Geospatial Deep Learning for Pomelo Tree Detection in Mixed Orchard Systems: A UAV-Based Assessment of YOLO Models

Worachairungreung, M.,[1] Kulpanich, N.,[1*] Sae-Ngow, P.,[1] Thanakunwutthirot, K.,[2] Doddacha, S.,[1] Nilnarong, J.[1] and Hemwan, P. [3]
[1]Geography and Geo-Informatics Program, Faculty of Humanities and Social Sciences, Suan Sunandha Rajabhat University, Bangkok, 10300, Thailand
[2]Digital Design and Innovation Program, Faculty of Fine and Applied Arts, Suan Sunandha Rajabhat University, Bangkok, 10300, Thailand, E-mail: nayot.ku@ssru.ac.th*
[3]Department of Geography, Faculty of Social Sciences, Chiang Mai University, Chiang Mai, 50200, Thailand
Corresponding Author

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Abstract
This study addresses the global transition in agricultural area monitoring and assessment from traditional field survey methods to the widespread use of geospatial technology and artificial intelligence under the concepts of precision agriculture and digital agriculture. Accordingly, this study aims to apply unmanned aerial vehicle (UAV) imagery in combination with deep learning techniques to classify pomelo trees in mixed orchard systems, while comparatively analyzing the performance of YOLO models in order to identify the most suitable model for complex terrain. The findings are expected to support the development of a precise farm-plot-level spatial database, which is important for the management of geographical indications (GI) pomelo, yield estimation, and effective regional agricultural planning. The results indicate that YOLOv5 is more suitable for tasks requiring high accuracy in tree counting and spatial density analysis, whereas YOLOv8 demonstrates architectural stability and potential for further development in the future. Overall, the findings will facilitate the selection of an appropriate model for developing an accurate farm-plot-level spatial database, which is important for the management of various orchard systems, as well as for yield estimation and effective regional agricultural planning.

Keywords: Geospatial Deep Learning, Pomelo tree detection, Spatial production monitoring, UAV imagery, YOLO

1. Introduction

At present, agricultural area monitoring and assessment worldwide are transitioning from traditional field survey methods toward the widespread use of geospatial technology and artificial intelligence under the concepts of precision agriculture and digital agriculture [1]. This transition involves the application of high-resolution satellite imagery, aerial imagery acquired from unmanned aerial vehicles (UAVs), as well as machine learning and deep learning techniques to analyze and classify vegetation accurately at the farm-plot level [2]. These technologies enable effective large-area monitoring of land use change [3], plant health assessment [4], yield estimation [5], and agricultural resource management [6]. Many countries and international organizations, such as FAO and NASA, have promoted the use of geospatial data and artificial intelligence to build spatial agricultural databases in support of food security and sustainable resource management [7]. Nevertheless, major challenges remain in agricultural areas with complex landscape structures, such as integrated farming systems or mixed orchards, which require advanced data analysis techniques and GeoAI models to further improve the accuracy of crop classification and the development of high-resolution spatial databases [8].

In addition, the agricultural areas of Samut Songkhram Province are distinguished by mixed orchard systems integrated with canal networks in the Mae Klong Basin, which are well suited to the cultivation of high-quality fruit crops, particularly pomelo, which has gained recognition both nationally and internationally [9]. This area is a renowned source of pomelo noted for its flavor,

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fragrant sweetness, dry flesh, and consistent quality, all of which result from its geographical setting, brackish alluvial soil, and the inherited local wisdom of raised-bed orchard management [10]. Pomelo from this area has been registered as a geographical indication (GI) product under the name Samut Songkhram pomelo, clearly reflecting the connection between product quality and geographical origin [11]. Economically, pomelo is a major economic crop that generates income for a large number of farmers in the province through fresh fruit sales, processing, and agricultural tourism. Market demand has continued to increase, particularly in premium markets that emphasize quality, food safety standards, and traceable sources of production, as well as in export markets across Asia that demand high-quality tropical fruit [12]. However, managing production volume in line with market demand still faces a major limitation: the lack of accurate and timely updated spatial data on planting area, tree numbers, and yield potential in each growing season.

Although deep learning, particularly the YOLO-family algorithms [13], has been widely recognized and applied in vegetation detection from aerial imagery, most existing studies still focus on large agricultural landscapes characterized by monoculture, where planting patterns and spacing are clearly defined. As a result, a significant research gap remains in the application of such technology within the context of mixed orchard systems, which exhibit high structural complexity [14], especially in Samut Songkhram Province. This area represents a traditional orchard landscape composed of a dense mixture of various fruit tree species cultivated within small farm plots. These characteristics give rise to diverse plant canopy structures, canopy overlap, and variable light and shadow conditions, making the differentiation of pomelo trees from other plant species more difficult and complex than in conventional monoculture systems [15]. Moreover, comparative studies between YOLOv5 and YOLOv8 remain lacking for evaluating the model best suited to landscapes with dense vegetation structures and complex light and shadow conditions, with implications for yield estimation, market planning, and future regional agricultural policy formulation [16].

Therefore, the objectives of this research are important in multiple respects. From an academic perspective, the study advances knowledge on the application of GeoAI through a comparative evaluation of YOLOv5 and YOLOv8 models for tropical fruit trees in the context of canal-side mixed orchards, an area that remains relatively underexplored in international literature. In policy and management terms, the findings can be applied to support decision-making and operational planning. The results will support the timely development of a spatial database of planting areas and the estimation of pomelo production in Samut Songkhram Province, enabling relevant agencies to improve market planning, supply chain management, and responses to environmental risks more effectively. Ultimately, this will contribute to enhancing the competitiveness of Thai GI pomelo in the international market and strengthening the economic sustainability of local farmers.

2. Materials and methods

2.1 Study Area

The UAV image dataset used in this study was collected from 10 mixed orchard plots located in Samut Songkhram Province, Thailand. Samut Songkhram Province was selected as the study area for this research because it is one of the most fertile provinces in the Mae Klong Basin. It is located in the central plain region of Thailand and covers an area of approximately 413.8 square kilometers. Its geographic coordinates are 13° 26′ 45″ N latitude and 100° 01′ 55″ E longitude. Samut Songkhram Province has distinctive hydrological characteristics, comprising three types of water sources: freshwater, saltwater, and brackish water [17]. These conditions have produced mineral-rich alluvial soils suitable for cultivating tropical fruit crops, particularly pomelo, which is well adapted to sandy loam soils and raised-bed orchard areas with appropriate water management. In addition, pomelo is an important economic crop of the province, renowned for its flavor quality, firm flesh, relatively dry flesh, and balanced sweetness and acidity, all of which result from the geographical environment and local wisdom. Pomelo from this area has been registered as a GI product under the name Samut Songkhram pomelo, clearly reflecting the connection between origin and product quality [18].

According to the most recent land use data, most of the province is used for agriculture, particularly mixed orchards along canal corridors. Pomelo orchards are distributed across several districts, especially Bang Khonthi District, Amphawa District, and Mueang Samut Songkhram District, where raised-bed orchard structures and traditional irrigation systems are conducive to high-quality pomelo cultivation, as shown in Figure 1.

2.2 Data Collection

This study used aerial imagery acquired from UAV to develop and evaluate the performance of deep learning models for pomelo tree detection in Samut Songkhram Province. A total of 10 experimental plots were selected, consisting of pomelo orchards

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with different management characteristics, including both monoculture orchards and mixed orchards, as well as varying tree ages and canopy densities, to ensure that the dataset captured environmental variability within the study area. Most experimental plots were located in Bang Khonthi District, which is one of the province's major pomelo-growing areas. Data collection was carried out through UAV survey flights equipped with a high-resolution RGB camera. RGB imagery was selected in this study because RGB cameras are widely available, cost-effective, and operationally practical for farm-plot-level monitoring in smallholder orchard systems. This approach allows the development of a low-cost workflow for tree detection using UAV imagery and deep learning. However, RGB imagery provides limited spectral information compared with multispectral, LiDAR, or thermal sensors, particularly when different tree species exhibit similar canopy shapes, textures, and colors. The flight altitude was set at 70 m, and the spatial resolution, expressed as ground sampling distance (GSD), was 2.03 cm per pixel, allowing the canopy structure of pomelo trees to be clearly distinguished. The forward overlap was set at 70% and the sidelap at 40%, which were sufficient for generating an orthomosaic and reducing geometric distortion. The georeferenced position data of the images were recorded in a geographic coordinate system for subsequent spatial analysis in conjunction with a geographic information system (GIS), as illustrated in Figure 2. The UAV imagery was then subjected to data preprocessing, which included image quality inspection, color and illumination correction, image tiling, and data formatting suitable for training the YOLOv5 model [19]. An annotated dataset was subsequently created by assigning a bounding box to each pomelo tree as reference data for model learning [20]. Six object classes identified in the study area were labeled: areca palm, banana, pomelo, lychee, coral tree, and built structures. The class distribution of the annotated dataset reflected the actual agricultural characteristics of the study area, where pomelo is widely cultivated and represents one of the major orchard crops in Samut Songkhram Province. Therefore, the higher number of pomelo instances was not merely a sampling artifact but corresponded to the real distribution of tree species observed in the selected orchard plots.

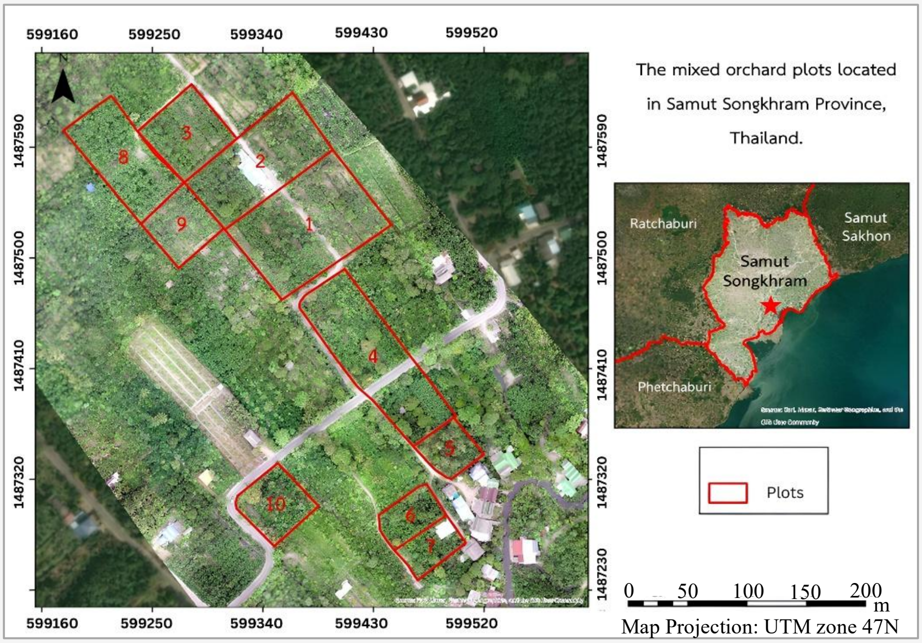

Figure 1: Mixed orchard plots in Samut Songkhram province, Thailand

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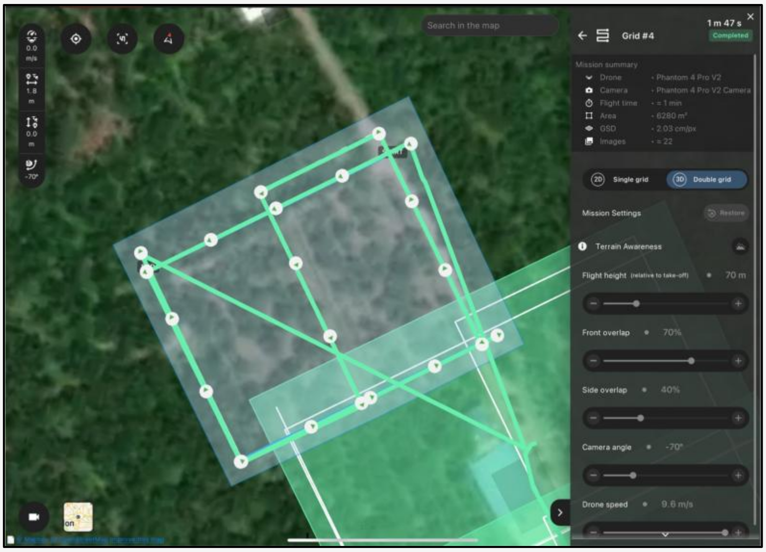

Figure 2: Data collection using UAV

Table 1: Class distribution and imbalance of annotated object instances

Class	Number of instances	Percentage (%)	Interpretation
banana	735	21.45	Moderate class
areca palm	319	9.31	Minority class
home/built structures	92	2.68	Minority / contextual class
lychee	121	3.53	Minority class
pomelo	2,055	59.97	Dominant class
coral tree	105	3.06	Minority class
Total	**3,427**	**100.00**	

Nevertheless, this uneven distribution was considered in the model evaluation because class imbalance may influence the learning process and affect detection performance across classes. After annotation, the full dataset derived from the 10 experimental plots was then divided into three subsets: 85% for the training set, 11% for the testing set, and 4% for the validation set. This allocation was intended to enable the model to learn the morphological patterns of pomelo canopies comprehensively while independently evaluating its ability to classify pomelo trees under different environmental conditions, as shown in Table 1.

2.3 Methods

After the pomelo orchard image dataset had been prepared and annotation completed, the next step was to allocate the data for the development and evaluation of pomelo tree detection models using the YOLO algorithm [21]. All image data from the 10 experimental plots in Samut Songkhram Province were randomly and systematically divided into three subsets in order to ensure reliable evaluation of model performance and reduce bias arising from repeated learning of the same data. In the model development stage, Python was used to implement the YOLOv5 and YOLOv8 algorithms for object detection [22]. Appropriate parameters were defined, including input size, learning rate, number of epochs, and non-maximum suppression (NMS), in order to improve model performance. To ensure a fair comparison and improve reproducibility, YOLOv5m and YOLOv8m were trained under the same controlled baseline configuration. Both models were fine-tuned from pretrained weights using an input image size of 832 × 832 pixels, a batch size of 8, 40 training epochs, an initial learning rate of 0.001, and the Adam optimizer. The model variants, pretrained weights, initialization strategy, input size, number of epochs, batch size, learning rate, optimizer, loss function, and model size are reported in Table 2. Using identical training settings reduced configuration-related bias and allowed the performance differences between the two models to be interpreted primarily in relation to their architectural characteristics and learning behavior.

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This study did not apply model-specific loss-function tuning, such as focal loss or weighted loss, because applying a model-specific loss function to only one architecture could introduce additional configuration-related bias and make the comparison less consistent. Nevertheless, the potential benefit of class-imbalance-aware loss functions is acknowledged in the Discussion as an important direction for future YOLOv8m optimization, particularly for improving convergence and minority-class detection performance, as shown in Table 2. The performance of the pomelo tree detection models was then evaluated using standard object detection metrics, namely Precision, Recall, and F1-score, together with mean Average Precision (mAP), in order to reflect the model's capability in terms of both accuracy and detection coverage [23]. Precision represents the proportion of pomelo trees correctly detected by the model relative to the total number of objects predicted by the model as pomelo trees. Recall represents the proportion of pomelo trees detected relative to the total number of actual pomelo trees in the image [24]. The F1-score reflects the balance between Precision and Recall and was used to assess the overall suitability of the model [25], as shown in Equations 1, and 2:

$$Precision = \frac{TP}{TP + FP}$$

Equation 1

$$Recall = \frac{TP}{TP + FN}$$

Equation 2

The F1-score is the harmonic mean of Precision and Recall and is used to evaluate the balance between the model's accuracy and detection capability, as shown in Equation 3:

$$F1\text{-}score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Equation 3

The confusion matrix was used to summarize the relationship between predicted and actual detection results [26]. In this study, true positive (TP) refers to an object that was correctly detected, false positive (FP) refers to an object incorrectly detected as the target class, false negative (FN) refers to a ground-truth object that the model failed to detect, and true negative (TN) refers to a case in which a non-target object or background area was correctly not detected as the target class [27]. These definitions were used to support the interpretation of model accuracy, detection errors, and class-wise confusion in the UAV-based object detection task, as shown in Table 3.

Table 2: Model Variants and Training Configuration for YOLOv5m and YOLOv8m

Parameter	YOLOv5m	YOLOv8m
Model variant	YOLOv5m	YOLOv8m
Pretrained weights	yolov5m.pt	yolov8m.pt
Pretrained weights source	COCO-pretrained weights	COCO-pretrained weights
Training strategy	Fine-tuning from pretrained weights	Fine-tuning from pretrained weights
Image size	832 × 832 pixels	832 × 832 pixels
Batch size	8	8
Epochs	40	40
Initial learning rate	0.001	0.001
Optimizer	Adam	Adam
Dataset split	85% train / 11% test / 4% validation	85% train / 11% test / 4% validation
Input data	UAV RGB imagery	UAV RGB imagery
Task	Object detection	Object detection
Model-specific loss tuning	Not applied	Not applied
Loss-function adjustment for class imbalance	Not applied; discussed as future work	Not applied; discussed as future work

Table 3: Confusion matrix used for accuracy assessment

	Predicted Positive	**Predicted Negative**
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

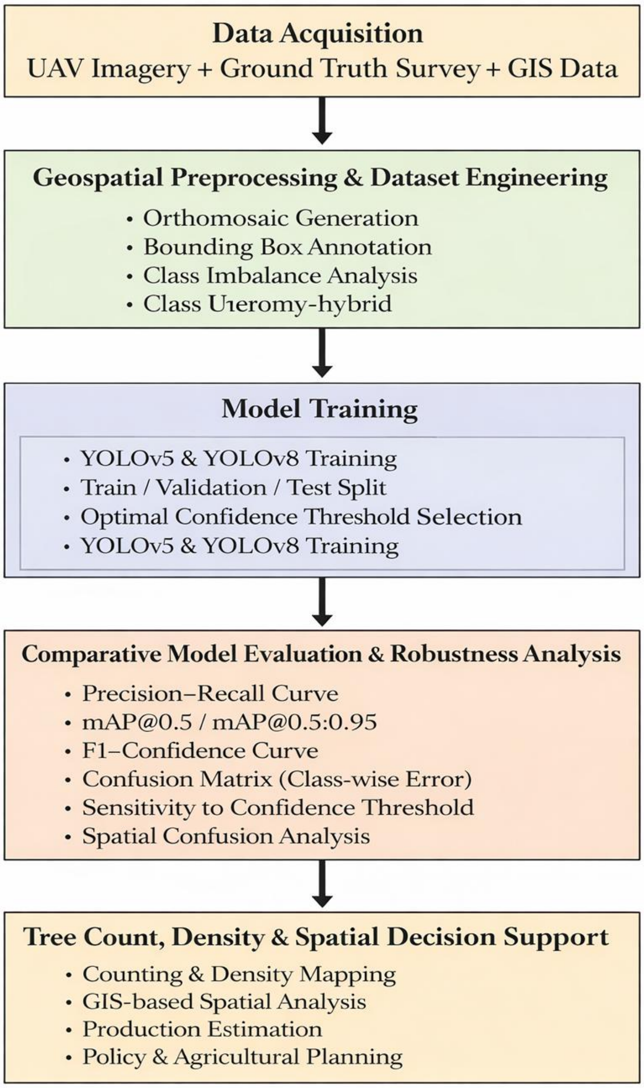


Figure 3: Deep learning for tree detection conceptual framework

In this study, field surveys were conducted in Samut Songkhram Province to collect data from 10 experimental pomelo orchard plots. Data recorded included the actual number of trees, age structure, planting patterns, and partial yield data, which were used as ground truth for model calibration and accuracy verification. At the same time, aerial imagery was collected using UAV to cover all experimental plots. The resulting images were processed into orthophotos and prepared in spatial data format for further analysis. The analysis employed the YOLO object detection model to identify and locate pomelo trees from UAV imagery using bounding box annotation for model training [28]. The system was able to detect canopy structure and count trees automatically, thereby improving speed and reducing errors associated with visual image interpretation. The detection results were compared with field data and evaluated using Precision, Recall, F1-score, and mAP to verify model accuracy. The overall research process is illustrated in Figure 3.

3. Results

3.1 Comparative Testing of YOLOv5 and YOLOv8 for Object Classification in Pomelo Orchard Plots in Samut Songkhram Province

The comparative evaluation of YOLOv5m and YOLOv8m for pomelo tree detection from UAV imagery demonstrates the feasibility of applying deep learning models to orchard data under real-world mixed-orchard conditions. In terms of learning behavior, both models showed decreasing training and validation losses during the training process, indicating their ability to learn object localization and classification patterns from the UAV image dataset. YOLOv5m exhibited a consistent decrease in box loss, object loss, and class loss, while YOLOv8m showed relatively smooth training and validation loss curves under the controlled training configuration. In terms of detection performance, the Precision–Recall analysis showed that YOLOv5m achieved higher AP@0.5 values than YOLOv8m across all object classes. The overall mAP@0.5 of YOLOv5m was 0.921, whereas YOLOv8m achieved an overall mAP@0.5 of 0.659. For the target pomelo class, YOLOv5m achieved an AP@0.5 of 0.899, while YOLOv8m achieved an AP@0.5 of 0.471. These results indicate that, under the current controlled experimental configuration, YOLOv5m performed better than YOLOv8m in the present UAV mixed-orchard dataset. However, this comparison should not be interpreted as a universal conclusion regarding the superiority of one architecture over the other, because YOLOv8m may require further model-specific optimization, including longer training, learning-rate adjustment, confidence threshold tuning, IoU threshold tuning, and loss-function configuration. These results are presented in Table 4.

Analysis of the annotated data revealed an imbalance in the number of samples across classes, with the pomelo class occurring substantially more frequently than the other classes, which may have affected model learning. Nevertheless, the distribution of bounding box positions and sizes was relatively consistent across the images, thereby supporting the annotation quality and dataset consistency. These results are illustrated in Figure 4, which presents the distribution of object classes and bounding box characteristics in the UAV training dataset. Additionally, examples of the detection outputs are provided in Figure 5, with Figure 5a representing the YOLOv5m model and Figure 5b representing the YOLOv8m model. Based on the quantitative evaluation and analysis of model learning behavior, YOLOv5 and YOLOv8 were found to exhibit clearly different strengths in the context of pomelo tree detection from UAV imagery. YOLOv5 demonstrated clearly superior quantitative performance in terms of Precision, Recall, and mAP, reflecting greater detection accuracy and more comprehensive object identification. It is therefore particularly suitable for tasks that require high accuracy in tree counting and spatial density analysis. However, YOLOv8 showed good training stability and an appropriate tendency toward generalization, with smoother and more consistent training-validation loss curves. This indicates greater architectural robustness and stronger potential for future development and refinement. In addition, both models were affected by class imbalance in the dataset, which may have caused the models to be biased toward the dominant class, namely pomelo, rather than the minority classes. Therefore, data balancing is an important issue for the next stage of development.

Table 4: Class-wise AP@0.5 and Overall mAP@0.5 of YOLOv5m and YOLOv8m in pomelo tree detection

Class / Metric	YOLOv5m	YOLOv8m	Comparative interpretation
banana	0.943	0.617	YOLOv5m achieved higher AP@0.5
areca palm	0.924	0.761	YOLOv5m achieved higher AP@0.5
built structures	0.929	0.701	YOLOv5m achieved higher AP@0.5
lychee	0.911	0.683	YOLOv5m achieved higher AP@0.5
pomelo	0.899	0.471	YOLOv5m achieved higher AP@0.5 for the target crop class
coral tree	0.919	0.721	YOLOv5m achieved higher AP@0.5
mAP@0.5, all classes	0.921	0.659	YOLOv5m showed higher overall detection performance under the current controlled configuration

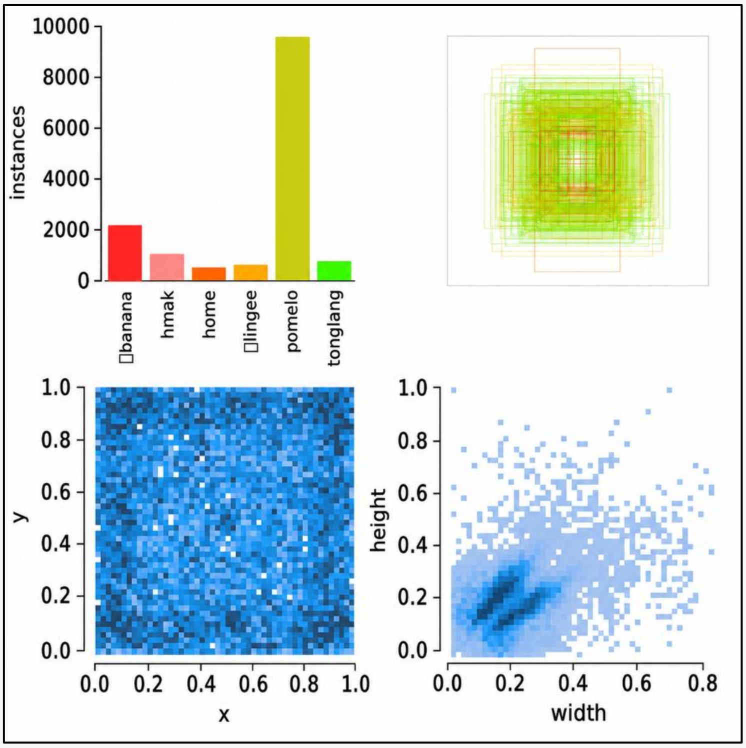
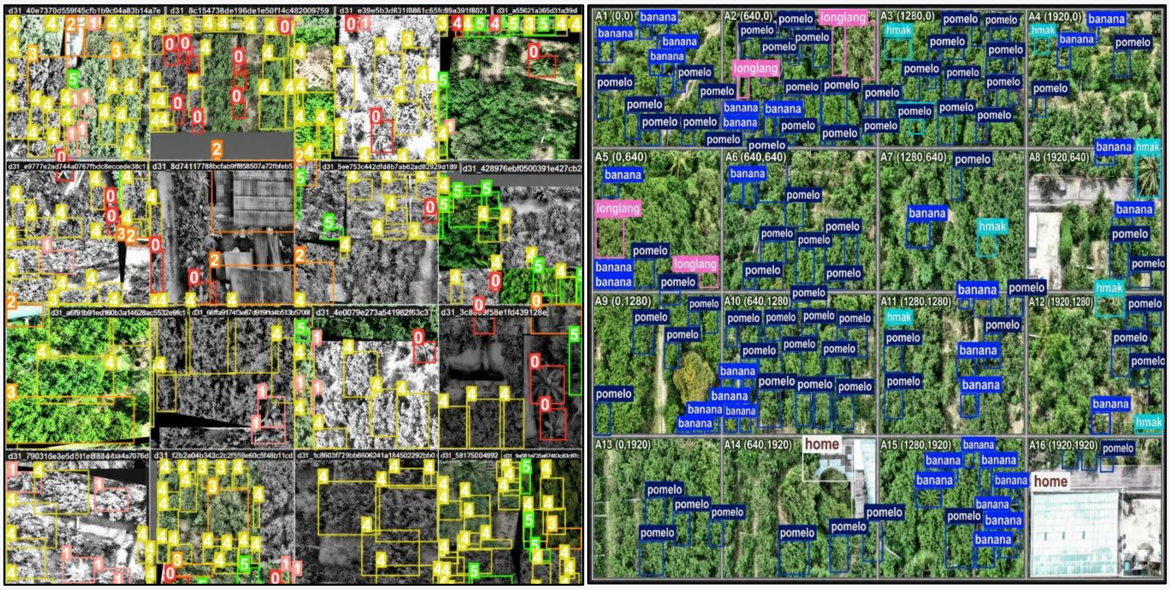


Figure 4: Distribution of object classes and bounding box characteristics in the UAV training dataset



(a) (b)

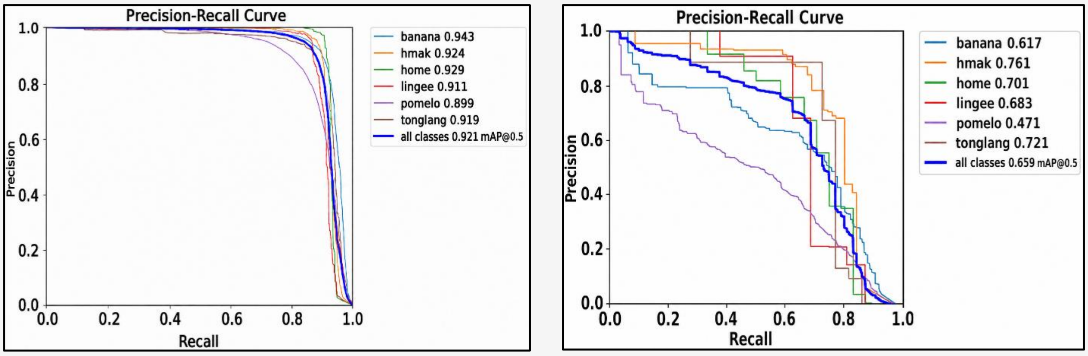
Figure 5: Examples of pomelo tree and other object detection results generated by the YOLO models from UAV imagery: (a) YOLOv5 (b) YOLOv8

3.2 Comparative Metric Interpretation and Model Robustness Analysis

The comparison of YOLOv5 and YOLOv8 based on the Precision-Recall curve clearly demonstrates differences in structural performance and model robustness. In the case of YOLOv8, the overall mean across all classes (mAP@0.5) was approximately 0.659, reflecting moderate performance. The curves for individual classes showed relatively high variability, particularly for the pomelo class, which had the lowest Average Precision (AP) at 0.471 and exhibited a continuous decline in Precision as Recall increased. This reflects a limitation in maintaining accuracy while attempting to achieve more complete object detection. In addition, some class curves were irregular, indicating sensitivity to the confidence ranking of predictions and suggesting the impact of class imbalance on generalization ability. In contrast, YOLOv5 achieved a much higher overall mAP@0.5 of 0.921, which is considered very high. The Precision-Recall curves for all classes consistently remained near the upper boundary of the graph and declined sharply only when Recall approached 1.0, indicating the model's ability to maintain high Precision across a broad Recall range. Moreover, the AP values for each class were closely aligned (0.899-0.943), reflecting inter-class stability and model robustness to structural differences among objects. Therefore, in terms of model robustness, YOLOv5 demonstrated stronger potential to maintain performance over a wider Recall range and was significantly less sensitive to declines in Precision than YOLOv8. By contrast, YOLOv8 showed a more gradual decrease in Precision, reflecting confidence ranking behavior that was not yet sufficiently stable in the context of mixed orchard data, particularly for classes with complex canopy structures or imbalanced sample numbers. The results are presented in Figure 6, where Figure 6(a) and 6(b) illustrate the precision–recall curves of the YOLOv5 and YOLOv8 models, respectively.

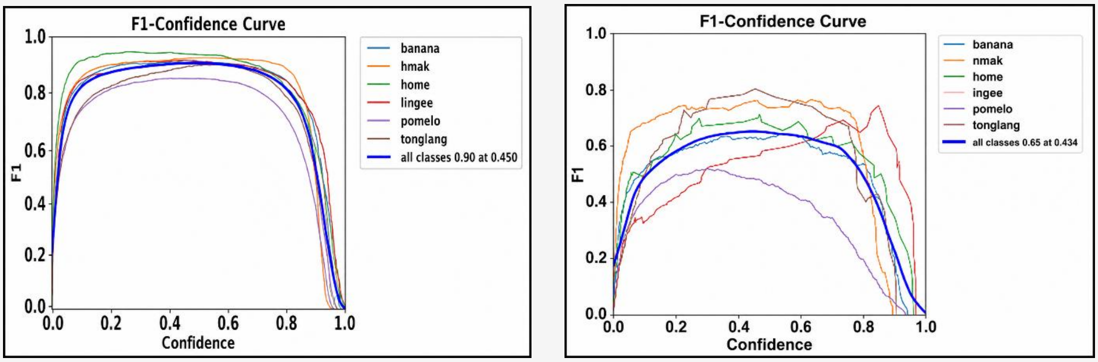
With respect to model sensitivity to changes in the confidence threshold, the comparative Precision-Recall curves of the two models show that YOLOv5 consistently maintained its curve near the upper-right corner of the graph and was able to preserve a high level of Precision even as Recall increased to nearly 1.0. This reflects high performance stability and limited sensitivity to changes across a broad threshold range, meaning that overall performance declined only slightly when the threshold was adjusted over a wide interval. In contrast, YOLOv8 showed a faster decline in Precision as Recall increased, indicating greater sensitivity to threshold variation, particularly in the medium to high Recall range. This suggests that threshold setting has a more pronounced effect on model balance in YOLOv8. Therefore, in terms of model robustness, YOLOv5 was more stable under changes in confidence values, whereas YOLOv8 required more careful threshold tuning in order to achieve optimal performance.

The confidence threshold refers to the minimum prediction confidence required for a detected bounding box to be retained as a valid detection. In this study, confidence threshold values were evaluated across the range of 0.00–1.00 using F1-confidence curves in order to examine the sensitivity of model performance to threshold adjustment. In addition, comparison of the F1-confidence curves between YOLOv5 and YOLOv8 reveals clear differences in model stability and robustness. In the case of YOLOv5, the overall average F1-score across all classes reached a maximum of approximately 0.90 at a confidence threshold of about 0.458. The curves for all classes were smooth and stable across a broad threshold range (approximately 0.1-0.7) before declining sharply as the threshold approached 0.85-0.90. This reflects the model's ability to maintain a strong balance of performance under varied confidence settings. Moreover, the values across classes were closely aligned, indicating inter-class stability and robustness to differences in object characteristics within mixed orchard areas. By contrast, YOLOv8 achieved a maximum average F1-score of approximately 0.65 at a threshold of about 0.434. Its curves declined more gradually and exhibited greater variability among classes, particularly for the pomelo class, which showed a clearly lower F1-score than the others. When the threshold increased beyond 0.7, the F1-score declined rapidly, reflecting the model's sensitivity to threshold settings and its vulnerability to changes in the confidence threshold.



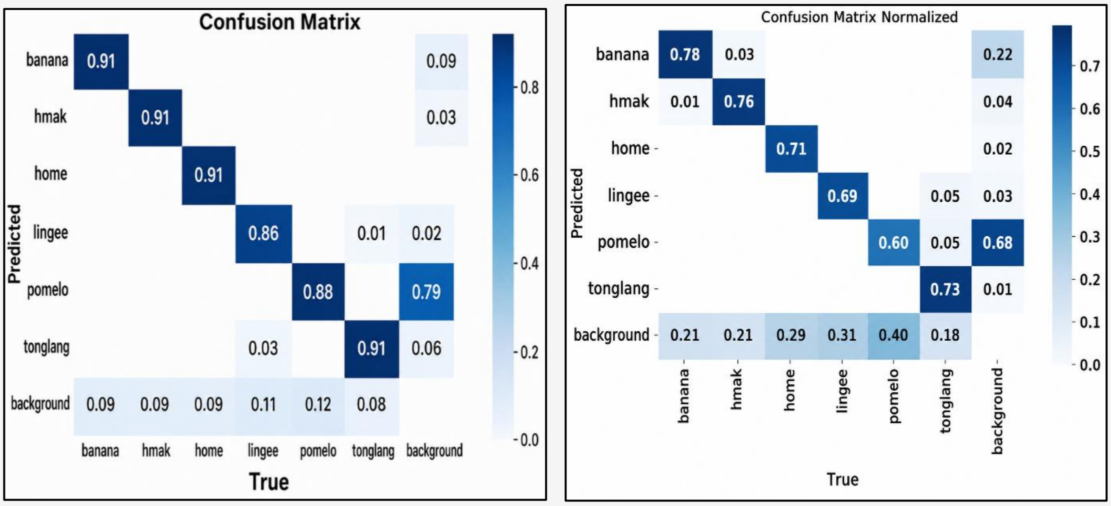
(a) (b)

Figure 6: Precision-Recall Curve Comparison of YOLOv5 and YOLOv8 for UAV-Based Pomelo Detection: (a) YOLOv5 and (b) YOLOv8



(a) (b)

Figure 7: Comparative F1-Confidence Analysis for Optimal Threshold Selection in UAV-Based Pomelo Detection: (a) YOLOv5 and (b) YOLOv8



(a) (b)

Figure 8: Confusion Matrix Comparison of YOLOv5 and YOLOv8: (a) YOLOv5 (b) YOLOv8

Therefore, from the perspective of model robustness, YOLOv5 demonstrated a greater ability to maintain high performance over a wider threshold range and showed better stability across classes. In contrast, YOLOv8 exhibited greater sensitivity to threshold variation and more evident effects of data imbalance, particularly in the dominant class with a complex structural pattern. The results are presented in Figure 7, where Figure 7(a) and Figure 7(b) illustrate the F1–confidence curves of the YOLOv5 and YOLOv8 models, respectively, for optimal threshold selection.

As shown in Figure 8, the analysis of class-wise error and spatial confusion between YOLOv5 and YOLOv8 based on the confusion matrix clearly reflects structural differences in error patterns. In the case of YOLOv5, the values along the main diagonal were high for almost all classes (approximately 0.86-0.91), indicating accurate and highly consistent class-level classification, particularly for banana, areca palm, built structures, and coral tree. Although the value for pomelo was slightly lower (approximately 0.88), it remained at a good level. The spatial confusion observed in YOLOv5 mainly occurred as false negatives assigned to the background rather than as direct cross-class confusion, indicating that the model was more likely to miss detections than to predict the wrong class. In contrast, YOLOv8 showed clearly lower diagonal values in several classes, especially pomelo (approximately 0.60) and lychee (approximately 0.69), reflecting significantly higher class-wise error than YOLOv5. In addition, greater spatial confusion was observed among plant classes with similar canopy characteristics, together with a higher proportion of predictions assigned to the background, particularly for pomelo (approximately 0.40). This indicates greater model sensitivity to spatial context and background complexity. It can therefore be concluded that YOLOv5 had an advantage in terms of class-level accuracy and classification stability, as shown in Figure 8(a), whereas YOLOv8 exhibited higher levels of spatial confusion and class-wise error, particularly among classes with morphological similarity, as shown in Figure 8(a). This reflects a clear difference in robustness between the two architectures in the context of crop detection from UAV imagery.

4. Discussion

The findings of this study reflect the potential of applying the GeoAI concept in combination with UAV imagery to systematically detect and analyze the pomelo production structure in Samut Songkhram Province. The comparison between YOLOv5 and YOLOv8 demonstrates clear differences in both quantitative performance and model robustness within the context of orchard systems characterized by spatial complexity and diverse canopy structures. Similar challenges related to canopy complexity, object scale, and heterogeneous agricultural landscapes have been reported in previous deep learning-based agricultural object detection studies [29] and [30]. In the present study, YOLOv5m achieved higher overall accuracy in terms of Precision, Recall, and mAP@0.5, suggesting its ability to maintain a strong balance between detection accuracy and detection coverage across a broad Recall range. Precision–Recall behavior and mAP are widely used to evaluate detection accuracy, coverage, and model robustness in object detection studies [31] and [32]. The Precision Recall curves of YOLOv5m remained close to the upper boundary of the graph and declined sharply only when Recall approached 1.0, indicating good inter-class stability and effective confidence ranking. In contrast, although YOLOv8 exhibited smoother and more stable learning curves during training, it produced lower average accuracy and greater variation in AP across classes, particularly in the pomelo class, which was the principal class of the study. Previous studies have similarly shown that YOLO-family models can exhibit different performance patterns depending on dataset structure, class imbalance, object scale, and canopy complexity [33] and [34].

These differences may be interpreted in terms of both model architecture and the characteristics of the spatial data. UAV imagery of pomelo orchards exhibits relatively uniform canopy forms, but these canopies overlap with other vegetation types and background features such as canals, pathways, and intercrops. The ability of YOLOv5m to maintain high precision across a broad confidence-threshold range suggests its stronger capacity to handle background complexity under the current dataset. Similar effects of background complexity and canopy overlap on detection performance have also been reported in UAV-based agricultural object detection studies [35]. By contrast, YOLOv8 was more sensitive to changes in the confidence threshold, as evidenced by the F1-confidence curve, in which the F1-score declined markedly as the threshold increased. This type of threshold sensitivity has been discussed as an important factor affecting the robustness of object detection models [36]. In terms of class-wise error and spatial confusion, analysis of the confusion matrix showed that YOLOv5 achieved high class-level accuracy values, approximately 0.86-0.91, and exhibited lower cross-class confusion. YOLOv8, by contrast, showed higher class-wise error levels, particularly for pomelo, which was more frequently assigned to the background. Similar background-confusion problems have been observed in complex agricultural image datasets [37]. This result reflects a false negative problem with important implications for spatial applications, because failure to detect pomelo trees directly affects tree count and density estimation, which are fundamental variables in production monitoring [38] and [39]. Although the class imbalance observed in this study reflects the real composition of mixed orchards in the study area, where pomelo trees are more abundant than other tree species, it remains an important methodological consideration for deep learning-based object detection. The dominance of the pomelo class may allow the models to learn its visual characteristics more effectively than those of underrepresented classes. Consequently, minority classes may show weaker detection performance due to fewer training samples, canopy similarity, spatial overlap, and partial occlusion. Future studies should therefore consider both ecological representativeness and model balance by expanding the dataset, increasing minority-class samples, and applying class-balancing strategies such as targeted augmentation, weighted loss functions, or focal loss [40]. These strategies may play an important role in reducing bias and improving the model's generalization ability [41].

This research is not merely an object detection experiment, but an integration of UAV imagery, field data, and GIS to establish a spatial analysis workflow ranging from pomelo tree detection and tree counting to density mapping and spatial production monitoring. Previous studies have similarly emphasized the value of integrating UAV imagery, deep learning, and GIS-based analysis for agricultural mapping and production monitoring [42][43][44] and [45]. Model accuracy, therefore, directly influences the reduction of estimation error at both the plot and provincial levels, particularly in areas with GI status, where product quality and production volume directly influence economic value. In the context of Samut Songkhram Province, with its mixed orchard systems and basin-based agricultural landscape structure, the use of such tools to detect and monitor pomelo tree numbers can help overcome the limitations of traditional field surveys while improving the timeliness and spatial granularity of production data [46]. In addition, a more robust model such as YOLOv5m may be appropriate for provincial-scale production monitoring systems under the current controlled configuration, whereas YOLOv8m may hold potential for further improvement if data balancing, model-specific optimization, and hyperparameter tuning are further refined [47]. However, this study still has certain limitations, including the use of data from only one province, the use of RGB imagery alone without integrating multispectral data and the exclusion of seasonal variation, all of which may affect detection accuracy under different temporal conditions [48] and [49]. In addition, this study compared YOLOv5 and YOLOv8 under a controlled model configuration rather than conducting a full hyperparameter optimization process. Although using the same experimental settings supports a fair comparison between the two architectures, the absence of systematic hyperparameter tuning and ablation experiments may limit the technical depth of the model evaluation.

Future studies should therefore conduct model-specific optimization for YOLOv8m, including extended training, learning-rate adjustment, repeated training runs, and ablation analyses to examine the effects of key hyperparameters and post-processing settings, such as batch size, number of epochs, augmentation strategy, confidence threshold, IoU threshold, and loss-function configuration [50]. In particular, class-imbalance-aware strategies, including class-balanced sampling, targeted data augmentation, weighted loss functions, and focal loss, should be considered to improve convergence, reduce bias toward dominant classes, and enhance minority-class detection performance under mixed-orchard conditions [51].

From an applied GeoAI perspective, the findings suggest that YOLOv5m may be suitable for pomelo tree detection and provincial-scale production monitoring under the current controlled experimental configuration. In contrast, although YOLOv8m demonstrated relatively stable training behavior, it may require further model-specific optimization, data balancing, and hyperparameter tuning to achieve a comparable level of detection accuracy. These findings provide an applied foundation for integrating UAV imagery, deep learning, and GIS-based workflows in spatial horticultural production management. Such an approach may support more timely and spatially detailed agricultural monitoring and contribute to evidence-based production planning in the Mae Klong Basin [52][53][54] and [55].

5. Conclusion

The comparative evaluation of YOLOv5m and YOLOv8m for tree detection from UAV imagery in mixed orchard environments in Samut Songkhram Province demonstrates the feasibility of applying deep learning models to support precision agriculture and spatial orchard monitoring. Under the current controlled experimental configuration, YOLOv5m achieved higher detection performance than YOLOv8m in terms of Precision, Recall, mAP, Precision–Recall behavior, F1-confidence stability, and class-wise classification accuracy. These results suggest that YOLOv5m is more suitable for applications requiring high detection accuracy, tree counting, and spatial density analysis within the current dataset.

However, the comparative findings should not be interpreted as a universal conclusion regarding the superiority of one architecture over the other. Model performance was affected by class imbalance, canopy similarity, and confusion between tree classes and background areas, particularly for underrepresented classes. In addition, YOLOv8m may require further model-specific optimization, including longer training, learning-rate adjustment, confidence threshold tuning, IoU threshold tuning, and loss-function configuration, to improve convergence and detection performance under mixed-orchard conditions. The dataset used in this study was limited to 10 orchard plots located within a single province. Therefore, the results should be interpreted as an applied case study and proof-of-concept rather than as evidence of a universally generalizable model. Future studies should expand the dataset across different regions, seasons, climatic conditions, and orchard management systems. Further improvements should also include class-balancing strategies, weighted loss functions, focal loss, advanced data augmentation, multispectral or RGB-NIR data fusion, repeated training runs, cross-validation, and comparison with additional object detection architectures such as Faster R-CNN, EfficientDet, and transformer-based detectors.

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