA to 580 μA by the end of the observation period. Small fluctuations in current between 10 and 50 min may reflect minor variations in electrode surface activity or ionic concentration gradients near the electrodes. Notably, a brief increase in current was observed shortly at 60 min, coinciding with the manual rewetting of the salt bridge, which likely enhanced ionic conductivity across the cell.

Figure 6 presents a preliminary Ragone representation of the Zn–Cu galvanic system based on the experimentally measured open-circuit voltage (OCV) and short-circuit current (I_{sc}). The OCV was measured as 5.495 V, whereas the short-circuit current reached 376 μA . These measurements provide an initial electrical characterization of the galvanic cell. However, since the open-circuit voltage and short-circuit current correspond to different operating conditions, they should not be interpreted as simultaneous parameters for determining the maximum power output. Using the total measured mass of the cell assembly (180.6 g), preliminary values of specific power (0.0114 W kg^{-1}) and specific energy (0.0114 Wh kg^{-1} , assuming a 1-h discharge period) were estimated for qualitative comparison with other low-power electrochemical systems [58,59]. These values are presented in the Ragone plot (Figure 6), together with reference lines indicating constant discharge durations. Since the electrical characterization was limited to open-circuit voltage and short-circuit current measurements, these estimates should be regarded as preliminary benchmarking indicators rather than rigorous electrochemical performance metrics.

A complete electrochemical characterization would require load-dependent I–V and P–V measurements to determine the actual maximum power point [60] and accurately evaluate the energy performance of the galvanic system. Nevertheless, the results place the proposed Zn–Cu galvanic cell within the expected performance range of simple, non-optimized aqueous electrochemical systems intended for low-power energy harvesting applications.

Despite the modest performance, the preliminary Ragone representation provides a useful qualitative benchmarking framework for comparing simple low-power galvanic systems and identifying potential optimization strategies, such as reducing internal resistance or structural mass. Although a complete Ragone characterization would require load-dependent discharge measurements, the present analysis provides an initial indication of the energy-harvesting capabilities of the proposed galvanic cell.

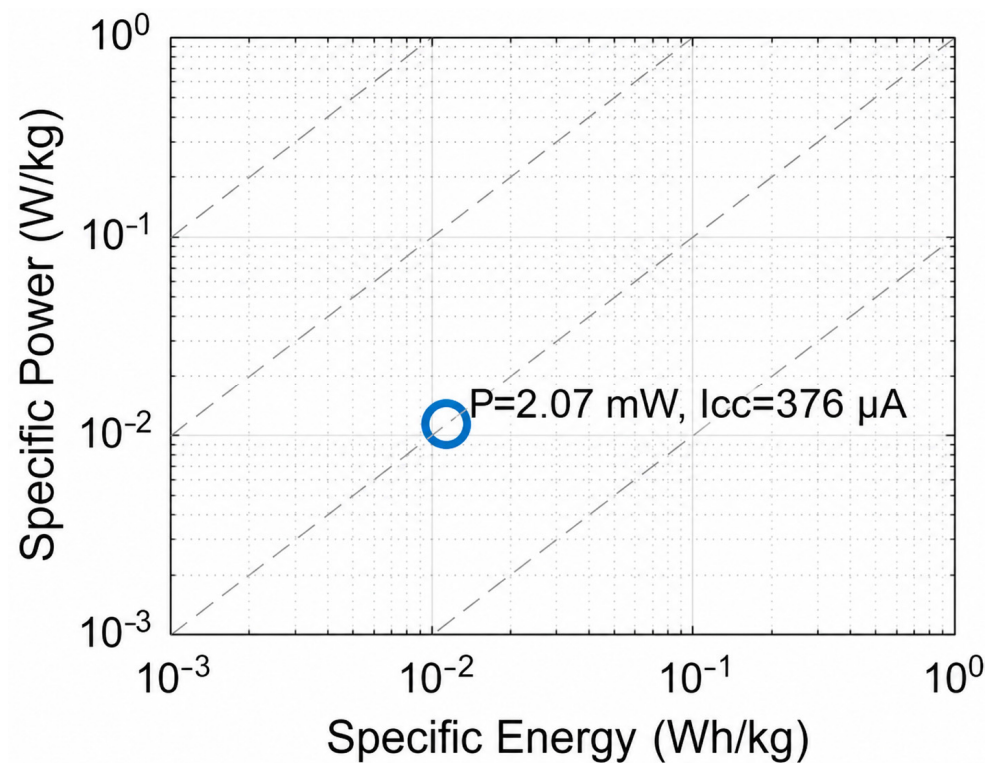


Figure 6. Preliminary Ragone representation of the proposed Zn–Cu galvanic system based on the experimentally measured electrical parameters.

4.2. Image Phenotyping

Plants supplemented with 10 and 50 mg L⁻¹ of Cu (T1) showed better vegetation. Figure 7 represents plants masks for nadir and lateral images.

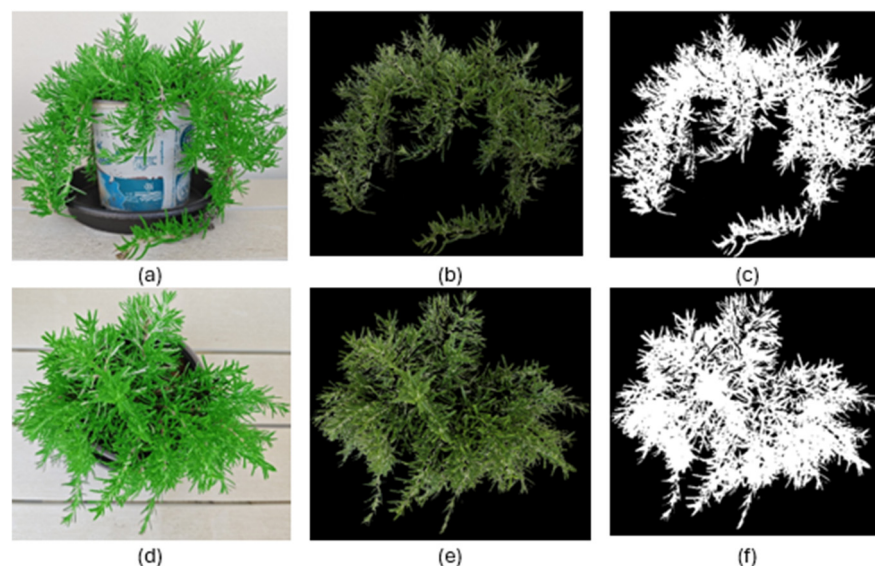


Figure 7. Romero plants: (a,d) original image, (b,e) segmented image, and (c,f) binary mask for lateral and nadir angles, respectively.

For lateral angle images, compared to the control (T0), treatments T1 and T2 led to significant improvements in several VIs associated with plant health (Table 2). In T1, an increase in red reflectance (EXR) may suggest enhanced photosynthetic activity. T2 showed better vegetation intensity (VID) and reduced stress signals (CIVE), along with higher greenness (TGI), indicating improved plant vitality. Although GLI remained relatively

stable across treatments, a slight enhancement in T2 further supported the positive impact of this treatment on plant growth.

Table 2. Summary of vegetation indexes (VI) calculate from images taken from a lateral angle. Values are expressed as mean $\pm$ standard error ($n = 4$). Means followed by different letters indicate statistically significant differences at $p < 0.05$, as determined by ANOVA with HSD post hoc test.

Vegetation Index	Treatment			<i>p</i> Value
	T0	T1	T2	
EXG	56.72 $\pm$ 0.62 a	51.17 $\pm$ 0.72 b	53.35 $\pm$ 1.25 b	2×10^{-4}
EXR	−20.26 $\pm$ 0.43 b	−17.67 $\pm$ 0.52 a	−20.78 $\pm$ 1.03 b	0.0057
NGRDI	0.36 $\pm$ 0.003	0.36 $\pm$ 0.003	0.38 $\pm$ 0.01	0.0687
GRVI	0.23 $\pm$ 0.002	0.23 $\pm$ 0.002	0.23 $\pm$ 0.003	0.117
VID	40.89 $\pm$ 0.51 a	37.63 $\pm$ 0.58 b	39.79 $\pm$ 1.06 ab	0.011
CIVE	−3.95 $\pm$ 0.25 b	−1.71 $\pm$ 0.3 a	−2.67 $\pm$ 0.52 a	3×10^{-4}
TGI	−2033 $\pm$ 45.4 b	−2078 $\pm$ 35.3 b	−1857 $\pm$ 52.1 a	0.002
VARI	7.46 $\pm$ 1.26	5.13 $\pm$ 0.72	4.71 $\pm$ 1.16	0.157
GLI	0.22 $\pm$ 0 a	0.22 $\pm$ 0 b	0.22 $\pm$ 0 ab	0.047

Furthermore, considering the color parameters from lateral images, R intensity decreased in T2, suggesting reduced stress-related pigmentation, while G intensity was lower in T1 and T2 compared to T0, possibly reflecting changes in leaf composition (Figure 7).

Hue values slightly decreased in T1 and T2, indicating subtle shifts in color tone. Saturation increased in T2, suggesting more vivid coloration, while V decreased in treated plants, possibly due to denser foliage. L^* was significantly reduced in T1 and T2, consistent with darker leaf appearance. The redness component (a^*) increased in T1 and T2, while b^* showed a slight but significant variation, indicating treatment-induced changes in leaf color dynamics. Analysis of nadir image color channels revealed significant differences among treatments in G, B, H, S, V, and CIELAB components (Figure 8).

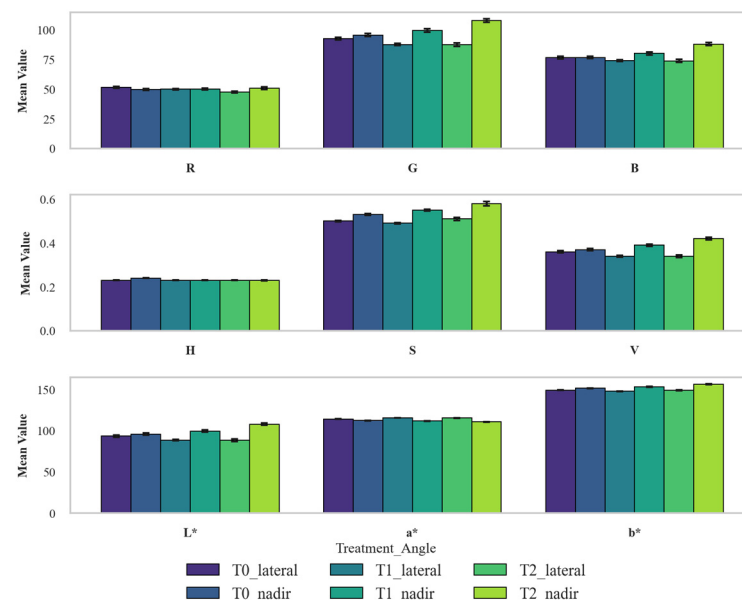


Figure 8. Image-based analysis results of plant spectral attributes.

T2 consistently showed enhanced G and B intensities, indicating improved foliage coloration. Hue decreased slightly in T2, while S and brightness increased, suggesting healthier and more vibrant leaves. In CIELAB space, L^* and b^* were highest in T2, reflecting better leaf development, whereas a^* slightly decreased, consistent with reduced stress.

These changes collectively point to improved plant condition under T2 compared to T0 and T1.

Likewise, results from nadir angle analysis also showed improvements in treatments T1 and T2 compared to the control (T0) (Table 3). T2 showed marked improvements in greenness (EXG), vegetation intensity (VID), and normalized greenness (NGRDI), indicating enhanced plant vigor. Red reflectance (EXR) decreased progressively from T0 to T2, suggesting reduced stress. GRVI also increased in T1 and T2, reflecting better chlorophyll content. Additionally, CIVE values became more negative in T2, consistent with healthier foliage, and GLI showed a slight but significant enhancement, further supporting improved plant condition under T2.

Table 3. Summary of vegetation indexes (VI) calculate from images taken from a nadir angle. Values are expressed as mean $\pm$ standard error ($n = 4$). Means followed by different letters indicate statistically significant differences at $p < 0.05$, as determined by ANOVA with HSD post hoc test.

Vegetation Index	Treatment			<i>p</i> Value
	T0	T1	T2	
EXG	64.89 $\pm$ 1.06 b	68.93 $\pm$ 1.21 b	76.67 $\pm$ 1.69 a	1×10^{-7}
EXR	−26.03 $\pm$ 0.72 a	−29.51 $\pm$ 0.81 a	−36.56 $\pm$ 1.81 b	1.3×10^{-7}
NGRDI	0.39 $\pm$ 0.005 c	0.41 $\pm$ 0.005 b	0.44 $\pm$ 0.01 a	1.5×10^{-5}
GRVI	0.25 $\pm$ 0.003 b	0.27 $\pm$ 0.003 a	0.28 $\pm$ 0.06 a	7.7×10^{-5}
VID	45.9 $\pm$ 0.81 b	49.48 $\pm$ 0.92 b	56.88 $\pm$ 1.54 a	5.6×10^{-9}
CIVE	−7.33 $\pm$ 0.44 a	−9.03 $\pm$ 0.5 a	−12.3 $\pm$ 0.72 b	8.4×10^{-8}
TGI	−1665 $\pm$ 32.52	−1578 $\pm$ 37.6	−1441 $\pm$ 103.2	0.06
VARI	3.33 $\pm$ 0.64 b	5.42 $\pm$ 1.05 ab	7.05 $\pm$ 1.06 a	0.05
GLI	0.24 $\pm$ 0 b	0.25 $\pm$ 0 ab	0.26 $\pm$ 0 a	0.02

4.3. Multivariate Analysis for Lateral Imaging

Principal Component Analysis revealed a strong treatment-dependent multivariate structure in the lateral imaging dataset. Five principal components were retained according to Kaiser's criterion, collectively accounting for 89.87% of the total variance (Figures 9 and 10). The ordination space was primarily structured along PC1, which explained 40.0% of the variance and clearly separated Cu-treated plants from controls. Plants exposed to the highest Cu concentration (T2) were displaced toward positive PC1 scores, whereas control plants (T0) clustered predominantly on the negative side, with T1 occupying an intermediate position. This distribution indicates a progressive phenotypic transition associated with increasing Cu concentration.

The variables contributing most strongly to PC1 were predominantly spectral and colorimetric descriptors. Positive loadings were associated with a^* , ExR, and CIVE, whereas negative loadings were dominated by ExG, VID, b^* , G, V, and L^* . Collectively, these opposing contributions define a dominant greenness-to-reddening gradient, indicating that Cu exposure primarily altered pigment-associated optical responses. PC2 explained an additional 22.4% of the variance and was strongly associated with vegetation indices related to canopy vigor and reflectance behavior, including TGI, NGRDI, GRVI, and GLI, further indicating substantial modulation of spectral signatures under Cu supplementation.

Morphological traits contributed primarily to higher-order components. PC3 was associated with area, perimeter, aspect ratio, and circularity, whereas PC4 and PC5 captured variation related to solidity and VARI. These results indicate that structural responses were detectable but contributed less strongly than spectral descriptors to overall treatment differentiation.

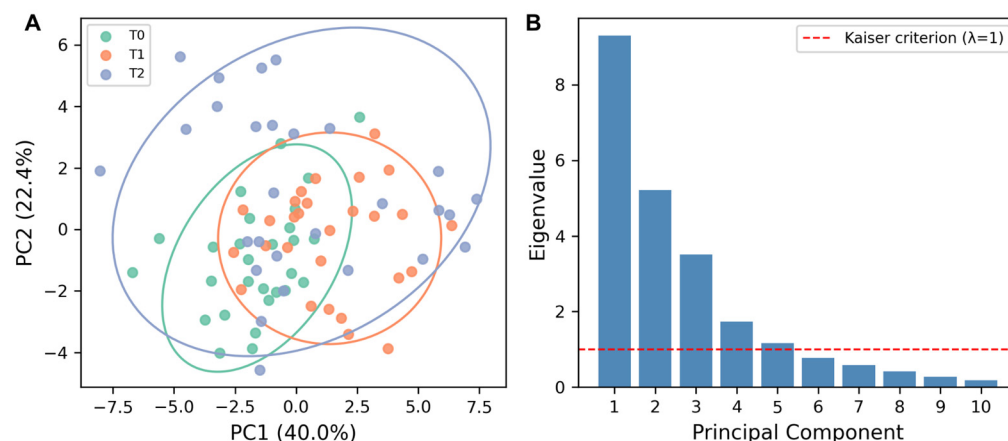


Figure 9. Principal Component Analysis (PCA) of lateral image features of *Rosmarinus officinalis*. (A) Score plot illustrating sample distribution along PC1 (40.0%) and PC2 (22.4%), showing treatment-related clustering. (B) Scree plot of eigenvalues with component selection based on Kaiser’s criterion ($\lambda = 1$).

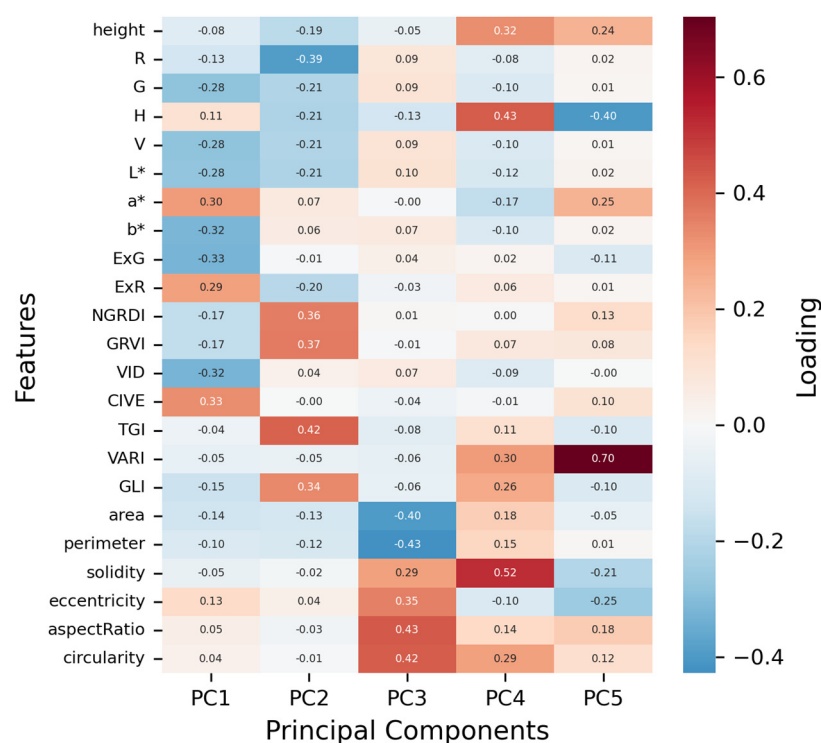


Figure 10. Principal component loadings for lateral image features of *Rosmarinus officinalis*. The heatmap shows the contribution of spectral, colorimetric, and morphological variables to the first five principal components (PC1–PC5). Warmer colors indicate positive loadings and cooler colors indicate negative contributions, highlighting the dominance of spectral indices in PC1–PC2 and structural traits in higher-order components.

The multivariate structure identified by PCA was strongly supported by MANOVA, which confirmed a highly significant treatment effect across the integrated phenotypic dataset (Table 4). All multivariate statistics were significant at $p < 0.001$, including Wilks’ $\lambda = 0.0999$ ($F = 15.57$), indicating a substantial reduction in unexplained variance attributable to Cu treatment. Similar trends were observed for Pillai’s trace, Hotelling–Lawley trace, and Roy’s greatest root, collectively confirming robust treatment-driven divergence in multidimensional space.

Table 4. Summary of multivariate analysis of variance (MANOVA) results for lateral imaging features. The *** sign indicates the statically significant values ($p < 0.001$).

Test Statistic	Value	Num DF	Den DF	F Value	p-Value
Wilks' Lambda	0.10	20	144	15.57	<0.001 ***
Pillai's Trace	1.27	20	146	12.75	<0.001 ***
Hotelling–Lawley Trace	5.28	20	117.97	18.81	<0.001 ***
Roy's Greatest Root	4.45	10	73	32.47	<0.001 ***

Linear Discriminant Analysis further resolved treatment separation and confirmed the dominant contribution of spectral traits to class discrimination (Figures 11 and 12).

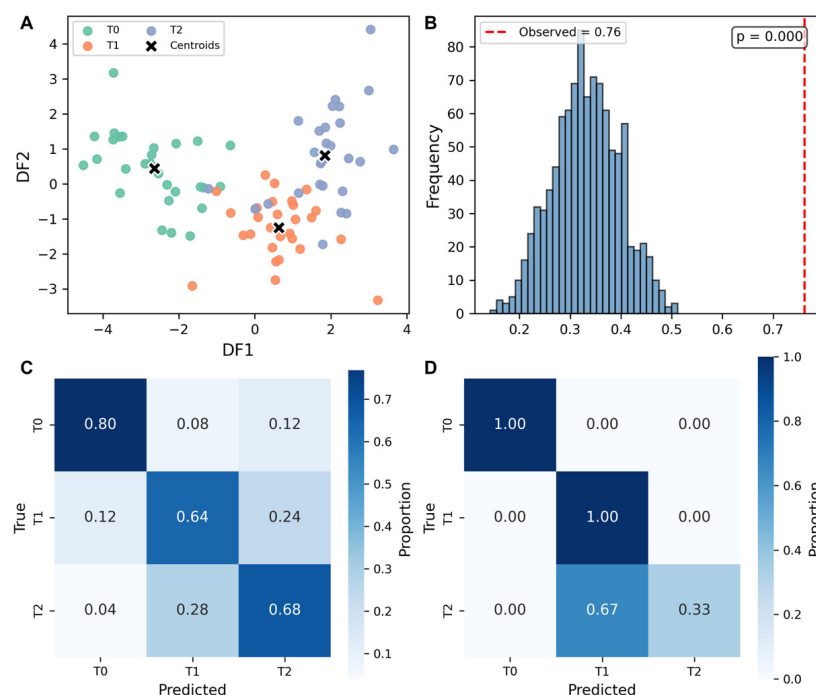


Figure 11. Linear Discriminant Analysis (LDA) results for lateral image features of *Rosmarinus officinalis*. (A) Projection of samples onto DF1–DF2 showing treatment separation and group centroids. (B) Permutation test confirming significant discrimination ($p < 0.001$). (C) Validation confusion matrix and (D) test confusion matrix (normalized), illustrating classification performance across treatments.

The primary discriminant axis clearly separated untreated plants from Cu-exposed groups, while the second axis provided weaker discrimination between T1 and T2, consistent with a dose-dependent but partially overlapping response (Figure 12). Permutation testing confirmed that the observed classification exceeded random expectation ($p = 0.000$).

Discrimination was driven principally by greenness-associated vegetation indices and color descriptors, particularly GRVI, a^* , ExR, ExG, L^* , and VID, whereas morphological traits contributed minimally to class separation. The independent test set yielded an overall classification accuracy of 77.78%. Control plants were classified with complete precision and recall, whereas overlap between T1 and T2 resulted in partial misclassification, indicating that Cu-treated plants shared convergent spectral characteristics at higher exposure levels.

Taken together, the lateral imaging analyses demonstrate that Cu supplementation induced a strong and statistically coherent phenotypic shift dominated by spectral and pigment-related responses, while structural modifications played a secondary role in treatment discrimination.

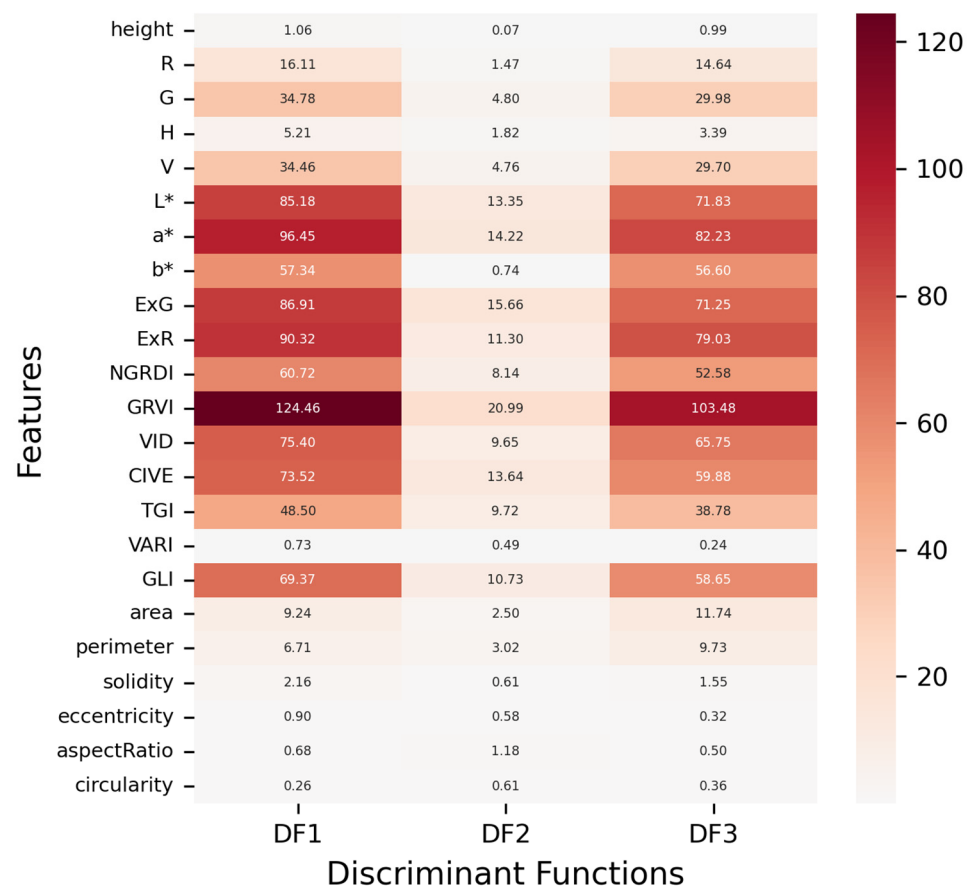


Figure 12. Canonical loadings of discriminant variables derived from Linear Discriminant Analysis (LDA) applied to lateral image features of *Rosmarinus officinalis* under different Cu treatments.

4.4. Multivariate Analysis for Nadir Imaging

Multivariate analysis of nadir images revealed a treatment-dependent structure comparable to that observed in lateral imaging, although with stronger variance concentration along the primary ordination axis. Five principal components explained 88.87% of the total variance (Figures 13 and 14), with PC1 alone accounting for 50.9%. Along this axis, control plants were clearly separated from Cu-treated groups, while T1 again occupied an intermediate position between T0 and T2, indicating a progressive response to increasing Cu concentration.

As observed in the lateral dataset, PC1 was dominated by spectral and colorimetric descriptors. Positive loadings were associated with b*, ExG, VID, NGRDI, GRVI, and GLI, whereas a*, ExR, and CIVE contributed negatively, confirming that the primary source of variance corresponded to a coordinated shift in pigment-related optical properties. The stronger variance captured by PC1 relative to lateral imaging indicates that nadir imaging enhanced sensitivity to treatment-induced spectral responses at the canopy level.

In contrast to the lateral perspective, morphological variation was more clearly resolved in secondary components. PC2 was strongly associated with area, perimeter, and solidity, indicating that nadir imaging improved detection of canopy architectural variation. Additional structural descriptors, including circularity and aspect ratio, contributed to higher-order components, suggesting that top-view imaging captured subtle alterations in canopy geometry accompanying Cu exposure.

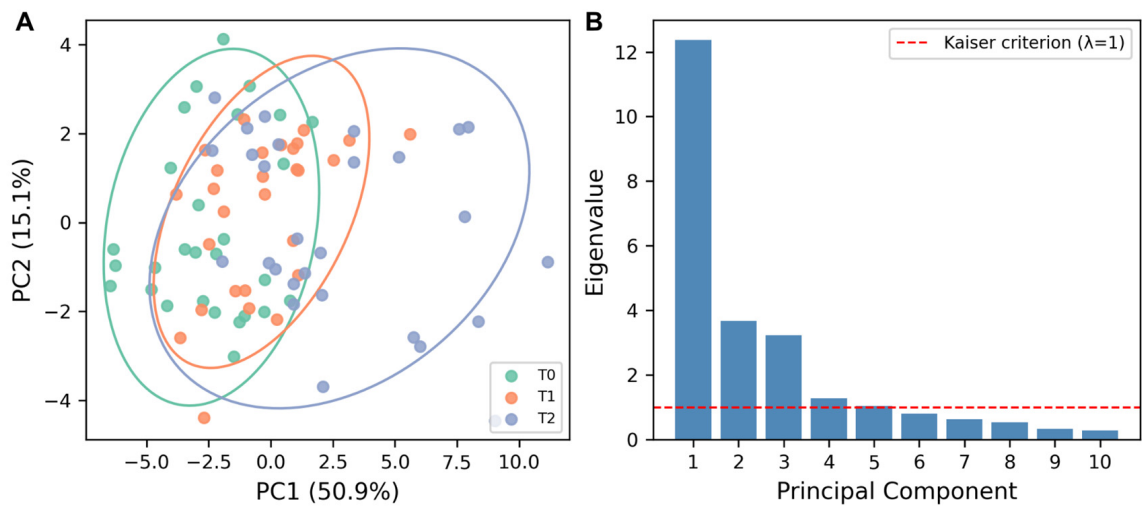


Figure 13. Principal Component Analysis (PCA) of nadir image features of *Rosmarinus officinalis*. (A) Score plot showing sample distribution across PC1 (50.9%) and PC2 (15.1%), illustrating treatment-related clustering. (B) Scree plot displaying eigenvalues and component selection based on Kaiser’s criterion ($\lambda = 1$).

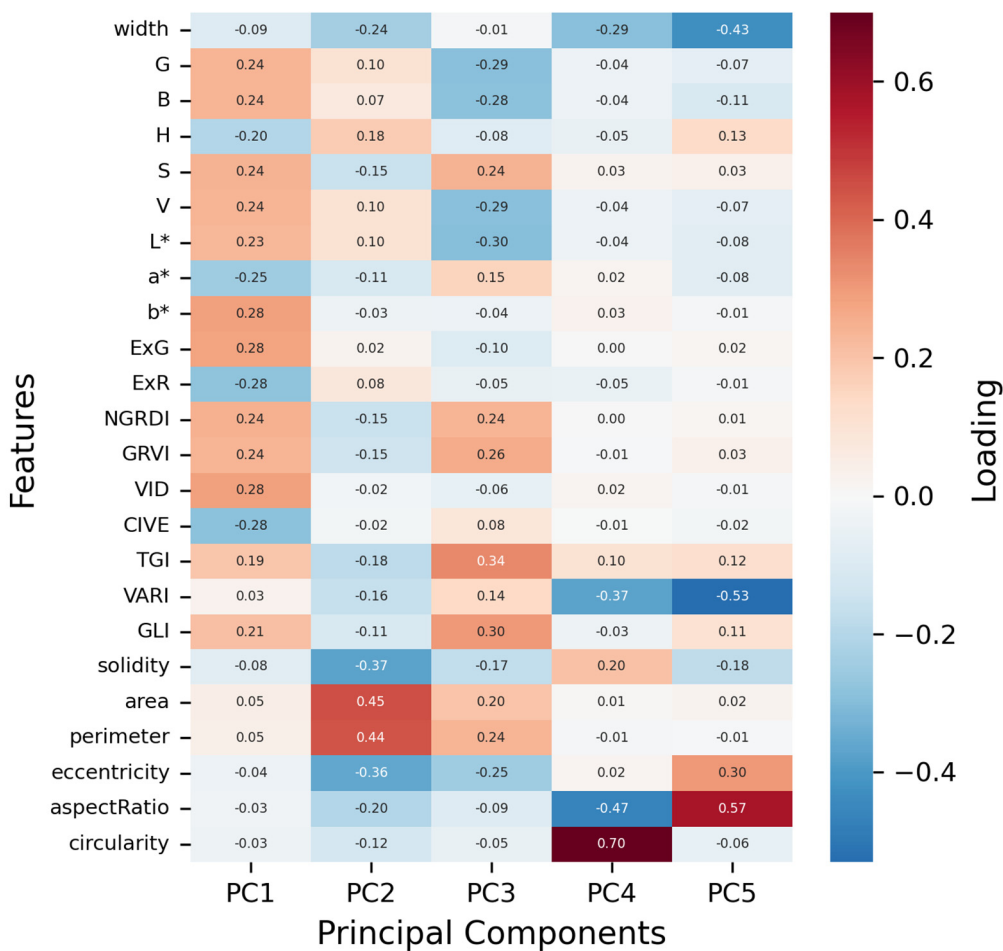


Figure 14. Principal component loadings for nadir image features of *Rosmarinus officinalis*. The heatmap shows the contribution of spectral, colorimetric, and morphological variables to the first five principal components (PC1–PC5). Warmer colors indicate stronger positive loadings and cooler colors indicate negative contributions, highlighting the dominant role of spectral indices in PC1–PC3 and structural traits in higher-order components.

MANOVA confirmed a highly significant multivariate treatment effect across nadir-derived traits (Table 5). All multivariate statistics were significant at $p < 0.001$, including Wilks' $\lambda = 0.1049$ ($F = 16.94$), supporting the strong treatment separation observed in PCA space. The consistency between ordination and inferential analyses indicates that Cu exposure produced coordinated changes across both spectral and structural dimensions of the canopy phenotype.

Table 5. Summary of multivariate analysis of variance results for lateral imaging features. The *** sign indicates the statically significant values ($p < 0.001$).

Test Statistic	Value	Num DF	Den DF	F Value	p-Value
Wilks' Lambda	0.105	18	146	16.94	<0.001 ***
Pillai's Trace	1.313	18	148	15.70	<0.001 ***
Hotelling–Lawley Trace	4.555	18	117.94	18.28	<0.001 ***
Roy's Greatest Root	3.376	9	74	27.76	<0.001 ***

Linear Discriminant Analysis demonstrated significant treatment discrimination, although with lower predictive performance than the lateral dataset (Figures 15 and 16). The first discriminant function separated T2 from T0, whereas T1 showed partial overlap with both groups, indicating weaker class boundaries from the nadir perspective. Permutation testing nevertheless confirmed that classification performance remained significantly above random expectation ($p = 0.000$).

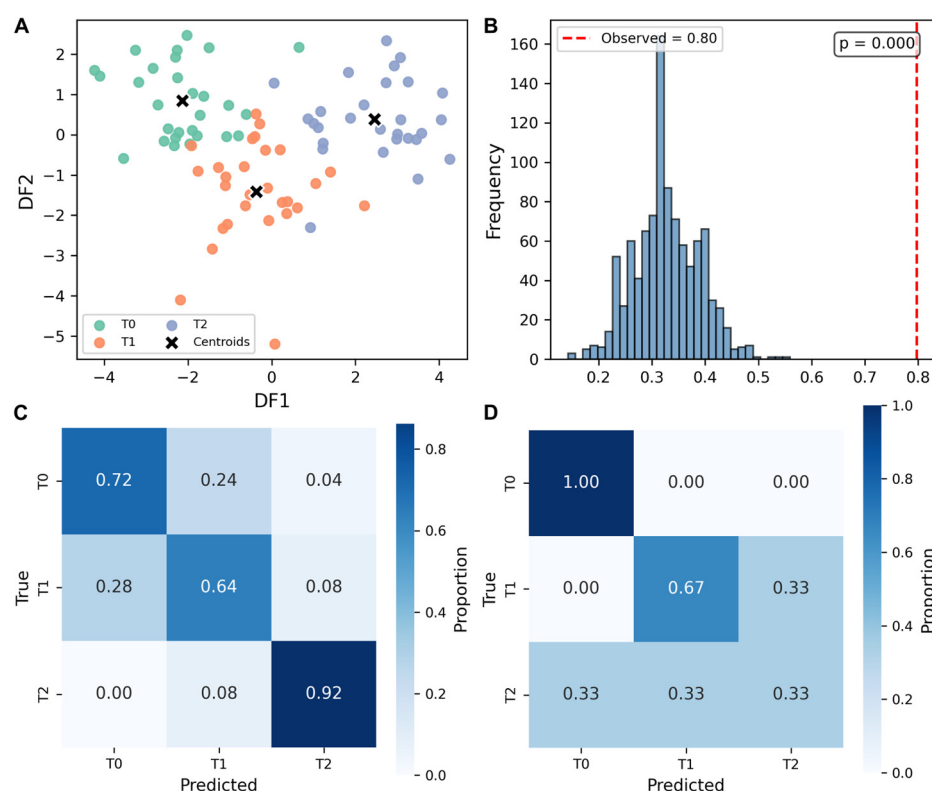


Figure 15. Linear Discriminant Analysis (LDA) results for nadir image features of *Rosmarinus officinalis*. (A) Projection of samples onto the first two discriminant functions (DF1–DF2) showing class separation and group centroids. (B) Permutation test confirming significant model performance ($p < 0.001$). (C) Validation confusion matrix and (D) test confusion matrix (normalized), illustrating classification accuracy and misclassification patterns among treatments.

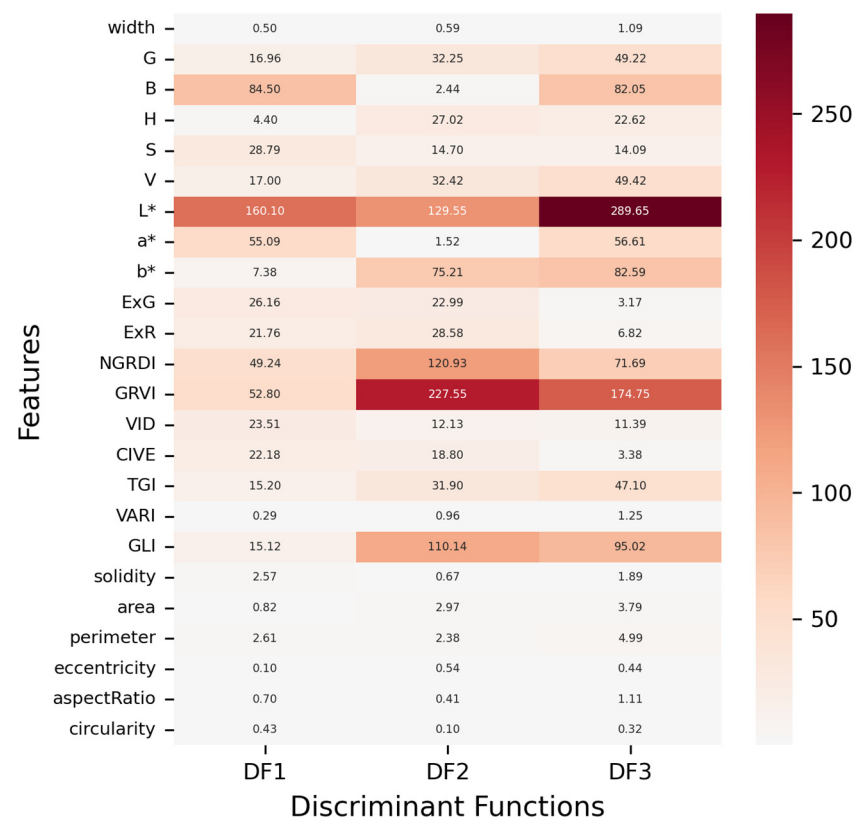


Figure 16. Canonical loadings of discriminant variables derived from Linear Discriminant Analysis (LDA) applied to nadir image features of *Rosmarinus officinalis* under different Cu treatments.

Discriminant loadings showed that separation was governed primarily by spectral descriptors, particularly L*, B, GRVI, and NGRDI, together with additional contributions from ExG, ExR, GLI, and TGI. Morphological variables contributed comparatively little to treatment classification, despite their greater representation in PCA secondary components. Classification accuracy reached 66.67% on the independent test set. Control plants remained highly distinguishable, whereas substantial overlap between T1 and T2 reduced discrimination among Cu-treated groups.

Overall, the nadir imaging analysis confirms that Cu supplementation induced consistent multivariate phenotypic changes dominated by spectral responses, while also improving sensitivity to canopy-level structural variation. In comparison with lateral imaging, nadir imaging enhanced detection of integrated canopy responses but reduced separability among treated classes, indicating that treatment discrimination is partially dependent on imaging perspective.

4.5. Real-Time Computer Vision Application

The image-based phenotyping framework developed in this study can be adapted for real-time deployment in intelligent WSN edge-computing environments as reported previously [61]. The proposed processing pipeline was intentionally designed using computationally lightweight operations, including RGB-to-HSV transformation, threshold-based segmentation, vegetation-index extraction, and multivariate statistical analysis, enabling compatibility with resource-constrained embedded platforms.

In the proposed real-time operational workflow, RGB images acquired by edge nodes are processed locally to identify treatment-induced physiological changes associated with copper supplementation and plant stress conditions. The segmentation process isolates plant regions from the background using predefined HSV thresholds, after which vegetation

indices such as ExG, ExR, GLI, VID, VARI, and NGRDI are computed directly on the edge device. These parameters provide rapid estimation of plant greenness, chlorophyll-related responses, and stress-related pigmentation dynamics without requiring cloud-based image processing.

The implementation of edge computing significantly reduces communication overhead within the WSN because only processed metrics, anomaly alerts, or compressed image summaries are transmitted to the central server instead of raw high-resolution images. This strategy improves scalability and reduces energy consumption in distributed agricultural deployments where multiple sensor nodes operate simultaneously under constrained power conditions. The proposed real-time edge-computing workflow anticipated for image-based plant monitoring is illustrated in Figure 17.

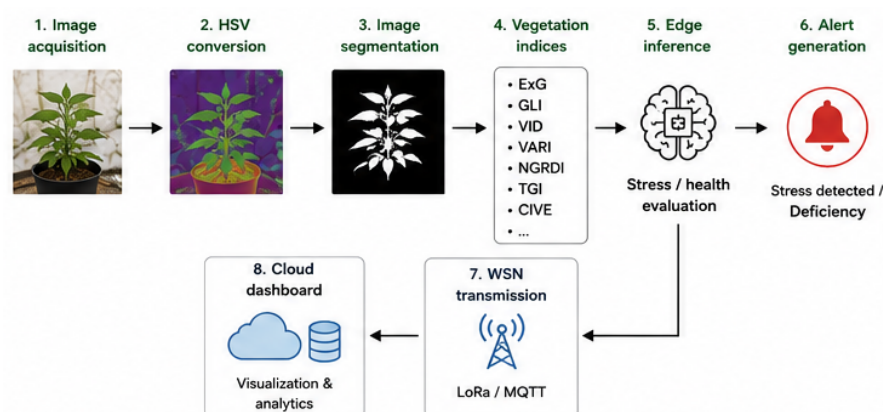


Figure 17. Real-time edge-computing workflow for image-based plant phenotyping and intelligent agricultural monitoring within the proposed WSN architecture.

Additionally, real-time edge inference enables the generation of immediate agricultural alerts associated with nutrient imbalance, vegetation degradation, or abnormal spectral responses. Such capabilities are particularly relevant for precision agriculture systems requiring continuous monitoring and rapid intervention. The proposed framework may therefore support autonomous crop supervision applications in greenhouses, urban farming systems, and remote agricultural environments.

The lightweight nature of the proposed computer vision workflow also facilitates future integration with TinyML and embedded artificial intelligence approaches. Future implementations may incorporate lightweight convolutional neural networks or machine-learning classifiers optimized for low-power hardware accelerators to improve classification robustness and automate stress detection under variable environmental conditions.

Furthermore, the proposed edge-computing approach enables decentralized agricultural monitoring architectures in which each node independently performs local analysis while participating in collaborative WSN communication. This distributed processing paradigm improves fault tolerance, reduces cloud dependency, and enhances overall network efficiency.

Overall, the proposed galvanic-cell-assisted monitoring framework could evolve toward intelligent real-time WSN systems combining sustainable energy harvesting, edge computing, and computer vision for next-generation precision agriculture applications.

5. Discussion

The present study demonstrates the feasibility of integrating a zinc–copper galvanic recovery system with potential agricultural micronutrient reutilization, thereby proposing a possible link between electrochemical resource recovery and circular plant production systems. The electrochemical characterization confirmed stable galvanic behavior consistent

with the theoretical thermodynamics of Zn–Cu redox pairs, with the five-cell assembly producing a cumulative open-circuit voltage of 5.286 V, corresponding to approximately 1.10 V per cell. This agreement with the theoretical electrode potential difference indicates effective coupling between zinc oxidation and copper reduction under the operational conditions employed. A comparative results summary is presented in Table 6.

Table 6. Comparative results summary of copper recovery approaches and their bioeconomic applications.

Study Aim	Method	Key Findings	Limitations	Ref.
Eco-friendly copper recovery from e-waste	Iron-based chemical leaching of PCBs with optimization modeling	Achieved 72.69% Cu recovery; safer alternative to aqua regia; strong economic potential (~35 million BDT/year)	Still relatively slow process (5 days); field practices remain unsafe; require controlled conditions	[3]
Simultaneous recovery of Cu, phosphate, and EDTA from wastewater	Self-driven electrochemical separation-recovery (SESR) system (galvanic-based)	High efficiency: 93.6% Cu recovery, selective phosphate recovery, no external energy input	System complexity; requires membrane optimization and controlled pH	[5]
Coupled copper recovery and energy generation	Microbial fuel cell (MFC) with modified cathodes (rGO/PANI)	Up to 99.3% Cu recovery and high-power density (981 mW/m ³); strong electrochemical performance	Long operation time (120 h); material cost and scalability challenges	[8]
Circular treatment of galvanic wastewater	Integrated membrane processes (UF + RO) for water and metal recovery	Achieved 86–99% contaminant removal; enables reuse of water and metal-rich streams	Requires infrastructure and post-treatment adjustments; capital intensive	[39]
Recycling industrial waste for metal removal	Ferritization producing magnetic sorbents	Up to 98.9% Zn removal; generates reusable materials; supports circular economy	Focus on wastewater treatment, not direct reuse of residual metals in agriculture	[62]
Recovery and agricultural reuse of Cu via galvanic system	Zn–Cu galvanic cell for Cu recovery + plant phenotyping (imaging + multivariate analysis)	Functional Cu recovery with dose-dependent enhancement of plant traits (ExG, GLI, NGRDI, TGI, etc.); supports circular bioeconomy	Lower energy output; requires dose optimization to avoid toxicity	Present study

Although the specific power and specific energy obtained in the present work were comparatively modest, the system was designed primarily as a proof-of-concept recovery platform rather than an optimized energy-storage device. Nevertheless, the progressive increase in current during operation suggests stabilization of ionic transport and electrode activity over time. Moreover, the rapid restoration of current following salt-bridge re-hydration demonstrates that ionic continuity strongly governs electrochemical stability and internal resistance. These observations indicate that electrolyte conductivity, membrane hydration, electrode spacing, and interfacial resistance collectively represent major determinants of system efficiency. The findings are conceptually consistent with electrochemical recovery systems that integrate material reclamation with energy generation. For instance, Samadi et al. [8] demonstrated that microbial fuel cells could simultaneously generate electricity and achieve copper recovery efficiencies approaching 99.3%, illustrating the broader potential of dual-function electrochemical technologies for sustainable resource management.

Beyond electrochemical performance, the biological evaluation demonstrated that residual copper from the galvanic process induced measurable and coordinated phenotypic responses in *Rosmarinus officinalis*. Univariate analyses showed that Cu supplementation, particularly at 50 mg L^{-1} , enhanced several vegetation-associated indices related to greenness and canopy vigor, including ExG, VID, GLI, and NGRDI. These responses are physiologically consistent with the established role of copper as an essential micronutrient involved in chloroplast function, photosynthetic electron transport, oxidative metabolism, and enzymatic activation [15]. The increase in greenness-related descriptors therefore may suggest improved pigment-associated optical characteristics and enhanced physiological status under moderate Cu supplementation.

The multivariate analyses substantially strengthened this interpretation by demonstrating that Cu exposure generated a coordinated shift across the integrated phenotypic feature space rather than isolated variation in individual descriptors. PCA consistently revealed that treatment separation was dominated by spectral and colorimetric variables, whereas morphological traits contributed mainly to secondary components. Across both imaging perspectives, the strongest loadings were associated with vegetation indices and color descriptors linked to greenness–reddening variations, including ExG, GRVI, VID, NGRDI, GLI, ExR, and CIVE. These patterns likely indicate that Cu supplementation primarily altered canopy reflectance behavior and pigment-associated optical signatures.

Importantly, the PCA ordinations revealed a progressive treatment gradient, with untreated plants consistently separated from Cu-treated groups and intermediate positioning of the lower concentration treatment. This structure indicates that the observed responses followed a concentration-dependent physiological trajectory rather than a simple binary stress response. The stronger variance concentration along PC1 in nadir imaging further suggests that top-view imaging may enhance sensitivity to canopy-scale spectral variation, whereas lateral imaging preserved stronger discrimination among treatment classes.

The MANOVA results confirmed that these treatment-driven changes were statistically robust at the multivariate level. The consistently low Wilks' lambda values obtained from both lateral and nadir datasets indicate that Cu supplementation substantially modified the integrated spectral and morphological phenotype of the plants. The strong agreement between PCA structure and MANOVA significance therefore strengthens confidence that the observed separations reflect biologically meaningful responses rather than stochastic variation within isolated features.

Additionally, the LDA results further clarified the discriminatory structure of the treatments and the predictive relevance of the extracted phenotypic descriptors. The strong classification performance obtained for lateral imaging, together with significant permutation outcomes, demonstrates that Cu treatments generated sufficiently distinct phenotypic signatures to permit reliable treatment discrimination. Control plants exhibited near-complete separation from Cu-treated plants, whereas partial overlap between T1 and T2 probably indicate increasing convergence of physiological responses at higher Cu availability. Consequently, such convergence may indicate saturation of pigment-associated optical responses or activation of similar physiological adjustment mechanisms under elevated copper exposure.

The predominance of spectral descriptors over morphological traits across both PCA and LDA possibly imply that optical changes preceded substantial structural modification during the experimental period. This observation is biologically plausible because pigment-related responses and reflectance alterations often emerge before visible architectural symptoms under micronutrient imbalance. The image-based phenotyping framework therefore proved capable of capturing subtle physiological variation at early stages of treatment response. Furthermore, the comparative behavior of lateral and nadir imaging

demonstrates that imaging perspective substantially influences phenotypic interpretation. While nadir imaging captured stronger canopy-level variance and greater sensitivity to structural descriptors, lateral imaging achieved superior treatment classification and clearer separation among Cu concentrations. Consequently, integrating multiple imaging perspectives may provide a more comprehensive representation of plant responses than reliance on a single acquisition geometry [18].

The observed dose-dependent responses are particularly important given the dual role of copper as both an essential micronutrient and a potential phytotoxic element. Although moderate Cu supplementation improved spectral indicators associated with plant vigor, excessive copper accumulation can disrupt photosynthesis, hormone regulation, nutrient balance, and cellular redox homeostasis. In agreement with this concept, Xing Xing et al. [18] demonstrated that elevated Cu concentrations negatively affect plant growth through impairment of physiological and metabolic pathways. The present findings therefore emphasize the importance of controlled dosing and monitoring when reutilizing residual metals in agricultural systems.

Moreover, the observed improvements in image-derived vegetation indices and morphological traits indicate a positive plant response associated with copper supplementation. Although these findings support the potential of recovered copper as a micronutrient source, direct confirmation of copper uptake, tissue accumulation, and physiological utilization requires complementary biochemical and chemical analyses, which should be addressed in future investigations.

From a broader sustainability perspective, the study contributes to the growing transition from waste treatment toward resource circularity. The reutilization of residual copper in agriculture reduces dependence on primary mining, which is associated with substantial environmental and energy costs. Similar circular approaches have been explored in industrial wastewater treatment and waste valorization systems. For example, Kowalik-Klimczak et al. demonstrated that membrane-based systems can simultaneously recover water and concentrate valuable metals for industrial reuse, thereby reducing waste generation. Likewise, Samchenko et al. [62] showed that industrial residues can be transformed into functional sorbent materials capable of heavy metal removal and water reutilization. Within this broader context, the present study extends existing knowledge by directly coupling electrochemical copper recovery with agricultural reuse supported by quantitative phenotypic evidence. Nevertheless, several challenges remain before practical implementation can be achieved.

The present study relied exclusively on image-derived phenotypic traits to evaluate plant responses to copper supplementation. Although complementary physiological and biochemical measurements, including biomass accumulation, chlorophyll content, tissue copper concentration, nutrient uptake efficiency, and root development, would provide additional biological validation, image-based phenotyping has become an established and widely accepted approach for assessing plant nutritional status and stress. Several recent studies have successfully inferred plant responses using RGB or multispectral imaging integrated with machine learning or deep learning methods without incorporating destructive physiological or biochemical analyses [63–65]. Nevertheless, the findings should be interpreted within the context of the present experimental design, which involved a relatively small sample size and a short observation period. Future studies incorporating complementary physiological measurements, longer exposure periods, and multiple crop species would further strengthen the biological interpretation and broaden the agronomic applicability of the proposed approach.

Considering the proposed WSN architecture, which demonstrates a feasible integration pathway for galvanic energy harvesting and intelligent agricultural monitoring, the present

study should be regarded as an initial proof of concept. The experimental work validated simultaneous electrical energy generation and copper reutilization but did not evaluate the capability of the harvested energy to sustain continuous sensing, image acquisition, edge computing, or wireless communication. Consequently, the proposed WSN architecture remains [63–65] conceptual and requires comprehensive experimental validation before practical deployment.

Several engineering challenges also remain to be addressed, including long-term electrochemical stability, electrode degradation, electrolyte management, energy storage, power conditioning, scalability to multi-node deployments, and complete system level validation under realistic agricultural conditions. Future research should therefore pursue the quantification of the energy budget of the proposed platform and experimentally evaluating its performance within an operational self-powered wireless sensor network.

Overall, this study provides proof-of-concept evidence that galvanic recovery systems can simultaneously support metal recovery and its potential reutilization in agriculture as a micronutrient source within a unified circular framework. The integration of electrochemical engineering with multiscale image-based phenotyping further demonstrates the potential of combining resource recovery technologies with advanced plant analytical approaches for sustainable nutrient management and circular bioeconomy applications.

Limitations

Several limitations should be considered when interpreting the findings of the present study. First, the Galvanic system was developed primarily as a proof-of-concept platform rather than an optimized electrochemical recovery device. Consequently, the electrochemical characterization focused on voltage generation and basic operational behavior, whereas critical performance parameters such as coulombic efficiency, internal resistance profiling, copper recovery yield, and long-term operational stability were not comprehensively quantified. In addition, the use of a vinegar–NaCl electrolyte as a substitute for conventional ZnSO_4 solutions introduced variability in ionic composition and conductivity that may have influenced electrochemical consistency and copper deposition dynamics.

A further limitation concerns the chemical characterization of the residual copper solution. Although the Residual Cu-containing solution was successfully reused for plant supplementation, the precise chemical speciation, purity, and concentration stability of the residual copper were not analytically verified using elemental or spectroscopic techniques. As a result, potential contributions from secondary ions, impurities, or pH-related effects cannot be fully excluded. Future studies should therefore incorporate analytical quantification methods Inductively Coupled Plasma Optical Emission Spectroscopy (ICP-OES), Inductively Coupled Plasma Mass Spectrometry (ICP-MS), or X-ray spectroscopy techniques to validate recovery efficiency and chemical composition.

From the biological perspective, the experimental duration was relatively short and focused primarily on early phenotypic responses. While image-based phenotyping successfully captured treatment-dependent spectral and morphological variation, the study did not evaluate long-term physiological consequences, biomass accumulation, root development, nutrient uptake efficiency, or potential phytotoxic effects associated with prolonged copper exposure. Because copper exhibits a narrow physiological threshold between essentiality and toxicity, longer exposure experiments and broader dose–response assessments are necessary to define agronomically safe application ranges.

The study was additionally limited to a single plant species, *Rosmarinus officinalis*, under controlled experimental conditions. Plant responses to micronutrient supplementation are strongly species-dependent and influenced by environmental interactions, soil properties, and microbial activity. Consequently, the generalizability of the present findings

to other crops, substrates, or cultivation systems remains uncertain. Validation under greenhouse and field conditions will therefore be required before broader agricultural applicability can be established.

Although quantitative recovery parameters such as recovered copper mass, electrode mass variation, Coulombic efficiency, and electrolyte copper depletion were not determined in the present proof-of-concept study, their determination will be essential for future optimization and benchmarking against conventional electrochemical recovery technologies.

Several methodological limitations associated with the imaging framework should also be acknowledged. Although the image-based phenotyping approach enabled non-destructive and sensitive monitoring of treatment responses, the analyses relied exclusively on visible-spectrum imaging. As a consequence, physiological processes beyond surface reflectance behavior, such as photosynthetic efficiency, stomatal conductance, or internal biochemical changes, could not be directly assessed. Moreover, segmentation thresholds and lighting conditions, despite being standardized, may still introduce variability in extracted spectral descriptors.

In addition, the proposed WSN architecture is presented as a conceptual low-power deployment framework intended to demonstrate the integration potential of galvanic energy harvesting with intelligent agricultural monitoring systems. Experimental validation of the complete WSN, including energy storage, power management, duty-cycle optimization, and long-term wireless communication performance, is beyond the scope of the present study and will be addressed in future investigations.

The developed galvanic cell should therefore be regarded as an initial proof of concept rather than a fully deployable energy harvesting solution. Although the system successfully demonstrated simultaneous electrical energy generation and copper reutilization, its power generation capability has not yet been quantitatively validated for sustained operation of practical sensing, data processing, image acquisition, or wireless communication tasks. Moreover, several engineering challenges remain to be addressed before field deployment becomes feasible, including long-term electrochemical stability, electrode degradation, electrolyte replenishment, energy storage and power management strategies, system scalability for multi-node sensor networks, and comprehensive validation under realistic operating conditions. Addressing these aspects will be essential for translating the proposed concept into a practical self-powered monitoring platform for precision agriculture.

Finally, the study did not include direct measurements of tissue copper accumulation, chlorophyll concentration, oxidative stress markers, or enzymatic activity. Therefore, the mechanistic interpretation of the observed spectral responses remains inferential rather than physiologically validated. Integrating image-based phenotyping with biochemical, elemental, and molecular analyses would substantially strengthen future evaluations of galvanically residual micronutrients and their effects on plant performance.

6. Conclusions

This study demonstrated the feasibility of a simple Zn–Cu galvanic system as a dual-function platform for copper recovery and subsequent reuse in plant nutrition as a potential micronutrient source. The five-cell configuration delivered an open-circuit voltage of 5.286 V, consistent with theoretical expectations for Zn–Cu electrochemical systems, while single-cell measurements confirmed stable electrochemical behavior over time. Variations in current response and the sensitivity of performance to salt-bridge hydration further emphasized the central role of ionic transport continuity and interfacial resistance in governing system stability and efficiency.

The proposed galvanic-cell platform demonstrated not only its feasibility for sustainable copper recovery and potential plant micronutrient reutilization while establishing a

conceptual foundation for future integration into intelligent WSN and edge-computing agricultural environments. Although the results may indicate that the system could serve as a low-power energy source, no complete sensor node or energy-harvesting architecture was experimentally implemented or validated. Consequently, the combination of galvanic energy harvesting, image-based phenotyping, and distributed sensing should be regarded as a prospective framework for future autonomous precision agriculture systems.

From an application perspective, the residual copper solution exhibited measurable effects on *Rosmarinus officinalis*, with the 50 mg L⁻¹ treatment producing the most favorable phenotypic response across image-derived vegetation indices. Multivariate analysis confirmed that these responses were primarily driven by spectral alterations associated with pigment balance and canopy reflectance, demonstrating that residual copper from the galvanic system may exert biologically relevant effects within a controlled dosage range. Although these findings support the potential of recovered copper as a micronutrient source, direct confirmation of copper uptake, tissue accumulation, and physiological utilization requires complementary biochemical and chemical analyses, which should be addressed in future investigations.

Despite these encouraging outcomes, the system remains in an early developmental stage. Electrochemical efficiency, copper recovery yield, and long-term operational stability were not fully optimized, and the absence of direct chemical quantification limits precise assessment of recovery performance. In parallel, the biological evaluation was restricted to short-term responses under controlled conditions, without assessment of tissue accumulation, soil dynamics, or potential phytotoxic thresholds.

Future work will be directed towards the experimental validation of the proposed WSN architecture through the implementation of a complete sensor node powered by the Zn–Cu galvanic-cell system. This will include the development and evaluation of power management circuitry, energy storage strategies, sensor-node power consumption, duty-cycle optimization, wireless communication performance, and edge-computing capabilities under realistic agricultural operating conditions, enabling a comprehensive assessment of the practical feasibility of the proposed energy-harvesting concept. Complementary studies will also provide comprehensive physicochemical and electrochemical characterization of the residual electrolyte, including copper recovery efficiency, dissolved metal concentrations, Faradaic efficiency, and long-term operational stability. In parallel, extended biological investigations involving tissue elemental analysis, dose–response experiments, long-term agronomic evaluation, and multi-crop field validation will be essential to establish the safety, scalability, and practical applicability of this circular agriculture approach.

To conclude, the present study provides the basis for electrochemical and biological components of the proposed platform, whereas the WSN-based energy-harvesting architecture remains a conceptual application that will be addressed through future system-level implementation and validation.

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Abbreviations

The following abbreviations are used in this manuscript:

CIVE	Color Index of Vegetation Extraction
ExG	Excess Green Index
ExR	Excess Red Index
GLI	Green Leaf Index
GRVI	Green–Red Vegetation Index
NGRDI	Normalized Green–Red Difference Index
OCV	Open-Circuit Voltage
TGI	Triangular Greenness Index
VARI	Visible Atmospherically Resistant Index
VID	Vegetative Index Difference

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