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EDITORIAL

Dear colleagues and readers:

This Winter/Spring double issue, Issue 1-2, 2026, of the ICUAS Association Unmanned Aviation eMagazine, the eUAM, includes three peer reviewed technical papers and a detailed pre-conference report about the annual conference, ICUAS 2026.

The first paper discusses drone-mounted multispectral cameras that provide high-resolution imagery for monitoring crop health and detecting preventable yield losses. The study centered around collected images of corn and soybean fields processed using vegetation indices such as NDVI and NDRE. Mosaicked datasets were converted into training panels through a MATLAB developed paint program to identify areas of stress linked to nutrient deficiencies, disease, or environmental variation. The AI analysis offers a scalable approach for improving agricultural sustainability, particularly for small and mid-sized farms.

The second paper presents the modeling, identification, and experimental control of a Parrot Mambo micro–Unmanned Aerial Vehicle (UAV) using a Linear Quadratic Gaussian (LQG) control framework. The control architecture follows a cascade structure that separates position and attitude control loops, and controller performance is evaluated through both simulation and real flight experiments using representative square and circular trajectories.

The third paper conducts a multi-dimensional analysis of licensing systems for unmanned aircraft (drone) operators in selected Member States of the European Union. It includes a legal analysis of national regulations implementing the EU regulatory framework, in particular Regulations (EU) 2019/947 and 2019/945, as well as an assessment of the practical functioning of these systems, with particular emphasis on the degree of their harmonization with EU regulations and their impact on operational safety and the development of the drone services market.

SUBMITTING A PAPER TO THE eUAM

Papers must be submitted electronically online, as follows:

1. Go to **<https://controls.papercept.net>**.
2. Find the "ICUAS Association Unmanned Aviation eMagazine (eUAM)".
3. Log In with your credentials – if you do not have a PIN and password, create an account.
4. Click on "**eUAM Information for Authors**" for information related to submissions and the paper review process.
5. Click on "**Submit a new paper to ICUAS eUAM**" and follow all steps to upload your paper.

Note that authors of submitted papers must classify their papers as Regular Paper, Short Paper, Technical Note, or Position Paper.

The Editorial Board is committed to providing a recommendation within 40 days after receipt of the paper.

PRE-CONFERENCE REPORT ON ICUAS 2026

The 2026 International Conference on Unmanned Aircraft Systems, ICUAS 2026 is expected to be very successful. An all-time record of 336 contributed and invited session papers, workshop and tutorial proposals from 43 different countries was received. 331 contributed and invited session papers went through a very detailed and rigorous review process. The

Technical Program includes 173 contributed papers, 16 invited session papers, and 2 papers that have been accepted and will appear in the ICUAS Unmanned Aviation Magazine, eUAM. The acceptance rate is 57% - this marks an all-time low since launching the annual Conference. The Table below shows the number of submitted and accepted papers per country.

SUBMITTED AND ACCEPTED PAPERS PER COUNTRY

COUNTRY	SUBMITTED	ACCEPTED	COUNTRY	SUBMITTED	ACCEPTED
Argentina	3	3	Luxembourg	2	2
Australia	7	4	Mexico	3	2
Austria	1	1	Morocco	1	0
Brazil	22	11	Netherlands	13	11
Canada	12	7	Norway	2	1
China	10	5	Poland	5	1
Colombia	1	1	Portugal	7	3
Croatia	7	5	Qatar	1	0
Cyprus	9	4	Romania	1	0
Czech Republic	4	2	Russia	4	3
Denmark	12	5	Saudi Arabia	3	1
Ecuador	2	2	Singapore	3	0
Finland	4	4	Slovakia	1	0
France	19	14	Spain	15	10
Germany	20	13	Sweden	3	2
Greece	9	5	Switzerland	2	0
Hungary	2	0	Turkey	3	3
India	14	2	Ukraine	1	0
Israel	3	2	United Arab Emirates	9	6
Italy	24	14	United Kingdom	5	2
Japan	1	1	United States of America	59	38
Korea, South	2	1	Total	331	191

ICUAS'26 offers three half-day Workshops/Tutorials, as shown below, addressing current and future topics in unmanned aircraft systems from experts in academia, national laboratories, and industry. Tutorials/Workshops will take place on Monday, June 15.

CALYPSO A

09:00-13:00 MoT2

**When Robotics Meet Wireless Communications:
A Tale of Two Interconnected Worlds**

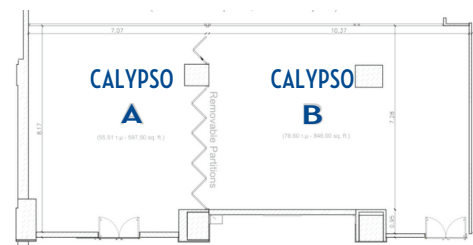
CALYPSO B

09:00-13:00 MoT4

Aerial Soft Robotics

14:00-18:00 MoT1

**Modeling Navigation and Control of Multirotor
UAVs: A Comprehensive Framework**



ICUAS'26 includes five Plenary Lectures given by leading authorities in their fields. We are proud to include them in the Technical Program. The lecture sequence is provided next.

TUESDAY, JUNE 16

- **Resilient Multi-UAS in Complex Missions**, Prof. Dimitra Panagou, University of Michigan, USA

WEDNESDAY, JUNE 17

- **Integrating Advanced UTM Services into a Co-Simulation Environment**, Prof. Antonios Tsourdos, Cranfield University, UK
- **Flying Robots That Touch the World: Are We There Yet?** Prof. Antonio Franchi, University of Twente, Netherlands and Sapienza University of Rome, Italy
- **Awards Luncheon**
- **CAT-A Ground Test to Class-A Miship: Case Study of an Uncrewed Military Helicopter with Lessons Learned for the R&D, T&E, and Academic Community**, Prof. Donald Costello University of Maryland, USA
- **HERON - Hellenic Robotics Center of Excellence: Research Directions and Goals**, Prof. Petros Maragos, HERON Director and Scientific Coordinator

The **2026 ICUAS UAV Competition** is organized (as in previous years) by the Laboratory for Robotics and Intelligent Control Systems, **LARICS**, University of Zagreb, Faculty of Electrical Engineering and Computing, Croatia, through the **CBRNe-HERO** project.

The competition will take place in two stages. The first stage is the qualifiers stage. Registered teams will develop their solution in a ROS-Gazebo environment. Submitted solutions will be evaluated and the 'top teams', up to six, will continue to the second and final stage. In the final stage, during the Conference, teams will present and will demonstrate their solution.

The competition scenario centers around *Multi-UAV System for Communication Network Establishment and Maintenance during CBRNe Incidents in Urban Environments*.

Following a rigorous evaluation procedure, the following teams emerged as top contenders and qualified for the finals at the conference venue in Corfu, Greece.

1st Place Team: AGH Avader, AGH University of Krakow, Poland

Team Leader: Kamil Jędrzejko. Team Members: Remigiusz Mietła, Mateusz Gołębek, Tymoteusz Domagała, Jan Jagodziński, Dominik Babiarczyk, Hubert Gąska, Krzysztof Jagiełło, Szymon Hołysz

2nd Place Team: QADT, Queen's University, Canada

Team leader: Ethan Milburn. Team Members: Abdullah Mohsin, Ashton Antony, Benjamin Cox, Cole Jowett, Erin Payne, Ethan Milburn, Gavin Tan, Kuzey Bilgin, Liam Shannon, Nishith Chowdary Ravuri, Purujit Kantiya, Visakan Makilrajah

3rd Place Team: ARRF, Kyungpook National University, South Korea

Team leader: Taeseung Woo. Team members: Seongjin Oh, Kangmin Kim, JinWan Kim, Jihyeong Ryu, Soyeon Park, Jiyoung Yoo

4th Place Team: CVRLs, Foundation for Research and Technology – Hellas (FORTH), Greece

Team leader: Michail Vangos. Team members: Michail Vangos, Iliana Platona, Michalis Savorianakis, Christos Trifinopoulos

5th Place Team: aeRAS, National Technical University of Athens, Greece

Team leader: Michalis Psychis. Team members: Zoi Tsouroufli, Maria-Rozina Bertou, Konstantinos Sarakis, Petros Pantazis, Elena Alevropoulou

6th Place Team: Aerial Robotics IITK, Indian Institute of Technology Kanpur, India

Team leader: Shivang Sonker. Team members: Ayush Goyal, Soumya Jhunjhunwala, Mansoju Vivekananda, Kritik Gupta, Krishna Agrawal

Details about the conference structure, the Technical Program and the UAV Competition may be found at **www.uasconferences.com**.

AI-Assisted Crop Damage Detection from UAV Multispectral Imagery Using a Patch-Based CNN Pipeline

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Abstract— Drone-mounted multispectral cameras provide high-resolution imagery for monitoring crop health and detecting preventable yield losses. In this study, imagery of corn and soybean fields was collected and processed using vegetation indices such as NDVI and NDRE. Mosaicked datasets were converted into training panels through a MATLAB developed paint program to identify areas of stress linked to nutrient deficiencies, disease, or environmental variation.

Training sets were used to develop convolutional neural networks (CNNs) for automated classification of crop health indicators. The system aims to provide actionable reports to farmers while reducing reliance on manual scouting. The methodology establishes a framework for validating AI-based predictions with tractor harvest data, enabling a direct comparison of stress detection with actual yield outcomes. This integration of multispectral sensing, photogrammetry, and AI analysis offers a scalable approach for improving agricultural sustainability, particularly for small and mid-sized farms.

Keywords Drone multispectral imaging; precision agriculture; convolutional neural network; corn; soybean; NDVI/NDRE and GeoTiff, Orthomosaic; drone sensing.

I. INTRODUCTION

A. Problem Context

Modern farming is increasingly dependent on external inputs, fertilizers, pesticides, fungicides, and genetically modified seeds, to secure consistent crop yields. Field crops operate within narrow margins, where even a 10–15% yield difference per acre can mean the difference between profit and loss. Large-scale monocultures, though efficient, often leave farmers uncertain from year to year as they struggle to interpret the causes of variability. For smaller farms, this challenge is magnified: they lack the economies of scale to absorb yield fluctuations and the resources to experiment with costly new technologies [1, 2].

B. Precision Agriculture and Multispectral Imaging

Emerging technologies such as drones, multispectral imaging, and Artificial Intelligence (AI) promise to

address these challenges by providing real-time, field-scale monitoring with plant-level resolution [3, 4]. Multispectral UAV imaging can highlight subtle indicators of stress and damage, such as nutrient deficiencies, water stress, or disease, weeks before symptoms are visible to the human eye [5,6]. However, current implementations are often time-consuming and expensive, limiting their adoption primarily to larger Midwestern farms with dedicated precision agriculture resources [7, 8].

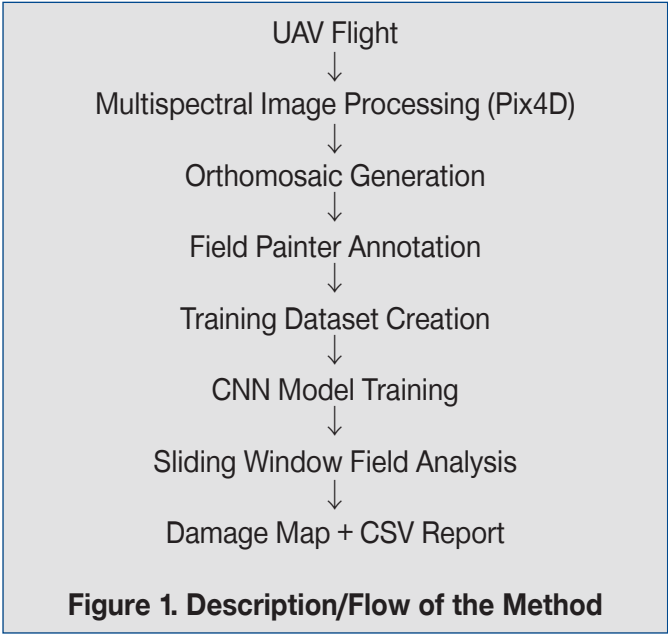
A critical limitation of multispectral imaging is that while it reveals stress and damage, it cannot by itself diagnose the underlying cause. Integrating UAV data with targeted ground-truth sampling, such as soil and tissue testing, has been shown to improve interpretability and reduce unnecessary sampling [9]. When combined with AI-driven analysis, these

integrated workflows offer the potential for automated detection of stress, classification of likely causes, and delivery of farmer-ready reports. Early work with convolutional neural networks (CNNs) demonstrates promising results in crop disease detection and stress classification [10,11].

C. Objectives of This Work

The central aim of this paper is to contribute one part of this larger vision: the development of an AI-enabled reporting framework that uses multispectral imagery and annotated training data to automate the generation of actionable insights for small and mid-sized farms. By automating the analysis of drone-based imagery, we seek to democratize access to technologies currently restricted to large-scale agriculture, thereby enabling smaller operations to make data-informed management decisions. This approach aligns with USDA priorities of improving farm profitability, reducing environmental impacts, and strengthening food security [12, 13].

The overall workflow of the proposed system is summarized in Figure 1. Multispectral imagery is first collected using an unmanned aerial vehicle and processed into orthomosaic datasets using Pix4D Fields. The imagery is then annotated using the Field Painter tool to generate labeled training data. A convolutional neural network (CNN) is trained on these samples and deployed using a sliding-window inference approach to produce probability maps, visual overlays, and quantitative damage estimates.



II. DATA COLLECTION

A. DJI Mavic 3M description and Spectral Bands

Multispectral imagery was collected using drone-mounted sensors capable of capturing reflectance across several key portions of the electromagnetic spectrum, including the visible bands (red and green), as well as the red-edge and near-infrared (NIR) regions. These spectral bands are widely used in agricultural remote sensing because plant health, chlorophyll concentration, and canopy structure influence how vegetation reflects and absorbs light at different wavelengths. In particular, healthy vegetation strongly absorbs red light for photosynthesis while reflecting higher levels of near-infrared radiation due to internal leaf structure. The red-edge band provides additional sensitivity to subtle changes in chlorophyll content and early plant stress that may not yet be visible in the standard RGB spectrum. By capturing

Camera	Band	Center Wavelength h (nm)	Bandwidth h (± nm)
RGB Camera	R, G, B (visible)	N/A	N/A
Multispectral Sensor 1	Green (G)	560	16
Multispectral Sensor 2	Red (R)	650	16
Multispectral Sensor 3	Red Edge (RE)	730	16
Near Infrared	NIR	860	26

TABLE I. Spectral Specifications of the DJI Mavic 3M Multispectral Sensor Suite

reflectance across these bands, multispectral sensors allow researchers to compute vegetation indices and identify variations in crop vigor, stress, and potential disease across a field. Table 1 summarizes the center wavelengths (frequencies) of the multispectral camera bands used in this study and provides a brief explanation of their relevance to plant health monitoring and agricultural analysis.

B. Multispectral Sensor Characteristics

Table 2 shows the resolution of the Multispectral cameras. The DJI Mavic 3M’s NIR (near-infrared) sensor is a 5 MP camera that captures light in the 860 ± 26 nm band.

Used together with the Green, Red, and Red Edge multispectral channels and the 20 MP RGB camera, it delivers a full visible-to-invisible dataset in a single flight. These data support generation of vegetation indices and crop-health assessments for precision mapping and field management.

Camera	Band	Approx. Megapixels (MP)	Notes
RGB Camera	R, G, B (visible)	20 MP	4/3-inch CMOS sensor used for true-color imagery and alignment with multispectral data
Multispectral Sensor 1	Green (G)	≈ 5 MP	Sensitive to plant chlorophyll reflection; useful for canopy vigor assessment
Multispectral Sensor 2	Red (R)	≈ 5 MP	Captures vegetation absorption in the red band for NDVI calculations
Multispectral Sensor 3	Red Edge (RE)	≈ 5 MP	Detects subtle changes in chlorophyll content, aiding early stress detection.
Near Infrared	NIR	≈ 5 MP	This allows the drone to capture both visible and invisible light data in a single flight

TABLE II.
Resolution Specifications of the DJI Mavic 3M
Multispectral Sensor Suite

C. Flight Details

Flights were conducted under FAA Part 107–compliant operations, and all imagery was processed into georeferenced mosaics using Pix4D Fields software [19]. Figure 2 shows the image capture locations within the example field, a ~17-acre corn crop where the farmer reported mechanical issues with the planter. The blue dots in the figure represent individual

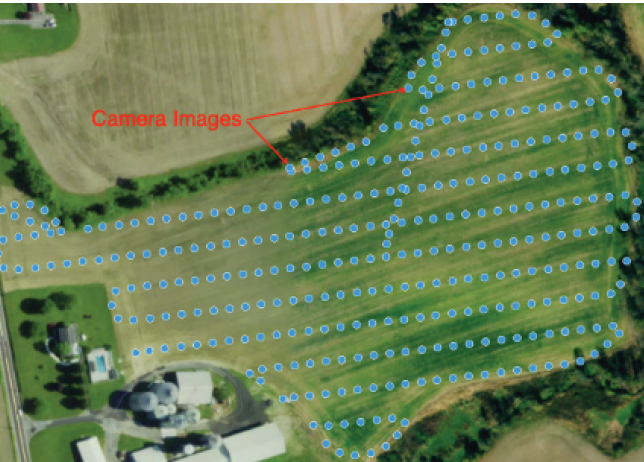


Figure 2

capture points along the programmed flight path. Prior to flight, the mission is generated using a KML or KMZ file, which defines the field boundary, start location, flight altitude, and coverage pattern. For agricultural mapping applications, the drone typically follows a standard “lawn-mower” pattern to ensure consistent overlap between images and complete field coverage.

During flight, the aircraft can maintain altitude using onboard vision and optical-flow sensing to track the crop canopy and terrain below. Alternatively, the drone can operate at a constant altitude relative to the takeoff location. However, maintaining constant elevation above ground level generally improves the quality of the photogrammetric reconstruction, particularly in fields with significant elevation variation where fixed altitude flights can introduce stitching errors in the final mosaic. In the present case the field was relatively flat with only minor elevation changes. The aircraft operated at an altitude of approximately 90 ft (27.4 m), yielding a ground sampling distance (GSD) of approximately 1.1 inches per pixel for the multispectral sensors.

An RTK (Emlid Reach RS2+) positioning unit [20] was used in coordination with the drone to improve the geospatial accuracy of the imagery collected



Figure 3.

RTK Base Station and UAV used for georeferenced crop imaging during field data collection.

during flight. Real-Time Kinematic (RTK) systems refine standard GPS measurements by applying correction data from a nearby reference station, allowing position estimates to be resolved to centimeter-level accuracy rather than the several-meter uncertainty typical of standalone GPS. When integrated with UAV mapping missions, this improved positional information allows each captured image to be tagged with more precise latitude, longitude, and altitude values. Accurate positioning is important for agricultural surveys because it improves the alignment of overlapping photographs and reduces cumulative error when the images are stitched together into a single orthomosaic. Surveying and mapping applications commonly rely on RTK-enabled drones for this reason, as the improved positional data leads to more reliable reconstruction of field geometry and crop features. In this study, the RTK system worked in conjunction with the drone's flight control and terrain-following functions to maintain accurate image locations throughout the mission. The resulting georeferenced imagery was then processed using photogrammetric reconstruction methods, as described in the following section. Figure 3 illustrates the field deployment used in this study, showing the RTK base station, the UAV platform, and the operator during data collection.

D. Pix4D Fields Processing

After data collection, the captured imagery was processed using Pix4D Fields software. The software reconstructs a georeferenced representation of the field by combining hundreds to thousands of individual images collected during flight. Several environmental and calibration parameters are incorporated during



Figure 4.

Example NDVI vegetation index map generated with Pix4D Fields for the study site. Red regions indicate lower vegetation vigor while green areas indicate healthier crop conditions.

processing to improve consistency and accuracy. Prior to the mission, the user specifies lighting conditions (e.g., sunny or overcast), and calibration images are collected using a reflectance calibration panel. To perform this step, the UAV is positioned directly above the panel and multiple images are captured while ensuring that shadows do not fall across the surface. The calibration panel contains a coded marker that allows the software to automatically identify and apply radiometric corrections across the dataset. These corrections help normalize image brightness and improve consistency when vegetation indices are calculated.

During processing, Pix4D Fields combines flight metadata, GPS coordinates recorded with each captured image, and camera calibration parameters to align overlapping photographs and generate a high-resolution orthomosaic of the field. Individual flights may include several hundred to several thousand images depending on the size of the field and the altitude of the UAV. Multiple flights can also be included in the image library if additional coverage is required. The resulting orthomosaic is exported as a large GeoTIFF file containing detailed spatial information for the entire field. In many cases the orthomosaic is then cropped so that analysis focuses only on the field of interest while removing surrounding terrain or structures.

Processing time depends on field size, flight altitude, and available computing resources. In this study the

data were processed on a laptop equipped with an Apple M2 Max processor with 32 GB of unified memory. Even with modern hardware, processing can take from several minutes to more than an hour as the software reconstructs the photogrammetric model and generates the orthomosaic. For the example shown in this paper, a 17-acre field was processed in less than one hour.

Pix4D Fields can also compute a variety of vegetation indices from the multispectral imagery. These indices provide quantitative indicators of crop condition and are useful for identifying areas of plant stress or abnormal growth. Common indices include the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Red Edge (NDRE), both of which are widely used as indicators of overall crop vigor and chlorophyll activity. In this work the default indices generated by the software were used, as their computation requires minimal additional processing time. Figure 4 shows an example NDVI map of the field, where green regions represent healthier vegetation and red regions indicate areas of lower vigor. The histogram scale at the bottom of the image provides a distribution of vegetation index values across the field.

These processed orthomosaic and vegetation index images form the basis for the training data used in the machine learning workflow described in the following section.

III. TRAINING DATA GENERATION

A. Field Painter Annotation Tool

Once the orthomosaic imagery has been generated, the next step is to construct training data for the convolutional neural network (CNN). Figure 5 shows an example GeoTIFF orthomosaic generated from the UAV imagery described in the previous section. While the visible-spectrum orthomosaic is used here to demonstrate the annotation process, the same procedure can be applied to vegetation index products such as NDVI or NDRE. To accomplish this, a custom MATLAB application called the Field Painter Annotation Tool was developed. The tool allows users to visually inspect aerial imagery and label regions of crop damage that will later be used as training data for the AI model.

In many cases the areas of concern are visually apparent to the farmer, as variations in crop vigor, planting gaps, or equipment tracks appear clearly in the aerial imagery. In the example shown, the farmer had already identified several issues in the field caused by planting errors,

overspray tracks, and other operational mistakes.

Although these issues may be easy to recognize visually, determining the total extent of damage across the field is far more difficult. Manually tracing and estimating affected regions can take several hours and is rarely performed in practice because the potential economic gain often does not justify the effort. The goal of this work is to automate this process. By labeling a subset of damaged and healthy regions, a CNN model can be trained to detect similar patterns automatically across the entire field. The trained model can then be applied to new imagery, allowing rapid assessment of crop damage and enabling farmers to better understand yield loss caused by preventable factors.

To evaluate this approach, fields with clearly visible damage patterns were intentionally selected. In the primary field shown in Figure 5, the damage was associated with planting errors and sprayer tracks. A second nearby field was later used for testing, where crop damage resulted from slug activity. Despite the difference in cause, the trained AI system was able to identify the affected regions, demonstrating that the tool focuses on detecting damaged crop structure rather than diagnosing the specific source of the damage.

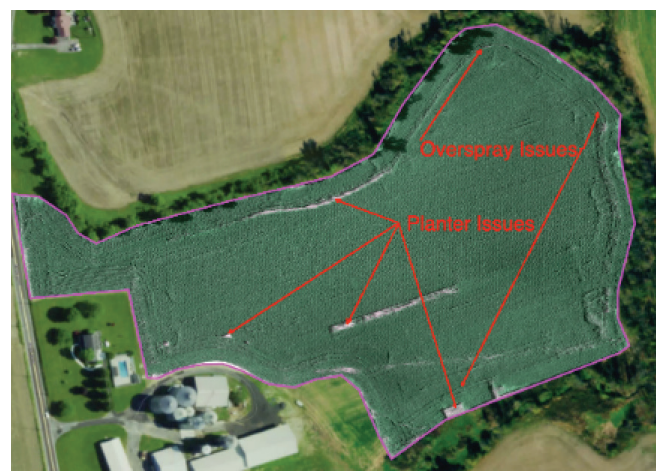


Figure 4.
Example showing how an orthomosaic image can be used to create the training data for the AI

B. Brush Size Selection

The annotation tool allows the user to define a spot or brush size that determines the region of the image labeled during annotation. This parameter is chosen to correspond to the ground sampling distance (GSD)

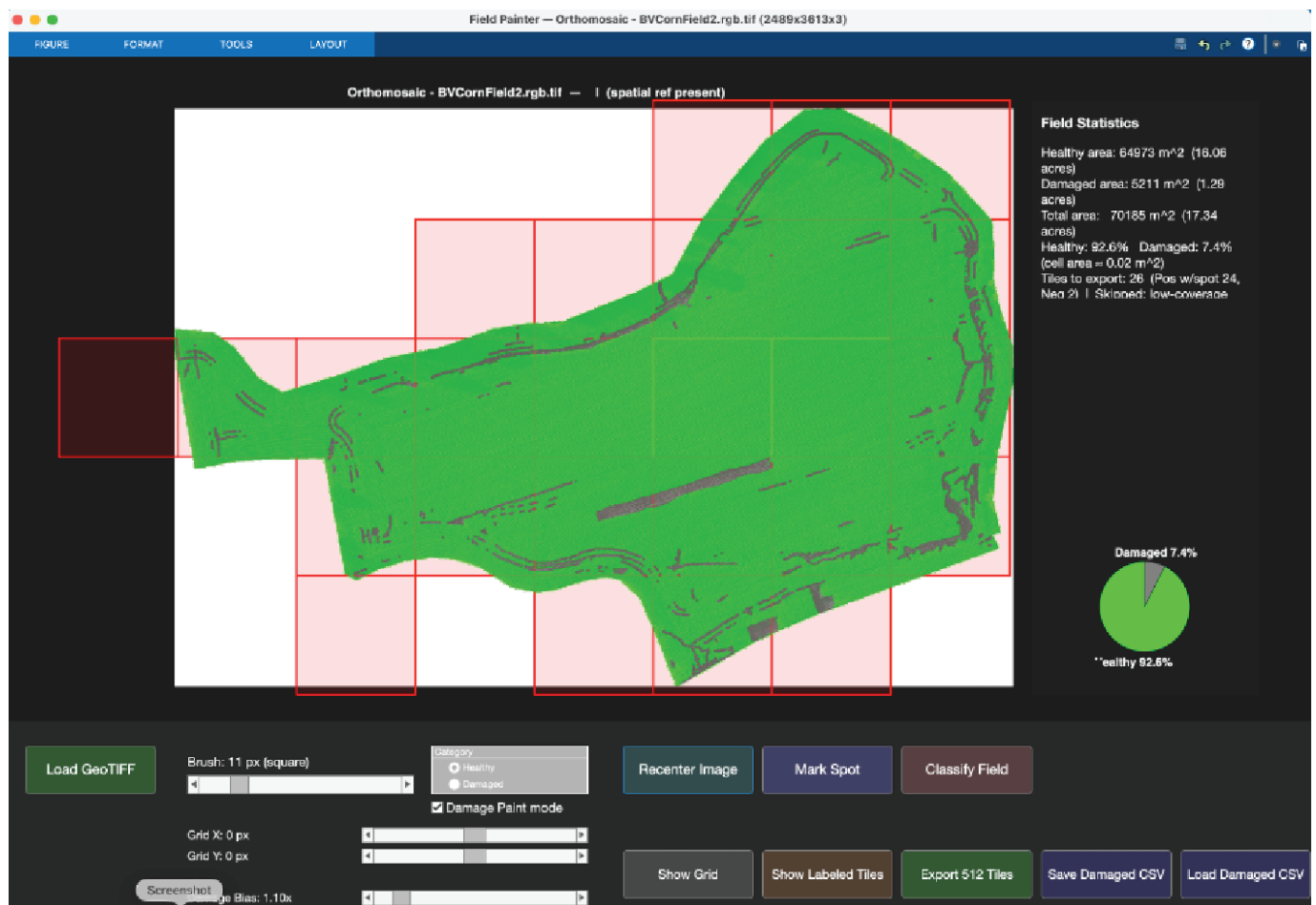


Figure 4. Field Painter Annotation Interface used to Generate Data

(GSD) associated with the UAV flight altitude and the image resolution produced during Pix4D Fields processing. Maintaining a consistent brush size throughout a labeling session ensures that training samples represent a uniform physical area within the field. Consistency is important because the CNN ultimately learns spatial patterns based on these labeled regions.

C. Labeling Healthy and Damaged Regions

The user interface of the Field Painter tool, shown in Figure 6, provides a straightforward workflow for generating labeled data. The process begins by loading the GeoTIFF orthomosaic using the Load GeoTIFF button. Once displayed, the image can be explored using standard navigation controls such as mouse-wheel zoom and click-and-drag panning. Hence, Field Painter annotation tool is a custom MATLAB-based tool developed for this project, is used to label damaged and healthy crop regions.

Classification begins by selecting the desired label using radio buttons that designate either Healthy or Damaged

crop regions. By pressing the Mark Spot button, the user can place labeled regions of the selected brush size onto the image. Holding the mouse button while moving across the image allows multiple adjacent regions to be labeled quickly. This approach allows the user to mark representative examples of both healthy and damaged crop conditions across the field.

The tool also includes a semi-automated classification mode. After a sufficient number of sample points have been provided, the Classify Field function evaluates surrounding image data and attempts to extrapolate the classification across the entire image. Because automated thresholding may overestimate or underestimate damage, a Bias slider allows the user to adjust the classification boundary and refine the segmentation result.

D. Exporting Training Tiles

Once representative regions have been labeled, the annotated field can be converted into training data suitable for CNN development. A grid overlay can be

enabled using the Show Grid option, allowing the user to visualize how the image will be divided into fixed-size training patches. Grid alignment can be adjusted using the Grid X and Grid Y controls to ensure that important image features fall within tile boundaries.

Selecting Show Labeled Tiles previews the 512×512 pixel image patches that will be exported for training. This step allows the user to verify that both healthy and damaged regions are properly represented before the dataset is generated.

E. Saving Annotation Data

When the dataset is finalized, the Export 512 Tiles function generates the training data used by the CNN. The export process produces two outputs:

- Image tiles saved to the *Images* directory
- Corresponding CSV files containing labeled coordinates stored in the *Spots* directory

Because manual labeling can require significant time, the software includes functionality to save progress during annotation. The Save Damage CSV feature records the current labeling session, allowing it to be resumed later using the Load Damage CSV option. Maintaining a consistent brush size between sessions is important to ensure that the spatial relationship between labeled regions and exported tiles remains accurate.

The resulting dataset provides the ground-truth examples used to train the AI model described in the following section.

F. Smoothing and Post Processing

After classification, a 3×3 median filter is applied to reduce isolated misclassifications and smooth boundaries, yielding a cleaner segmentation mask. The resulting map is then color-coded and overlaid on the source image, providing an intuitive visualization

IV. MATHEMATICAL BASIS FOR AUTOMATED FIELD CLASSIFICATION

A. Feature Representation

The automated classification procedure in Field Doctor Paint applies a threshold-based segmentation derived from the statistical distribution of pixel intensities within user-defined “Healthy” and “Damaged” regions. Each pixel p_i in the multispectral image is represented by a feature vector:

$$x_i = [R_i, G_i, B_i, NIR_i, RE_i] \quad (1)$$

where R_i , G_i , B_i , NIR_i , and RE_i denote reflectance values in the red, green, blue, near-infrared, and red-edge bands, respectively.

B. Class Mean and Covariance

For each class (Healthy and Damaged), the mean vector and covariance matrix are defined as:

$$\mu_H = (1/n_H) \sum_{i=1}^n x_i, \quad \mu_D = (1/n_D) \sum_{i=1}^n x_i \quad (2)$$

$$C_H = \left(\frac{1}{n_H - 1} \right) \sum_{i=1}^n (x_i - \mu_H)(x_i - \mu_H)^T \quad (3)$$

$$C_D = (1/(n_D - 1)) \sum_{i=1}^n (x_i - \mu_D)(x_i - \mu_D)^T \quad (4)$$

Here, μ_H and μ_D represent the mean spectral vectors for healthy and damaged crops, while C_H and C_D are the covariance matrices describing variability within each class.

C. Discriminant Function

Each pixel is then classified using the Mahalanobis [21] distance to each class mean:

$$d_H(x_i) = (x_i - \mu_H)^T C_H^{-1} (x_i - \mu_H) \quad (5)$$

$$d_D(x_i) = (x_i - \mu_D)^T C_D^{-1} (x_i - \mu_D) \quad (6)$$

The pixel is assigned to the class with the smaller distance (i.e., the more probable spectral match).

D. Bias Adjustment

The Bias slider introduces a weighting factor $\beta \in [0, 1]$ to adjust the decision threshold between the two classes:

$\text{Class}(x_i) = \{\text{Damaged, if } d_D(x_i) < \beta d_H(x_i); \text{ Healthy, otherwise.}\}$

When $\beta = 0.5$, the decision boundary is neutral. Increasing β (>0.5) biases the classifier toward labeling fewer pixels as damaged, while decreasing β (<0.5) expands the damaged classification area.

V. CNN MODEL

A. Overview of Model Development

To automatically identify damaged crop regions, a convolutional neural network (CNN) was trained

using image patches extracted from the annotated orthomosaics described in the previous section. The model was implemented in MATLAB using the Deep Learning Toolbox. The overall workflow consists of four primary stages: (1) preparing training data from exported image tiles and annotation coordinates; (2) defining the CNN architecture; (3) training the network or loading a previously trained model; and (4) testing the model on new GeoTIFF imagery through a visualization interface that provides summary statistics and damage estimates. The GeoTIFF orthomosaics are generated automatically by Pix4D Fields from the multispectral images collected by the UAV platform.

The objective of the model is to learn local visual patterns associated with damaged and healthy crop regions so that similar patterns can be automatically detected in new imagery.

B. Training Data Preparation Strategy

The data preparation stage is designed to provide the CNN with precisely the visual context required for classification while minimizing label noise and class imbalance. Instead of feeding entire image tiles to the network, compact patches centered on expert-labeled

coordinates are extracted from the orthomosaic. This patch-based approach focuses the model on local texture, color, and edge information associated with the target class while avoiding large regions of unlabeled background.

Each training example consists of a 7×7 pixel RGB patch centered on a labeled point. A receptive field of this size (approximately a 3-pixel radius) was found to capture the local visual signature while keeping the input dimension small. Small inputs stabilize optimization and reduce the likelihood of overfitting when training datasets are modest in size.

To ensure reliable supervision, patches are only extracted when they lie completely within the image boundaries. This prevents truncated objects or padding artifacts from entering the training data. Each positive example is paired with a negative sample drawn from surrounding background regions beyond a defined margin distance. This “distance guard” ensures that negative samples represent true background rather than ambiguous near-miss examples. Maintaining this separation improves the sharpness of the decision boundary and reduces noise during training.

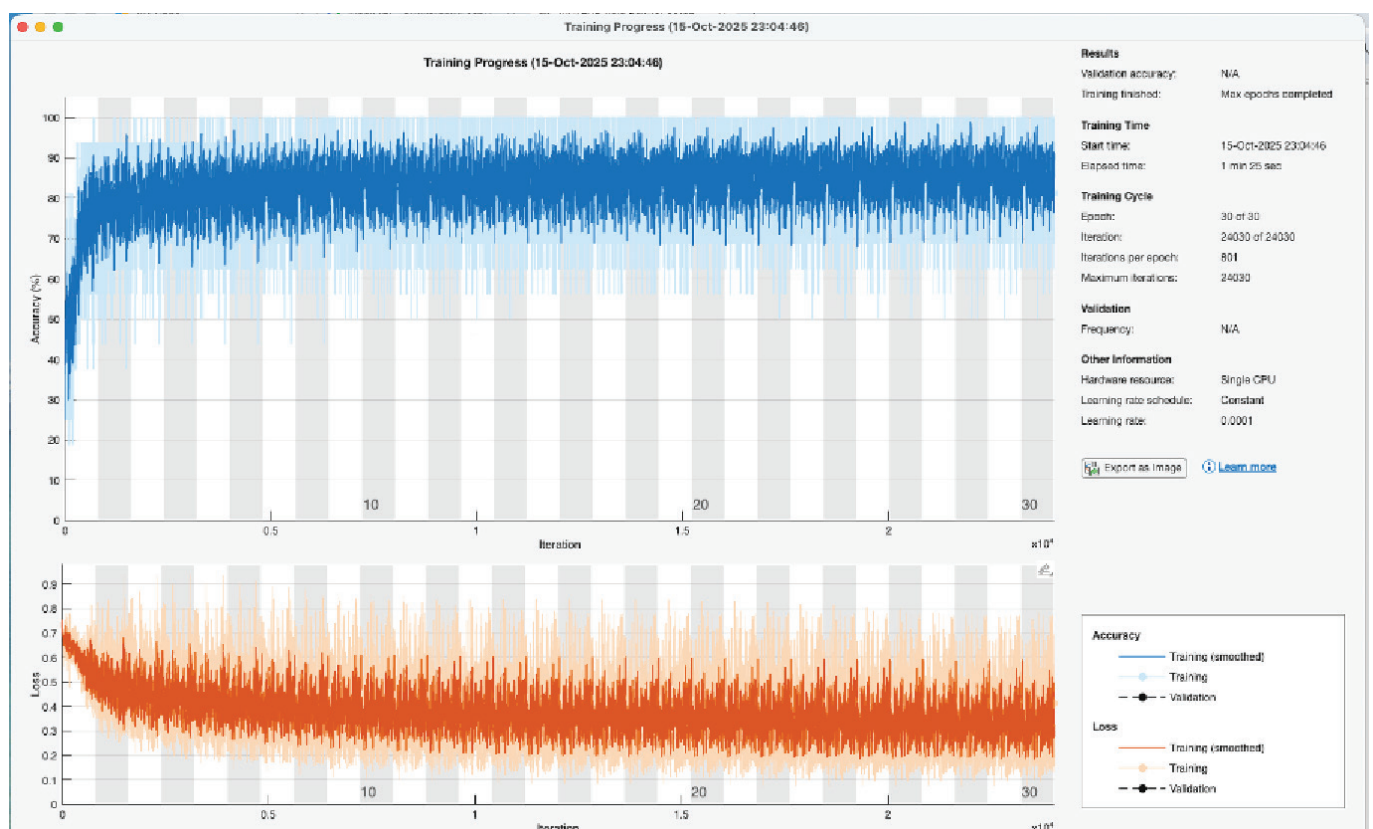


Figure 7. Preliminary training run used to verify model behavior as a first Step quality check.

Input imagery is standardized prior to training. Grayscale images are promoted to three channels when necessary so that all samples match the expected CNN input shape. Pixel intensities are normalized to floatingpoint values in the range $[0,1]$, improving gradient stability during optimization. Labels are encoded categorically to ensure consistency during loss computation.

Before training begins, a lightweight quality check is performed that reports the number of positive and negative samples and displays a visual grid of randomly selected patches. This diagnostic step helps verify class balance and annotation integrity before the network is trained.

C. Initial Training Verification

After defining the network architecture, a brief training run is performed as a diagnostic to verify that the extracted patches provide a learnable signal. During this step validation is intentionally disabled, as the goal is only to confirm stable optimization and compatibility between the data and the network structure.

Figure 7 shows the training progress during this initial verification stage. Accuracy rapidly increases toward the high-80% to 90% range while the cross-entropy loss decreases steadily. Although minibatch updates introduce noise in the traces, the smoothed curves remain monotonic. This behavior indicates that the dataset provides consistent supervision and that the model is capable of learning the relevant visual cues. Full training and validation are performed later in the workflow.

This diagnostic step functions as a preliminary training run used to verify model behavior for the training pipeline. If the training curves showed instability or stagnant performance, the issue would likely originate in the training data preparation stage rather than the model architecture.

D. Patch Dataset Verification

Figure 8 presents a grid of randomly sampled 7×7 training patches along with their assigned labels (“Positive” or “Negative”). This visualization provides an immediate sanity check on the dataset used for training. Positive samples clearly contain the texture and structure associated with damaged crop regions, while negative samples represent true background areas rather than ambiguous boundaries.

Number of positive samples: 6363
 Number of negative samples: 6465
 Training data prepared with patches and labels.

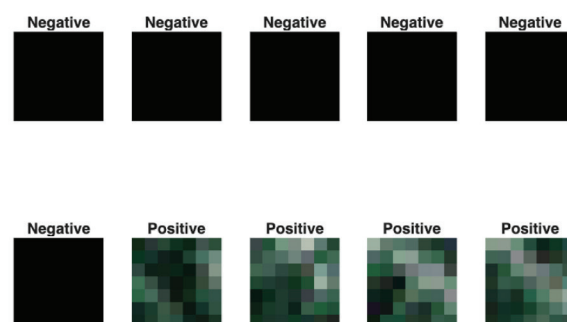


Figure 8.

Example training patches and class balance.

The accompanying counts of positive and negative examples also confirm that the dataset remains balanced. Such checks are important because many failures in machine learning workflows originate in data preparation rather than model design. If the sampled patches appeared visually inconsistent, misaligned, or poorly balanced, the extraction procedure would be revised before proceeding to full training.

E. CNN Architecture

The CNN architecture used in this work is intentionally compact because the prediction task itself is local. Each input to the network is a small 7×7 RGB patch centered on an expert-labeled coordinate. A large image-scale network would introduce unnecessary capacity and risk learning irrelevant background context.

The architecture consists of two 3×3 convolution layers followed by a single 2×2 max-pooling operation. These layers capture local texture, color contrast, and edge features that determine the classification within the limited field of view. Padding is applied to maintain spatial dimensions so that information near patch borders is preserved. This is important because annotation clicks may not be perfectly centered on the target region.

Pooling reduces the spatial dimension slightly, introducing limited translation tolerance while maintaining meaningful spatial structure. Channel depth increases modestly from 16 to 32 filters, allowing the network to learn a richer set of local features without creating an excessive number of parameters.

The classification head consists of a fully connected layer with 64 units followed by a two-class softmax output representing damaged and healthy crop regions. The complete model contains approximately 2.4×10^4 parameters, which is appropriate for the available dataset size and reduces the likelihood of overfitting.

Nonlinear activation functions are implemented using ReLU units due to their computational simplicity and stable gradients. Batch normalization was evaluated but did not significantly improve performance for these small patches and modest batch sizes.

F. Training Objective

The network is trained by minimizing the cross-entropy loss between the predicted class probabilities and the ground-truth labels. For a single training example the loss function is defined as

$$\mathcal{L} = -\sum_{k \in \{0,1\}} y_k \log \hat{p}_k \quad (8)$$

Where y^* represents the one-hot encoded ground-truth label $\hat{p}^*$ is the predicted probability of class k computed using the softmax function

$$\hat{p}_k = \frac{e^{z_k}}{e^{z_0} + e^{z_1}} \quad (9)$$

where z^* denotes the output logit from the final linear layer.

This formulation provides stable gradients and produces calibrated probability estimates that are useful for threshold-based classification of crop damage.

VI. SYSTEM DEPLOYMENT AND FIELD ANALYSIS

A. Sliding Window Inference

After training, the CNN is applied to previously unseen GeoTIFF imagery to identify damaged crop regions across an entire field. Because the network operates on small image patches, the full orthomosaic is analyzed using a sliding-window approach. A fixed-size window matching the training patch dimensions is moved systematically across the image, and each region is evaluated by the trained model.

For each window position, the CNN produces a probability estimate indicating whether the region corresponds to healthy or damaged crops. By scanning the entire image in this manner, the system generates a dense set of predictions that collectively describe the

condition of the field.

This approach allows the model to evaluate large aerial datasets while still relying on the local feature representation learned during training.

B. Probability Map Generation

The predictions produced by the sliding-window process are aggregated into a probability map representing the likelihood of crop damage across the field. Regions with higher probabilities indicate spectral and structural characteristics similar to the damaged training examples.

The probability map provides a continuous representation of crop health rather than a simple binary classification. This allows users to visualize gradients of crop stress and identify emerging patterns that may warrant further investigation.

C. Visualization Interface

To support practical field analysis, the results are displayed within a graphical interface that allows users to inspect classification results interactively. The interface displays the orthomosaic image alongside the predicted damage regions and summary statistics

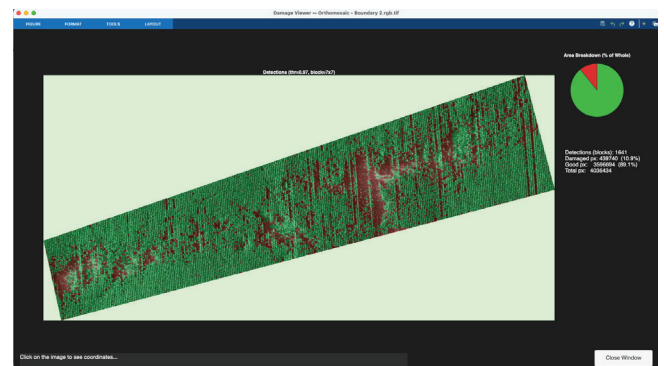


Figure 9.
Example training patches and class balance.

describing the overall field condition.

An example interface is shown in Figure 9. The system provides several useful outputs, including:

- a visual overlay highlighting predicted damage
- a pie-chart summary showing the proportion of healthy and damaged areas
- interactive controls for exploring the image

These tools allow farmers and researchers to quickly interpret the results without requiring specialized knowledge of machine learning techniques.

D. CSV Export and Reporting

In addition to visual outputs, the system exports numerical results describing the detected crop damage. The classification results can be saved as CSV files containing the coordinates and labels of the analyzed regions. These files provide a portable format that can be used for further analysis, reporting, or integration with other agricultural data systems.

The ability to generate both visual and quantitative outputs makes the system suitable for real-world agricultural workflows. Farmers can quickly assess the extent of damage within a field and estimate potential yield loss, while researchers can use the exported data to refine models and evaluate performance across multiple sites.

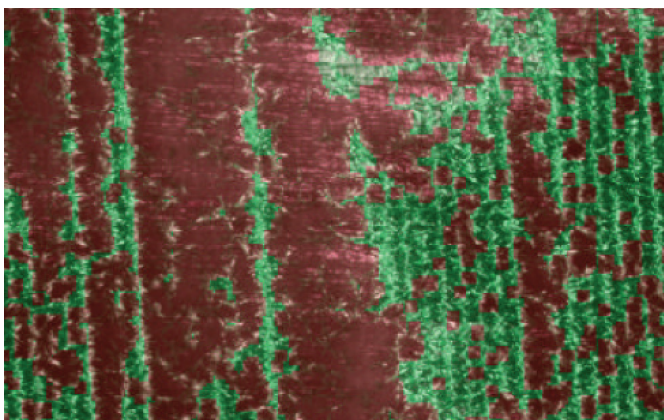


Figure 10.
A Zoomed view of predicted damage overlay from image 9.

VII. RESULTS

Below we evaluate generalization on a different corn field, flown on a different day, by testing a clipped section known to exhibit slug damage. We keep the inference settings close to training, sliding a 7×7 window and thresholding the positive class probability, and adjust only the decision threshold. As expected for a well-calibrated patch classifier, small threshold changes materially alter the mask without changing the underlying score landscape. For this run we set the probability threshold to 0.97, which yields a clean separation of damaged versus healthy areas while suppressing spurious speckles.

Figure 9 shows the program's final output window: the orthomosaic on the left with a translucent red overlay for predicted damage and a green underlay for healthy regions, a percent pie summarizing area on the right,

and text statistics reporting detected block count and pixel-area totals. The wheel-zoom and pan allow rapid navigation across rows and headlands; at a glance, the overlay aligns with agronomic patterns (row-wise streaking and patchy clusters) rather than random noise, indicating that the model is reading genuine local cues rather than memorizing a single field.

To verify behavior at field scale, we zoom into a representative with mixed outcomes. Figure 10 (called out in the next paragraph) shows the same overlay at high magnification. The damage mask tracks the textured, desiccated leaf structure and the linear gaps characteristic of slug pressure, while adjacent intact rows remain predominantly green. The transitions are crisp rather than blotchy, which is what we expect from a patch-level classifier that votes only where it is confident (here, ≥ 0.97).

Together, Figures 4 and 9 show that the trained network successfully transfers to imagery from a new flight. The predicted damage regions align with visible crop issues and produce consistent estimates of affected area, suggesting that the model captures meaningful agronomic patterns. It is noteworthy that the field damage in this case was caused by slugs, whereas the training data primarily reflected planting-related damage. This distinction underscores the model's capacity to generalize across different stress types.

VIII. DISCUSSION

This work shows that a compact, patch-level CNN, trained on small, curated image patches extracted from expert annotations, can generalize beyond the training mosaics and produce field-scale stress maps that agronomists can interpret and act on. By holding the training–test contract fixed (the model always decides from the same 7×7 local context) and changing only the decision threshold at inference, we obtain stable, transferable behavior on a different flight and field. The single-window UI makes that generalization visible: the overlay tracks agronomic structure (row-wise streaking, clustered patches) rather than random speckle, and the accompanying area statistics summarize results in plain terms (percent of field flagged) that align with how growers make decisions.

Compared with traditional scouting, which is constrained by time and spatial coverage, this approach scales cleanly across large mosaics while

preserving local detail. The stride and tiling choices let operators trade speed for resolution transparently, and the progress bar and immediate overlays build trust by making the computation auditable. Equally important, storing the trained network and lightweight metadata enables both “run-as-is” use for routine scouting and incremental improvement when new annotations arrive; teams can add training sets, retrain or fine-tune, and reproduce past results without changing downstream tools.

Performance hinges on two design choices that also guard against overfitting: (i) patch-centered supervision with well-separated negatives, which concentrates the learning signal on stable, local cues; and (ii) a small network whose capacity matches the dataset. The result is a classifier that responds smoothly to threshold adjustments and yields coherent masks at field scale. The percent-pie and text readouts are intentionally simple, an accessible bridge from model scores to management actions, while CSV exports of detections (with pixel and, when available, lat/lon) integrate directly with GIS workflows and tractor prescriptions.

Limitations remain. Mixed pixels at row edges, within-row canopy variation, and illumination differences between flights can still introduce borderline regions that move with the threshold. Our binary setting also collapses diverse stressors into a single “damaged” class; without targeted labels, the map indicates *where* to look, not *why*. Finally, RGB-only inference will miss purely spectral signatures that multispectral indices can capture; the current system favors visible-texture problems (e.g., slug injury patterns) and may underperform on stresses that are primarily biochemical.

Future work will expand the labeled corpus across crops, phenological stages, and stress types; incorporate multispectral channels and soil/tissue measurements for multimodal fusion; and explore lightweight edge deployment for in-field, real-time feedback. Critically, we will integrate tractor harvest (yield) data as a supervision signal, both to validate predictions and to retrain/retune thresholds so that map outputs align with realized yield loss, thereby improving model accuracy and practical relevance. Beyond algorithmic refinements, we will evaluate agronomic impact by pairing stress maps with yield and treatment records to quantify gains in input targeting and economic return. In short, the present results demonstrate a practical path from annotated mosaics to reliable, field-scale decision support, while outlining clear steps to increase scope, robustness, and operational value.

IX. CONCLUSIONS

We integrated drone sensing, photogrammetry, and AI into a practical pipeline that turns mosaicked imagery into actionable crop-stress maps for corn and soybean fields. Multispectral flights were processed (including NDVI/NDRE products) and converted into labeled training panels with a MATLAB paint tool; a compact, patch-level CNN was then trained on those expert annotations and deployed in a single-window viewer that overlays red/green masks, reports percent area, exports GIS-ready CSVs, and supports rapid zoom-and-pan inspection. Tested on a different field and flight, the model produced coherent, agronomically plausible patterns, consistent with observed slug injury, while requiring only minor adjustment of the decision threshold, indicating stable generalization from curated training data.

Equally important, the implementation is reproducible and extensible. The “train-or-load” design lets practitioners run the model immediately or incorporate additional panels as they accumulate, preserving speed for routine scouting and a clear path for iterative improvement. The resulting outputs (area percentages, overlays, and georeferenced detections) align with how growers and agronomists make decisions, lowering the barrier to adoption for small and mid-sized farms.

Finally, the project establishes a concrete framework for validating AI-based stress detection against tractor harvest records. That linkage, spatially comparing predicted stress with realized yield, enables the next phase: quantifying economic impact and refining prescriptions for fertilizer, pesticide, and replanting decisions. In summary, we demonstrate a scalable, field-ready approach that moves beyond manual scouting toward data-driven management, while laying the groundwork for robust yield-based validation and expansion across crops, seasons, and stress types.

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System Identification and State-Space Control of a Small Unmanned Aerial Vehicle (UAV)

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Abstract— This paper presents the modeling, identification, and experimental control of a Parrot Mambo micro–Unmanned Aerial Vehicle (UAV) using a Linear Quadratic Gaussian (LQG) control framework. A dynamic model of the quadrotor is developed by combining physical inspection with experimental system identification to estimate key parameters such as inertial properties, thrust coefficients, and geometric characteristics. The resulting model is expressed in state-space form and used to design an optimal state-feedback controller coupled with Kalman filtering for state estimation.

The control architecture follows a cascade structure that separates position and attitude control loops, enabling stable and reliable trajectory tracking under sensor noise and model-ing uncertainties. Controller performance is evaluated through both simulation and real flight experiments using representative square and circular trajectories.

Experimental results show accurate trajectory tracking and improved transient behavior compared with a conventional PID baseline. In addition, the study provides an experimentally validated dynamic model of the Parrot Mambo platform, highlighting the importance of parameter identification and state estimation in achieving reliable control of micro-UAV systems.

Keywords: Quadrotor UAV, system identification, LQG con-trol, Kalman filtering, trajectory tracking.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have experienced rapid growth in recent years due to advances in embedded elec-tronics, sensing technologies, and autonomous navigation algorithms [1]. These platforms are increasingly used in a wide range of applications including environmental moni-toring, infrastructure inspection, precision agriculture, disaster response, mapping, and logistics operations [2]. In particular, quadrotor UAVs have become one of the most widely adopted aerial platforms because of their mechanical simplicity, vertical take-off and landing capabilities, and high maneuverability [3], [4].

Despite their structural simplicity, quadrotor systems

present significant control challenges. Their dynamics are inherently nonlinear, strongly coupled, and sensitive to mod-eling uncertainties, sensor noise, and external disturbances [5], [3], [4]. Achieving reliable trajectory tracking and atti-tude stabilization therefore requires accurate system models together with robust control strategies capable of handling uncertainties and disturbances in real operating conditions [6], [7].

Several control approaches have been proposed in the liter-ature for quadrotor systems, including classical PID control, adaptive control, nonlinear backstepping strategies, and opti-mal control methods [7], [5].

Among these approaches, PID controllers remain widely used in practical implementations due to their simplicity and ease of tuning [3]. However, PID-based solutions often exhibit limitations when dealing with aggressive maneuvers, model uncertainties, or measurement noise. Nonlinear techniques such as backstepping have been proposed to explicitly address the nonlinear dynamics of quadrotors [8], while optimal control strategies, including the Linear Quadratic Regulator (LQR) and Linear Quadratic Gaussian (LQG) control, provide a systematic framework for balancing tracking performance and control effort while incorporating state estimation through Kalman filtering [4].

However, the effectiveness of these control strategies strongly depends on the availability of accurate dynamic models and reliable state estimation. In practice, obtaining precise parameter values for small UAV platforms remains challenging due to sensor limitations, aerodynamic uncertainties, and variations in manufacturing characteristics [9], [10]. In addition, the quality of onboard sensing and state estimation algorithms significantly influences the overall control performance, particularly in small aerial vehicles operating with lightweight sensors and limited computational resources [11]. Consequently, experimental identification and validation of UAV dynamic models have become critical steps for achieving high-performance control and improving the reliability of model-based control strategies [12], [13].

In this context, this paper presents the identification, modeling, and experimental control of a Parrot Mambo micro-UAV using an LQG-based control architecture. A dynamic model of the quadrotor is obtained by combining experimental measurements with gray-box identification techniques to estimate key parameters such as inertia, thrust coefficients, and geometric characteristics. The resulting state-space representation is used to design a state-feedback controller integrated with Kalman filtering for state estimation.

The proposed control scheme is implemented within a cascade architecture separating position and attitude loops, allowing robust trajectory tracking under sensor noise and modeling uncertainties. Controller performance is evaluated through both simulation and real flight experiments using square and circular reference trajectories. A comparison with a classical PID controller is also presented to assess the advantages of the proposed approach.

The main contributions of this work are summarized as follows:

- Experimental identification of key dynamic parameters of the Parrot Mambo UAV platform.
- Development of a state-space model suitable for optimal control design.
- Implementation of an LQG-based flight controller with Kalman state estimation.
- Experimental validation of trajectory tracking performance and comparison with a PID baseline.

The remainder of this paper is organized as follows. Section 2 presents the dynamic modeling and parameter identification of the UAV. Section 3 describes the design of the LQG control strategy and state estimation scheme. Section 4 reports simulation and experimental results, including the quantitative performance analysis for square and circular trajectories. Finally, Section 5 summarizes the main conclusions and outlines future research directions.

II. DYNAMIC MODEL OF THE DRONE

Quadrotor platforms constitute a widely used class of Unmanned Aerial Vehicles (UAVs) due to their mechanical simplicity, vertical take-off and landing capability, and high maneuverability. The Parrot Mambo employed in this work follows the conventional X-shaped configuration composed of four fixed-pitch propellers driven by independent electric motors. By modulating the rotational speed of each rotor, the vehicle is capable of controlling its six degrees of freedom (DOF), which consist of three translational motions in the inertial frame (x, y, z) and three rotational motions in the body frame corresponding to roll (ϕ), pitch (θ), and yaw (ψ).

The thrust generated by each propeller produces both forces and reaction torques that determine the translational and rotational dynamics of the vehicle. These forces allow the UAV to achieve stable hovering as well as trajectory tracking through coordinated variations in rotor speeds.

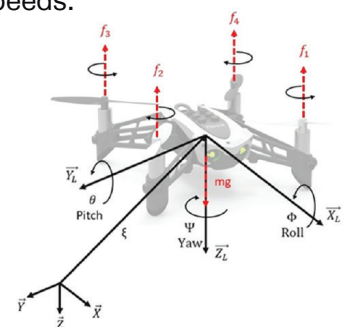


Fig. 1.
Free-body diagram
and reference frames
for the Parrot Mambo
quadrotor.

Figure 1 illustrates the free-body diagram and reference frames of the quadrotor. Roll motion (ϕ) is generated by differential thrust between rotor pairs (f_1, f_4) and (f_2, f_3). Similarly, pitch motion (θ) is obtained from the imbalance between thrust pairs (f_1, f_2) and (f_3, f_4). Yaw rotation (ψ) results from the reaction torques created by the counterrotating propellers. The total thrust acting along the bodyfixed -z axis is given by the sum of the individual rotor thrusts $f_1 + f_2 + f_3 + f_4$.

The nonlinear dynamics of the quadrotor can be derived using the Newton–Euler formulation, where translational motion is expressed in the inertial reference frame and rotational motion is expressed in the body frame using angular rates p , q , and r . The resulting equations of motion are given by

$$\begin{aligned}\ddot{x} &= (\sin \psi \sin \phi + \cos \psi \sin \theta \cos \phi) \frac{-u_1}{m}, \\ \ddot{y} &= (-\cos \psi \sin \phi + \sin \psi \sin \theta \cos \phi) \frac{-u_1}{m}, \\ \ddot{z} &= g + (\cos \theta \cos \phi) \frac{-u_1}{m}, \\ \dot{p} &= \frac{I_{yy} - I_{zz}}{I_{xx}} q r + \frac{l u_2}{I_{xx}}, \\ \dot{q} &= \frac{I_{zz} - I_{xx}}{I_{yy}} p r + \frac{l u_3}{I_{yy}}, \\ \dot{r} &= \frac{I_{xx} - I_{yy}}{I_{zz}} p q + \frac{u_4}{I_{zz}},\end{aligned}\quad (1)$$

where m denotes the mass of the UAV, g represents the gravitational acceleration, l is the distance from the vehicle center of mass to each rotor, and I_{xx} , I_{yy} , and I_{zz} correspond to the principal moments of inertia.

The control inputs u_1 , u_2 , u_3 , and u_4 represent the total thrust and the control torques acting around the body axes. These inputs are generated by the squared angular velocities of the propellers Ω_i through the thrust and drag coefficients b and d , according to

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \end{bmatrix} = \begin{bmatrix} b(\Omega_1^2 + \Omega_2^2 + \Omega_3^2 + \Omega_4^2) \\ b(\Omega_4^2 + \Omega_3^2 - \Omega_1^2 - \Omega_2^2) \\ b(\Omega_2^2 + \Omega_3^2 - \Omega_1^2 - \Omega_4^2) \\ d(\Omega_1^2 + \Omega_3^2 - \Omega_2^2 - \Omega_4^2) \end{bmatrix}. \quad (2)$$

Due to the counter-rotating configuration of the propellers, the yaw torque can also be interpreted through the signed rotor speed combination

$$\Omega_\Delta = \Omega_1 - \Omega_2 + \Omega_3 - \Omega_4, \quad (3)$$

which reflects the contribution of rotor drag torques to the yaw dynamics.

Accurate knowledge of the inertial parameters is essential for reliable model-based control design. To estimate the inertia components I_{xx} , I_{yy} , and I_{zz} , an experimental identification procedure was performed using a pendulum-based test rig. The drone was mounted on a rigid rod and allowed to oscillate freely around a pivot. The angular displacement of the rod relative to the vertical axis was measured using a magnetic potentiometer and recorded as angle–time data in SIMULINK.

The identification process was conducted using a grey-box parameter estimation approach implemented in MATLAB. The dynamic behavior of the test rig is described by the damped pendulum equation

$$(mr_c^2 + I_{zz}) \ddot{\theta}_p + mgr_c \sin \theta_p + c \dot{\theta}_p = \tau, \quad (4)$$

where r_c represents the distance from the pivot to the center of mass of the system, θ_p denotes the pendulum angular displacement, c is the viscous damping coefficient of the experimental setup, and τ is the applied torque.

Using the measured oscillation data and the grey-box estimation procedure, the principal inertial parameters of the quadrotor were identified. The resulting dynamic model parameters are summarized in Table I.

TABLE I
PARAMETERS OF THE QUADROTOR DYNAMIC MODEL.

Parameter	Value	Units
m	7.2×10^{-2}	kg
I_{xx}	1.66944×10^{-4}	kg·m ²
I_{yy}	1.7119×10^{-4}	kg·m ²
I_{zz}	2.5418×10^{-4}	kg·m ²
b	3.99×10^{-8}	N·s ²
d	3.29×10^{-10}	N·m·s ²
l	6.24×10^{-2}	m

III. CONTROLLER DESIGN

A. Linearization and State-Space Representation

The nonlinear quadrotor model presented in the previous section was linearized around the hover equilibrium condition. At this operating point, the translational and angular velocities are zero, the attitude angles satisfy $\phi = \theta = \psi = 0$, and the total thrust balances the vehicle weight. Therefore, the nominal inputs are

$$u_1^* = mg, \quad u_2^* = u_3^* = u_4^* = 0. \quad (5)$$

Using the Jacobian of the nonlinear vector field evaluated at the hover condition, the linearized dynamics can be written in deviation variables as

$$\dot{\tilde{x}} = A\tilde{x} + B\tilde{u}, \quad y = C\tilde{x}, \quad (6)$$

where $\tilde{x}$ and $\tilde{u}$ denote deviations with respect to the hover equilibrium. The state vector is defined as

$$\tilde{x} = \begin{bmatrix} \phi & \theta & \psi & \dot{\phi} & \dot{\theta} & \dot{\psi} & z & x & y & \dot{z} \end{bmatrix}^T, \quad (7)$$

and the input vector is

$$\tilde{u} = [\tilde{u}_1 \quad u_2 \quad u_3 \quad u_4]^T, \quad \tilde{u}_1 = u_1 - mg. \quad (8)$$

The matrices A and B describe the linearized translational and rotational dynamics around hover, while C selects the measured or estimated variables used for feedback. This state-space model is the basis for the LQG design.

B. Kalman Filter-Based State Estimation

Since not all states are directly measured during flight, the controller uses estimated states obtained from the onboard sensing system. The estimation problem was formulated in discrete time as

$$\tilde{x}_{k+1} = A_d \tilde{x}_k + B_d \tilde{u}_k + w_k, \quad (9)$$

$$y_k = C_d \tilde{x}_k + v_k, \quad (10)$$

where A_d , B_d , and C_d are the discrete-time state-space matrices, w_k is the process noise, and v_k is the measurement noise. These noise terms are assumed to be zero-mean with covariance matrices

$$E[w_k w_k^T] = W, \quad E[v_k v_k^T] = V. \quad (11)$$

The Kalman filter is implemented through the prediction and correction stages. In the prediction stage, the state and covariance are propagated as

$$\hat{x}_{k|k-1} = A_d \hat{x}_{k-1|k-1} + B_d \tilde{u}_{k-1}, \quad (12)$$

$$P_{k|k-1} = A_d P_{k-1|k-1} A_d^T + W. \quad (13)$$

The Kalman gain is then computed as

$$L_k = P_{k|k-1} C_d^T (C_d P_{k|k-1} C_d^T + V)^{-1}. \quad (14)$$

Finally, the state and covariance are corrected according to

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + L_k (y_k - C_d \hat{x}_{k|k-1}), \quad (15)$$

$$P_{k|k} = (I - L_k C_d) P_{k|k-1}. \quad (16)$$

In the experimental implementation, attitude variables were estimated from inertial measurements using complementary and Kalman filtering. Horizontal position and velocity were obtained from the onboard visual positioning system based mainly on optical-flow measurements, while altitude and vertical velocity were estimated using the ultrasonic and air-pressure sensors. This sensor-fusion structure provided the estimated state vector $\hat{x}$ required by the feedback controller during real-flight operation.

C. LQG Control Law

The LQG controller combines the Kalman state estimator with an optimal state-feedback controller. The general control action is expressed as

$$\tilde{u} = -K\hat{x}, \quad (17)$$

where K is the LQR gain matrix and $\hat{x}$ is the estimated state vector provided by the Kalman filter. The LQR gain is obtained by minimizing the quadratic cost function

$$J = \int_0^\infty (\tilde{x}^T Q \tilde{x} + \tilde{u}^T R \tilde{u}) dt. \quad (18)$$

The matrix Q penalizes deviations of the states from the hover condition, whereas R penalizes the control effort. The weighting matrix Q was selected as

$$Q = \begin{bmatrix} Q_\eta & \mathbf{0}_{3 \times 3} & \mathbf{0}_{3 \times 3} & \mathbf{0}_{3 \times 3} \\ \mathbf{0}_{3 \times 3} & Q_{\dot{\eta}} & \mathbf{0}_{3 \times 3} & \mathbf{0}_{3 \times 3} \\ \mathbf{0}_{3 \times 3} & \mathbf{0}_{3 \times 3} & Q_p & \mathbf{0}_{3 \times 3} \\ \mathbf{0}_{3 \times 3} & \mathbf{0}_{3 \times 3} & \mathbf{0}_{3 \times 3} & Q_v \end{bmatrix}, \quad (19)$$

with

$$Q_\eta = \begin{bmatrix} 3.39 & 0 & 0 \\ 0 & 3.35 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad Q_{\dot{\eta}} = \begin{bmatrix} 0.01 & 0 & 0 \\ 0 & 0.01 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad (20)$$

$$Q_p = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.0001 & 0 \\ 0 & 0 & 0.0001 \end{bmatrix}, \quad Q_v = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.0001 & 0 \\ 0 & 0 & 0.0001 \end{bmatrix} \quad (21)$$

The control-effort weighting matrix was selected as

$$R = \begin{bmatrix} 200 & 0 & 0 & 0 \\ 0 & 200 & 0 & 0 \\ 0 & 0 & 200 & 0 \\ 0 & 0 & 0 & 200 \end{bmatrix}. \quad (22)$$

The selection of Q and R was guided by the control objectives and by experimental constraints. Larger weights were assigned to the roll and pitch angles because these variables strongly influence horizontal

motion and trajectory tracking. Moderate weights were assigned to yaw, altitude, and vertical velocity to maintain bounded attitude and height variations. Smaller weights were used for horizontal position and velocity states to avoid excessively aggressive corrections from the inner control loop, since the position dynamics are handled through the cascade structure. The matrix R was chosen with relatively large and equal weights to limit control effort, reduce actuator saturation, and generate smoother commands compatible with the physical constraints of the Parrot Mambo platform. The final values were tuned by evaluating tracking behavior and integral performance indices on square and circular trajectories.

D. Cascade Implementation

Although the general LQG control law is given by (17), the experimental implementation was organized in a cascade structure. The outer position loop generates the roll and pitch references, ϕ_{ref} and θ_{ref} , from the horizontal position errors. The inner attitude loop then regulates the roll and pitch dynamics using the estimated attitude states.

For this reason, the implemented feedback gain corresponds to the roll–pitch attitude subsystem. This reduced gain is denoted as K_{att} to distinguish it from the full LQR gain matrix K . It has two rows because it generates two virtual control inputs: the roll control torque u_2 and the pitch control torque u_3 . The implemented gain is

Therefore, the inner attitude control action is

$$K_{\text{att}} = \begin{bmatrix} 0.0128 & 0 & -0.0030 & 0 \\ 0 & 0.0128 & 0 & -0.0030 \end{bmatrix}. \quad (23)$$

The remaining virtual inputs, associated with thrust and

$$\begin{bmatrix} u_2 \\ u_3 \end{bmatrix} = -K_{\text{att}} \begin{bmatrix} \hat{\phi} - \phi_{\text{ref}} \\ \hat{\theta} - \theta_{\text{ref}} \\ \hat{\phi} \\ \hat{\theta} \end{bmatrix}. \quad (24)$$

yaw, are handled by the altitude and yaw control channels of the cascade architecture. This implementation preserves the LQG structure by combining optimal state feedback with Kalmanbased state estimation, while adapting the controller to the practical organization of the Parrot Mambo flight-control system.

E. PID Baseline Controller

For quantitative comparison, a classical cascade controller was also implemented as a baseline.

According to the Simulink implementation, this baseline combines a PD controller for yaw, a PD outer-loop controller for horizontal position, and a PID inner-loop controller for pitch–roll attitude regulation. This structure follows the standard control architecture provided by the Simulink Support Package for Parrot Minidrones. The yaw channel is regulated through a PD law of the form

$$e_{\psi} = \psi_{\text{ref}} - \psi, \quad (25)$$

$$\tau_{\text{yaw}} = K_{p,\psi} e_{\psi} - K_{d,\psi} \hat{r}, \quad (26)$$

where $\hat{\psi}$ and $\hat{r}$ are the estimated yaw angle and yaw rate, respectively. From the implemented block diagram, the controller parameters are

$$K_{p,\psi} = 0.004, \quad K_{d,\psi} = 0.3 \times 0.004 = 0.0012. \quad (27)$$

The horizontal-position controller generates the pitch and roll commands from the position error. Let

$$e_{xy} = \begin{bmatrix} x_{\text{ref}} - \hat{x} \\ y_{\text{ref}} - \hat{y} \end{bmatrix}, \quad \hat{v}_{xy} = \begin{bmatrix} \hat{\dot{x}} \\ \hat{\dot{y}} \end{bmatrix}. \quad (28)$$

The position error is first rotated according to the estimated yaw angle,

$$e_{xy}^b = R(\hat{\psi}) e_{xy}, \quad (29)$$

with

$$R(\hat{\psi}) = \begin{bmatrix} \cos \hat{\psi} & \sin \hat{\psi} \\ -\sin \hat{\psi} & \cos \hat{\psi} \end{bmatrix}. \quad (30)$$

Then, the pitch–roll command is computed by

$$\begin{bmatrix} \theta_{\text{ref}} \\ \phi_{\text{ref}} \end{bmatrix} = K_{p,xy} \text{sat}(e_{xy}^b) + K_{d,xy} \hat{v}_{xy}, \quad (31)$$

where the proportional and derivative gains are given by

$$K_{p,xy} = \begin{bmatrix} -0.24 & 0 \\ 0 & 0.24 \end{bmatrix}, \quad K_{d,xy} = \begin{bmatrix} 0.1 & 0 \\ 0 & -0.1 \end{bmatrix}. \quad (32)$$

Finally, the pitch–roll inner loop is implemented as a PID controller with anti-windup compensation. The attitude error and angular-rate vectors are defined as

$$e_{pr} = \begin{bmatrix} \theta_{\text{ref}} - \hat{\theta} \\ \phi_{\text{ref}} - \hat{\phi} \end{bmatrix}, \quad (33)$$

$$\hat{\omega}_{pr} = \begin{bmatrix} \hat{\dot{\theta}} \\ \hat{\dot{\phi}} \end{bmatrix}. \quad (34)$$

The pitch–roll control action is given by

$$\tau_{pr} = K_{p,pr} e_{pr} + K_{i,pr} \xi - K_{d,pr} \hat{\omega}_{pr}, \quad (35)$$

where

$$\tau_{pr} = \begin{bmatrix} \tau_{\text{pitch}} \\ \tau_{\text{roll}} \end{bmatrix}, \quad (36)$$

and ξ denotes the integral state. The implemented gains are

$$K_{p,pr} = \begin{bmatrix} 0.013 & 0 \\ 0 & 0.010 \end{bmatrix}, \quad (37)$$

$$K_{i,pr} = \begin{bmatrix} 0.010 & 0 \\ 0 & 0.010 \end{bmatrix}, \quad (38)$$

$$K_{d,pr} = \begin{bmatrix} 0.0020 & 0 \\ 0 & 0.0028 \end{bmatrix}. \quad (39)$$

The anti-windup gain is

$$K_{aw} = 0.001. \quad (40)$$

Both the proposed LQG controller and this cascade PID baseline were evaluated under the same experimental flight conditions using square and circular reference trajectories. In the final version of this paper, the PID controller is retained mainly as a numerical baseline through the tracking performance indices, thus enabling a compact but fair comparison with the proposed model-based strategy.

IV. EXPERIMENTAL VALIDATION

A. Experimental Setup and Flight Conditions

The experimental validation was carried out using a Parrot Mambo micro-UAV in an indoor laboratory environment, as shown in Fig. 2. The platform was operated under controlled low-altitude flight conditions with bounded reference trajectories, allowing the proposed controller to be evaluated under real sensing, actuation, and communication constraints.



Fig. 2. Indoor experimental setup for real-flight validation of the Parrot Mambo micro-UAV.

The experimental architecture included the Parrot Mambo drone, a host computer running the control and data acquisition algorithms, and the onboard sensing system. Attitude variables were estimated from inertial measurements using complementary and Kalman filtering, while translational states were obtained from the onboard visual positioning system. This setup provided the controller with position, velocity, and

TABLE II
EXPERIMENTAL SETUP AND FLIGHT CONDITIONS.

Item	Description
UAV platform	Parrot Mambo micro-UAV
Flight environment	Indoor laboratory environment
Main control strategy	LQG controller
Baseline strategy	PID controller for quantitative comparison
Test trajectories	Square and circular references
Measured variables	Position and attitude signals
State estimation	Complementary filter and Kalman filtering
Position estimation	Onboard visual positioning system
Implementation software	MATLAB/Simulink environment
Flight condition	Low-altitude bounded flight
Main limitations	Sensor noise, visual errors, actuator limits, surface texture, and illumination

attitude estimates during real flight, although practical limitations such as sensor noise, visual estimation errors, communication delays, actuator saturation, and battery-dependent behavior were present. Square and circular reference trajectories were used to evaluate two different tracking conditions. The square trajectory tests transient response and attitude coordination due to abrupt changes in direction, whereas the circular trajectory evaluates smoother steady tracking. The LQG controller was used as the main experimental strategy, while a conventional PID controller was retained as a quantitative baseline through standard performance indices.

Special attention was given to the floor surface and illumination conditions because the Parrot Mambo relies on onboard visual information for horizontal position estimation. Feature-rich and high-contrast patterns improved visual tracking, while poor or repetitive textures degraded the closed-loop response. The main experimental conditions are summarized in Table II.

B. Square-Trajectory Tracking

The square trajectory constitutes a demanding benchmark because it contains abrupt reference changes and sharp corner transitions, thus requiring fast transient response and effective attitude regulation. Figures 3–8 present the simulated and experimental performance of the LQG controller for the square trajectory.

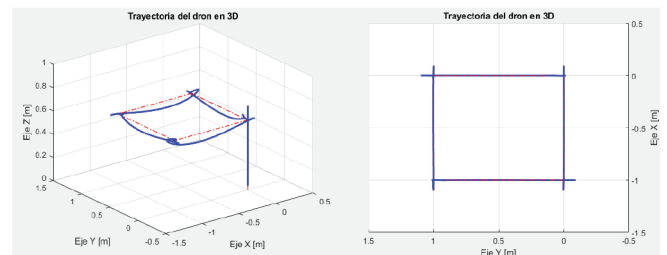


Fig. 3. Isometric and top views of the simulated square trajectory under LQG control.

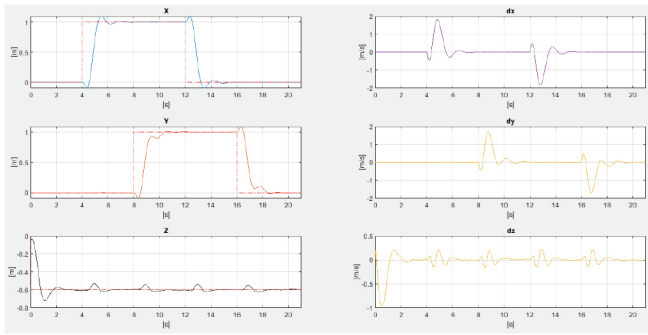


Fig. 4. Position responses for the simulated square trajectory under LQG control.

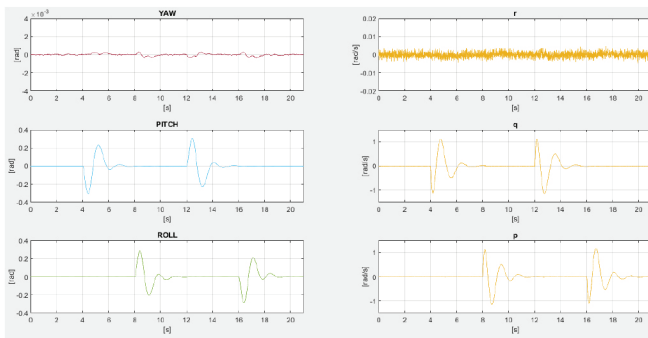


Fig. 5. Attitude responses for the simulated square trajectory under LQG control.

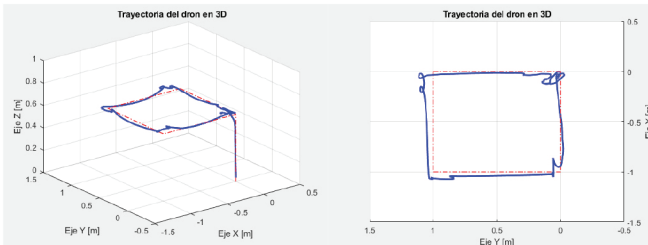


Fig. 6. Isometric and top views of the experimental square trajectory under LQG control.

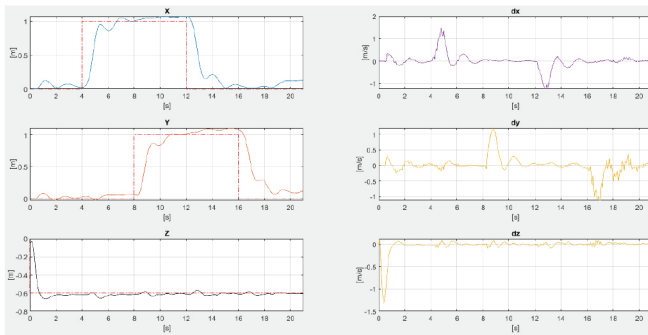


Fig. 7. Position responses for the experimental square trajectory under LQG control.

In simulation, the LQG controller reproduces the reference with high precision, preserving the square geometry and showing well-regulated transitions at the corners. The corresponding position signals closely follow the commanded references, while the attitude

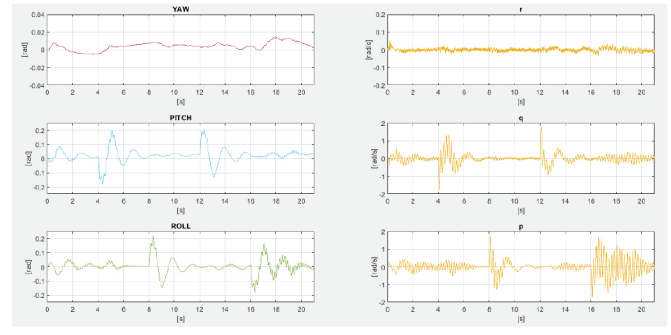


Fig. 8. Attitude responses for the experimental square trajectory under LQG control.

variables remain bounded and consistent with the required maneuver.

In the experimental tests, the LQG controller also maintains the square path with good fidelity. Although small deviations appear at the corners due to sensor noise, actuator limitations, and unmodeled dynamics, the vehicle preserves the overall geometry of the reference. The transient response remains well behaved, and the attitude signals indicate that the controller generates the necessary corrections without excessive oscillations. These results suggest that the LQG structure is particularly effective for trajectories involving abrupt directional changes.

C. Circular-Trajectory Tracking

The circular trajectory represents a smoother and more

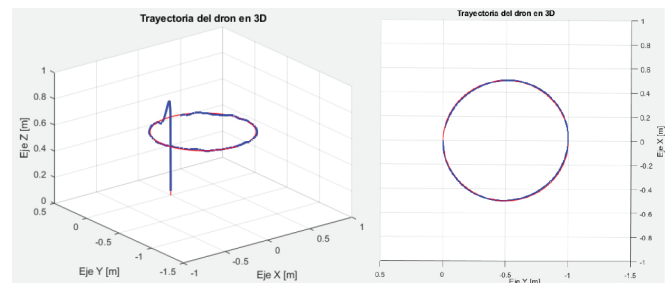


Fig. 9. Isometric and top views of the simulated circular trajectory under LQG control.

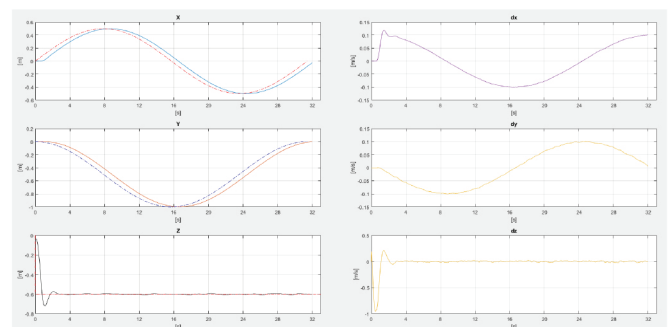


Fig. 10. Position responses for the simulated circular trajectory under LQG control.

continuous reference. In contrast with the square path, this test emphasizes steady tracking capability and consistency during sustained motion.

Figures 9–11 illustrate the simulated response of the LQG controller for the circular trajectory.

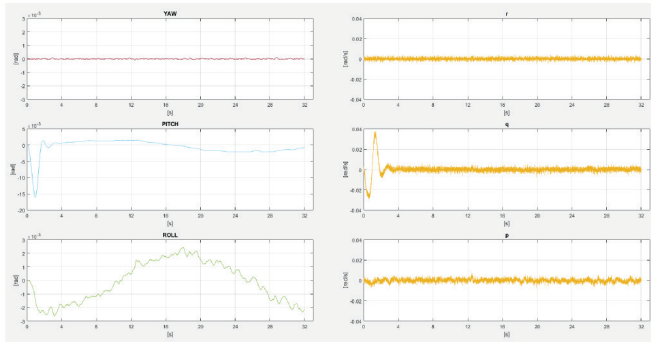


Fig. 11. Attitude responses for the simulated circular trajectory under LQG control.

In simulation, the LQG controller tracks the circular path accurately, with smooth position evolution and bounded attitude motion. The reference is followed with small deviations, confirming that the linearized model and the observer-based control law are adequate in nominal conditions.

D. Quantitative Performance Comparison

Table III summarizes the tracking-performance indices obtained for the LQG controller and the PID baseline in simulation and real-flight experiments. The indices were computed for the horizontal position coordinates x and y , using the tracking error

$$e_i(t) = i_{\text{ref}}(t) - i(t), \quad i \in \{x, y\}. \quad (41)$$

The considered criteria were the Integral of Squared Error (ISE), Integral of Time-weighted Squared Error (ITSE), Integral of Absolute Error (IAE), and Integral of Timeweighted Absolute Error (ITAE), defined as

$$\text{ISE}_i = \int_0^{t_f} e_i^2(t) dt, \quad (42)$$

$$\text{ITSE}_i = \int_0^{t_f} t e_i^2(t) dt, \quad (43)$$

$$\text{IAE}_i = \int_0^{t_f} |e_i(t)| dt, \quad (44)$$

$$\text{ITAE}_i = \int_0^{t_f} t |e_i(t)| dt. \quad (45)$$

The PID controller is retained as a quantitative baseline through Table III, while the graphical validation focuses on the proposed LQG controller. For the square trajectory, the experimental LQG controller reduces several error indices along the x direction and shows favorable behavior in abrupt directional changes, although the PID baseline achieves lower values in some y -axis metrics. For the circular trajectory, the PID controller obtains lower experimental indices, indicating that classical control remains competitive for smooth references under the sensing and actuation limitations of the Parrot Mambo platform.

Overall, the comparison shows that controller performance depends on the reference trajectory and experimental conditions. The contribution of the LQG approach is therefore not restricted to minimizing all scalar indices, but to providing a model-based framework that integrates state estimation, multivariable feedback, and real-flight implementation for micro-UAV trajectory tracking.

V. CONCLUSIONS

This work presented the modeling, identification, and experimental validation of a Parrot Mambo micro-UAV using a cascade control architecture based on Linear Quadratic Gaussian (LQG) control. The proposed framework integrates state-feedback control with Kalman-based state estimation, enabling real-flight trajectory tracking under sensing, actuation, and communication constraints. Square and circular trajectories were used for validation, while a PID controller was retained as a quantitative baseline through standard performance indices.

The identification stage showed that experimental characterization is essential to obtain a practical model for control design. Although the estimated parameters provided a useful approximation of the platform dynamics, the process was affected by sensor noise, limited excitation, and unmodeled effects. Future work should improve the identification protocol by including richer excitation maneuvers, refined sensor calibration, actuator dynamics, aerodynamic effects, and more advanced parameter estimation techniques.

The experiments also confirmed the importance of visual state estimation in indoor flights. Since the Parrot Mambo relies on onboard visual information for horizontal position estimation, surface texture and

TABLE III
TRACKING-PERFORMANCE INDICES FOR SQUARE AND CIRCULAR TRAJECTORIES.

Trajectory	Control	ISE		ITSE		IAE		ITAE	
		x	y	x	y	x	y	x	y
Square	PID exp.	1.796	1.454	31.650	30.960	3.710	2.770	14.277	17.739
	PID sim.	1.475	1.652	15.765	28.793	1.832	2.234	12.317	20.620
	LQG exp.	1.564	1.674	29.252	41.593	2.930	3.153	14.237	22.247
	LQG sim.	1.658	1.648	16.649	25.392	1.941	2.017	13.939	20.487
Circular	PID exp.	0.226	0.392	33.323	47.329	2.166	2.844	3.239	6.427
	PID sim.	0.104	0.142	26.490	30.688	1.634	1.901	1.693	2.284
	LQG exp.	0.860	2.008	80.966	100.830	4.877	7.245	14.332	24.227
	LQG sim.	0.107	0.146	26.838	31.263	1.655	1.932	1.739	2.364

illumination conditions strongly affected the closed-loop response. Feature-rich and high-contrast surfaces improved the reliability of the position estimates, while poor or repetitive patterns degraded tracking performance.

Regarding control performance, the LQG controller achieved stable trajectory tracking and adequate attitude regulation in real flight. It showed favorable behavior for the square trajectory, where abrupt

direction changes require stronger coordination between position and attitude dynamics. However, the PID baseline remained competitive for smooth circular trajectories, achieving lower experimental error indices in that case. Overall, the results show that the proposed LQG framework provides a systematic modelbased approach for micro-UAV control, while future research should explore adaptive or gain-scheduled schemes combining the structure of LQG with the practical simplicity of PID control.

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LICENSING OF DRONE OPERATORS IN THE EUROPEAN UNION: A COMPARATIVE LEGAL ANALYSIS

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Abstract— The paper conducts a multi-dimensional analysis of licensing systems for unmanned aircraft (drone) operators in selected Member States of the European Union. The research includes a legal analysis of national regulations implementing the EU regulatory framework, in particular Regulations (EU) 2019/947 and 2019/945, as well as an assessment of the practical functioning of these systems, with particular emphasis on the degree of their harmonization with EU regulations and their impact on operational safety and the development of the drone services market. The study also seeks to identify similarities and differences between the solutions adopted in individual Member States and to assess their impact on the development of the drone services market, the level of operational safety, and the mobility of operators within the EU internal market.

1. INTRODUCTION

The growing importance of Unmanned aerial systems (UAS) which have become widely used tools in many fields shows the need for coherent, transparent, and safe operational principles, particularly concerning the competencies and responsibilities of operators.⁽¹⁾

In order to harmonize regulations and enhance operational safety, the European Union has introduced uniform rules (Regulations 2019/947 and 2019/945). However drone operator licensing practices in individual Member States continue to exhibit noticeable differences in terms of training, examinations, and administrative organization.⁽²⁾

The aim of this article is to compare drone operator licensing systems in selected EU Member States taking into account their role in the European drone market, assess their consistency with EU law, and identify factors affecting the effectiveness, transparency, and accessibility of training and certification systems. The study employs legal, comparative, and qualitative research methods.

The research involves identification and characterization of national licensing systems in selected EU Member States, including Poland, Germany, France, Spain, and the Netherlands, which represent diverse regulatory and organizational approaches.

These countries were selected because they represent significant drone markets within the EU and provide examples of different administrative approaches to the implementation of EU drone regulations. The selection therefore allows for a comparative analysis of how the regulatory framework is applied in practice across different national contexts.

The study also shows the barriers and facilitators encountered by drone operators as a result of differences between national licensing systems. It is important to identify the degree of harmonization between national practices and to examine the impact of existing licensing systems on the development of the drone market.

The main thesis of the paper is that, despite the existence of common EU regulations, national drone operator licensing systems exhibit significant differences in training, examination, and administrative requirements, which have a major impact on both operational safety and operator mobility.

The hypothesis of the paper are the followings:

- the discrepancies are evident especially in the open and specific operation categories, where practical national requirements are diversified despite formal legal harmonization
- those Member States which implement more comprehensive and rigorous training systems achieve higher levels of drone operational safety
- the differences in licensing procedures constitute a significant barrier to the cross-border services within the EU single market
- there is a positive relationship between the level of digitization of licensing processes and the accessibility and effectiveness of operator training systems.

2. REGULATORY FRAMEWORK FOR DRONE OPERATIONS IN THE EU

On 11 June 2019 a package of regulations relating to the use of UAS within Europe was published in the Official Journal of the European Union. This 'EU UAS Regulation Package' consists of two separate, but interlinked regulations: Commission Delegated Regulation (EU) 2019/945 of March 12, 2019, on unmanned aircraft systems and third-country operators of unmanned aircraft systems. – Commission Implementing Regulation (EU) 2019/947 of 24 May 2019 on the rules and procedures for the operation of unmanned aircraft.⁽⁸⁾

The objective of introducing the new regulations are primarily to ensure safety during unmanned aircraft operations. It will also help to protect privacy, personal data, and the environment, while enabling unimpeded access to airspace for UAS.^(3, 12)

The regulations establish technical and operational requirements, including provisions for the operation of unmanned aircraft systems and for personnel (minimum pilot training requirements), including remote pilots and organizations involved in operations using them. The most important change is the introduction of a mandatory registration requirement for all UAS weighing more than 250 grams, which will facilitate the identification of operators in the event of damage to third parties. Regulation 2019/947 introduces three categories of UAS:

- open, which does not require a permit, but introduces numerous restrictions, e.g., regarding weight (up to 25 kg), operations (only operations within visual line of sight, except when the flight is conducted in base station-following mode or an unmanned aircraft observer is used), safety requirements (drones must comply with EU product conformity and safety requirements, in particular the applicable conformity assessment procedures and CE marking, before being placed on the market), the obligation to register operators, and the introduction of geofencing systems; the pilot must maintain a safe distance from people and ensure that their flight does not take place over crowds, maintain a distance of no more than 120 m from the nearest point of the ground, except when overflying an obstacle, and not carry or drop hazardous materials;
- specific, which requires authorization from the aviation authority based on risk analyses of the proposed operations; the competent authority determines whether the operational permit applies to the approval of a single operation or multiple operations specified as to time or location;
- certified, associated with the highest risk activities, related to the category of manned aircraft; this category requires UAS certification under Regulation (EU) 2019/945 and operator certification and, in some cases, obtaining a license by the UAS pilot; operations in this category are performed in any of the following conditions: over gatherings of people; they involve the transport of persons or they involve the transport of dangerous goods which, in the event of an accident, may pose a high risk to third parties.^(2,3,8)

Therefore, the regulatory framework for unmanned aerial vehicles (UAS), in the European Union is founded on two principal legal instruments : Commission Implementing Regulation (EU) 2019/947 establishes the rules governing drone operations and the licensing of operators and Delegated Regulation (EU) 2019/945 which defines the technical requirements for drone design and introduces a classification of drones into classes C0 to C6, primarily based on their maximum take-off mass and specific technical characteristics.⁽¹⁴⁾

While these regulations provide a uniform legal framework across the EU, they deliberately allow Member States considerable discretion in national implementation. The consequences are the followings: variations exist in the organization of examinations, the delivery and format of training, identity verification methods, administrative fees, and the use of digital systems for operator registration. This flexibility, while facilitating national adaptation, results in practical divergences that affect operator mobility, market dynamics, and the consistency of safety standards across the Union.⁽⁷⁾

It should be noted that EU regulations are directly applicable in Member States and, unlike directives, there is no obligation to implement them into national law through laws or regulations. While this generally ensures a high degree of regulatory harmonization across the European Union, the EU's drone regulatory framework still leaves some areas to the discretion of national authorities. For example, with regard to administrative procedures and the organization of training or licensing systems, such discretion has been maintained, and such regulatory flexibility can facilitate adaptation to individual national contexts and technological developments. This can, however, lead to differences in implementation between Member States, but such differences appear to reflect deliberate regulatory design rather than a regulatory gap, as the EU legal framework deliberately combines harmonized technical rules with a degree of national discretion.

3. LICENSING SYSTEMS IN SELECTED EU MEMBER STATES

The aim of the paper is to illustrate the practical implications of this regulatory flexibility and therefore this study examines the licensing systems in five EU Member States: Poland, Germany, France, Spain, and the Netherlands. The reason of choosing these countries is simply their specific role in the European drone market.

The European drone industry is increasingly asserting itself on the global stage, with Germany and France leading the charge. Across the continent, drones are being deployed in industrial inspection, defense operations, and agricultural management, and the growth is still expected through 2030–2035. Germany currently dominates in commercial value, exceeding €404 million, thanks to its strong focus on large-scale industrial applications and logistics solutions.⁽¹⁷⁾ Meanwhile, France has carved out a reputation as a hub for advanced software and AI-powered drone technologies, particularly in defense and analytical services.⁽²¹⁾

Poland is emerging as an important center for both drone manufacturing and software development, driven by an energetic startup ecosystem that focuses on niche, high-performance solutions.⁽¹⁸⁾ Spain's market is expanding rapidly, with agricultural drones leading the growth, as farms increasingly adopt automation to boost efficiency. (19) The Netherlands plays a critical role as a major European importer and user of drones, especially for specialized commercial services, reinforcing Europe's position as a global innovator in unmanned aerial technologies.⁽²⁰⁾

Poland implements its licensing system under the supervision of the Civil Aviation Authority (ULC). A1/A3 exams are conducted online and free of charge, while the A2 exam is a paid theoretical test held at designated examination centers. Standard Scenario (STS) training is provided by certified organizations. Poland has developed a digital platform (drony.ulc.gov.pl) that enables operator registration and online training, reflecting a high degree of system digitalization and accessibility. ⁽¹¹⁾

Germany is supervised by the Luftfahrt-Bundesamt (LBA). While A1/A3 exams are conducted online for a fee, the A2 exam can also be completed online with identity verification. Germany places a strong emphasis on digitalization and electronic certification, and its licensing system includes additional requirements such as a higher minimum

age for operators. This approach exemplifies a highly formalized and technologically advanced regulatory model. (https://www.lba.de/DE/Home/home_node.html)

France, under the Direction Générale de l'Aviation Civile (DGAC), offers online A1/A3 exams but mandates compulsory practical training for the A2 category. The French system is recognized as one of the most restrictive in Europe, reflecting a strong supervisory approach that emphasizes operational safety over market accessibility. (<https://www.ecologie.gouv.fr/direction-generale-laviation-civile-dgac-0>)

Spain, supervised by the Agencia Estatal de Seguridad Aérea (AESA), provides fully digital training and examinations for all categories, with a wide availability of STS training centers. This approach encourages competition among training providers and facilitates rapid market growth, demonstrating how accessibility and digitalization can accelerate sector expansion. (<https://www.seguridadaerea.gob.es>)

The Netherlands, overseen by Inspectie Leefomgeving en Transport (ILT), combines online free A1/A3 exams with strongly supervised A2 examinations, which achieve high pass rates. The Netherlands demonstrates a fully digitized licensing system in which all documentation is electronic, reflecting a balance between accessibility, efficiency, and regulatory oversight. (<https://www.ilent.nl>)

4. COMPARATIVE ANALYSIS OF LICENSING SYSTEMS AND IMPLICATIONS FOR THE DRONE SECTOR

A1/A3 and A2 drone licenses are issued and registered by the country of issuance rather than the drone pilot's country of residence. The A1/A3 qualification requires a relatively limited commitment, as it involves completing an online training course followed by a theoretical online examination. The A2 qualification, which is mainly pursued by commercial drone pilots, builds on the A1/A3 requirements and additionally includes practical training and a written examination conducted by a National Aviation Authority or an approved entity. This results in a significantly higher investment of time and resources.⁽¹⁶⁾

During the COVID-19 pandemic, many approved entities transitioned to offering A2 training and examinations online. Together with the open European market and the mutual recognition of licenses, this enabled a substantial number of cross-border trainings and examinations. Consequently, pilots—for instance, residents of Germany holding a German operator ID—were able to complete A2 online training and exams through approved entities based in countries such as Poland or the Netherlands.⁽¹⁶⁾

Previous research conducted by Janke and de Haag examined the recognition and distribution of A1/A3 and A2 drone licenses within the European Union. Their findings indicate that licenses issued under both categories are valid across all EU Member States, irrespective of the country of issuance. Owing to the relatively low time and financial investment required to obtain an A1/A3 license, the authors concluded that A1/A3 training and certification are predominantly completed within the pilot's country of residence, typically through the respective competent authority, certification body, or National Aviation Authority. This conclusion was supported by evidence from multiple qualitative interviews with designated Points of Contact reported in their study.⁽¹⁶⁾

The study further highlights that mutual recognition of licenses across the EU, combined with price competition among recognized training entities, creates incentives for pilots to obtain A2 training and certification outside their country of residence. As a result, authorized legal entities frequently issue A2 certificates of competency to EU citizens residing in other Member States. Given that A2 certificates issued in accordance with the relevant EU regulatory framework are valid throughout the Union, the authors argue that tracking and analyzing the number of A2 licenses by issuing country has limited analytical value.⁽¹⁶⁾

In contrast, Janke and de Haag identify the number of registered UAS Operator IDs per Member State as a more meaningful statistical indicator. In accordance with EU regulations, UAS operators are required to register in the Member State of their residence in the case of natural persons, or in the Member State of their principal place of business in the case of legal entities. Moreover, operators are prohibited from being registered in more than one Member State at the same time.⁽¹⁶⁾

A comparative shows substantial differences in training requirements, examination modalities, STS training availability, the level of digitalization, and administrative costs. France and Germany have a rigorous, highly supervised training and licensing models that correlate with higher operational safety, although fragmented statistical data limit the ability to perform comprehensive quantitative comparisons. Poland and Spain, in contrast, prioritize accessibility and market growth through lower barriers to entry, enabling rapid expansion of the operator base but potentially at the cost of stricter operational control. The Netherlands creates an intermediate model, combining accessible entry with advanced digital monitoring and verification systems.

These differences have significant implications. First of all, safety outcomes appear to improve in states with more demanding training requirements, supporting the hypothesis that rigorous education and practical training enhance operational security. Secondly, the heterogeneity of administrative procedures, identity verification methods, and fees impedes cross-border service provision, limiting operator mobility despite formal EU harmonization. Finally, the extent of digitalization positively correlates with system efficiency and accessibility, as seen in Germany, Spain, and the Netherlands, confirming the hypothesis that digital platforms improve the usability and reach of licensing systems.

Implications for the Drone Sector can be seen in three fields: operational Safety, operator Mobility and Commercial Market Dynamics.

Regarding the first field, countries with more comprehensive training and strict oversight, like France and Germany, show fewer operational incidents, which might suggest a positive link between licensing rigor and safety outcomes. The absence of harmonized statistical reporting prevents to show the reliable results.

For the second field, different administrative and identity verification procedures, and inconsistent fee structures continue to limit cross-border drone operations. Unfortunately these undermine one of the primary objectives of EU harmonization which is the creation of a single, fluid European drone market.

Finally, Spain and Poland demonstrate rapid market expansion due to lower entry barriers, facilitating commercial adoption and entrepreneurial activity. Conversely, France's restrictive model supports more advanced operations, including beyond visual line-of-sight (BVLOS) missions, reflecting a trade-off between market growth and operational control.

5. HYPOTHESIS VERIFICATION. CONCLUSIONS AND RECOMMENDATIONS

Maintaining an adequate level of operational safety requires drone operators to be well acquainted with the legal framework governing the safe conduct of unmanned flights. Awareness and compliance with applicable regulations constitute a fundamental prerequisite for ensuring the safety of operators themselves as well as third parties. For the purpose of supporting the awareness and compliance EASA created a list with states drone website references by country, as supplied by the respective National Aviation Authority (NAA) which ensures a quick access to information on drones and details for the registration proces (<https://www.easa.europa.eu/en/domains/civil-drones/naa>). However, the system of aviation safety law is inherently complex and multi-layered with a variety of legal sources, including international conventions, European Union regulations and national legislation, each of which applies within a distinct personal and material scope. Moreover, aviation safety norms are highly detailed, addressing organizational structures, technical requirements and operational procedures.

Formal harmonization at the EU level does not guarantee practical uniformity; training, examinations, administrative procedures, and fees vary significantly between countries.

The analysis of this paper confirms the main hypothesis that unfortunately significant differences exist in drone licensing systems across EU Member States. The othe hypotesis are largely supported. Hovewer second hipotesis is only partially confirmed due to limited statistical data, the remaining hypotheses find strong empirical and

qualitative support, emphasizing the importance of harmonized and digitized licensing frameworks for the EU drone market.

The regulations require training for certain categories of drone operations but leave some discretion regarding the organisation and delivery of such training. As a result, specialised training providers have emerged, often operating under the oversight of national aviation authorities (NAAs). This approach differs to some extent from manned aviation, where pilot training and licensing are subject to a more harmonised regulatory framework at the EU level under EASA rules.

The results of the research conducted in this article lead to the following conclusions. First of all, digitalized licensing systems, as exemplified by Germany, Spain, and the Netherlands, enhance efficiency, accessibility, and operator engagement. Secondly, France and Germany implement the most advanced supervisory models, emphasizing operational control and safety. Finally, Poland and Spain provide the lowest barriers to entry, facilitating rapid market growth and increased operator numbers.

The research conducted in this project resulted in specific recommendations, which are the followings. First of all, there is a need for harmonization of the A2 examination across the EU which could be done via a centralized EASA platform in order to ensure consistency and comparability. Secondly, in order to replace fragmented national databases a single European operator registry could be created. Thirdly, it is necessary to encourage increased digitalization in Member States lagging in technological integration. Four, there is a demand for a standardization of administrative procedures and fees to facilitate operator mobility. Finally, it is called for development of the EU-wide practical training standards for STS and A2 operations in order to ensure consistent skill development and operational safety.

In summary, although the EU provides a consistent legal framework for drone operations, significant differences remain between countries regarding licensing. A balance must be struck between accessibility, digitalization, and operational oversight to achieve a safer, more competitive, and more integrated European drone market. As the analysis in this article demonstrates, there is a need for further harmonization efforts, greater standardization of training and examinations, and the development of digital infrastructure to optimize the efficiency and safety of drone operations across Europe.

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