



Article

Spectral Detection of Kinetic Stress Dynamics in Ornamental Foliage Plants

Kornél Szalay, Gábor Bércesi * and Szilvia Erdei-Gally *

Institute of Technology, Hungarian University of Agriculture and Life Science, Páter Károly utca 1,
2100 Gödöllő, Hungary; szalay.kornel@uni-mate.hu

* Correspondence: bercesi.gabor@uni-mate.hu (G.B.); erdeine.kesmarki-gally.szilvia@uni-mate.hu (S.E.-G.)

Abstract

Kinetic shock triggers thigmomorphogenetic responses in plants, posing both an unintended handling risk and a deliberate technique to enhance ornamental value. Detecting its immediate, non-visual impacts remains a challenge. This study used non-destructive contact spectroscopy to detect short-term kinetic stress in three species with distinct leaf anatomies (*Alocasia* sp., *Monstera deliciosa*, *Ficus elastica*) under 20 s and 40 s stimuli. While a pooled global classification model failed due to anatomical variations masking the universal stress signal (70% accuracy), optimized species-specific models revealed distinct dynamics. At 0 min post-stress, high variance and low separability occurred across all species. However, a diagnostic change emerged within 30 min for *Alocasia* sp. (79.37%) and *Ficus elastica* (77.50%); the same tendency could not be confirmed for *Monstera deliciosa*, and further investigation is needed to support this pattern. *Ficus elastica*'s distinct architecture also proved consistently the least sensitive of three species in the pooled control-versus-treated comparison. A significant dosage effect was captured only in *Alocasia* sp. (87.50% accuracy). Spectral index analysis showed the dominance of the Normalized Difference Water Index (NDWI), suggesting the change reflects micro-structural leaf turgor modifications rather than biochemical changes. Results indicate that leaf spectroscopy has the potential to diagnose transport injury and monitor conditioning.

Keywords: kinetic shock; indoor farming; spectroscopy; PLS-DA

1. Introduction

In commercial horticulture, kinetic stimuli exhibit dual nature. Unintended shock from transport or handling induces post-harvest injury, compromising aesthetic quality. Conversely, deliberate thigmomorphogenetic conditioning, like controlled vibration, is used to dwarf plants, creating a compact architecture with higher market value. Because these immediate cellular shifts are non-visual, traditional assessments fail. This creates a need for rapid, non-destructive tools like contact leaf spectroscopy to optimize both stress mitigation and automated growth regulation.

1.1. Physiological Triggers to Manipulate Plant Growth

Indoor ornamental production encompasses a wide diversity of species selected almost exclusively for visual traits, compact canopy symmetry, and structural form [1]. To consistently achieve these target aesthetics, modern greenhouse operators possess an array of physiological triggers to manipulate plant growth and architecture.



Academic Editors: Dario Lodi Rizzini,
Francesco Paciolla and Marco Sozzi

Received: 30 June 2026

Revised: 30 July 2026

Accepted: 31 July 2026

Published: 5 August 2026

Copyright: © 2026 by the authors.
Licensee MDPI, Basel, Switzerland.
This article is an open access article
distributed under the terms and
conditions of the [Creative Commons
Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

As part of genetic and transgenic regulation, targeted gene expression edits can permanently suppress stem elongation and yield dwarf phenotypes [2]. Exogenous hormonal growth regulators like paclobutrazol or chlormequat chloride suppress gibberellin biosynthesis, reliably forcing a more compact canopy [3]. Nutritional deprivation strategies can deliberately activate systemic architectural defense mechanisms that curtail vertical stem elongation [4]. Photomorphogenetic lighting regimes can activate phytochrome and cryptochrome photoreceptors to guide stem extension [5]. While the other four methodologies remain established options in the commercial toolkit, a chemical-free, sustainable architectural manipulation lies in thigmomorphogenesis—the structural alteration of plant growth patterns in direct response to mechanical stimulation [6,7]. It operates completely free of synthetic chemicals, ensuring operator safety, while carrying no risk of the irreversible visual blemishes caused by localized nutrient starvation [8]. Mechanical stimulation can deliver a clean and easily automated physical input that optimizes ornamental compact form while preserving tissue integrity and product marketability.

1.2. Mechanical Stress in Commercial Practice

To successfully integrate physical conditioning into indoor facilities, the mechanical stimulus needs to be scalable and repeatable. Historically and commercially, greenhouse operators have relied on distinct categories of physical interventions to suppress stem elongation and encourage compact growth. Brushing and stroking are commonly deployed in high-density seedling and plug production: PVC pipes, canvas sheets, or horizontal bars physically sweeping across plant canopies multiple times a day [9–11]. Direct physical rubbing can micro-wound the leaf cuticle and easily vector foliar pathogens [12]. Forced air and wind-sway are rooted in classic forestry nursery concepts. This method exposes crops to high-velocity fans or localized air jets to induce structural stunting and stem thickening [7,13]. It can trigger immediate spikes in transpiration rates, localized leaf cooling, and microclimatic humidity fluctuations [7]. Acoustic pressure waves involve the application of specific sound frequencies to stimulate plant tissues without physical contact [14,15]. Manual flexing and rubbing are applied primarily in small-scale viticulture or high-value boutique horticulture [6,9]. While highly targeted, manual flexing causes microscopic tissue micro-fractures and stress-induced cellular necrosis if executed unevenly. Because it is completely unquantified, labor-intensive, and prone to human error, it remains entirely unviable for commercial vertical farming frameworks. A special type of mechanical stress is transportation and logistical vibration. Plants routinely experience chronic, multi-axis kinetic stress during post-harvest logistical chains. Commercial vehicle transportation subjects ornamental foliage crops to continuous low-frequency vibrations (typically ranging from 1 to 20 Hz) with high-amplitude transient shocks from road unevenness. During road transport, potted ornamentals may be exposed to vibration-induced mechanical stress. Under simulated transport conditions, visible leaf and flower damage was observed in several pot-plant species, with part of the injury attributable to contact with packaging and support materials [16,17]. Consequently, evaluating this unintended post-harvest kinetic signature is a critical economic priority for logistics quality assurance, yet it remains unquantified due to the lack of non-destructive diagnostic tools capable of tracking cellular-level shock signatures prior to the onset of visible cosmetic damage.

1.3. Quantified Mechanical Stress

In nature and commercial production, plants are subjected to a wide range of kinetic energies, from subtle vibrations to high-acceleration events. As characterized by De Langre [18], the lower end of this range is dominated by aerodynamic drag and boundary

layer fluctuations, which primarily influence gas exchange and transpiration rather than permanent structural form.

Transitioning these stimuli into reliable agronomic inputs requires an understanding of dose-responsiveness; [19] established that thigmomorphogenetic outcomes are fundamentally proportional to the strain energy or bending moment applied to the plant tissue. While commercial interventions like mechanical brushing have been proven to apply sufficient force to control height and induce stunting [11], these contact-based methods often deliver high localized accelerations (exceeding 5 g) that carry a significant risk of cuticular micro-wounding and biological liability [9].

The 2 g target threshold utilized in this research represents a “high-intensity, non-destructive” dosage. It is calibrated to provide sufficient inertial loading to trigger acute physiological signaling (particularly in large-leaved ornamentals where the leaf mass acts as a natural lever) without reaching the mechanical failure point of the petiole or leaf lamina. Table 1 shows different magnitudes of mechanical stimuli.

Table 1. Mechanical stimuli affecting plants: source-specific stimulus descriptors and biological outcomes.

Source of Mechanical Stress	Recommended Descriptor	Main Reported Outcome	Key Reference(s)
Ambient airflow	Air velocity and exposure duration	Modifies boundary-layer conditions, gas exchange and plant hydraulics; effects may differ from stem flexure.	[20]
Wind-induced sway	Wind speed, gustiness, and stem or leaf deflection	May reduce elongation and induce mechanical acclimation, depending on species and exposure conditions.	[18,21]
Transport vibration	Random-vibration profile, duration, plant fixation and packaging configuration	May cause visible leaf and flower damage, particularly through rubbing and contact with packaging materials.	[16]
Controlled vibration (present study)	Peak platform acceleration: 2.0 g; treatment duration: 20 or 40 s	Acute spectral response evaluated in the present study.	Present study
Mechanical brushing	Number of strokes per day; crop developmental stage	Can reduce stem elongation; the response is strongly species- and dose-dependent.	[10,11]
Controlled bending	Applied bending strain; number and duration of bending events	Strain-dependent mechanosensitive growth responses may occur.	[22]

1.4. The Role of Spectroscopy in Horticulture

The technical evolution of indoor farming systems relies on advanced control and automation networks. Historically, environmental regulation focused on macro-level adjustments, utilizing static sensors to log ambient air temperatures, humidity, and substrate electrical conductivity. However, maintaining a truly dynamic feedback loop requires shifted emphasis from tracking the room’s atmosphere to actively observing the plant’s immediate physiological status [23]. Remote sensing and spectroscopy serve as highly sensitive diagnostic tools to bridge this gap, gathering high resolution, multi-layered physiological and environmental information directly from the living tissue canopy [1,24–26]. By capturing non-destructive optical and spectral data, these technologies sense real-time micro-fluctuations in light energy absorption, photon scattering, and chemical reflection profiles [24]. High-resolution spectroscopy can be leveraged as a real-time feedback loop to assess whether an applied physical stress was sufficient to trigger the target thigmomorphogenetic change, or conversely, if it was excessive enough to induce cellular damage [23]. This precise optical monitoring window allows automated indoor systems to tune and validate stress dosages, ensuring crops receive an optimal, productive conditioning regimen before any macroscopically visible morphological adjustments or injuries manifest.

1.4.1. Spectral Regions

Plant reflectance spectra captured across the contiguous 350–2500 nm range provide a continuous diagnostic look into leaf physiology. The full spectrum is divided into three major optical bands sensitive to specific anatomical features and stress-induced chemical transitions.

Visible (VIS) region (350–700 nm) is governed by light absorption from key photosynthetic pigments (Chlorophyll a, Chlorophyll b, and carotenoids). Sudden physical stress triggers a rapid biochemical signaling loop, which can alter chloroplast alignment and generate reactive oxygen species (ROS) [8,27]. As established by Frampton et al. [27], the red-edge spectrum (specifically the transition zone near 700 nm) operates as an ultra-sensitive indicator of early stress; oxidative cellular environments and ROS accumulation degrade pigment concentrations, causing the red-edge position to rapidly shift toward shorter wavelengths.

Near-Infrared (NIR) region (700–1300 nm) is controlled by internal leaf macro-structure and cellular arrangement. The high scattering and reflectance observed in the NIR plateau do not depend on chemical absorption but are instead a function of the physical boundaries between cell walls and intercellular air spaces within the mesophyll layer [27]. Long-term thigmomorphogenetic adaptation directly alters cell wall viscoelasticity, micro-fibril orientation, and intercellular packing to structurally fortify tissues against mechanical stress, fundamentally reorganizing these internal NIR scattering interfaces [14,28].

Short-Wave Infrared (SWIR) region (1300–2500 nm) is sensitive to water content, along with structural biochemical components like proteins, lignin, and cellulose. Liquid water absorbs heavily in the SWIR bands (characterized by distinct O-H bond stretching near 1400 nm and 1900 nm) whereas organic molecules like structural proteins display strong absorption features near 2200 nm [27]. Sudden mechanical stress can trigger immediate turgor loss, rapid stomatal closure, or localized protein modifications, driving measurable reflectance shifts across these long-wave infrared water bands [23,27].

1.4.2. Vegetation Indices

To compress multi-dimensional spectral information, mathematical band formulations known as vegetation indices are utilized [24]. Rather than relying on isolated, uncalibrated raw reflectance bands, vegetation indices isolate specific wavelength ratios or normalized difference equations to emphasize subtle physiological transformations. It can also minimize background atmospheric noise or leaf geometry scattering in imaging [29]. When isolating the structural and metabolic shifts triggered by automated kinetic forces, specific narrow-band indices (Table 2) serve as the diagnostic tools to systematically differentiate between acute physiological shock and permanent structural acclimation [29,30].

Table 2. Narrow-band vegetation indices examined to characterize acute and chronic plant response against mechanical stress.

Category	Index Name	Abbrev.	Equation	Physiological Significance	Reference
Acute Stress	Photochemical Reflectance Index	PRI	$(R_{531} - R_{570}) / (R_{531} + R_{570})$	Tracks xanthophyll cycle shifts and instantaneous photosynthetic light-use efficiency.	[31]
Acute Stress	Water Band Index	WBI	R_{970} / R_{900}	Detects rapid cellular turgor drops and initial stomatal closure events.	[32]
Chronic Stress	Modified Red Edge NDVI	MRENDVI	$(R_{750} - R_{705}) / (R_{750} + R_{705} - 2 \cdot R_{445})$	Maps long-term structural changes with specular surface correction.	[33]

Table 2. Cont.

Category	Index Name	Abbrev.	Equation	Physiological Significance	Reference
Chronic Stress	Normalized Difference Water Index	NDWI	$(R_{860} - R_{1240}) / (R_{860} + R_{1240})$	Evaluates deep canopy fluid volumes, cellular packing, and specific leaf area.	[34]
Chronic Stress	Normalized Difference Red Edge	NDRE	$(R_{790} - R_{720}) / (R_{790} + R_{720})$	Red-edge chlorophyll and nitrogen indicator; sensitive to pigment decline and sub-visible physiological stress.	[35]

1.5. Research Objectives

Transitioning thigmomorphogenesis from a qualitative concept into a reliable agronomic input requires a precisely quantified stress stimulus. In this study, a new solution is introduced and tested with an automated, non-contact horizontal oscillation regime yielding a peak acceleration of 2 g (19.6 m/s²) applied for durations of 20 and 40 s, utilizing an exact and precisely reproducible kinetic dosage where the physical load experienced by the foliage is a direct mathematical product of the plant's own mass. Because the mechanical stress is completely non-contact, driven purely by leaf inertia, there is no risk of cuticle abrasion or pathogen transmission [11,12], or disruptions caused by wind-sway [7], providing a clean baseline for spectral tracking. To validate this approach, our experimental design translates core physiological observations into three verifiable research hypotheses across three target indoor species (*Alocasia* sp., *Monstera deliciosa*, and *Ficus elastica*).

1.5.1. Spectral Detectability of Kinetic Stress

Mechanical disturbance triggers immediate biochemical signaling. These internal transitions alter leaf water status and pigment cycles, creating subtle reflectance variations across the full spectrum (350–2500 nm) that should be mathematically isolatable using supervised machine learning.

Research question 1: Can multivariate classification models (PLS-DA) successfully differentiate between control plants and those subjected to non-contact 2 g kinetic shock before macroscopic changes manifest?

1.5.2. Temporal Sensitivity of the Shock Response

Plant physiological responses to kinetic loading are transient and dynamic. The biological signal likely requires a brief ‘incubation’ period post-stimulus to reach a peak reflectance divergence (driven by stomatal regulation and turgor fluxes) that provides the highest statistical contrast against the pre-treatment state.

Research question 2: At what specific interval within the acute post-stress window (0, 15, and 30 min) does the spectral signature of thigmomorphogenetic signaling reach its maximum separability?

1.5.3. Influence of Kinetic Dosage

Thigmomorphogenesis is documented as a dose-dependent phenomenon. By comparing two different durations at a constant acceleration magnitude, we aim to determine if a longer stimulus transfers sufficient additional energy to the plant to yield a more robust and easily classified spectral footprint.

Research question 3: Does increasing the duration of the 2 g stimulus from 20 s to 40 s result in a significantly different or more intense spectral signature?

1.5.4. Anatomical and Morphological Divergence

The inertial load experienced by a leaf is a product of its mass and leverage. Species with compliant, broad, and high-mass leaves (*Alocasia*, *Monstera*) undergo more significant physical deformation and petiole bending during horizontal oscillation than rigid, cuticular species (*Ficus*). We expect these herbaceous morphologies to produce more pronounced, high-amplitude shifts in their spectral profiles. This expectation is grounded in plant biomechanics: a plant's dynamic response to vibration is governed by how close the excitation frequency lies to the natural (resonant) frequencies of its stem–petiole–leaf system, which are set by tissue stiffness and mass distribution [36]. Stiff, high-leaf-mass-per-area species such as *Ficus* have higher natural frequencies and resist deformation, and may additionally mask internal change through their thick, reflective cuticle [37,38].

Research question 4: How does baseline leaf anatomy (flexible/herbaceous vs. rigid/cuticular) dictate the amplitude and accuracy of the spectral stress signature?

2. Materials and Methods

2.1. Plant Material and Controlled Growth Conditions

The experiment was conducted at the Hungarian University of Agriculture and Life Sciences (MATE), Institute of Technology, within a specialized indoor farming facility [39]. Three ornamental species were selected for study: *Ficus elastica*, *Alocasia* sp. (dwarf variety), and *Monstera deliciosa* (Figure 1).



Figure 1. Experimental plants.

Plants were grown in a climate-controlled chamber (Figure 2) maintained at a constant 22 °C. A 12-h photoperiod (12 h light/12 h dark) was provided by 12 Gro-Lux T8 fluorescent tubes (58 W each), specifically designed for plant growth. The plants were grown in Wilma drip-irrigation pots (ATAMI B.V., Rosmalen, The Netherlands) containing a 3 cm base layer of clay pebbles topped with general-purpose potting soil. Nutrient supply was maintained via two slow-release fertilizer sticks per pot. Irrigation was automated, providing 2 min of dripping water supply twice a week. To ensure physiological stability and representative baseline data, all plants underwent a month-long undisturbed acclimation period under these conditions prior to the commencement of mechanical stress treatments.



Figure 2. Plant growing chamber.

2.2. Mechanical Stress Induction

Mechanical stress was delivered using a refurbished and specially retrofitted Fritsch Analyzette 18.002 oscillation sieving machine (FRITSCH GmbH, Idar-Oberstein, Germany) (Figure 3).



Figure 3. Modified Fritsch Analyzette 18.002 oscillation sieving machine.

2.2.1. Custom Securement Framework

To accommodate the high-intensity agitation, a custom-engineered mounting frame was retrofitted to the machine's platform. This frame was specifically designed to hold the plant pots in a fixed position, ensuring that the containers remained secured and that the 2 g acceleration was transferred directly to the plant–soil system without lateral slippage or dampening.

2.2.2. Stress-Level Determination

To define the optimal experimental parameters, preliminary destructive testing was conducted on a separate group of test plants. These individuals were subjected to increasing acceleration magnitudes until macroscopic tissue failure and permanent mechanical damage occurred. Based on these threshold trials, a 2 g peak acceleration (19.6 m/s^2) was selected as the study's intensity dosage; this level was found to be the maximum intensity capable of eliciting a robust physiological response while remaining safely below the limit of irreversible structural injury.

2.2.3. Frequency and Calibration

The oscillation speed was regulated via an electronic potentiometer. For all experimental groups, the device was set to level 8, corresponding to a shaft speed of 286 rpm. To confirm the precise kinetic load, the system was mapped using a Kelag KAS903-02A dual-axis accelerometer (KELAG Künzli Elektronik AG, Schwerzenbach, Switzerland) (measurement range $\pm 12 \text{ g}$). Data recorded at 9600 Hz confirmed that the radial path of the secured frame yielded a consistent 2 g peak acceleration (19.6 m/s^2) at an excitation frequency of 4.77 Hz (corresponding to the 286 rpm motor speed). The movement pattern of the system is described below (Figure 4).

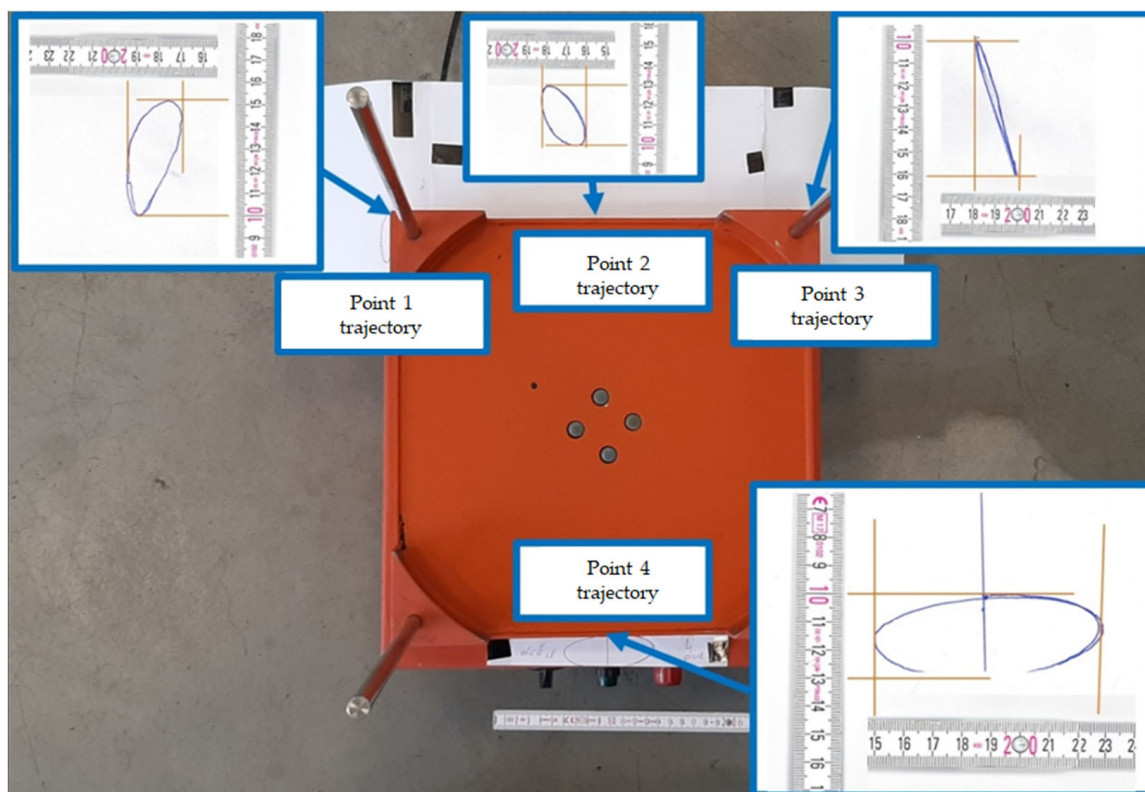


Figure 4. Oscillation characteristics.

The equipment and methodology were refined as follows.

2.2.4. Experimental Durations

Using this standardized 2 g (19.6 m/s^2) peak acceleration, plants were divided into two treatment groups to evaluate temporal dosage: Group I received a 20-s oscillation, while Group II received a 40-s oscillation. A third group was maintained as a non-agitated control.

2.3. Proximal Spectral Measurements

Leaf reflectance spectra (350–2500 nm) were captured using an ASD FieldSpec 3 MAX spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA) (Figure 5).



Figure 5. ASD FieldSpec 3 MAX Spectroradiometer.

To eliminate interference from ambient lighting and ensure high signal-to-noise ratios, an ASD Plant Probe (Analytical Spectral Devices Inc., Boulder, CO, USA) (contact probe) with an internal halogen light source was utilized (Figure 6).



Figure 6. Plant probe sensorhead.

The measurement protocol followed a strict sequence:

2.3.1. Calibration

The instrument warmed up for 30 min. Before each measurement series, a white reference calibration was performed using a Zenith Reflectance Target (95% reflectance).

2.3.2. Sampling

Three leaves per plant were marked for the entire duration of the experiment. Measurements were taken at the adaxial surface. To prevent background scattering, a specialized black rubber sheet was placed behind the leaf during every scan (Figure 7).



Figure 7. Contact measurement.

2.3.3. Data Integration

Each saved spectrum was the average of 7 internal scans.

2.3.4. Temporal Resolution

Measurements were recorded at four intervals: pre-treatment (baseline), immediately post-treatment (0 min), 15 min post-treatment, and 30 min post-treatment. This sequence allowed for the tracking of the acute physiological ‘shock’ and early recovery phases.

2.4. Spectral Data Pre-Processing and Multivariate Statistics

2.4.1. Computational Environment and Software

All data processing, visualization, and statistical modeling were performed using the Python programming language (version 3.13) within the Microsoft Visual Studio Code Integrated Development Environment (IDE) (version 1.130.0). The analytical pipeline relied on the following scientific libraries: *NumPy* (version 2.2.6) and *Pandas* (version 2.3.3) for data manipulation; *Matplotlib* (version 3.10.7) and *Seaborn* (version 0.13.2) for graphical representation; *Specdal* (version 0.2.1) for specialized spectral handling; and *Scikit-learn* (version 1.8.0) for multivariate modeling and machine learning.

2.4.2. Spectral Pre-Processing Pipeline

To eliminate instrument noise and physical scattering effects, a pre-processing workflow was applied to the raw reflectance spectra (350–2500 nm).

Detector Splice (Jump) Correction

To account for the inherent sensitivity shifts between the three detectors of the ASD FieldSpec 3 MAX, jump correction was applied at the 1000 nm and 1830 nm splice points. Using the *specdal.Collection.jump_correct()* function with an ‘additive’ method, the central region (1000–1830 nm) was utilized as a reference to parallelly shift the flanking regions.

Smoothing and Derivation

A Savitzky–Golay filter was utilized to minimize high-frequency noise while preserving physiological signal features. The entire spectrum was smoothed using a window length of 10 and a 4th-order polynomial. Simultaneously, the first derivative of the spectra was calculated to resolve overlapping absorption features and remove baseline shifts.

Logarithmic Transformation

For specific sub-analyses, a base-10 logarithmic transformation was applied to the first derivative spectra to enhance the linearity of the relationship between reflectance and chemical concentrations.

Standardization

To mitigate the influence of leaf geometry and light scattering variations, Standard Normal Variate (SNV) transformation was performed. It removes physical multiplicative scattering and baseline shifts caused by leaf surface texture, thickness, and probe contact angles. This centered each spectrum to a mean of zero and scaled it to unit variance (standard deviation of 1).

2.4.3. Partial Least Squares Discriminant Analysis (PLS-DA)

To differentiate between experimental groups (control vs. treated) and to evaluate the influence of kinetic dosage (20 s vs. 40 s), Partial Least Squares Discriminant Analysis (PLS-DA) was employed. The models were implemented using the *sklearn.cross_decomposition.PLSRegression* object.

Model Architecture

The models were fitted using three latent variables (LVs) to maximize the explained covariance between the spectral predictors (explanatory variables) and the binary/categorical group assignments (response variables).

Data Partitioning and Independence

To ensure the statistical independence of the results and avoid overfitting, the dataset was split into training and testing sets based on individual leaves rather than random spectral sampling. From each plant, two leaves were assigned to the training set, while the third leaf was reserved exclusively for the test set. This “held-out leaf” approach ensures the model’s predictive accuracy is validated on biologically independent tissue.

2.4.4. Statistical Validation and Effect Size Interpretation

The significance of the spectral divergence was assessed by performing a Mann–Whitney U test on the first latent variable (LV1) scores. Beyond traditional *p*-values, which indicate whether a difference exists, the magnitude and practical significance of the physiological response were quantified using four distinct effect size metrics:

Cohen’s *d*

Measures the standardized difference between group means, providing a scale-independent metric to evaluate the strength of the spectral shift between control and treated states.

Rank-Biserial Correlation (*r*)

A non-parametric measure used to evaluate the strength and direction of the association between the mechanical treatment and the resulting spectral variation.

Cliff’s Delta (δ)

A robust, non-parametric effect size metric that quantifies the degree of overlap between the distributions of the two groups, representing how consistently the treated samples deviate from the control baseline.

Common Language Effect Size (CLES)

Expresses the results in probabilistic terms, representing the likelihood that a randomly selected plant from the treated group will exhibit a more intense spectral response than a randomly selected plant from the control group.

2.4.5. Classification Metrics

To evaluate the “spectral detectability” of the thigmomorphogenetic shock and the diagnostic utility of the PLS-DA models, the predictive performance was assessed using the following classification indicators:

Accuracy

Calculated as the proportion of correctly classified instances (both true positives and true negatives) out of the total number of samples in the independent test set. This provides a baseline measure of the model’s ability to distinguish between treated and untreated physiological states.

Weighted F1-Score

The harmonic mean of Precision and Recall. By utilizing a “weighted” average, this metric accounts for potential class imbalances in the dataset (e.g., varying sample sizes between control and treatment groups), ensuring that the model’s performance is not artificially inflated by a majority class and that both the sensitivity and specificity of the shock detection are balanced.

Cohen’s Kappa Coefficient (κ)

A robust metric that evaluates the degree of agreement between the predicted and actual class assignments while adjusting for the probability of agreement occurring by chance. This coefficient is critical for validating that the spectral classification is driven by actual physiological signatures rather than random statistical noise, with values closer to 1.0 indicating near-perfect model reliability.

3. Results

3.1. Global Discriminant Analysis of Kinetic Stress

The initial phase of the evaluation focused on determining whether a universal hyperspectral response to mechanical vibration could be identified across the entire dataset, regardless of species-specific anatomical variations. To establish this, all spectral samples from *Alocasia* sp., *Monstera deliciosa*, and *Ficus elastica* were pooled, creating a comprehensive database for multivariate analysis ($n_1 = 360$ control vs. $n_2 = 2880$ treated samples).

Before model fitting, a pre-processing and quality control pipeline was implemented. This included a preliminary spectral screening to identify and remove outliers, primarily those affected by instrument noise so that the underlying physiological signal remained unclouded. To maintain biological independence and prevent overfitting, the dataset was partitioned using a ‘held-out leaf’ approach: two leaves from each plant were assigned to the training set, while the third leaf was reserved exclusively for independent validation ($n = 1080$ for the global test set). The global analysis described in this section was performed exclusively on the filtered and normalized (SNV) reflectance spectra.

Non-parametric statistical analysis of PLS-DA transformed data (Figure 8) confirmed that mechanical stimulation triggers a highly significant shift in the leaf reflectance profiles. A Mann–Whitney U test performed on the first latent variable (LV1) scores revealed a definitive spectral divergence between the control and treated populations ($p < 0.001$). Despite this high level of statistical significance, the magnitude of the global effect size remained

relatively modest, with a Cliff’s Delta of -0.289 and a Cohen’s d of -0.480 (Table 3). The Common Language Effect Size (CLES) of 64.44% indicates a moderate probability that a randomly selected treated plant will exhibit a more intense spectral response than a control plant when species are not analyzed individually.

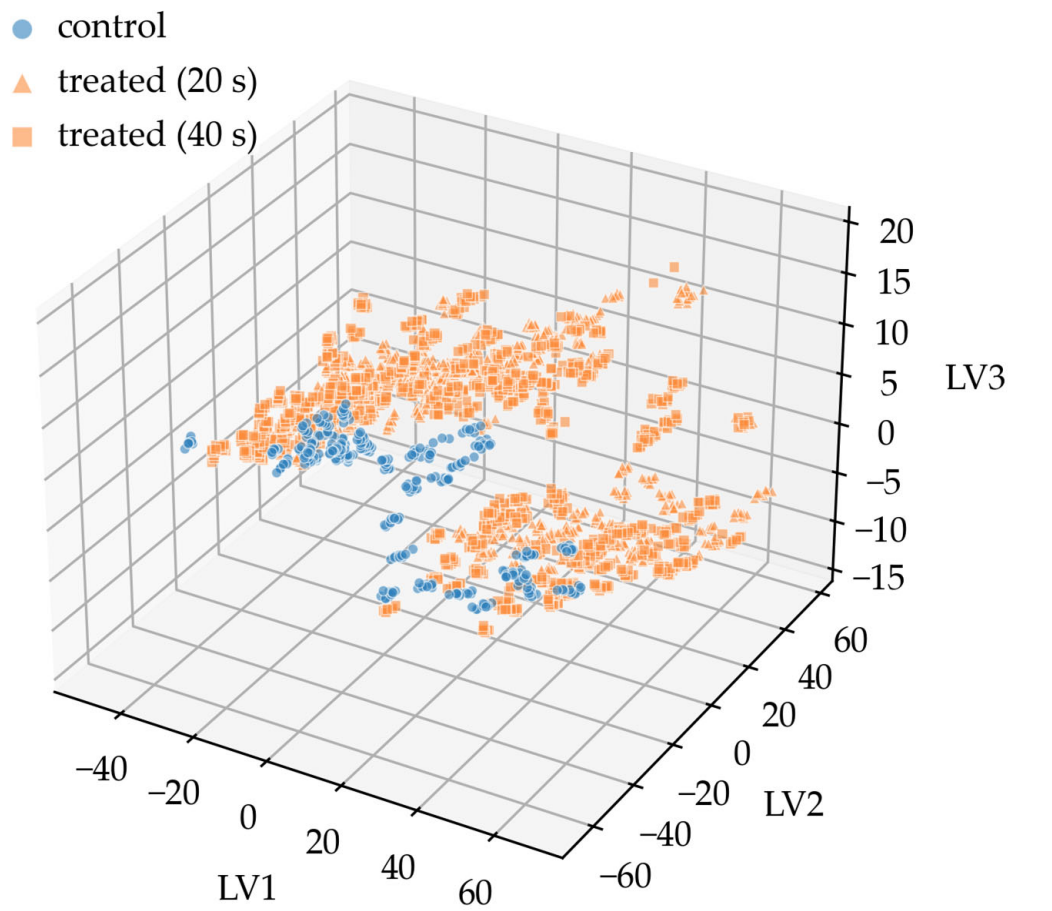


Figure 8. Global PLS-DA 3D Score Plot (all species pooled), highlighting the initial overlap and clustering trends. The visualization illustrates the statistical separation between control (pre-treatment) and kinetic shock (post-treatment) groups. While the populations are statistically distinct ($p < 0.001$), the overlap in the latent variable space highlights the masking effect of inter-species anatomical diversity on the universal shock signature.

Table 3. Global statistical significance and classification performance metrics (pooled species).

Category	Metric	Value	Statistical Notes
Group Separation (Pooled Data)	Mann–Whitney p -value	1.5506×10^{-18}	Highly Significant
	Cohen’s d	-0.4798	Small effect size
	Cliff’s Delta (δ)	-0.2888	Small effect size
	CLES (Probability)	64.44%	Moderate separability
Classification Performance	Training Accuracy ($n = 1680$)	86.25%	$\kappa = 0.840$
	Test Accuracy ($n = 840$)	69.64%	$\kappa = 0.2119$
	Weighted F1-score (Test)	0.7386	Balanced Precision/Recall

The predictive performance of the global PLS-DA model further illustrated the complexity of a species-independent monitoring approach. While the model achieved a robust training accuracy of 86.25%, its performance on the independent test set was moderate, yielding an overall accuracy of 69.64% and a Cohen’s Kappa of 0.212. This notable reduction in classification precision—and the associated confusion between classes—is primarily

attributed to the significant spectral variance introduced by the diverse leaf morphologies of the three species. The broad, herbaceous leaves of *Alocasia* and *Monstera* produce high-amplitude response signatures that differ fundamentally from the dampened spectral shifts observed in the rigid, cuticular tissue of *Ficus*. These findings suggest that while a global ‘shock’ signature is statistically present, the anatomical baselines of different ornamental species mask the universal signal, necessitating the more granular, species-specific modeling approach detailed in the following sections.

3.2. Species-Specific Predictive Modeling

To overcome the masking effect identified in the global analysis, the dataset was partitioned by species to develop optimized, autonomous classification models. This approach allowed for the adjustment of spectral pre-processing techniques to match the unique optical and anatomical characteristics of each plant. For *Alocasia* sp. and *Ficus elastica*, the models were trained on first-derivative spectra to enhance subtle absorption features, while for *Monstera deliciosa*, the raw reflectance spectra provided the most accurate classification.

3.2.1. *Alocasia* sp.: The High-Leverage Morphological Response

The most definitive spectral response was observed in *Alocasia* sp., where the non-contact kinetic stimulus triggered a clear shift in transformed data (Figure 9). The species-specific PLS-DA model achieved a near-perfect classification performance, with a test accuracy of 96.43% and a Cohen’s Kappa of 0.8372. The statistical separation was exceptionally robust ($p < 0.001$), supported by a “Large” effect size (Cohen’s d : -3.47).

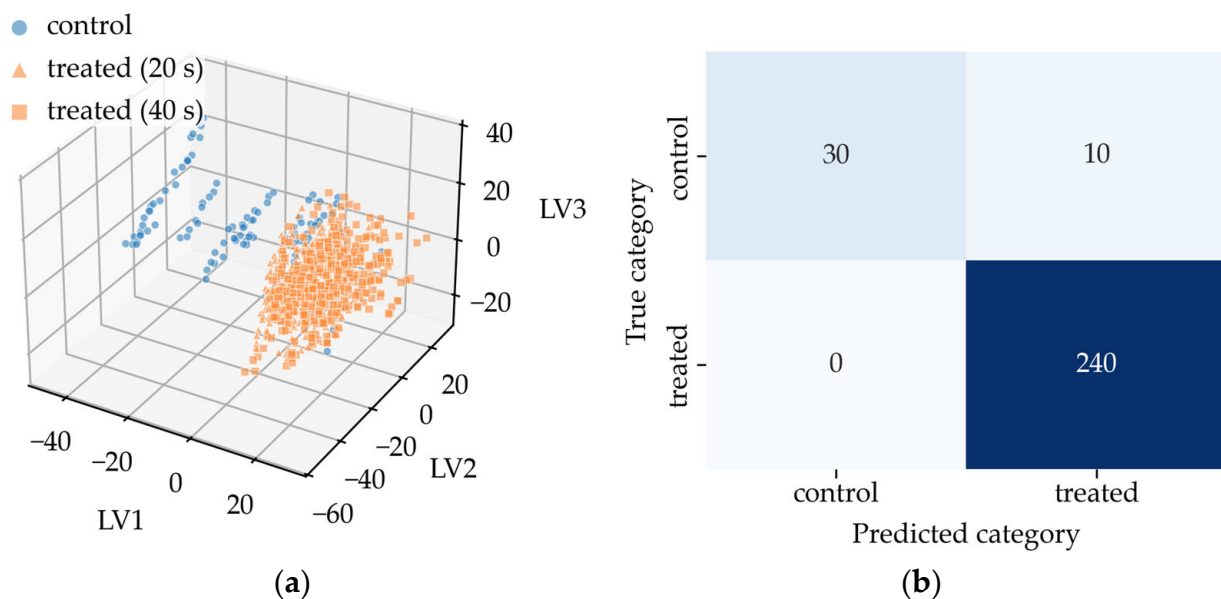


Figure 9. Species-specific PLS-DA results for *Alocasia* sp. (a) 3D score plot showing a definitive separation between physiological states. (b) Confusion matrix for the independent test set ($n = 280$), achieving a near-perfect classification accuracy of 96.43%. The results suggest that the flexible, high-mass leaves of this species act as amplifiers of the 2 g inertial load.

This high detectability is likely linked to the plant’s herbaceous architecture; the broad, high-mass leaves of *Alocasia* act as amplifiers of the 2 g inertial load. During horizontal oscillation, the long petioles and large leaf lamina experience significant mechanical strain, leading to rapid, uniform changes in leaf turgor and internal scattering interfaces. These results establish *Alocasia* as a sensitive indicator for spectral thigmo-monitoring.

3.2.2. Monstera Deliciosa: High-Confidence Detection

Monstera deliciosa also exhibited a high sensitivity to mechanical stress, with the model reaching a test accuracy of 91.79%. Although the Mann–Whitney U test confirmed a highly significant divergence ($p < 0.001$), the model showed slight confusion compared to *Alocasia*, as reflected by a Cohen’s Kappa of 0.6299. The effect size remained ‘Large’ (Cohen’s d : 1.17), indicating a stabilized and distinct thigmomorphogenetic footprint. The high predictive accuracy in *Monstera* validates that even species with slightly more rigid stems than *Alocasia* provide sufficient inertial leverage to trigger a systemically detectable spectral response.

3.2.3. Ficus Elastica: Anatomical Damping and Detection Limits

In stark contrast to the herbaceous species, *Ficus elastica* presented a significant challenge for spectral classification. While the underlying physiological shift was statistically significant ($p < 0.001$) and the effect size was surprisingly “Large” (Cohen’s d : 2.64), the predictive accuracy on the independent test set was consistently the lowest among the studied species (Table 4). Figure 10 shows the score plot of the PLS-DA transformed *Ficus* dataset and visualizes the test set classification accuracy on a confusion matrix.

Table 4. Summary of species-specific classification performance and effect sizes.

Species	Model Input	Test Accuracy	Cohen’s Kappa (κ)	Cohen’s d	Effect Size Interpretation
<i>Alocasia</i> sp.	1st Derivative	96.43%	0.8372	−3.4650	Large/Near-Perfect
<i>Monstera deliciosa</i>	Normal Spectra	91.79%	0.6299	1.1664	Large/High
<i>Ficus elastica</i>	1st Derivative	76.43%	0.4296	2.6433	Large/Lowest of three

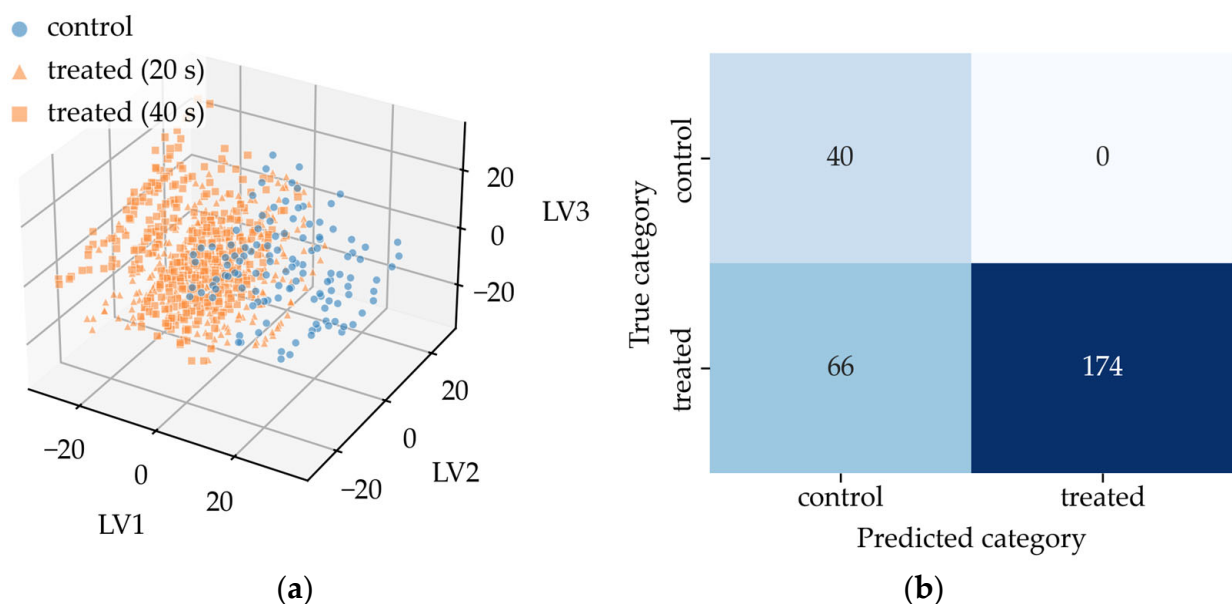


Figure 10. Species-specific PLS-DA results for *Ficus elastica*. (a) 3D score plot exhibiting substantial overlap between classes. (b) Confusion matrix illustrating the high misclassification rate. The comparatively low predictive accuracy—the lowest of the three species tested—indicates that the rigid, thick-cuticled leaf anatomy acts as a barrier, potentially hiding the spectral manifestation of the thigmomorphogenetic response.

This result indicates a ‘limit of detection’ for the current spectral model when applied to rigid, thick-cuticled species. Two coupled factors likely decrease the response of *Ficus*. Mechanically, its stiff, woody architecture—reflected in the lowest Leaf Weight Ratio of the three species—raises the natural frequencies of the stem–petiole–lamina system well

above the 4.77 Hz excitation, so it operates far from resonance and its rigid tissues undergo minimal deformation [36]. Optically, its high leaf mass per area and thick, multi-layered cuticle increase specular surface reflectance and, with the dense mesophyll, mask the smaller internal turgor-linked changes that the water indices track [35,37]. Together these reduce or delay the transmission—and the optical expression—of the kinetic load reaching the internal mesophyll. Furthermore, the high variance in the test set suggests that the physiological response to vibration is less uniform in *Ficus*; the algorithm frequently misclassified treated plants as ‘control’, likely because the mechanical shock did not consistently cross the threshold required for a measurable optical change in all leaf samples. Table 4 shows effect size and classification accuracy metrics for species-specific predictive modeling.

3.3. Temporal Dynamics of Spectral Sensitivity

The spectral manifestation of the thigmomorphogenetic response appears to be a transient and dynamic process. To evaluate the evolution of this signal, leaf reflectance was monitored at three intervals post-treatment (0, 15, and 30 min) and compared against the pre-stress baseline. This temporal analysis was performed using the first derivative of the reflectance spectra for all three species to better resolve overlapping absorption features and mitigate baseline shifts. This specific sequence aimed to capture the transition from the initial mechanical disturbance to a potentially stabilized physiological state within the first half-hour.

3.3.1. Immediate Post-Stress Variance

Immediately following the kinetic vibration (0 min), the spectral data was characterized by high intra-group variance and limited separability. Although the Mann–Whitney U test confirmed a statistically significant difference from the baseline ($p < 0.001$), the PLS-DA models showed a high degree of overlap between control and treated samples.

This initial phase likely represents a ‘shock’ state. Spectrally, the widening of distributions in the water-sensitive regions (SWIR) suggests that the plant might undergo rapid, non-uniform fluctuations in leaf turgor or localized redistribution of intercellular fluids. However, as these parameters were not directly measured via invasive methods, these spectral shifts are considered proxies for an immediate but unstable physiological disturbance.

3.3.2. Observed Separability Within the 0–30 Min Window

The data showed a temporal trend that was clearest in *Alocasia* sp. and *Ficus elastica*: classification accuracy for both species was near chance immediately post-stress and then increased across the successive timepoints, reaching its highest value of the three tested timepoints at the 30-min mark. *Monstera deliciosa*, by contrast, showed no consistent improvement across the same window, with its 30-min separability remaining comparable to its immediate post-stress value.

At this 30-min interval, *Alocasia* sp. and *Ficus elastica* reached their highest classification accuracies of the three timepoints tested (79.37% and 77.50%, respectively, up from 62.50% and 51.88% immediately post-stress), and their effect sizes increased over the same window (e.g., *Alocasia* Cohen’s d : 1.25). We interpret this progressive rise as a ‘biological latency’ hypothesis—the time potentially required for the initial mechanosensory signal to translate into a stable optical change—though the pattern did not hold for *Monstera deliciosa*, whose 30-min accuracy (68.13%) was statistically comparable to its 0-min value (69.37%), indicating this species-dependent latency remains a hypothesis rather than a universal finding. Figure 11 shows three levels of temporal progression in spectral separability of PLS-DA transformed spectra on score plots.

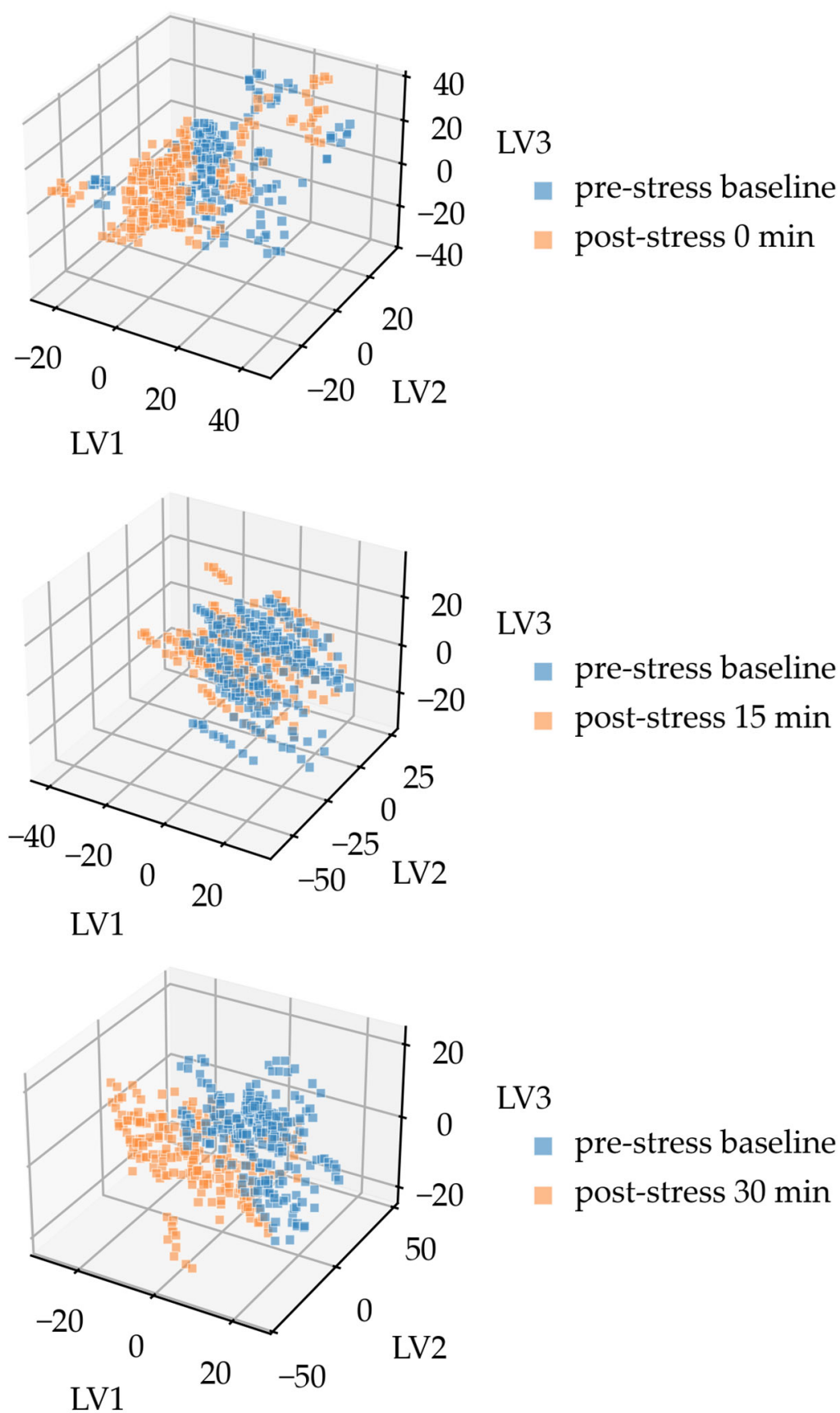


Figure 11. Temporal progression of spectral separability in *Alocasia* sp. (0, 15, and 30 min). The series of 3D score plots illustrates the ‘biological latency’ effect. Separability increases progressively from the immediate post-shock state (0 min) to the maximum observed contrast at 30 min, where the highest classification reliability ($\kappa = 0.59$) was recorded.

It is important to note that since measurements were not continued after 30 min, it remains unknown whether the spectral divergence continues to increase or begins to decline after this point. However, plants measured one week later appeared close to their baseline spectral profiles, which suggests that the response may be transient. This suggests a recovery phase where the acute shock-induced alterations, which might involve stomatal regulation or turgor stabilization, eventually subside. To fully map the recovery curve and identify the true peak of the response, further investigations with an extended temporal resolution (e.g., 60–120 min) and simultaneous invasive physiological measurements are required. Table 5 shows a comparison of classification accuracy metrics of pre-stimulus and post-stimulus spectral data for the tested plant species.

Table 5. Temporal evolution of classification reliability (Cohen’s kappa, κ) and effect sizes post-stimulus.

Time Interval	Species	Test Accuracy	Cohen’s Kappa (κ)	Cohen’s d	Classification Reliability
0 min	<i>Alocasia</i> sp.	0.6250	0.2500	0.5749	Medium agreement
15 min	<i>Alocasia</i> sp.	0.6000	0.2000	0.9541	Large agreement
30 min	<i>Alocasia</i> sp.	0.7937	0.5875	1.2554	Large agreement
0 min	<i>Monstera deliciosa</i>	0.6937	0.3875	0.7999	Medium agreement
15 min	<i>Monstera deliciosa</i>	0.6000	0.2000	1.1508	Large agreement
30 min	<i>Monstera deliciosa</i>	0.6813	0.3625	1.3529	Large agreement
0 min	<i>Ficus elastica</i>	0.5188	0.0375	0.6566	Medium agreement
15 min	<i>Ficus elastica</i>	0.7250	0.4500	1.0461	Large agreement
30 min	<i>Ficus elastica</i>	0.7750	0.5500	1.1137	Large agreement

3.4. Evaluation of Kinetic Dosage

To determine whether the plant’s response is sensitive to the total energy transferred during mechanical stimulation, a binary classification was performed between the two treatment durations (20 s and 40 s). For this analysis, the control (pre-treatment) group was excluded, focusing exclusively on the 30-min post-stress window to evaluate if the spectral signatures of the different dosages are distinct enough for automated separation. The analysis utilized the base-10 logarithm of the normal reflectance spectra, as this transformation was found to yield the most favourable classification results during initial model optimization trials.

3.4.1. Dosage Separation in *Alocasia* sp.

The results for *Alocasia* sp. confirmed a highly significant dosage dependency. The PLS-DA model successfully differentiated between the 20-s and 40-s treatments, achieving a test accuracy of 87.50% and a Cohen’s Kappa of 0.75. The statistical distance between the two doses along the first latent variable was substantial ($p < 0.001$, Cohen’s d: 2.03). Figure 12 illustrates the separability of *Alocasia* sp. plants by kinetic dosage interval on PLS-DA score plot and confusion matrix.

This high degree of separability suggests that for flexible-leaved species, a 40-s vibration transfers a quantifiably higher amount of kinetic energy than a 20-s dose, resulting in a distinct physiological state. The 40 s treatment appears to drive the plant into a ‘deeper’ stress state, likely due to increased inertial strain on the herbaceous tissue, which manifests as a unique spectral footprint that the algorithm can reliably identify.

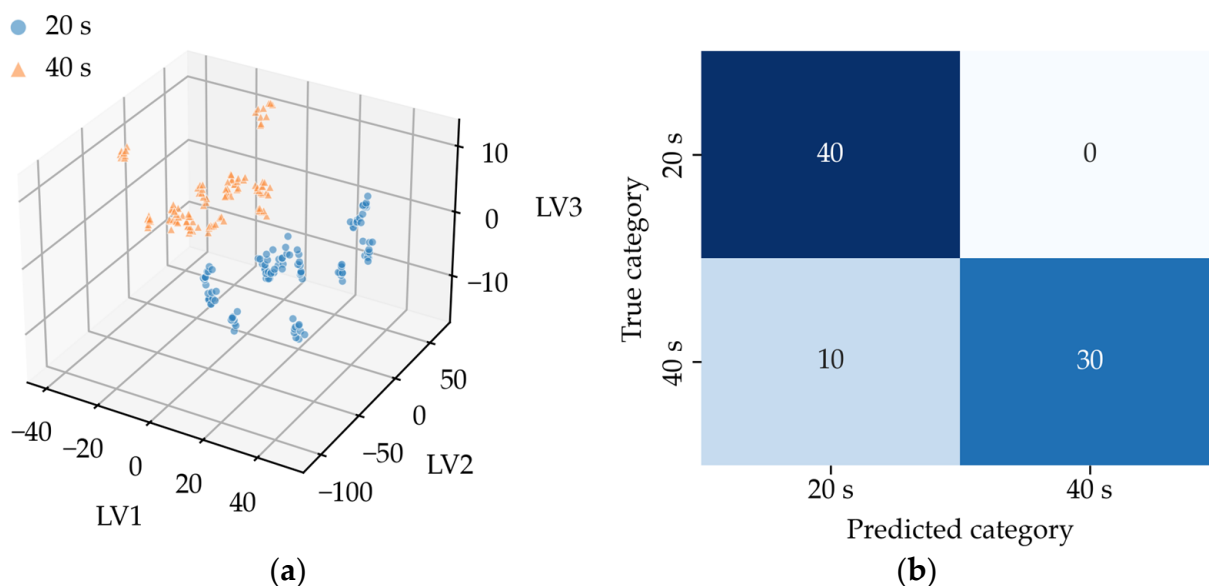


Figure 12. PLS-DA comparison of kinetic dosages (20 s vs. 40 s duration) for *Alocasia* sp. (a) 3D score plot based on log10-transformed reflectance spectra. (b) Confusion matrix for dosage separation. The model successfully differentiates between the two energy levels (accuracy: 87.50%), confirming that higher kinetic energy transfer results in a distinct, dose-dependent spectral footprint.

3.4.2. Overlap and Classification Uncertainty in *Monstera* and *Ficus*

In contrast, *Monstera deliciosa* and *Ficus elastica* showed significantly lower separability between the two dosages (Figures 13 and 14). For *Monstera*, the test accuracy dropped to 78.75% ($\kappa = 0.575$), while for *Ficus*, it reached only 62.50% ($\kappa = 0.25$). Although the difference between the doses remained statistically significant ($p < 0.001$), the spectral overlap between the 20 s and 40 s populations was substantial.

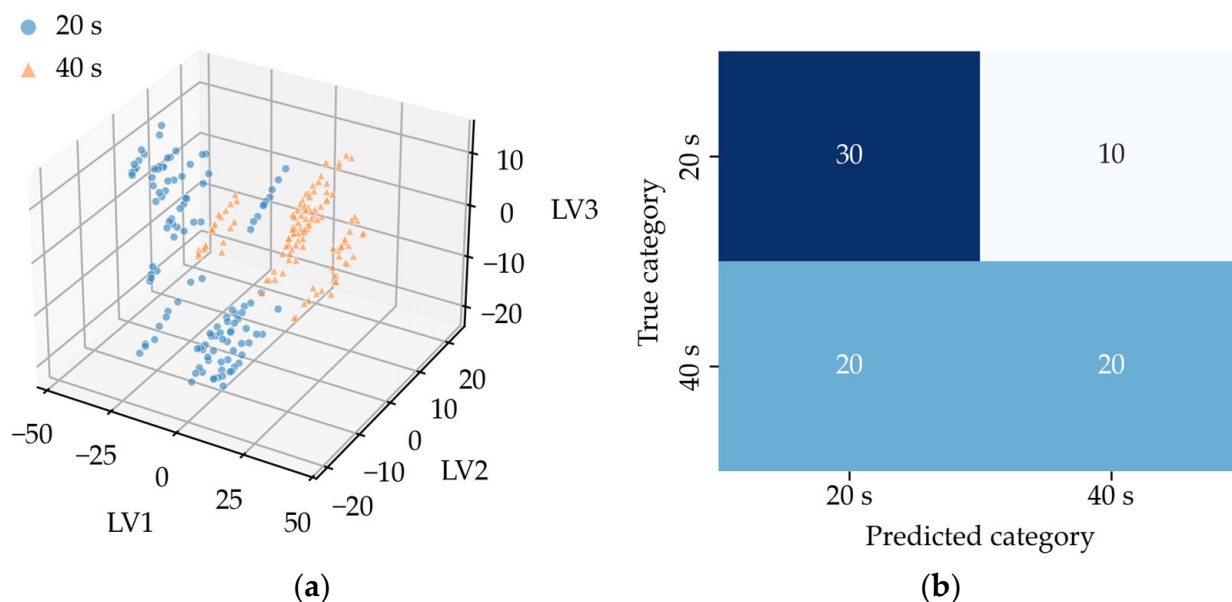


Figure 13. PLS-DA comparison of kinetic dosages (20 s vs. 40 s) for *Ficus elastica*. (a) 3D score plot illustrating significant spectral overlap and a lack of clear clustering between the two treatment durations. (b) Confusion matrix for the test set ($n = 80$). The low predictive accuracy (62.50%) and slight agreement ($\kappa = 0.250$) suggest that for rigid, thick-cuticled species, the spectral response reaches a saturation point where increasing the kinetic dosage does not result in a uniformly distinguishable physiological state.

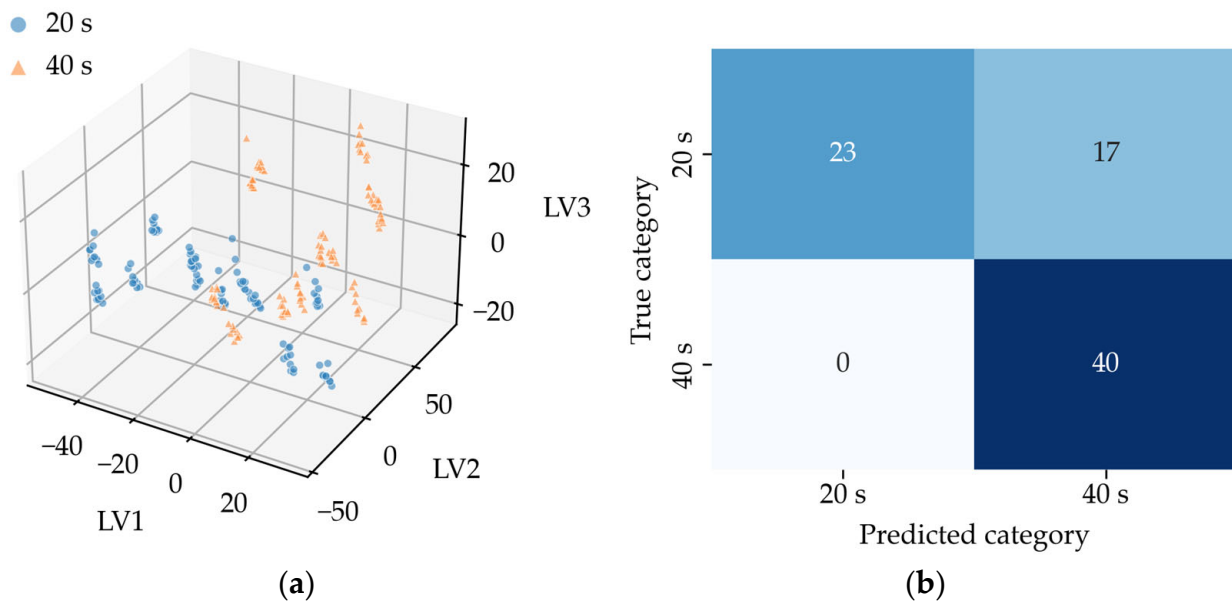


Figure 14. PLS-DA comparison of kinetic dosages (20 s vs. 40 s) for *Monstera deliciosa*. (a) 3D score plot showing moderate overlap between the 20-s and 40-s treatment clusters using $\log_{10}$ -transformed spectra. (b) Confusion matrix for the independent test set ($n = 80$). The recorded classification accuracy (78.75%) and Cohen’s Kappa ($\kappa = 0.575$) indicate that while a dosage effect is present, individual plant variance begins to interfere with the distinctness of the spectral footprint.

The lower classification precision in these species indicates that the physiological responses to 20 s and 40 s stimuli are not as clearly differentiated as in *Alocasia*. In *Ficus*, the rigid, thick-cuticled leaves may reach a saturation point early in the vibration process, where additional kinetic energy (from 20 to 40 s) does not produce a proportional or uniform shift in the internal scattering properties. The ‘random errors’ and misclassifications observed in the confusion matrices suggest that at these dosages, individual plant variance and ‘noise’ exceed the signal difference between the two treatments. For automated monitoring, this implies that while kinetic stress is detectable, distinguishing between dosage levels is highly species-dependent and may require more sensitive spectral bands or higher energy thresholds in rigid-leaved plants.

3.5. Sensitivity Profiling of Vegetation Indices

In addition to the multivariate analysis, a targeted evaluation of standardized vegetation indices was performed to determine if simpler univariate biomarkers could track the thigmomorphogenetic response. While vegetation indices are computationally efficient, the results of this study suggest they possess limited diagnostic power compared to full-spectrum PLS-DA models. The observed changes in these indices were generally subtle, and their ability to differentiate between physiological states was found to be secondary to the multivariate approach.

3.5.1. NDWI: A Consistent but Subtle Indicator of Water-Status Shifts

The Normalized Difference Water Index (NDWI) was identified as the most responsive univariate indicator, specifically within the acute post-stress window (0–30 min). During this interval, NDWI exhibited a consistent negative trend (Figure 15) across all species, with the highest observed effect sizes among the tested indices. For *Alocasia* sp. ($\delta = -0.399$) and *Ficus elastica* ($\delta = -0.432$), these values represent a “moderate” effect, suggesting a subtle, reproducible reorganization of the internal mesophyll structure or leaf water status immediately following vibration.

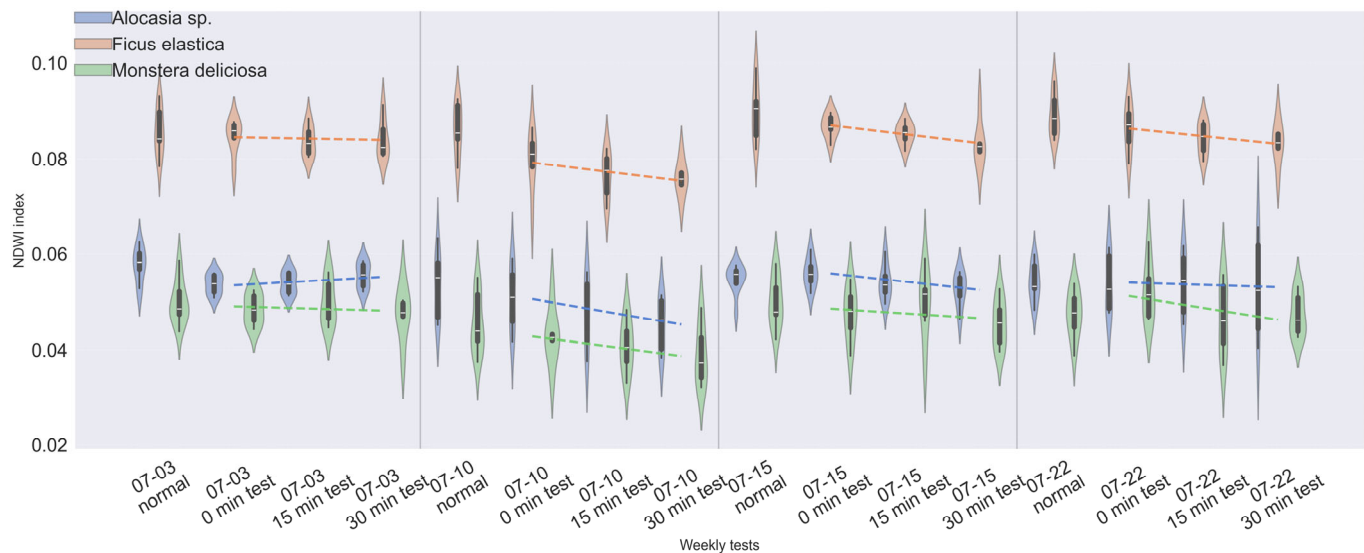


Figure 15. Sensitivity profiling of the Normalized Difference Water Index (NDWI). Violin plots showing the distribution of NDWI values across the acute post-stress window. The consistent negative shift 30 min post-vibration (moderate effect size, $\delta > 0.33$) suggests a subtle reorganization of the internal mesophyll structure or leaf water status.

However, this sensitivity did not translate into a detectable chronic trend. Multi-week monitoring of the treated plants revealed that NDWI values (and other related indices) did not undergo a cumulative or permanent shift. Instead, the values appeared to fluctuate inconsistently or return to the baseline level by the subsequent weekly measurement. This lack of a stable chronic trajectory indicates that the applied kinetic dosage triggers a transient ‘shock’ rather than a permanent structural modification detectable by simple ratio-based indices.

3.5.2. Evaluation of Secondary Indices

The evaluation of other standardized indices, such as the Photochemical Reflectance Index (PRI) and the Normalized Difference Vegetation Index (NDVI), yielded even less conclusive results. For most species and time points, the calculated Cliff’s Delta (δ) values remained below or near the threshold for “negligible” or “small” effects (typically $\delta < 0.33$). For instance, while the NDVI showed slight weekly variations, the effect sizes were inconsistent (ranging from $\delta = 0.44$ to $\delta = -0.05$ in *Monstera*), failing to establish a reliable diagnostic pattern. These findings suggest that while mechanical stress induces complex physiological changes, standardized vegetation indices are not sensitive enough to provide a robust feedback loop for automated growth regulation in these ornamental species.

4. Discussion

The results of this study demonstrate that spectral measurements can detect acute and dosage-dependent thigmomorphogenetic responses in indoor ornamental crops. By utilizing a non-contact 2 g kinetic shock, we isolated the mechanosensory pathway from the confounding variables of desiccation and physical wounding, providing a high-resolution look into the immediate physiological ‘shock’ phase.

4.1. Non-Contact Inertial Loading

The near-perfect classification accuracy (96.43%) observed in *Alocasia* sp. provides strong evidence that non-contact inertial loading at 2 g is sufficient to trigger a systemic physiological transition. Historically, commercial height control has relied on mechanical brushing, which utilizes contact friction to suppress elongation [10,11]. Our results suggest

that direct physical contact is not a prerequisite for thigmomorphogenetic induction. Instead, we propose that the inertial leverage provided by the plant's own leaf mass under 2 g oscillation creates enough internal strain to activate stretch-activated Ca^{2+} ion channels, as described in the mechanosensing models of Coutand [19] and Brenya et al. [28]. This finding has implications for vertical farming, as it validates a manipulation method that carries no risk of pathogen vectoring or cuticular abrasion.

4.2. Biological Latency and the 30-Min Window

A key finding of this research is the temporal evolution of the spectral signal in two of the three species tested: *Alocasia* sp. and *Ficus elastica* both reached their highest classification accuracy and largest effect sizes at 30 min post-stress, rather than immediately after the mechanical shock. We interpret this progressive rise as a tentative 'biological latency' hypothesis—the time potentially required for the initial mechanosensory signal to translate into a measurable optical change. While the mechanical loading is instantaneous, the changes in leaf turgor are time-dependent processes [14]. The acute widening of the Water Band Index (WBI) and Normalized Difference Water Index (NDWI) distributions immediately post-shock (0 min) likely represents transient, localized turgor fluctuations. The stabilization of these signals into a distinct, larger effect size at 30 min in *Alocasia* sp. and *Ficus elastica* suggests a transition from a shock state to a stabilized physiological response. For *Monstera deliciosa*, however, this tendency could not be proven under the present sampling design, and further investigation is needed to properly support the 'lag phase' hypothesis in this species. This observation may align with the findings of Cotrozzi et al. [23], who noted that multi-stress responses in protected environments often exhibit a 'lag phase' before reaching peak spectral detectability.

The observed temporal and dosage dynamics provide frameworks for ornamental crop management. The 30-min post-stress optimization window demonstrates that logistics stress cannot be accurately evaluated immediately upon arrival due to early, fluid dynamics. Waiting 30 min offers a more reliable diagnostic window for responsive species like *Alocasia* sp. (79.37% accuracy) and *Ficus elastica* (77.50% accuracy); the same improvement could not be confirmed for *Monstera deliciosa*, and further investigation is needed before drawing conclusions for this species. Furthermore, the clear spectral separation between 20- and 40-s stimulus durations in *Alocasia* sp. (87.50% dosage accuracy, Cohen's $d = 2.03$) proves that contact spectroscopy can calibrate deliberate treatments, ensuring plants receive the precise kinetic dose required to optimize market value without causing permanent tissue damage.

4.3. Anatomical Damping and Signal Masking

The divergence in classification accuracy between *Alocasia* (96.43%) and *Ficus elastica*—consistently the lowest-detected of the three species—highlights the critical role of plant anatomy in remote sensing diagnostics. The rigid, multi-layered epidermis, dense cuticle and woody architecture of *Ficus* altogether are the reasons for the different results, and reduce detectable stress reaction. We hypothesize that a plant's specific architecture (woody or herbaceous, leaf mass ratio, weight distribution, root-soil matrix) is a factor responsible for the plant's fundamental frequency, sensitivity to the applied mechanical stress and signal masking.

While the 2 g shock was statistically significant for *Ficus*, the species' inherent structural stiffness likely decreases the transmission of kinetic energy to the internal mesophyll. Furthermore, the high variance in the *Ficus* test set suggests that its physiological response to vibration is less uniform than that of herbaceous species. In contrast, the flexible, high-mass leaves of *Alocasia* act as amplifiers of the 2 g load. This supports the rationale that 'spectral thigmo-monitoring' efficacy is species-dependent, a factor that needs to be

considered when testing or implementing automated sensing networks in polyculture indoor farms.

4.4. Structural Reorganization vs. Pigment Degradation

The sensitivity of the NDWI over more traditional pigment-based indices like the NDRE provides information about the nature of acute mechanical stress. Because NDWI is sensitive to the mesophyll air-to-water interfaces, the consistent negative trend observed in this study (Cliff's Delta < −0.40) indicates that the 2 g shock likely induces a micro-structural reorganization of the intercellular air spaces or a change in cellular packing density. This interpretation suggests that the initial thigmomorphogenetic response is physical and structural rather than biochemical. We assume that the vibration causes a compression of the mesophyll layers, affecting the internal scattering profiles within the NIR and SWIR regions. The 'overcompensation' observed in the PRI of *Ficus* at 30 min further suggests a metabolic defensive reaction, possibly involving the xanthophyll cycle, which appears to be a protective response to the kinetic energy transfer even when structural changes are dampened.

4.5. Broader Context and Future Research

In the broadest context, this study establishes a framework for chemical-free, data-driven plant growth regulation. As indoor vertical farming continues to scale, the ability to 'dose' mechanical stress and validate the plant's response at-line via spectroscopy could significantly reduce the industry's reliance on electrical lighting shifts or synthetic growth retardants. Future research should focus on the repetition effect, investigating how these acute 30-min 'shock' signatures consolidate into the chronic structural changes (lignification and dwarfing) over multi-week growth cycles. Additionally, scaling these proximal measurements to automated imaging systems or UAS (Unmanned Aerial Systems) platforms could enable facility-wide, real-time monitoring of crop 'vitality' and architectural development in response to automated mechanical conditioning.

5. Conclusions

This study demonstrates that contact spectral measurements, integrated with multi-variate PLS-DA modeling, provide a high-resolution diagnostic window into the thigmomorphogenetic status of indoor ornamental crops. By utilizing a precisely quantified 2 g horizontal oscillation, we have moved thigmomorphogenesis from a qualitative observation one step closer toward a reproducible, data-driven agronomic input.

Scientifically, the research provides a critical distinction between the 'mechanical damping' provided by cuticular morphologies and the 'amplification' observed in herbaceous species. The near-perfect classification accuracy (96.43%) in *Alocasia* sp. forms the ground for spectral thigmo-monitoring, proving that for flexible, high-leverage species, the physiological shock signature is definitive and reproducible. Furthermore, the dominance of the Normalized Difference Water Index (NDWI) over pigment-based indices suggests that the primary mechanism of acute mechanical stress is a micro-structural reorganization of the mesophyll air-to-water interfaces and turgor-mediated cellular packing, rather than immediate photochemical degradation. This shifts the theoretical focus of acute thigmo-responses toward internal leaf architecture and water status.

Practically, this research opens the path towards a non-contact method of architectural manipulation. For indoor farming operators, the identification of a 30-min diagnostic window in *Alocasia* sp. and *Ficus elastica* provides an optimized temporal window for automated monitoring in these species. This at-line feedback loop allows greenhouse

control systems to instantly validate whether an applied physical stimulus has successfully triggered the target developmental pathway, or if the dosage requires adjustment.

This study establishes a framework for chemical- and GMO-free growth regulation and the possibility of replacing synthetic growth retardants and artificial lighting shifts. Future research should investigate the transition from these acute 30-min ‘shock’ signatures to the chronic structural acclimations observed over entire growth cycles, enabling autonomous crop architecture management in future indoor farms.

Despite the high predictive accuracy achieved for herbaceous species, this study is subject to limitations that need to be addressed. The relatively poor classification performance for *Ficus elastica*—consistently the lowest-detected of the three species tested—indicates a ‘limit of detection’ for current spectral models when applied to rigid, thick-cuticled species. The lowest Leaf Weight Ratio of the three species reflects the woody growth form of *Ficus elastica*; mechanically, this high stiffness places the natural frequencies of its stem–petiole–lamina system well above the 4.77 Hz excitation, so the plant operates far from resonance and transmits little deforming strain to the leaf tissue [36]. Protected further by the thickest of all multi-layered epidermal cushions, the interior cells and chloroplasts experience minimal physical deformation or stretching. Without mechanical cellular distortion, the plant avoids triggering the rapid biochemical cascades that alter leaf reflectance, keeping the contact spectral reading the closest to stable. Because the mechanical explanation (off-resonance rigidity) and the optical explanation (a thick, reflective cuticle masking internal change) both predict a decreased signal and were not measured independently here, they remain confounded; separating them would require leaf-level strain or accelerometer measurements alongside the spectra. Such rigid morphologies may also require higher kinetic intensities or more sensitive signal-processing techniques to resolve a response [38].

While the spectral shifts in NDWI and WBI are consistent with alterations in turgor and internal leaf structure, this study relied on optical signals rather than direct, invasive physiological measurements. Specifically, no direct quantification of leaf cell turgor pressure or endogenous hormone content was performed, so the correlation reported here between spectral change and physiological state is an indirect inference rather than a demonstrated causal relationship. This prevents a definitive causal link between specific molecular pathways and the observed reflectance changes.

The experiment was conducted within a single controlled growth chamber. The spectral signatures of mechanical stress may be influenced by confounding environmental factors in larger-scale commercial facilities, such as fluctuating humidity or varied light quality, which were not accounted for in this controlled pilot study. Dedicated follow-up trials that systematically vary ambient humidity and light background will therefore be required to confirm the stability of these spectral signatures before the models can be deployed in large-space commercial greenhouses.

To build upon these findings, future investigations should focus on the following trajectories. Research should expand from acute ‘shock’ signatures to the long-term (multi-week) consolidation of these signals into permanent structural acclimations, such as lignification and dwarfing. This would allow for the development of ‘growth trajectory’ models. Transitioning from contact ‘point’ sensors to hyperspectral imaging or UAS (Unmanned Aerial Systems) platforms would enable facility-wide, non-contact monitoring. This is essential for the practical implementation of autonomous thigmomorphogenetic regulation in vertical farming. Future trials should explore a wider range of kinetic energies (e.g., 0.5 g to 3.0 g) to identify species-specific reaction thresholds where architectural optimization is maximized and the risk of cellular damage is minimized. Combining spectral tracking with destructive metabolic profiling (e.g., jasmonic acid and ethylene quantification) would provide the necessary biochemical evidence to fully ground the ‘spectral rationales’ proposed

in this study. Direct anatomical quantification—in particular leaf cuticle thickness and mesophyll cell arrangement density across species—should also be undertaken to supply the measured structural evidence that the present study could only infer. Crucially, pairing such anatomical parameters with leaf-level strain or accelerometer recordings acquired simultaneously with the spectra would disentangle the currently confounded mechanical (off-resonance rigidity) and optical (cuticular masking of internal change) explanations for the reduced signal in rigid, thick-cuticled species such as *Ficus elastica*. The integration of direct leaf-level biomechanical sensors, such as surface micro-strain gauges, with dynamic reflectance spectroscopy may facilitate the separation of cuticular optical filtering effects from the intrinsic structural stiffness of the mesophyll in the future.

This research shows that non-destructive contact leaf spectroscopy is a dual-purpose asset for the ornamental industry, capable of both diagnosing transport injury and monitoring physiological manipulation. However, baseline leaf anatomy and plant architecture in general can act as either an amplifier or a mechanical damper, so future automated greenhouse and logistics systems need to utilize species-specific classification for precise temporal windows.

Author Contributions: Conceptualization, K.S.; methodology, K.S. and G.B.; software, G.B.; validation, K.S., G.B. and S.E.-G.; formal analysis, G.B.; investigation, G.B. and K.S.; resources, K.S.; data curation, G.B.; writing—original draft preparation, K.S. and G.B.; writing—review and editing, S.E.-G.; visualization, G.B.; supervision, K.S.; project administration, K.S.; funding acquisition, K.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: The authors would like to express their gratitude to the following researchers of the Hungarian University of Agriculture and Life Sciences for their valuable contributions to this project: J. Deákvári, Zs. Olasz, Zs. Lehoczki, S. Takács. During the preparation of this study, the authors utilized Google Gemini 3 Flash to assist with literature review synthesis, English language proofreading, and manuscript formatting in accordance with the journal's template. The authors have thoroughly reviewed and edited all generated outputs and take full responsibility for the content and integrity of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CLES	Common Language Effect Size
F1-score	Harmonic mean of precision and recall
GMO	Genetically modified organism
IDE	Integrated Development Environment
LV	Latent variable
MRENDVI	Modified Red-Edge Normalized Difference Vegetation Index
NDRE	Normalized Difference Red Edge index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NIR	Near-infrared
PLS-DA	Partial Least Squares Discriminant Analysis

PRI	Photochemical Reflectance Index
SNV	Standard Normal Variate
SWIR	Short-wave infrared
UAS	Unmanned Aerial Systems
VIS	Visible
WBI	Water Band Index
κ	Cohen's kappa coefficient
δ	Cliff's delta

References

- White, J.W.; Andrade-Sanchez, P.; Gore, M.A.; Bronson, K.F.; Coffelt, T.A.; Conley, M.M.; Feldmann, K.A.; French, A.N.; Heun, J.T.; Hunsaker, D.J.; et al. Field-Based Phenomics for Plant Genetics Research. *Field Crops Res.* **2012**, *133*, 101–112. [[CrossRef](#)]
- Azadi, P.; Bagheri, H.; Nalouisi, A.M.; Nazari, F.; Chandler, S.F. Current Status and Biotechnological Advances in Genetic Engineering of Ornamental Plants. *Biotechnol. Adv.* **2016**, *34*, 1073–1090. [[CrossRef](#)] [[PubMed](#)]
- Rademacher, W. Plant Growth Regulators: Backgrounds and Uses in Plant Production. *J. Plant Growth Regul.* **2015**, *34*, 845–872. [[CrossRef](#)]
- Niu, Y.F.; Chai, R.S.; Jin, G.L.; Wang, H.; Tang, C.X.; Zhang, Y.S. Responses of Root Architecture Development to Low Phosphorus Availability: A Review. *Ann. Bot.* **2013**, *112*, 391–408. [[CrossRef](#)] [[PubMed](#)]
- Demotes-Mainard, S.; Péron, T.; Corot, A.; Bertheloot, J.; Le Gourrierc, J.; Pelleschi-Travier, S.; Crespel, L.; Morel, P.; Huché-Thélier, L.; Boumaza, R.; et al. Plant Responses to Red and Far-Red Lights, Applications in Horticulture. *Environ. Exp. Bot.* **2016**, *121*, 4–21. [[CrossRef](#)]
- Jaffe, M.J. Thigmomorphogenesis: The Response of Plant Growth and Development to Mechanical Stimulation: With Special Reference to Bryonia Dioica. *Planta* **1973**, *114*, 143–157. [[CrossRef](#)] [[PubMed](#)]
- Telewski, F.W. Thigmomorphogenesis: The Response of Plants to Mechanical Perturbation. *Italus Hortus* **2016**, *23*, 1–16. [[CrossRef](#)]
- Telewski, F.W. Mechanosensing and Plant Growth Regulators Elicited During the Thigmomorphogenetic Response. *Front. For. Glob. Change* **2021**, *3*, 574096. [[CrossRef](#)]
- Biddington, N.L. The Effects of Mechanically-Induced Stress in Plants—A Review. *Plant Growth Regul.* **1986**, *4*, 103–123. [[CrossRef](#)]
- Latimer, J.G. Mechanical Conditioning to Control Height. *HortTechnology* **1998**, *8*, 529–534. [[CrossRef](#)]
- Garner, L.C.; Björkman, T. Mechanical Conditioning for Controlling Excessive Elongation in Tomato Transplants: Sensitivity to Dose, Frequency, and Timing of Brushing. *J. Am. Soc. Hortic. Sci.* **1996**, *121*, 894–900. [[CrossRef](#)]
- Sparke, M.-A.; Wegscheider, A.; Winterhagen, P.; Ruttensperger, U.; Hegele, M.; Wünsche, J.N. Air-Based Mechanical Stimulation Controls Plant Height of Ornamental Plants and Vegetable Crops under Greenhouse Conditions. *HortTechnology* **2021**, *31*, 405–416. [[CrossRef](#)]
- Jacobs, M. The Effect of Wind Sway on the Form and Development of *Pinus Radiata* D. Don. *Aust. J. Bot.* **1954**, *2*, 35–51. [[CrossRef](#)]
- Chehab, E.W.; Eich, E.; Braam, J. Thigmomorphogenesis: A Complex Plant Response to Mechano-Stimulation. *J. Exp. Bot.* **2008**, *60*, 43–56. [[CrossRef](#)] [[PubMed](#)]
- López-Ribera, I.; Vicient, C.M. Drought Tolerance Induced by Sound in Arabidopsis Plants. *Plant Signal. Behav.* **2017**, *12*, e1368938. [[CrossRef](#)] [[PubMed](#)]
- Bulle, A.A.E.; Slootweg, G.; Vonk Noordegraaf, C. Effects of Vibration During Transport on the Quality of Pot Plants. *Acta Hortic.* **2000**, *518*, 193–200. [[CrossRef](#)]
- Collins, P.C.; Blessington, T.M. Postharvest Effects of Shipping Temperatures and Subsequent Interior Keeping Quality of Ficus Benjamina. *HortScience* **1983**, *18*, 757–758. [[CrossRef](#)]
- De Langre, E. Effects of Wind on Plants. *Annu. Rev. Fluid Mech.* **2008**, *40*, 141–168. [[CrossRef](#)]
- Coutand, C. Mechanosensing and Thigmomorphogenesis, a Physiological and Biomechanical Point of View. *Plant Sci.* **2010**, *179*, 168–182. [[CrossRef](#)]
- Smith, V.C. The Effects of Air Flow and Stem Flexure on the Mechanical and Hydraulic Properties of the Stems of Sunflowers *Helianthus annuus* L. *J. Exp. Bot.* **2003**, *54*, 845–849. [[CrossRef](#)] [[PubMed](#)]
- Hunt, E.R.; Jaffe, M.J. Thigmomorphogenesis: The Interaction of Wind and Temperature in the Field on the Growth of *Phaseolus vulgaris* L. *Ann. Bot.* **1980**, *45*, 665–672. [[CrossRef](#)]
- Coutand, C. Biomechanical Study of the Effect of a Controlled Bending on Tomato Stem Elongation: Local Strain Sensing and Spatial Integration of the Signal. *J. Exp. Bot.* **2000**, *51*, 1825–1842. [[CrossRef](#)] [[PubMed](#)]
- Cotrozzi, L.; Couture, J.J. Hyperspectral Assessment of Plant Responses to Multi-stress Environments: Prospects for Managing Protected Agrosystems. *Plants People Planet* **2020**, *2*, 244–258. [[CrossRef](#)]
- Thenkabail, P.S.; Lyon, J.G. (Eds.) *Hyperspectral Remote Sensing of Vegetation*; CRC Press: Boca Raton, FL, USA, 2016.

25. Varga, Z.; Vörös, F.; Pál, M.; Kovács, B.; Jung, A.; Elek, I. Performance and Accuracy Comparisons of Classification Methods and Perspective Solutions for UAV-Based Near-Real-Time “Out of the Lab” Data Processing. *Sensors* **2022**, *22*, 8629. [[CrossRef](#)] [[PubMed](#)]
26. Lausch, A.; Bumberger, J.; Jung, A.; Pause, M.; Selsam, P.; Zhou, T.; Herzog, F. Monitoring Agricultural Land Use Intensity with Remote Sensing and Traits. *Agriculture* **2025**, *15*, 2233. [[CrossRef](#)]
27. Frampton, W.J.; Dash, J.; Watmough, G.; Milton, E.J. Evaluating the Capabilities of Sentinel-2 for Quantitative Estimation of Biophysical Variables in Vegetation. *ISPRS J. Photogramm. Remote Sens.* **2013**, *82*, 83–92. [[CrossRef](#)]
28. Brenya, E.; Pervin, M.; Chen, Z.; Tissue, D.T.; Johnson, S.; Braam, J.; Cazzonelli, C.I. Mechanical Stress Acclimation in Plants: Linking Hormones and Somatic Memory to Thigmomorphogenesis. *Plant Cell Environ.* **2022**, *45*, 989–1010. [[CrossRef](#)] [[PubMed](#)]
29. Boiarskii, B. Comparison of NDVI and NDRE Indices to Detect Differences in Vegetation and Chlorophyll Content. *J. Mech. Contin. Math. Sci.* **2019**, *4*, 20–29. [[CrossRef](#)]
30. Behmann, J.; Steinrücken, J.; Plümer, L. Detection of Early Plant Stress Responses in Hyperspectral Images. *ISPRS J. Photogramm. Remote Sens.* **2014**, *93*, 98–111. [[CrossRef](#)]
31. Gamon, J.A.; Serrano, L.; Surfus, J.S. The Photochemical Reflectance Index: An Optical Indicator of Photosynthetic Radiation Use Efficiency across Species, Functional Types, and Nutrient Levels. *Oecologia* **1997**, *112*, 492–501. [[CrossRef](#)] [[PubMed](#)]
32. Peñuelas, J.; Filella, I.; Biel, C.; Serrano, L.; Savé, R. The Reflectance at the 950–970 Nm Region as an Indicator of Plant Water Status. *Int. J. Remote Sens.* **1993**, *14*, 1887–1905. [[CrossRef](#)]
33. Al-Tamimi, N.; Langan, P.; Bernád, V.; Walsh, J.; Mangina, E.; Negrão, S. Capturing Crop Adaptation to Abiotic Stress Using Image-Based Technologies. *Open Biol.* **2022**, *12*, 210353. [[CrossRef](#)] [[PubMed](#)]
34. Gao, B. NDWI—A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space. *Remote Sens. Environ.* **1996**, *58*, 257–266. [[CrossRef](#)]
35. Barnes, E.M.; Clarke, T.; Richards, S.E.; Colaizzi, P.D.; Haberland, J.; Kostrzewski, M.; Waller, P.M.; Choi, C.Y.; Riley, E.; Thompson, T.L.; et al. Coincident Detection of Crop Water Stress, Nitrogen Status and Canopy Density Using Ground-Based Multispectral Data. 2000. Available online: <https://www.tucson.ars.ag.gov/unit/publications/PDFfiles/1356.pdf> (accessed on 12 April 2026).
36. De Langre, E. Plant Vibrations at All Scales: A Review. *J. Exp. Bot.* **2019**, *70*, 3521–3531. [[CrossRef](#)] [[PubMed](#)]
37. Wright, I.J.; Reich, P.B.; Westoby, M.; Ackerly, D.D.; Baruch, Z.; Bongers, F.; Cavender-Bares, J.; Chapin, T.; Cornelissen, J.H.C.; Diemer, M.; et al. The Worldwide Leaf Economics Spectrum. *Nature* **2004**, *428*, 821–827. [[CrossRef](#)] [[PubMed](#)]
38. Onoda, Y.; Westoby, M.; Adler, P.B.; Choong, A.M.F.; Clissold, F.J.; Cornelissen, J.H.C.; Díaz, S.; Dominy, N.J.; Elgart, A.; Enrico, L.; et al. Global Patterns of Leaf Mechanical Properties. *Ecol. Lett.* **2011**, *14*, 301–312. [[CrossRef](#)] [[PubMed](#)]
39. Olasz, Z.; Lehoczki, Z.; Deákvári, J.; Szalay, K. Mechanikai Rezgések Hatása a Növények Spektrális Tulajdonságaira. *Mezőgazdasági Tech.* **2025**, *6*, 2–7.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.