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Integration of UAV Photogrammetry and AI-based Image Recognition for Investigating Occupation of Irrigation Public Lands

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Abstract

This study presents an innovative approach combining Unmanned Aerial Vehicles (UAVs) and AI-based image recognition to investigate unauthorized occupation of irrigation public lands. Traditional land survey methods are labor-intensive, time-consuming, and often constrained by inaccessible terrain. By integrating UAV-based photogrammetry and deep learning techniques—particularly the YOLOv7 object detection framework—this research enables efficient acquisition of high-resolution orthophotos and automatic detection of land use violations. Case studies from southern Taiwan demonstrate improved survey accuracy and significant time savings compared to manual inspection. This method provides a scalable, repeatable framework for land resource monitoring and supports more transparent and standardized land management operations.

Keywords: UAV, Artificial Intelligence, Image Recognition, Public Land Management

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Highlights

- UAVs and AI streamline irrigation land surveys, reducing time and increasing accuracy.
- YOLOv7 effectively detects illegal land occupation from orthophotos with high precision.
- The integrated method offers a scalable, repeatable, and conflict-free survey solution.

1 Introduction

Irrigation public lands—areas formerly managed by Taiwan's Irrigation Agency—play a pivotal role in maintaining water infrastructure and agricultural sustainability. However, irrigation public lands increasingly suffer from unauthorized use, including illegal construction, informal agriculture, and encroachment by industrial or residential facilities. These activities often obstruct maintenance access, disrupt hydrological functions, and impose financial burdens on local governments through unpaid land rent and increased land tax obligations.

Conventional field surveys rely heavily on manual inspection, cadastral comparison, and documentation, which, while valid, are limited in their scalability and efficiency. Challenges such as inaccessible terrains, extensive land coverage, and occupant resistance frequently hinder the effectiveness of traditional approaches. In regions with dense vegetation or informal settlements, visual confirmation is often unfeasible or inconsistent, leading to gaps in enforcement and data reliability.

The rapid development of Unmanned Aerial Vehicles (UAVs) has transformed the landscape of geospatial data collection. UAVs equipped with high-resolution cameras and GNSS positioning systems can produce orthophotos with centimeter-level accuracy (Colomina and Molina 2014). These orthophotos provide a robust foundation for spatial analysis and change detection, even in remote or restricted areas Moreover, modern photogrammetric software such as Pix4D enables efficient orthophoto generation and supports overlay with cadastral or zoning data.

Complementing UAV capabilities, advances in Artificial Intelligence (AI)—particularly deep learning and computer vision—have enabled rapid and automated detection of objects and patterns in imagery. The YOLO (You Only Look Once) framework has gained prominence for its balance of detection speed and accuracy. In the YOLOv7 version, it introduces architectural enhancements that improve inference performance while reducing training time (Wang et al. 2023). These features make YOLOv7 suitable for large-scale surveillance and land-use classification tasks(Albaghdadi and Manaa 2022).

This study proposes an integrated approach that combines UAV photogrammetry and YOLOv7-based object detection to survey and analyze the occupancy of irrigation public lands. By leveraging AI to identify encroachments from UAV-derived orthophotos, the method significantly improves operational efficiency and provides a scalable workflow for governmental land monitoring initiatives.

2 Literature Review

2.1 UAV Applications in Land Surveying

Unmanned Aerial Vehicles (UAVs) have revolutionized the field of geospatial data acquisition and remote sensing. These systems, equipped with GPS, Inertial Measurement Units (IMUs), and high-resolution cameras, can autonomously navigate complex terrains to collect detailed visual and spatial data. Unlike satellite imagery or manned aerial surveys, UAVs offer higher spatial and temporal resolution at lower operational costs, making them suitable for periodic land use monitoring and environmental inspection (Adade et al. 2021).

Orthophotos generated through UAV photogrammetry are geometrically corrected to eliminate distortions from perspective and terrain elevation, allowing accurate measurement of area, distance, and object positions. These images are widely used in cadastral mapping, change detection, infrastructure inspection, and agriculture. For example, Liu et al. highlighted that UAV remote sensing with HD cameras enhances land surveying efficiency and supports precise environmental monitoring in both urban and rural areas (Liu et al. 2020). Similarly, Guimarães et al. emphasized that UAVs offer high-resolution, flexible, and cost-effective data collection for land monitoring, outperforming traditional platforms in addressing environmental challenges and climate-sensitive systems (Guimarães et al. 2020). Moreover, software such as Pix4Dreact and DroneDeploy streamline the photogrammetric workflow, enabling non-specialists to generate orthomosaics, elevation models, and annotated reports efficiently. These tools are crucial for real-time applications like disaster response or field-based land classification (Chaudhry et al. 2020)(Jarahizadeh and Salehi 2024).

2.2 AI Image Recognition and Deep Learning

Artificial Intelligence (AI), particularly deep learning techniques such as Convolutional Neural Networks (CNNs), has drastically enhanced the capabilities of image classification and object detection. These models learn complex spatial patterns from large labeled datasets, allowing them to identify subtle visual features that may be difficult for humans to distinguish. CNNs form the backbone of modern object detection frameworks including Faster R-CNN, RetinaNet, and the YOLO (You Only Look Once) family (Zaidi et al. 2022).

YOLOv7 integrates efficient network layers, anchor-free detection modules, and better loss functions to improve both speed and accuracy. It is especially suited for real-time applications in mobile or edge computing environments, making it ideal for UAV-based deployments in the field.

Beyond engineering, AI-powered image recognition has seen adoption in sectors like precision agriculture—detecting crop diseases or mapping yield zones—and cultural heritage preservation, where historic buildings are digitized and monitored using AI-driven photogrammetry. These diverse applications highlight the adaptability of deep learning models in spatial and visual data processing.

2.3 Land Management Regulations

Effective land management requires a comprehensive understanding of legal frameworks, ownership data, and usage rights. In Taiwan, irrigation public lands are governed under the jurisdiction of the Irrigation Agency and are subject to specific regulations concerning usage, rental, and tax obligations. Land occupation assessments must consider cadastral boundaries, land-use zoning, legal tenancy agreements, and history of tax payments.

Unauthorized occupation—such as construction without permits, agricultural expansion onto public land, or illegal parking facilities—can lead to complications including disputes, legal action, and administrative penalties. In addition, such encroachments can obstruct access for maintenance vehicles or emergency response, particularly when service roads are blocked.

To address these challenges, recent guidelines by the Ministry of Agriculture emphasize the importance of geospatial tools in improving land audits. UAV and AI-integrated systems are increasingly being considered for deployment in routine land monitoring, offering objectivity and consistency that surpass manual surveys.

3 Methodology

This study integrates UAV-based photogrammetry and AI-based object detection to identify unauthorized occupancy within designated irrigation public lands. The methodology includes four major components: (1) data collection via UAV flights, (2) orthophoto generation, (3) AI training and recognition using YOLOv7, and (4) ground truth validation.

3.1 Study Area and Target Features

This study was conducted in two representative sites located in southern Taiwan, each encompassing several parcels of irrigation public land managed by the regional irrigation agency. These areas were selected based on previous reports of land use disputes, illegal occupancy records, and accessibility for UAV deployment.

The study focused on detecting three primary types of land occupation:

- Buildings: unauthorized structures built on public land, including permanent and temporary constructions
- Cultivated Land: areas illegally used for farming or agricultural activities
- Waste Piles: unauthorized accumulation of materials such as construction debris, discarded items, or agricultural waste

To define the spatial boundaries of investigation and train the AI model accurately, multiple data sources were utilized:

- Interviews were conducted with irrigation officials to understand local land issues, identify critical parcels, and determine common types of occupation.
- Historical cadastral data and land ownership maps were acquired from the Land Administration System to serve as ground truth reference.
- Preliminary field visits were undertaken to verify site accessibility, determine UAV launch zones, and inspect possible obstructions (e.g., trees, buildings, or electric wires).

These preparatory steps ensured both the reliability of UAV imagery collection and the relevance of the annotated training dataset.

3.2 UAV Survey and Orthophoto Generation

A DJI Mavic 2 Pro drone, equipped with a 1-inch CMOS sensor and a 20-megapixel camera, was deployed for aerial data collection. The UAV supports automated flight planning through the DJI GS Pro application, which was used to define waypoints, set altitude, and ensure comprehensive coverage of each site (Figure 1).

Flight parameters were configured to achieve high overlap for accurate photogrammetric reconstruction:

- Front overlap ratio: 77%
- Side overlap ratio: 55%
- Flight altitude: 59 meters

Figure 1. UAV flight path generated using DJI GS Pro software to ensure optimal site coverage and image overlap.

The captured images were processed using Pix4Dreact, a rapid photogrammetry software optimized for emergency mapping and field processing. The software generated georeferenced orthophotos by aligning overlapping images and correcting for camera tilt and terrain distortion (Figure 2). These orthophotos were further cropped and resized to meet the input resolution standards of the YOLOv7 AI detection pipeline.

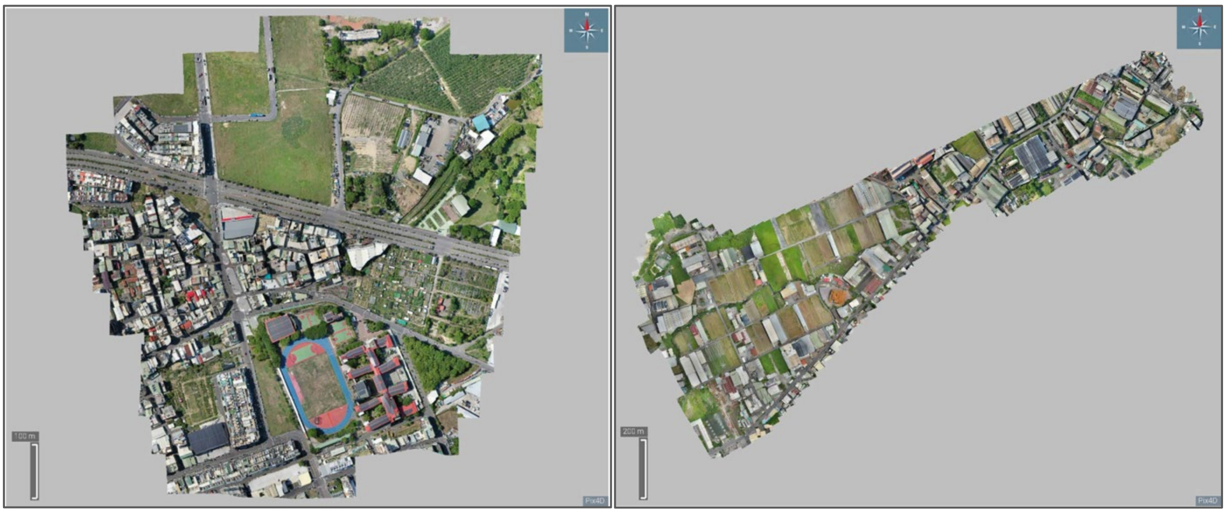

Figure 2. Sample orthophoto output from Pix4Dreact software

3.3 AI Object Detection Setup (YOLOv7)

To detect and classify unauthorized occupation features in the orthophotos, the YOLOv7 deep learning architecture was adopted. YOLOv7 was selected for its high speed, ease of implementation, and state-of-the-art detection accuracy across varied object classes.

The following environment and tools were used:

- Programming Language: Python 3.8
- Deep Learning Framework: PyTorch
- Annotation Tool: LabelImg
- Training Hardware: NVIDIA RTX 3060 GPU

The occupancy types are classified as buildings, cultivated land, and waste piles:

- Buildings (including permanent or semi-permanent structures occupying public land)
- Cultivated Land (areas used for unauthorized agricultural activities)
- Waste Piles (stacked construction debris, discarded materials, and other solid waste)

After completing manual annotation (Figure 3), label files were generated at the designated storage path, with the leading digit indicating the object class and the following decimal values representing the bounding box coordinates. The dataset was then divided into training, validation, and test sets in a 6:2:2 ratio.

Model training was carried out using the pretrained YOLOv7 weight file (yolov7.pt), followed by continued training to generate task-specific weights. The number of epochs was set to 200 and the batch size to 8, adjusted based on system performance. The output included key weight files such as last.pt and best.pt, along with performance plots and test results.

Evaluation metrics included precision, recall, F1-score, and mAP at IoU thresholds of 0.5 and 0.95. The F1-score curve showed optimal confidence values between 0.4 and 0.6, which were used for inference threshold settings. Training loss curves for bounding box regression, objectness score, and classification accuracy, as well as their respective validation metrics, converged steadily during training, indicating model stability and consistent learning behavior. The results folder also included visualized labels of the training set (Figure 4), allowing for assessment of both training outcomes and validation annotations. In the deployment stage, the trained model was used to analyze the entire orthophoto of each site. Detected objects were automatically bounded with colored rectangles and labeled for post-analysis.

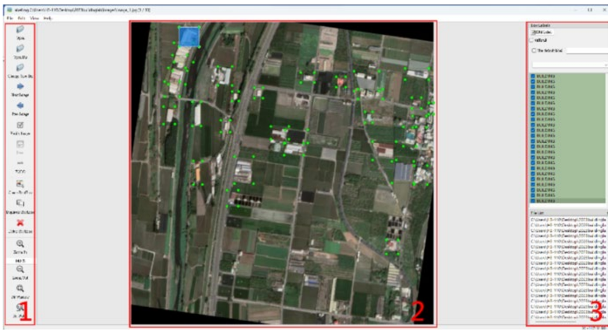

Figure 3. YOLOv7 dataset annotation using LabelImg.

Figure 4. Training results and validation annotations.

3.4 Ground Truth Verification

To evaluate the accuracy of the AI-based recognition system, manual field surveys were conducted in both Area A and Area B. A total of 8 occupied features were measured on-site using tape measures, GPS devices, and UAV height markers.

Each feature's area and spatial coordinates were compared with the detection results from the AI-inferred orthophotos. The deviation in measurement was recorded and analyzed. The average area error was within ±3.2%, confirming the high reliability of the combined UAV and AI detection workflow.

This verification step served to:

- Validate the effectiveness of YOLOv7 object localization
- Ensure measurement consistency for policy enforcement
- Build stakeholder confidence in automated methods

4 Results and Discussion

4.1 Case Study Overview

To validate the proposed method, two representative areas were selected for field testing. These areas reflect typical scenarios of irrigation public land occupation in suburban and peri-urban regions of southern Taiwan.

- Area A has a total land area of 35.75 hectares, within which 4 parcels of irrigation public land are located. This area is relatively flat and includes a mix of farmland and semi-developed zones. Observed occupancy types included illegal roofing extensions, small-scale parking spaces, and sporadic waste piles.
- Area B covers 58.84 hectares, containing 16 parcels of irrigation public land. This region exhibits more complex land use patterns, with large industrial facilities, informal housing, and a higher density of paved surfaces. Some parcels were partially obscured by vegetation, making ground inspection more difficult.

Occupancy was detected in both areas through the automated image recognition pipeline. UAV orthophotos enabled identification of features partially obscured by trees or fencing. In Area B, several encroachments that were not clearly visible from ground level were successfully classified using UAV imagery, highlighting the added perspective and spatial coverage advantage (Figure 5).

The AI-generated bounding boxes aligned closely with the actual footprints of illegal occupation features, and results were subsequently verified with manual inspection.

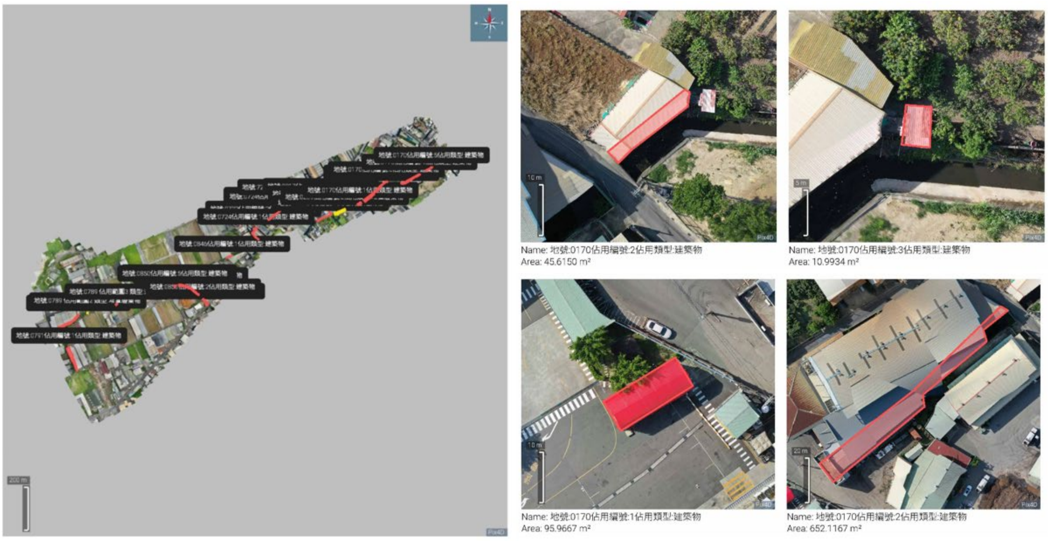

Figure 5. Detection results overlay on orthophoto (Area B)

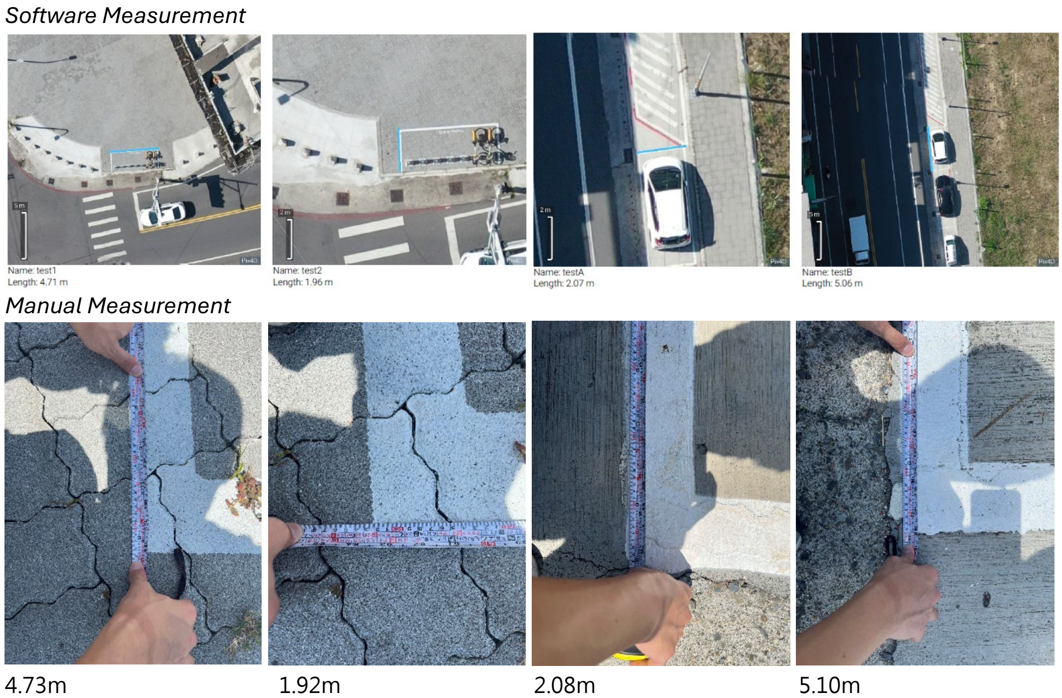

Figure 6. Visual comparison of manual measurement vs system output

4.2 Comparison of Manual and AI Measurements

To quantify the effectiveness of the UAV + AI method, time consumption and measurement accuracy were compared between manual survey results and AI-assisted detection. Each parcel was analyzed for both area coverage and classification accuracy.

The results indicate that the AI-assisted workflow reduced survey time by nearly 80%, while maintaining a high degree of measurement fidelity. The ±3.2% deviation in area estimates was deemed acceptable for preliminary classification and enforcement purposes.

Furthermore, the automated pipeline allowed rapid processing of all image tiles in batch mode, making it feasible to reprocess datasets in future when updated aerial imagery or detection models become available. This retrainable and scalable approach is especially advantageous in dynamic land use environments.

4.3 Advantages and Limitations

The integration of UAVs and AI image recognition offers significant improvements over conventional land survey methods, but also comes with certain practical considerations.

Advantages:

- High Efficiency: Capable of scanning and analyzing large areas in short time spans, ideal for periodic inspections.
- Repeatable & Traceable: Digital workflows can be archived and reprocessed, ensuring transparency and auditability.
- Labor Savings: Minimizes the need for extended on-site personnel, lowering operational risk and cost.

- Conflict Avoidance: Reduces face-to-face confrontations with illegal occupants during sensitive investigations.

Limitations:

- Initial Cost: Investment in UAV hardware, AI training infrastructure, and software licenses may be a barrier for smaller agencies.
- Environmental Obstacles: Shaded areas, dense vegetation, and low-light conditions can degrade detection accuracy.
- Legal Interpretability: Automated detection outputs must often be manually verified or supported by legal documentation before administrative enforcement can proceed.

In conclusion, while some technical and legal challenges remain, the UAV + AI methodology represents a major step toward modernizing land resource audits and enhancing the integrity of public land management systems.

5 Conclusion

This study demonstrates the potential of integrating UAV photogrammetry with AI-based image recognition for efficient and scalable investigation of irrigation public land occupancy. By replacing traditional manual surveys with automated workflows, the process becomes faster, more objective, and safer.

Key findings include:

- UAVs provide accurate and timely orthophotos of large areas, even in regions difficult to access by foot.
- YOLOv7 effectively detects various types of land occupation with high precision after targeted training.
- The combined system reduces manpower requirements by over 80% and allows regular monitoring with repeatable procedures.

Future research may focus on integrating multispectral sensors to detect under-vegetation occupation, improving detection accuracy in complex environments, and deploying models on mobile edge devices for real-time field analysis.

This methodology not only supports regulatory compliance and land protection but also offers a reproducible framework for other public land management applications.

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Data Availability Statement

The data supporting the findings of this study are not publicly available due to privacy and confidentiality restrictions.

Conflicts of Interest

The authors declare no conflict of interest.

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