

Automated System for Spraying Herbicides on Weeds Using a Drone in United Kingdom

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Abstract

This article presents an autonomous drone system that precisely sprays herbicides on weeds, significantly reducing chemical waste and crop damage. Using cameras and sensors, the drone identifies weeds in real time and targets only infested areas. The proposed solution integrates IoT with the YOLOv9 deep learning model to achieve accurate weed detection and mapping for optimized spraying. Field tests showed that the drone adapts its spray based on weed density and location, minimizing herbicide use, lowering costs, and reducing environmental impact. Its intelligent algorithm manages flight paths and spraying operations even in complex farm layouts. Overall, the system offers a faster, more sustainable, and environmentally friendly alternative to conventional weed-control methods, enhancing agricultural productivity and contributing to economic growth of United Kingdom.

1. Introduction

Weeds continue to represent a major constraint on agricultural productivity at the global scale, as they compete with crops for indispensable resources such as nutrients, water, and solar radiation. This competition can lead to yield reductions that exceed 30 percent in key crops, including wheat. Conventional weed control relies primarily on broadcast herbicide application; however, this approach is inherently inefficient, environmentally unsustainable, and a significant contributor to the evolution of herbicide-resistant weed species. For example, the persistence of glyphosate residues in poultry manure used as fertilizer in traditional agricultural systems may inadvertently suppress crop germination and reproductive development. Moreover, broadcast spraying frequently results in excessive herbicide application across areas where treatment is unnecessary, with studies showing that 80–95 percent of sprayed land may contain no weed infestation. Emerging precision agriculture technologies offer potential solutions by enabling localized, site specific interventions. Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, have become instrumental in this context, integrating high-resolution remote sensing for weed detection with selective herbicide spraying mechanisms. UAV based systems are capable of identifying weed patches with centimeter level precision and administering herbicides exclusively at infested locations, thus reducing chemical usage by 20–75 percent while preserving the effectiveness of weed control strategies. For instance, integrated UAV spraying systems (UAV-IS) decreased herbicide consumption by 39 percent in sod fields by targeting clustered weed patches rather than applying herbicides uniformly across entire fields. Additionally, the combination of knapsack pre-emergence application with UAV postemergence spraying improved weed control efficiency to 94.8 percent. When deployed for herbicide spraying, agricultural drones provide substantial benefits by increasing operational efficiency, enhancing crop productivity, and enabling continuous field monitoring. The integration of sensors and digital imaging technologies facilitates the observation of remote or inaccessible field areas, thereby supporting comprehensive data collection [1]. The aerial perspective afforded by drones further enables the identification of agronomic challenges, including irrigation discrepancies, soil heterogeneity, pest pressure, and fungal infestation. The capacity of drones to capture both visible and near infrared imagery enhances the detection of plant health anomalies or stress conditions that may not be perceptible to the unaided eye. Consequently, farmers can undertake

precise crop assessments and conduct frequent field inspections, allowing for timely interventions and mitigation strategies [2]. Simultaneously, rural regions continue to experience critical labor shortages, resulting in a considerable disparity between agricultural labor demands and the available workforce. As a result, the adoption of mechanization and automation has become increasingly necessary to sustain agricultural productivity [3]. Crop production is further constrained by pests and diseases, prompting the widespread use of chemical insecticides to reduce yield losses [4]. In addition, numerous other variables such as fluctuations in rainfall, soil quality, temperature variations, wind patterns, and the prevalence of weeds and pests can influence the viability of farming operations. Consequently, farmers must adopt innovative strategies to enhance productivity and satisfy growing food demands [5]. Digital and smart agricultural technologies have demonstrated significant potential to support farmers by providing actionable insights that inform decision-making and operational management. Among these innovations, agricultural drones have gained notable prominence due to their versatility and applicability across diverse farming operations. Their use has expanded substantially in recent years, supporting activities such as crop monitoring, pest management, and the optimization of agricultural processes. Therefore, drones constitute an increasingly important asset in modern agricultural systems and facilitate a wide array of field operations, as illustrated in Figure 1 drone spraying on weeds [6]. Recent developments in pump and spray head design

have markedly improved the reliability and performance of aerial spraying systems in agriculture. These enhancements demonstrate that the application of reduced agrochemical quantities can constitute a viable and environmentally responsible strategy. The improved delivery mechanisms enable precise chemical deposition with minimal input, achieving both economic efficiency and enhanced operational effectiveness [7]. The integration of Unmanned Aerial Vehicles (UAVs) for crop spraying further augments these advancements by offering several distinct advantages. UAVs substantially reduce operational expenditure, provide extensive spatial coverage, and facilitate uniform pesticide distribution with optimized droplet size to improve canopy penetration [8]. In addition, UAV-assisted spraying minimizes drift, evaporation losses, and chemical wastes, thereby enhancing leaf adherence and maximizing the biological efficacy of applied agents. These capabilities underscore the potential of UAVs to support sustainable, economically viable, and technologically advanced agricultural aviation.

Agricultural drones, comparable in function to helicopters and multi-rotor aircraft, possess vertical takeoff and landing capabilities, ensuring safe and efficient deployment. Their ability to operate at low altitudes typically only a few meters above the crop canopy enables highly localized and site-specific spraying. UAVs can be utilized on heterogeneous terrains and across crops of varying heights, and their relatively simple operational protocols reduce the learning curve for field personnel and facilitate rapid user training [9]. From an environmental and occupational health perspective, UAVbased spraying systems offer significant advantages. Reduced pesticide volumes lead to lower levels of environmental contamination and mitigate the risk of crop injury. Furthermore, remote spraying protects agricultural workers by decreasing direct exposure to hazardous chemicals and limiting the labor required for manual spraying activities [10]. Precision agriculture—also referred to as precision farming aims to optimize input management, including water, fertilizers, and pesticides, to enhance crop productivity,

quality, and yield while mitigating risks associated with pests, flooding, and diseases. UAV enabled monitoring and spraying provide farmers with high resolution decision support and more accurate application control than conventional tractor based techniques. Consequently, this technology reduces production costs and minimizes human exposure to chemical agents typically encountered during manual field spraying operations.

2. Literature Review

The integration of drones, or Unmanned Aerial Vehicles (UAVs), into agricultural weed management has significantly transformed traditional practices by enabling precise and efficient herbicide application. UAV-based spraying systems minimize labor requirements and reduce environmental contamination, positioning them as a sustainable alternative to manual weed-control techniques [11]. Equipped with multispectral imaging, GPS navigation, and advanced spraying mechanisms, drones facilitate highly accurate pesticide delivery and support the core principles of precision agriculture, which prioritize resource efficiency and long-term conservation [12]. Through the use of remote sensing and machine learning algorithms, UAVs can detect weed-infested zones and selectively apply herbicides, reducing chemical usage by 30–65 percent compared with traditional knapsack sprayers [13]. Empirical findings further indicate that drones enable ultra low volume application rates of approximately 30 L/ha without compromising herbicide performance, particularly in direct-seeded rice cultivation systems [14]. Hybrid approaches integrating drones with conventional spraying equipment have demonstrated synergistic benefits. For example, the deployment of pre-emergence herbicides via knapsack sprayers followed by post-emergence drone application yields enhanced weed suppression, lower weed indices, and lower chemical inputs than when either method is used independently. Such strategies leverage the extensive coverage capabilities of ground based sprayers while capitalizing on the precision targeting of UAV platforms. Field evaluations further reveal that optimized UAV spraying improves crop yields by reducing weed competition for water, nutrients, and light, while simultaneously contributing to environmentally friendly agricultural practices through reduced labor demand, minimized soil disturbance, and reduced herbicide runoff. Despite these advantages, several challenges continue to hinder widespread adoption. Technical constraints such as limited battery endurance, payload restrictions, and performance variability across weather conditions pose operational barriers. Additionally, the effective implementation of UAV spraying necessitates trained operators and standardized guidelines to ensure safe and efficient field deployment. UAV configurations, including rotary wing multi rotor and fixed wing designs, serve diverse agricultural functions; however, rotary wing drones remain the preferred choice for spraying due to their hovering capability and stable low altitude operation. Key operational parameters flight altitude, speed, nozzle type, droplet size, spray volume, and meteorological factors substantially influence spray deposition patterns, coverage uniformity, and application efficiency. While drone technology holds considerable potential to transform weed management into a more sustainable, cost effective, and precision-oriented practice, future research must address regulatory constraints and environmental dependencies. Furthermore, advancements in AI driven control systems and hybrid UAV

ground spraying platforms are anticipated to expand capabilities, although equitable access and context-specific adaptation remain critical considerations for diverse farming landscapes [15].

3. Methodology

This project consists of several sequential stages, each of which plays a critical role in achieving the overall objective, as illustrated in Figure 2. The systematic execution of these stages ensures smooth progress, reduces potential errors, and supports successful project completion. The methodology adopted in this study is outlined as follows:

1. **Literature Review:** The methodology begins with a comprehensive review of existing literature to identify the current challenges in weed management and evaluate the techniques and technologies employed to address these issues.

At the beginning of the project, a brief literature review is conducted to identify existing difficulties and explore how they are being addressed.

2. **Material Selection:**

Following the review, appropriate materials and components required for system development are identified and selected based on suitability, performance, and project requirements.

3. **Deep-Learning-Based Weed Detection Model Development:**

In this stage, a deep learning approach is utilized to develop a weed detection model capable of identifying and classifying various weed species. The model is trained using annotated datasets and relevant preprocessing techniques to enhance detection accuracy and localization performance.

3.1 YOLOv9 Model for Object Detection:

A key component of the proposed system is the integration of the YOLOv9 (You Only Look Once) deep-learning framework, which serves as the primary model for real-time weed detection. Renowned for its speed and high accuracy, YOLOv9 is well suited

for identifying and distinguishing weed species efficiently, thereby minimizing processing time and enhancing field-level decision making [16]. Its capability to perform rapid inference makes it an optimal choice for agricultural applications where timely detection is essential. As a single-stage object detector, YOLOv9 simultaneously executes detection and classification within a unified network architecture, eliminating the need for separate processing pipelines and thereby accelerating computational performance [17]. The general workflow of the YOLOv9 algorithm can be summarized in the following steps:

1. **Grid Division:** The input image is partitioned into a fixed-size grid of $S \times S$ cells, with each cell responsible for predicting the presence of an object (bounding box) and determining its associated

class probabilities [18]. This grid-based approach forms the foundation for localized object detection and classification.

2. Class Prediction and Bounding Box Estimation:

Each cell predicts multiple bounding boxes, along with their spatial coordinates (x,y) , dimensions (w,h) , and confidence scores. Additionally, each bounding box is associated with probabilities corresponding to predefined classes, enabling the model to simultaneously localize and classify objects within the image.

3. Final Detection:

For each predicted bounding box, a final score is calculated by combining the box confidence score with the class probability. This allows the algorithm to prioritize high-confidence detections while suppressing overlapping or low-confidence predictions. Non-Maximum Suppression (NMS) is applied to retain only the most accurate bounding boxes and discard redundant or low-confidence detections. The final output of the algorithm comprises the bounding box coordinates (x,y,w,h) , the predicted class label, and an associated confidence score [19, 20].

4. Hardware Development:

In this stage, the project's hardware components are developed. This includes the design and fabrication of the printed circuit board (PCB), schematic creation, and PCB layout optimization to ensure functional integration with the software and UAV system.

3.2 Interfacing a Radar Sensor to a Processor Raspberry Pi

A radar sensor, interfaced with a Raspberry Pi processor, continuously monitors the drone's altitude and the underlying terrain profile, ensuring precise herbicide application even in uneven or variable fields. The radar module communicates with the Raspberry Pi using standard protocols such as I²C, UART, or SPI, facilitating realtime data acquisition. The Raspberry Pi integrates these radar measurements with the outputs from the YOLOv9 weed detection model, dynamically adjusting the spray nozzle height and flow rate to maintain optimal precision under changing field conditions.

3.3 Interfacing Raspberry Pi to the Camera and capturing image data

The Raspberry Pi serves as the drone's onboard processor and is directly interfaced with a high-resolution camera mounted on the drone chassis. During flight, the camera continuously captures real-time images of the crop and surrounding soil. These images are transmitted to the Raspberry Pi for pre-processing, which includes adjustments to brightness, contrast, and resolution to facilitate subsequent analysis. The pre-processed images are then fed into the YOLOv9 weed detection model, which can be executed either locally on the Raspberry Pi or on a connected processing module. The model identifies

and annotates weeds within the captured frames. Upon detection, the Raspberry Pi generates control signals for the spraying mechanism, enabling herbicides to be applied exclusively to targeted areas. This integration of camera vision with the onboard processor ensures precise spraying, minimizes chemical usage, and supports real-time decision-making during flight.

3.4 Make a weed-detection system

The proposed methodology combines an AI-based weed detection system with a precision spraying drone to optimize herbicide application in agricultural fields. Utilizing the YOLOv9 object detection model, as illustrated in Figure 3, the system processes real-time aerial images captured by the drone's high-resolution camera, achieving weed detection accuracy of up to 97 percent. This allows for reliable discrimination between weeds and crop plants, even under variable field conditions. Upon detection, the onboard controller activates a targeted spraying mechanism, delivering herbicide directly to the identified weed patches. This approach substantially reduces chemical usage and prevents unnecessary exposure of healthy crops to herbicides.

4. Model Performance Analysis

4.1 Key Metrics and Curves

1. **Precision–Recall Performance:** The model achieves a precision of 1.00 at a confidence threshold of 0.982, indicating that all predictions classified as “Weeds” with confidence levels of 98.2% Recall reaches 0.99 at a confidence threshold of 0.000, demonstrating that nearly all actual weeds are successfully detected, with very few false negatives.

2. **Optimal F1-Score:**

The F1-score reaches a maximum of 0.95 at a confidence threshold of 0.519, representing the optimal balance between precision and recall. This threshold provides the best trade-off between minimizing false positives and avoiding missed detections.

3. **Threshold Behavior:**

- High confidence thresholds (≥ 0.982) yield perfect precision but lower recall, resulting in some weeds being missed.
- Low confidence thresholds (≤ 0.519) provide high recall but increase false positives.
- The optimal threshold (0.519) achieves balanced performance, maximizing detection accuracy while minimizing unnecessary spraying actions.

The simulation outputs give a dynamic graph of major fetal growth factors – namely weight and height (or length – see note) – plotted over simulated gestational Weeds. The model output displays the

expected gradual increase in fetal height over time, consistent with the basic principles of prenatal development. Although the trend in the simulation data requires additional context-based interpretation (e.g., demerging in the available snippet, which may indicate a particular modeled situation, normalization, or the need for data validation), overall, the simulation effectively captures the temporal dynamics of these key growth indicators. These models are useful for depicting average developmental pathways, investigating possible deviations under various conditions, and gaining insight into fetal growth patterns for pedagogical or analytical purposes. • The simulation outputs provide a dynamic representation of key fetal growth parameters—specifically weight and height (or length, as noted)—plotted

across the simulated gestational timeline. The model captures the expected progressive increase in fetal height, in line with established principles of prenatal development. While certain trends in the simulation data may require context-specific interpretation—such as demerging effects, normalization procedures, or further validation—the overall simulation effectively reflects the temporal dynamics of these critical growth indicators. Such models are particularly useful for visualizing typical developmental trajectories, investigating potential deviations under varying conditions, and gaining deeper insights into growth patterns for both analytical and educational purposes.

The confusion matrix further evaluates the model’s ability to discriminate between

“weeds” and “background” regions in the dataset. The results indicate that 97

- **True Positive (TP):** 97 percent of actual weeds correctly identified.
- **False Negative (FN):** 3 percent of actual weeds misclassified as background.
- **False Positive (FP):** 20 percent of actual background misclassified as weeds.
- **True Negative (TN):** 80 percent of actual background correctly identified.

5. Benefits of Automated Drone Spraying

Leveraging YOLOv9 with 97 percent weed detection accuracy, the drone system precisely targets infested areas, reducing herbicide use by up to 90 percent compared to conventional blanket spraying. This precision enhances resource efficiency, lowers operational costs, and minimizes chemical contamination, thereby protecting soil health, preserving groundwater quality, and maintaining beneficial soil microbes, pollinators, and overall ecosystem balance. Autonomous spraying also improves worker safety by limiting direct exposure to toxic chemicals. By removing weed competition without affecting crops, the system promotes healthier plant growth, stronger root development, and enhanced resilience, ultimately increasing crop yields and farm profitability.

Environmental Impact: Reduced chemical use preserves soil and water quality and supports ecosystem resilience. **Worker Safety:** Minimizes exposure to hazardous agrochemicals. **Higher Crop Yields:** Targeted herbicide application supports efficient and robust crop growth.

Environmental Impact: Using fewer chemicals means profound benefits for soil health, water quality, and ecosystem resilience.

Worker Safety: The chemicals on the farm are less dangerous to them.

Higher Crop Yields: Using herbicide spraying effectively can help crops grow more efficiently.

6. Challenges for Development

Although the drone-based weed-spraying system offers substantial advantages, several challenges must be addressed to enable wider adoption. Regulatory constraints remain a primary concern, as many governments enforce strict rules on drone operations in agriculture, potentially requiring special licenses or limiting usage. Weather conditions, including wind and rain, can compromise spraying precision and reduce system efficacy. Scalability also poses a challenge, as larger farms may necessitate multiple drones, enhanced detection algorithms, or more sophisticated technologies to maintain operational efficiency. These challenges, however, present opportunities for future research and innovation, guiding the development of improved designs and operational strategies. As agriculture increasingly transitions toward AI-driven automation, drone-based systems represent a pivotal advancement, supporting more sustainable, economical, and efficient farming practices and contributing to the restructuring of global food production.

Regulatory Issues: Compliance with governmental laws governing agricultural drone use.

Weather Dependency: Wind and rain can adversely affect spraying accuracy.

Scalability: Large-scale farms may require advanced technologies, additional drones, or enhanced detection systems to ensure efficiency. Despite these challenges, continued research and technological development will help overcome current limitations, advancing the adoption of AI-powered precision agriculture and reinforcing the role of drones in creating sustainable and cost-effective farming solutions.

7. Future Directions

Improving the model's performance requires prioritizing the reduction of false positives. Expanding the training dataset with diverse background examples can enhance the model's ability to distinguish weeds from non-weedy areas. Maintaining the confidence threshold at the optimal value of 0.519 ensures a balanced F1-score, preserving high precision while sustaining strong recall. Further improvements can be achieved by analyzing visual features—such as color, texture, and shape—that contribute to background misclassification and refining the model accordingly. Post-processing strategies, including size and shape filtering, can eliminate unlikely detections. Threshold selection should align with operational goals: a higher threshold (0.982) is suitable when minimizing false positives is critical, whereas a lower threshold (0.000) maximizes recall to detect every potential weed.

8. Discussion

The integration of AI-driven UAVs in modern agriculture represents a significant advancement in precision weed management. By combining deep learning-based weed detection with YOLOv9 object recognition, drones can accurately identify and target weed-infested areas, ensuring efficient herbicide application while minimizing chemical waste and environmental impact. The system's ability to fly over diverse terrains, provide uniform spray coverage, and reduce soil compaction makes it a versatile tool for both small- and large-scale farming. When integrated with traditional methods, such as knapsack spraying, drones can further enhance weed control by leveraging the strengths of each approach. Field trials demonstrate that UAV spraying achieves weed control efficiencies exceeding 97 percent, particularly in pre-emergence applications, while maintaining or improving crop yields. Precision spraying ensures that herbicides are applied only to affected regions, reducing labor input, environmental disturbance, and unnecessary chemical exposure to crops. Despite operational constraints, such as limited battery life, payload capacity, and the need for trained operators, the benefits of precision, sustainability, and cost-effectiveness underscore the potential of dronebased weed management as a key component of future agriculture. Continued research and technological development will further optimize performance, expanding adoption and supporting environmentally responsible farming practices.

9 Conclusion

Automated herbicide-spraying drones represent a major step forward in sustainable and efficient agriculture. Leveraging YOLOv9-based deep learning for real-time weed detection, these systems reduce chemical usage, protect soil and water quality, and minimize farmworker exposure to pesticides. Their ability to provide targeted spraying across varied terrains, coupled with integration with traditional methods, ensures high weed control efficiency and enhanced crop yields. While challenges such as regulatory constraints, weather dependence, and hardware limitations remain, ongoing innovation and AI-driven automation will continue to refine these systems. Overall, drone-based precision spraying offers a promising solution for modern, environmentally responsible, and cost-effective weed management, marking a transformative shift in the future of precision agriculture of United Kingdom.

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Figures



Figure 1

Drone Spraying on Weeds

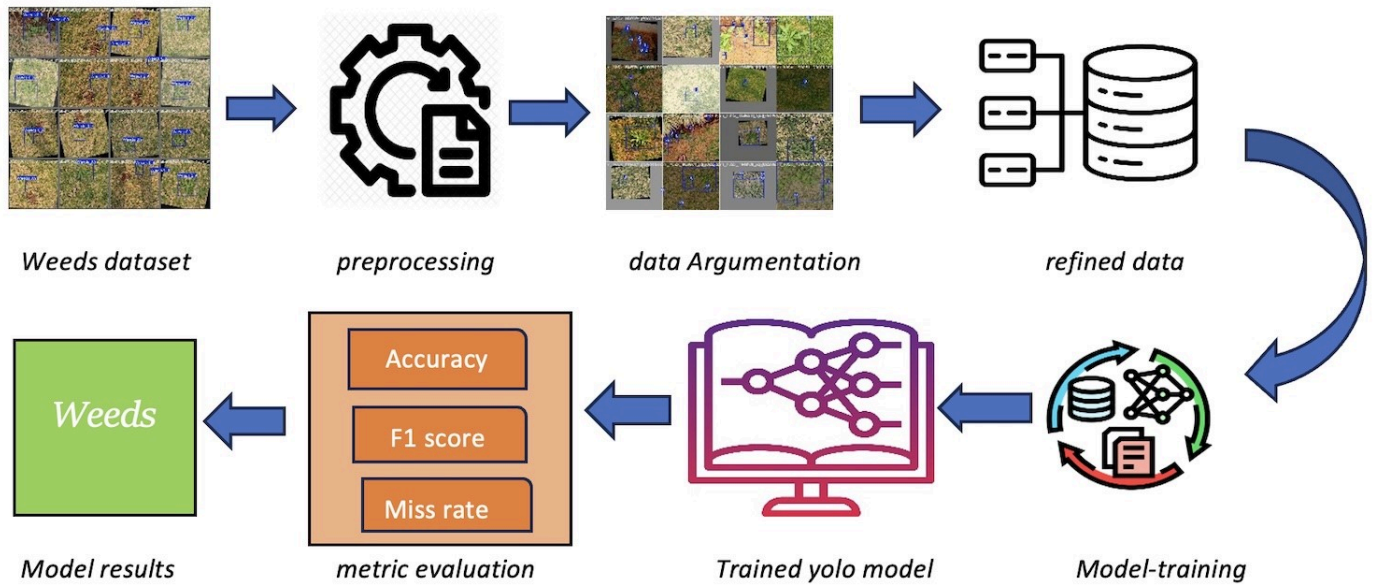


Figure 2

Steps involved in research work

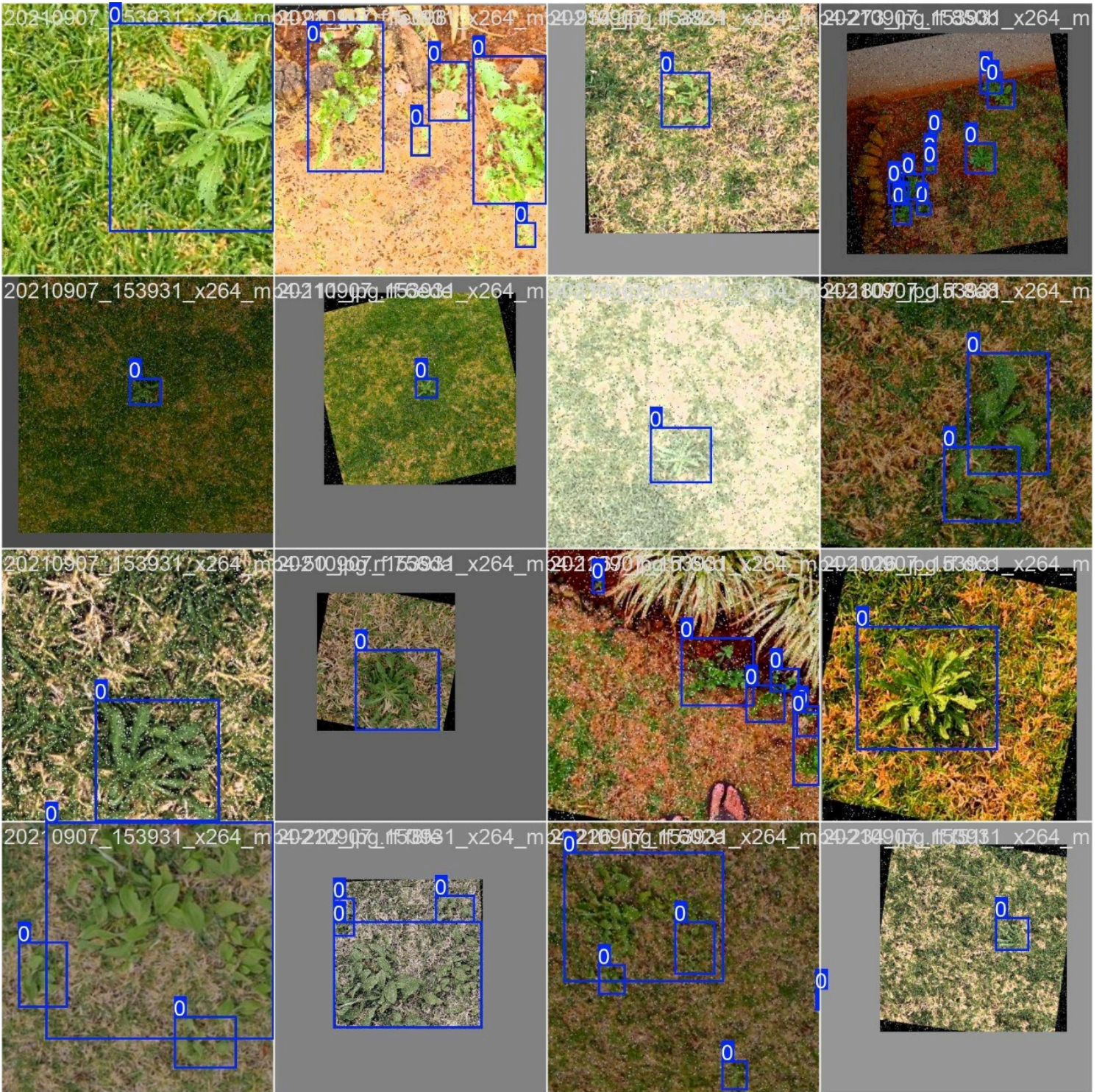


Figure 3

Model simulation

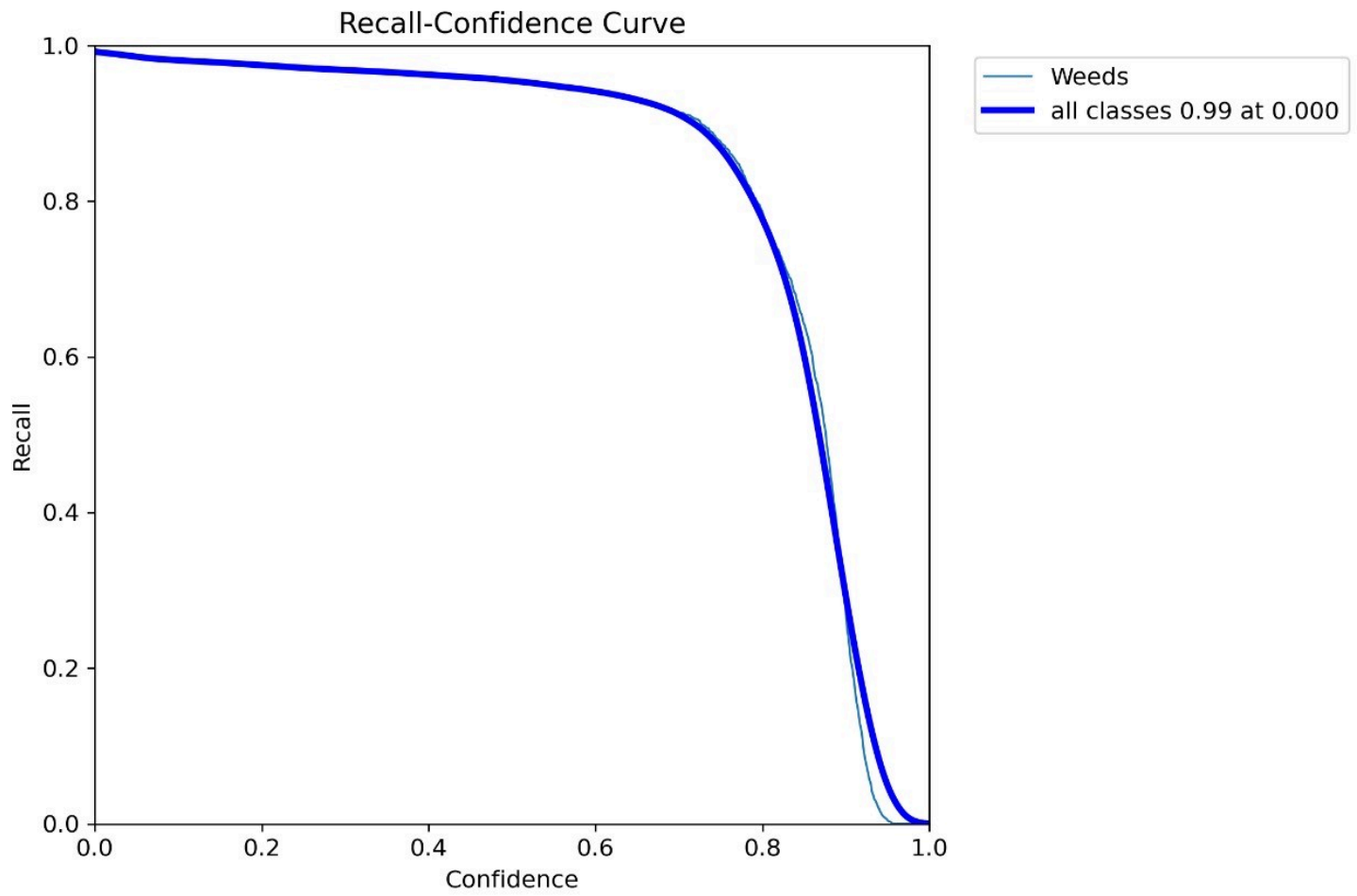


Figure 4

Confidence Curve and Weeds Dataset

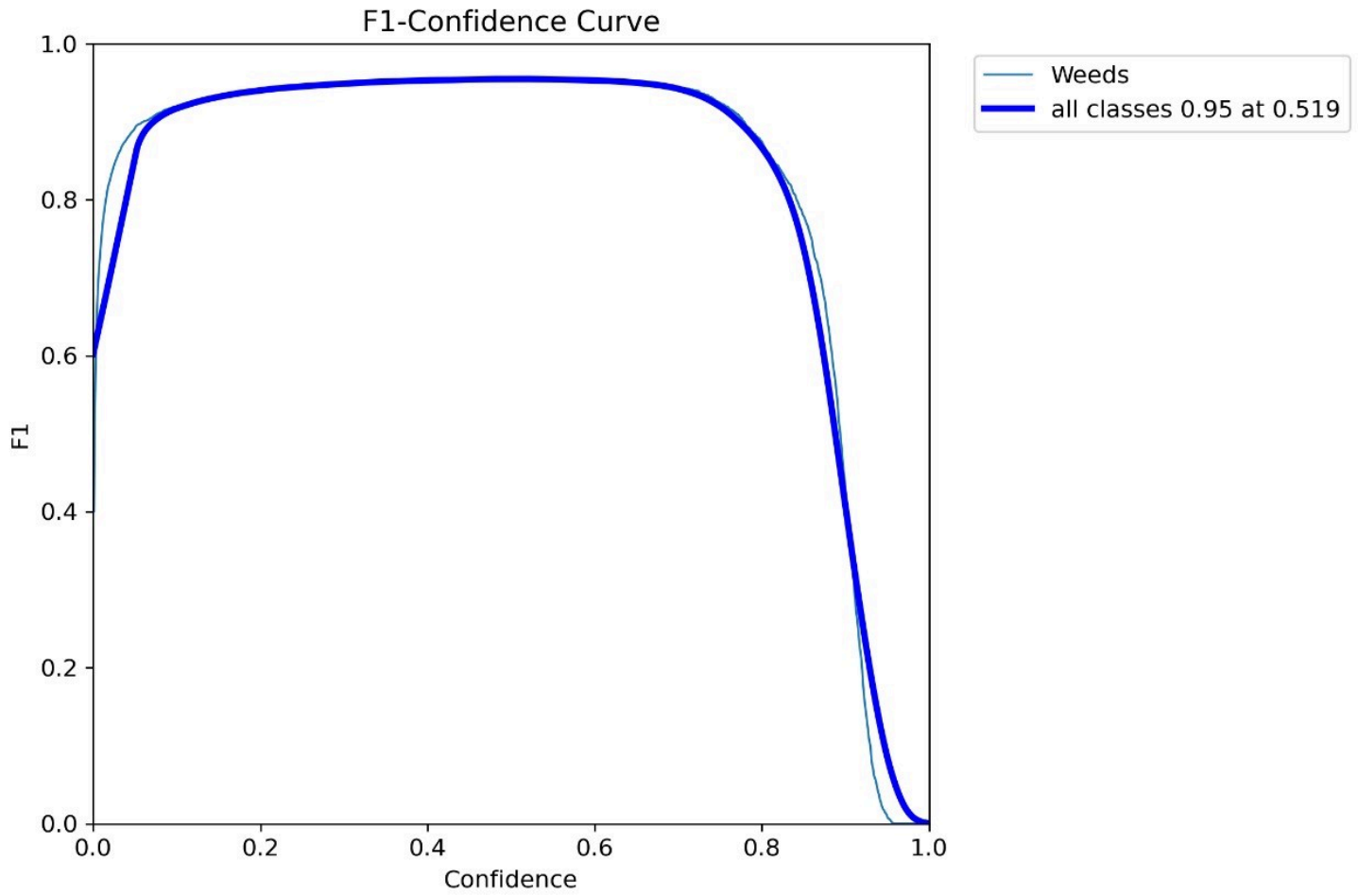


Figure 5

F-1 Confidence Curve

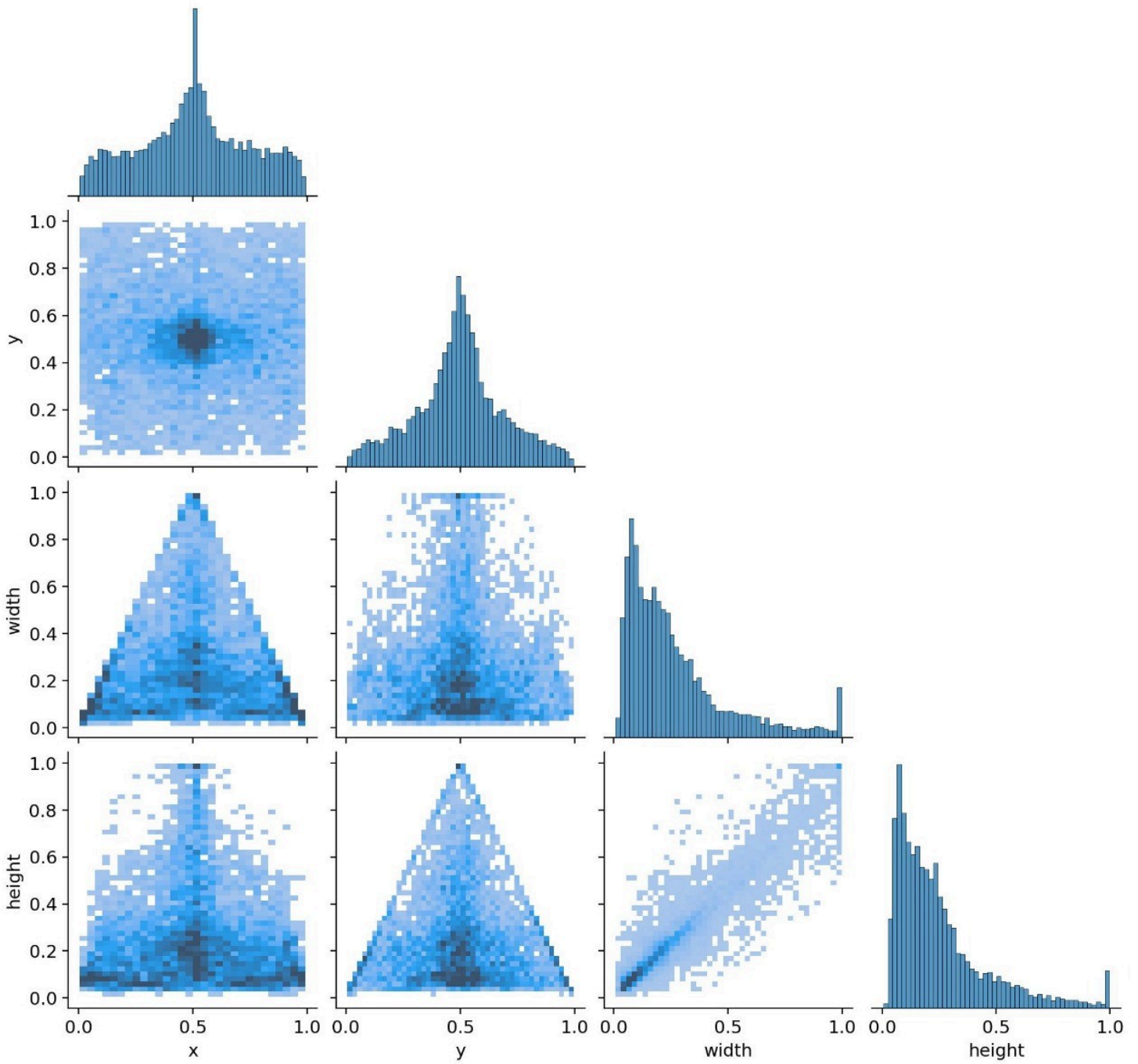


Figure 6

Dataset interpretation

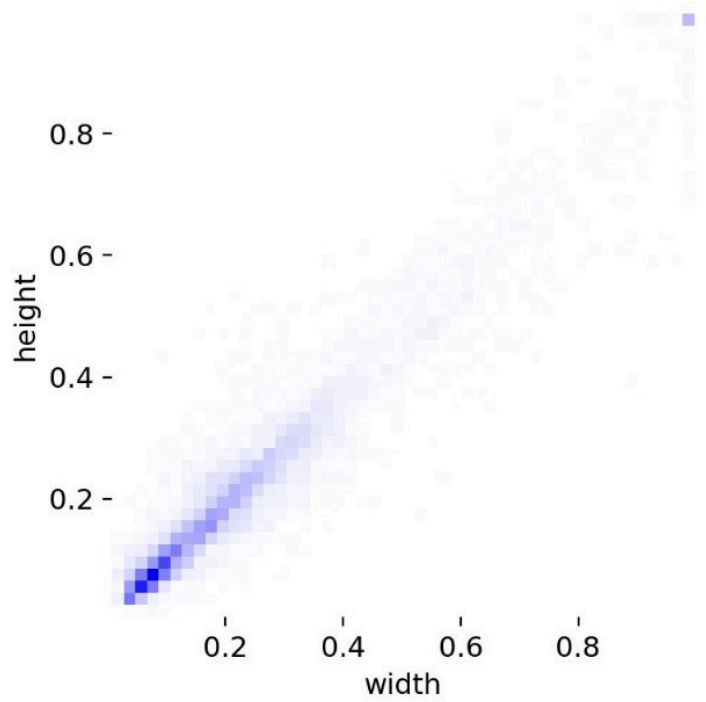
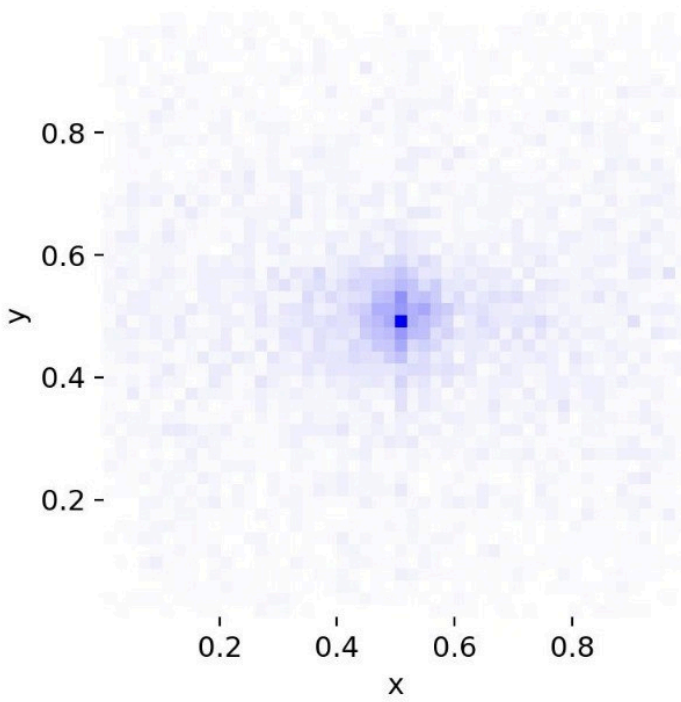
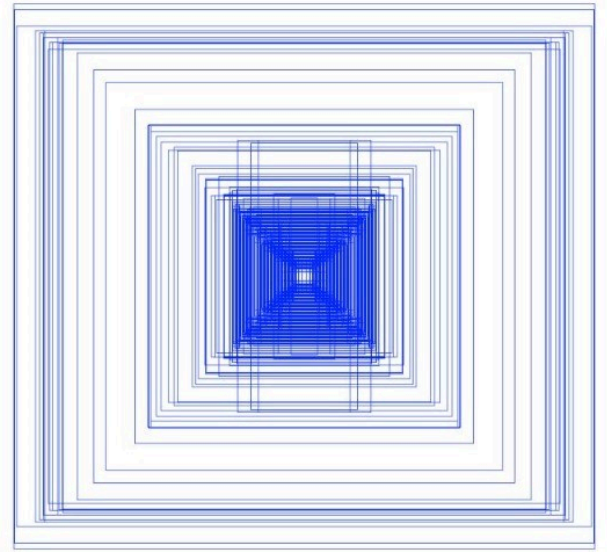
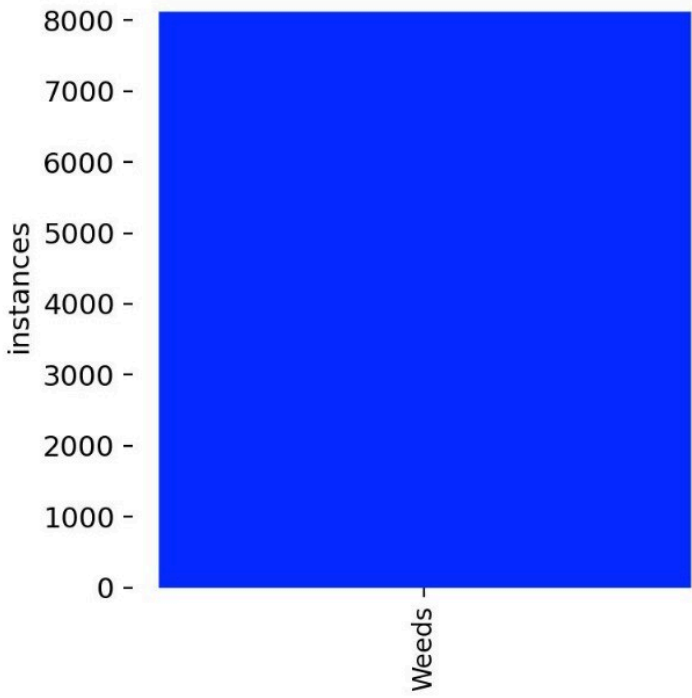


Figure 7

Data spreading

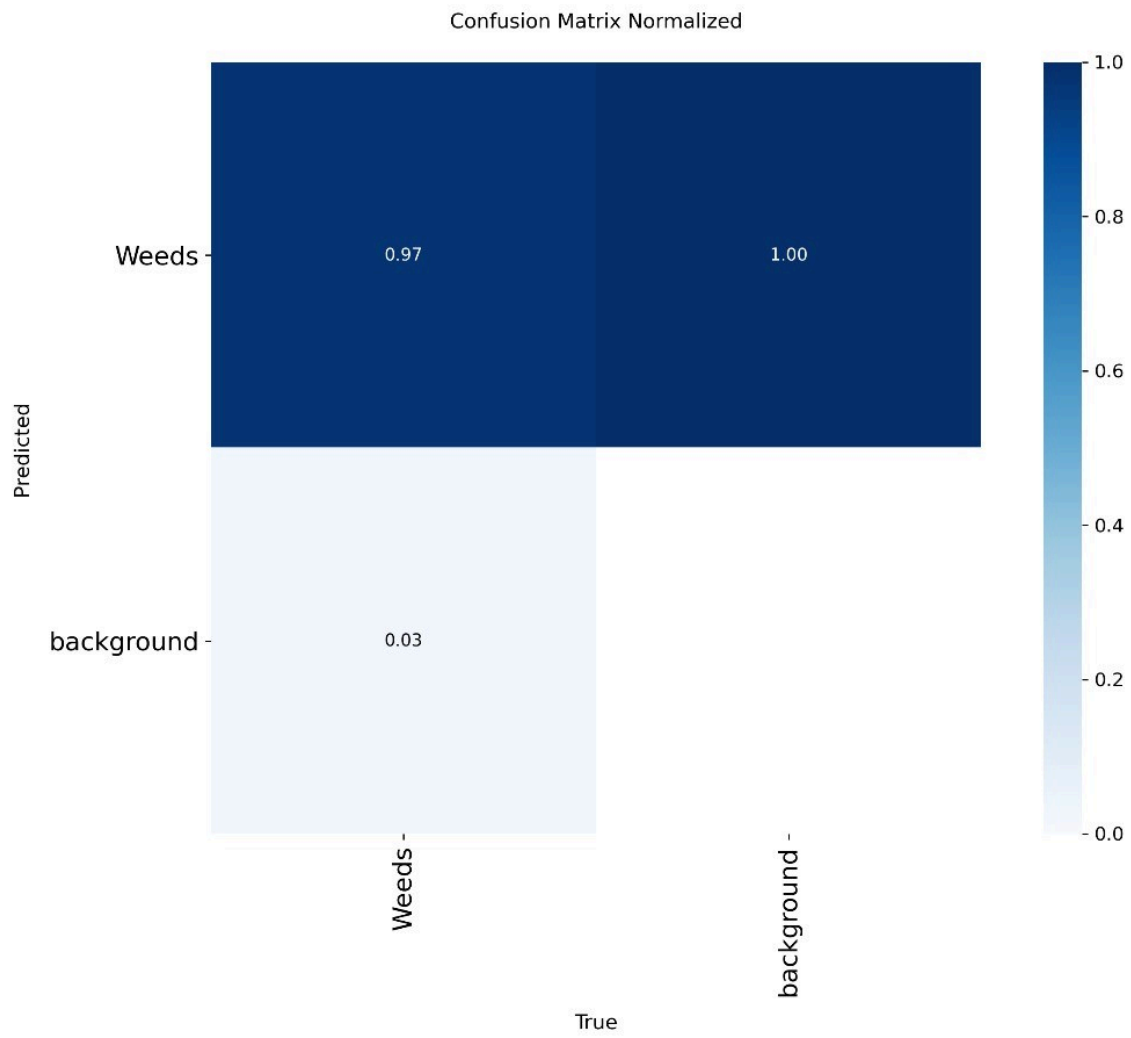


Figure 8

Confusion Matrices