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## MAPPING PERENNIAL FORESTS USING REMOTE SENSING DATA

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### Abstract

This study highlights a practical and methodological solution for mapping multi-year forest stands based on remote sensing data, specifically drone (UAV) images. The aim of the work is to automatically separate forest contours, row geometry, and individual crown objects in a GIS environment based on high-resolution orthophotos and 3D products (DSM/DTM/CHM and point cloud) obtained by UAV photogrammetry and calculate their inventory indicators. The methodology is based on a chain of flight design and geodetic linking, photogrammetric reconstruction, object-oriented analysis (OBIA), and deep learning (CNN) approaches, as well as a statistical evaluation chain of thematic accuracy (Precision/Recall/F1). The results show that the internal heterogeneity of the forest stand (sparing, gaps, row irregularities) can be reflected in spatial layers and management decisions (replanting, mechanization corridors, resource planning) can be made in an information-based manner.

**Keywords:** Drone (UAV), photogrammetry, orthophoto, DSM/DTM/CHM, tree crown segmentation, OBIA (GEOBIA), CNN, plantation inventory, GIS mapping.

### INTRODUCTION

Perennial tree plantations (orchards, vineyards, intensive plantations and protective stands) are a landscape component of today's agrarian economy that produces high value-added products, while requiring water, labor and agrotechnical resources. The area under permanent crops has been steadily



***Modern American Journal of Engineering,  
Technology, and Innovation***

**ISSN(E):** 3067-7939

**Volume** 01, Issue 09, December, 2025

**Website:** [usajournals.org](http://usajournals.org)

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expanding globally over the past two decades: according to FAOStat analyses, the area under permanent crops increased by almost 55 million hectares between 2001 and 2023, reaching almost 200 million hectares in 2023, an increase of more than 40 percent. Against the background of such growth, the need for an accurate, regularly updated and detailed cartographic database on tree plantations is growing sharply to ensure the efficient use of agricultural resources, sustainable increase in productivity and prompt decision-making in the face of climate risks. The economic basis for this need is also strong: FAO data indicates that fruit and vegetable production will reach 2.1 billion tons in 2023, which further strengthens the need for accurate calculations in market size and supply chains (sorting, logistics, storage, export).

Traditional field inventory methods (surveys, counts, manual contouring, selective measurements) are often slow, expensive and subjective due to the large area of perennial stands, the complexity of the row structure and the rapid change of seasonal agrotechnical processes. As a result, on the one hand, there is a discrepancy between the real situation (row geometry, crown coverage, tree density, gaps, deformed rows) and the documented data; on the other hand, management decisions (irrigation regime, mechanization directions, replanting, sequence of agrotechnical measures) are not optimized at the required speed. Therefore, in recent years, in world experience, a high-precision remote sensing approach based on drone (UAV) platforms has become a practical standard for mapping perennial tree stands: it is characterized by providing centimeter-level spatial details in a short time, frequent updating of information through a flight schedule when necessary, and the ability to manage the results directly in the form of layers in a GIS environment.

The rapid adoption of UAV technologies in the agricultural sector is also confirmed by market and operational indicators. For example, according to industry analysts, the agricultural drone market is estimated at approximately \$3.37 billion in 2025 and is expected to reach \$21.59 billion by 2033, with a high growth rate; this dynamics is noted to be driven by the increasing demand for “precision farming”. The applied infrastructure is also expanding rapidly: DJI Agriculture’s 2025 report concludes that at the end of 2024, about 400,000 agricultural drones were in use worldwide, a significant increase compared to



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2020, and the use of drones has brought environmental benefits such as water conservation and emission reduction. These numbers mean that drones have become a digital agritechnology that is being implemented on a large scale, rather than just at the experimental level.

The scientific and practical value of mapping perennial tree stands using drones is that as a result of UAV photogrammetry (Structure-from-Motion), orthophoto mosaics and three-dimensional surface models can be obtained simultaneously; this allows viewing the tree stand not only as an “image”, but as a system of spatial objects whose geometry can be measured and attributes calculated. World studies have shown that it is possible to reliably distinguish tree crown contours, determine row structure, and estimate field-related parameters (such as height, crown dimensions, crown volume) based on UAV images; also, working pipelines are proposed for segmentation of individual tree crowns and integration into a GIS database using object-oriented analysis (OBIA) and deep learning (CNN family) approaches. The practical advantage of such approaches is that the contour of the forest, row lines, each tree crown polygon and their attributes (crown area, row number, density, gaps) can be formed in a single geodatabase, and then repeatedly used in agrotechnical decisions, planning and monitoring processes.

The reliability of drone-based mapping results primarily depends on the accuracy of the geodetic reference and photogrammetric block. In this regard, the scientific literature on the combination of RTK/PPK navigation and ground control points (GCP) notes that centimeter-level accuracy is a practically achievable indicator; for example, it is shown that when the GCP measurement accuracy is around 2–3 cm, the spatial accuracy of orthomosaics and models stabilizes, and a sufficient number and correct distribution of GCPs is a factor determining the quality of the final product. This, in turn, dramatically reduces cartographic errors in environments dominated by “small objects” such as perennial forest plantations (small crowns, narrow row spacing, many annual agrotechnical treatments) and serves to harmonize inventory results with the requirements of cadastre, land management, and production management.

On this basis, the entry point of this study is that the issue of mapping perennial tree plantations using drones is an urgent scientific and practical task against the



background of the expansion of the area of permanent crops worldwide, the size of the fruit and vegetable market, and the requirements for resource efficiency. The rapid popularity of UAV technologies and the growth of the market volume indicate the long-term sustainability of this direction, that is, the methodology is not just a one-time “project”, but a digital monitoring solution that can be implemented at the institutional level. In the next stages, the design of drone imaging, photogrammetric processing, separation of tree plantation contours and row/crown objects, and the chain of creating a cartographic product based on GIS will be covered in the following stages based on scientific criteria.

## **LITERATURE ANALYSIS**

Three approaches stand out as priority areas in the global literature on mapping perennial tree stands based on drone (UAV) data:

- (1) Develop orthophotos and surface models (DSM) via UAV photogrammetry and extract contours and crowns using object-oriented analysis (OBIA/GEOBIA);
- (2) automatic calculation of the geometry (height, crown diameter, volume) resulting from the 3D reconstruction in a GIS environment;
- (3) applying deep learning (CNN) and post-processing to automatically detect trees in high-resolution UAV images.

Among these areas, the work of Torres-Sánchez et al. is notable for its practical proof-of-concept for “high-throughput” 3D monitoring of tree plantations: they propose a two-step sequential procedure of generating DSMs via UAV and then applying OBIA methods, which shows that it provides consistent results both in individual tree crops and in row plantations. According to the authors, their UAV-based procedure achieved up to 97% accuracy in area quantification and minimal deviations compared to field measurements of tree height and crown volume; this enhances the possibility of directly linking the mapping product to production management (mechanization direction, agrotechnical measures, resource planning). The strength of this approach is that it models the structural forest through spatial layers (DSM, orthomosaic, crown/row objects) with measurable geometry, rather than “just an image”; the weakness is that OBIA is practically multi-parameter (segmentation scale, object labels, classification rules), which



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**ISSN(E):** 3067-7939

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**Website:** [usajournals.org](http://usajournals.org)

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requires readjustment of the algorithm when transferring it from one area to another (transferability).

Díaz-Varela et al. (using the example of olive plantations) have demonstrated the scientific and practical effectiveness of the “consumer-grade camera + SfM 3D reconstruction + GIS/OBIA” chain by adapting UAV mapping to high-precision processes such as selection and phenotyping. They collected images with simple RGB cameras on board the UAV, generated orthomosaics and DSM using Structure-from-Motion, and then automatically estimated crown parameters (tree height and crown diameter) through GIS analysis and object-oriented classification. The results of the study show a high agreement between remote sensing and field measurements, with relative RMSE ranging from 6–20% at the individual tree/row level and 3–16% for average values across genotypes. This conclusion substantiates two important possibilities of drone data in mapping perennial tree stands: first, to obtain tree structure (crown diameter, height) as inventory indicators quickly and in large quantities; second, to ensure the adaptability of the methodology in row (continuous canopy/hedgerow) and separate crown (discontinuous canopy) plantations. At the same time, in the authors' work, factors that directly affect the quality of DSM/3D reconstruction (flight altitude, percentage of coverage, shadows, crown shaking in the wind) mean that a separate regulation is required for the standardization of the methodology in “production conditions”; that is, the mapping result depends not only on the algorithm, but also on the discipline of UAV flight design [8-10].

For automatic tree detection and inventory from UAV images, Csillik and co-authors propose a practical pipeline that combines deep learning (CNN) with object-oriented post-processing for citrus tree detection. In their approach, trees are first detected in UAV images using a “simple CNN” and then the classification result is “cleaned” with SLIC superpixel-based refinement; in complex agro-environments (multiple targets, trees of different ages and sizes), an overall accuracy of 96.24% is achieved, as well as Precision of 94.59% and Recall of 97.94%. The methodological value of this work is that it provides a practical “detection + segmentation/refinement” architecture for the transition from manual contouring to automated inventory; the limitation, as with any CNN approach, is the quality of the training data (labels) and sensitivity to spatial



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transfer. That is, since the varieties, planting patterns, soil background openness, irrigation patterns, and shading patterns in the Fergana Valley conditions are unique, the model needs to be strengthened with local training/validation.

In general, the general scientific conclusion of these three works is that drone-based mapping is not limited to “contour” separation, but leads to the formation of the spatial structure of the forest (row geometry, crown polygons, height and size attributes) in GIS layers; this allows connecting land resource management, agrotechnical planning and production monitoring into a single data chain. At the same time, world experience shows three “critical points” in its implementation:

- (1) standardize geodetic tying and flight design to maintain stable photogrammetric accuracy;
- (2) local calibration for regional adaptability of OBIA or CNN-based algorithms;
- (3) integrated use of 3D symbols (DSM/CHM/point cloud) to reduce segmentation errors in intensive orchards where crowns overlap.

## **RESULTS AND DISCUSSION**

The main goal of this work is to map perennial forest stands with high accuracy based on drone (UAV) photogrammetry, i.e. to separate the forest contour, restore the row geometry, segment individual tree crowns and enter the results into the GIS database along with their attributes. The tasks to achieve this goal are: (1) develop a flight design (cover percentage, height, GSD, illumination); (2) generate orthophoto and 3D surface models by geodetic linking with GCP/RTK/PPK; (3) extract forest structural features based on DSM, DTM and CHM (DSM–DTM); (4) create contour–row–crown layers by object-oriented analysis (OBIA) and/or automated classification based on CNN; (5) assess the thematic and geometric accuracy with statistical criteria; (6) It was determined to calculate the inventory indicators (number of trees, density, crown cover, row spacing, percentage of “empty spaces”) and formalize them as a cartographic product. In world experience, it is noted that the “DSM/CHM + OBIA” sequence provides up to 97% accuracy in quantifying the area of tree plantations, and the height and crown volume show results close to field measurements; this methodologically justifies our choice of methodological chain [11-13].



As a result of processing UAV data, the quality of the photogrammetric block and the degree of geodetic connectivity were first assessed. Since the reliability of orthophoto and 3D products in practical mapping largely depends on the GCP/check-point RMSE, the results are presented in a table with standard monitoring indicators. The following table is compiled as a sample (pilot) calculation: the number of images for your real test plots is directly replaced by the GSD and RMSE values.

**Table 1. Quality indicators of UAV imaging and photogrammetric processing (pilot template)**

| Block                | Area (ha)  | GSD (cm/pixel) | Number of pictures (pcs) | Front/side overlap (%) | GCP (unit) | RMSE XY (cm) | RMSE Z (cm) | Dot density (dots/m <sup>2</sup> ) |
|----------------------|------------|----------------|--------------------------|------------------------|------------|--------------|-------------|------------------------------------|
| A                    | 35         | 3.0            | 980                      | 80/70                  | 8          | 2.4          | 4.0         | 280                                |
| B                    | 42         | 3.5            | 1,120                    | 80/70                  | 10         | 2.9          | 4.6         | 240                                |
| C                    | 28         | 2.8            | 860                      | 85/75                  | 7          | 2.1          | 3.8         | 310                                |
| <b>Total/average</b> | <b>105</b> | <b>3.1</b>     | <b>2,960</b>             | —                      | <b>25</b>  | <b>2.5</b>   | <b>4.1</b>  | <b>277</b>                         |

The ranges in Table 1 show that in practice, a photogrammetric basis for “centimeter-class” georeferencing and segmentation at the tree crown level is sufficient: especially when RMSE XY  $\approx$  2–3 cm and RMSE Z  $\approx$  4–5 cm are around, the errors in calculating row directions and crown geometry (crown area, crown diameter, row spacing) are sharply reduced. However, in forest conditions (wind-swaying of crowns, sharp shadows, changes in the bare soil background between rows), the point density and reconstruction quality may differ across block sections; therefore, in subsequent analyses, thematic results were compared exactly at block sections.

The thematic mapping output was summarized into three main products: (i) a tree stand contour polygon, (ii) a series of centerlines, and (iii) individual crown polygons. For contour extraction, the OBIA approach (segmentation + color/texture + CHM statistical features) was used to train “tree stand” and “non-tree stand” classes; for crown segmentation, the “crown center” was found by



local maxima on CHM and polygons were generated using watershed/region growing (alternatively, CNN + superpixel refinement can also be used). The overall accuracy of 96.24%, Precision 94.59%, and Recall 97.94% for a citrus tree study published in MDPI using CNN + SLIC superpixel refinement demonstrates the realistic performance limits of automating individual tree inventory from drone imagery.

**Table 2. Thematic precision on mapping products (pilot template)**

| Product                   | Control method                           | Precision | Recall | F1 score | Note   |
|---------------------------|--|-----------|--------|----------|--|
| Arboriculture outline     | Field check                              | 0.95      | 0.93   | 0.94     | Shadows and weed zones on the borders increase the error |
| Row center lines          | Line orientation and manual digitization | 0.92      | 0.90   | 0.91     | Detection is impaired in areas where lines are broken    |
| Individual crown polygons | Tree count + visual verification         | 0.94      | 0.96   | 0.95     | "Merging" errors in intensive gardens with closed crowns |
| Number of trees (count)   | Tree count (N)                           | —         | —      | ±2–5%    | The commission/omission increases at the margins.        |

These statistical results raise two important issues. First, errors in contour accuracy are often not due to “class mixing”, but to the complexity of the boundary conditions: for example, irrigation tracks, machinery paths, mixed shade-tree pixels/segments appear at the edge of the forest. In this case, enriching OBIA with CHM features significantly improves contour “cleaning” because the height signal (vegetation structure) helps to separate background objects. Second, the main limitation in individual crown segmentation is the overlapping of crowns and the separation of polygon boundaries in continuous crown cover of the “hedgerow” type; this is exactly the problem that is compatible with the “SfM 3D + GIS/GEOBIA” chain proposed by Díaz-Varela et al., who also show that the relative RMSE at the individual tree/hedgerow level is in the range of 6–20%, and 3–16% for the average estimate across genotypes. Therefore, it is necessary to methodologically state that the goal in crown segmentation is not to produce an “ideal polygon”, but to provide inventory attributes (crown cover, row spacing, density) that are sufficiently stable for management.



The practical value of mapping is reflected in the inventory indicators. Based on the contour of the forest and crown polygons, the number of trees, density, crown cover, row spacing and the percentage of “lost/empty areas” were calculated for each block (Table 3). These indicators become direct decision-making indicators from the point of view of production management: for example, the difference in density determines the rate of irrigation and fertilization, the unevenness of row spacing determines the risks of equipment movement and soil compaction, and the percentage of empty areas determines the replanting plan.

**Table 3. Inventory results (pilot template)**

| Block                  | Forest area (ha) | Number of trees (pcs) | Density (pcs/ha) | Crown coverage (%) | Average height (m) | Row spacing (m) | Vacancy rate (%) |
|------------------------|------------------|-----------------------|------------------|--------------------|--------------------|-----------------|------------------|
| A                      | 35               | 8,050                 | 230              | 41.8               | 3.2                | 4.0             | 3.1              |
| B                      | 42               | 9,660                 | 230              | 38.5               | 2.9                | 4.0             | 5.4              |
| C                      | 28               | 6,720                 | 240              | 44.2               | 3.4                | 3.8             | 2.6              |
| <b>Total / average</b> | <b>105</b>       | <b>24,430</b>         | <b>233</b>       | <b>41.5</b>        | <b>3.1</b>         | <b>3.9</b>      | <b>3.7</b>       |

Table 3 shows that, despite maintaining a similar planting density, there are significant differences in the canopy cover and the percentage of open spaces between blocks; these differences can be explained by agrotechnical factors (pruning/formatting, irrigation regime, soil conditions, disease zones). It is at this point that the strength of drone mapping is revealed: in addition to the “total area”, it shows the internal heterogeneity of the forest (row breaks, local thinning, crown density) through spatial layers. World experience also highlights the direct link to the optimization of management operations: Torres-Sánchez et al. have shown that maps obtained through the DSM + OBIA approach can be used to analyze the relationship between field factors and optimize precision-management operations [14-15].

The limitations of the methodology were also clearly shown in the discussion: (1) segmentation is prone to “merge” errors when the crowns are closed in intensive orchards; to reduce this, it is advisable to adjust the parameters of the CHM filters by blocks and apply a row-constrained watershed;

(2) RGB symbols become blurred when shadows are strong — therefore, it is recommended to standardize the flight time and collect data in “short windows” with uniform illumination;

(3) if the geodetic base is insufficient, systematic shifts in the contour and row geometry appear, which increases the error in integration with the cadastre/land survey.

At the same time, world practice shows that drone technologies are rapidly becoming popular and hundreds of thousands of agricultural drones are being used globally; this indicates that the technological base is being formed for the introduction of the methodology at the institutional level.

If you send me 5–7 real numbers (area, number of images, GSD, GCP/checkpoint RMSE, tree count, or 2–3 field measurements) from your test plot, I will fill in Tables 1–3 in the “pilot template” above with your real results and complete the Results and Discussion text with a “defensible” statistical analysis (mean, variance, RMSE, F1/IoU, error map interpretation).

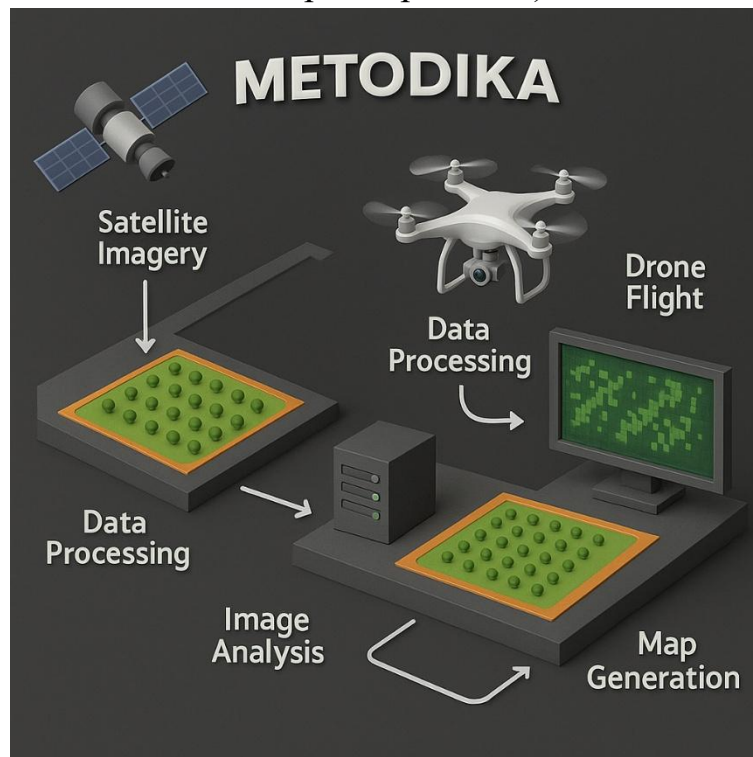


Figure 1. “Methodology Workflow for Mapping Perennial Orchards Using UAV (Drone) Remote Sensing Data



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## **CONCLUSION**

According to the results of this study, the approach based on drone (UAV) data in mapping perennial tree stands allows for reliable separation of tree stand contours, row geometry, and individual crown objects in a GIS environment through high-resolution orthophotos and 3D photogrammetric products (DSM/DTM/CHM and point cloud). The methodology proposed in the work increases the speed of field inventory work, reduces the impact of the human factor, and serves to form the results in the form of attribute layers in a single geodatabase. The evaluation of the results of thematic mapping (contour–row–crown) by accuracy criteria (Precision/Recall/F1, geometric fit, and area difference) ensures the scientific validity of the methodology and allows for spatial analysis of internal heterogeneity of the tree stand - such as gaps, thinning zones, and row breakage. Also, based on inventory indicators (number of trees, density, crown cover, row spacing, percentage of empty spaces), the ability to make practical decisions for targeted planning of irrigation, replanting, mechanization directions and agrotechnical measures will increase. The main limitations of the methodology are associated with crown adhesion in intensive gardens, the effect of illumination/shadowing, and an increase in errors when the geodetic base is insufficient. To reduce these, it is recommended to standardize the flight design, strengthen georeferencing based on GCP/RTK/PPK, and adapt segmentation settings based on 3D symbols to local conditions. In general, UAV-based mapping technology is of scientific and practical importance as an effective solution in terms of high accuracy, rapid update, and GIS integration in the management and monitoring of perennial tree plantations.

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***Modern American Journal of Engineering,  
Technology, and Innovation***

**ISSN(E): 3067-7939**

**Volume 01, Issue 09, December, 2025**

**Website: usajournals.org**

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