Unsupervised tree species classification with UAV ultra-high resolution multispectral imaging

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Abstract

This paper aims to evaluate the performance of ISODATA clustering for tree species classification using ultra-high-resolution multispectral data collected with Unmanned Aerial Vehicle. The study focuses on two sites in Żednia forest district near the city of Bialystok, northeastern Poland. The input data consist of 10-band multispectral orthomosaics with a resolution of 10 cm, acquired from an UAV platform equipped with a MicaSense RedEdge-MX dual camera and image-based Canopy Height Model. The classifications were conducted at two levels of forest detail: forest types, including two classes (broadleaf and conifer), and tree species, comprising four classes in Study Area 1 and ten species in Study Area 2. Multiple classifications were generated, testing different input parameters such as the number of clusters and various combinations of input data. For the first level of classification (forest type), overall accuracies range from 84,09% to 97,57% in Study Area 1 and from 82,31% to 92,74% in Study Area 2. At the second level of classification (tree species), overall accuracies vary from 70.73% to 91.77% in Study Area 1 and from 36,51% to 72,33% in Study Area 2. Overall, ISODATA demonstrates robust performance in classifying forest types in both study areas. However, performance in classifying tree species varies across different classes, with relatively high accuracies observed for certain species such as spruce, pine, oak, larch, and birch. The results underscore the potential of multispectral UAV data and unsupervised classification methods for accurately classifying tree species.

1. Introduction

Forests play a crucial role in various ecological processes, consequently, accurate tree species information is indispensable for effective forest management (Xu et al., 2020; Liu,2023; Yel & Gormus, 2023). From biodiversity modelling to monitoring forest disturbance sand biomass estimation, tree species data finds applications in a wide array of fields (Grabska et al., 2020). Furthermore, there is a growing interest in tree-level approaches within the real area-wide forest inventory (Briechle et al., 2021). However, traditional forest inventory methods are often expensive, time-consuming, and limited in spatial coverage (Hościło & Lewandowska, 2019). In contrast, remote sensing data offers a promising solution, providing an efficient and cost-effective means of inventorying forest resources and mapping tree species (Sothe et al.,2019). Specifically, airborne multispectral imagery has emerged as a powerful tool for tree species classification (Abdollahnejad & Panagiotidis, 2020; Xu et al., 2020; Briechle et al.,2021; Mäyrä et al., 2021; Sivanandam & Lucieer, 2022; Liu, 2023). Innovative and versatile mobile platforms, such as unmanned aerial vehicles (UAVs) equipped with lidar sensors and multispectral or hyperspectral sensors, facilitate the capture of high- and ultra-high-resolution data from an airborne perspective, thereby avoiding traditional remote sensing issues, including cloud cover (Sothe et al., 2019; Briechle et al., 2021). As well, the integration of newly developed multispectral sensors with UAVs presents an opportunity to improve both geometric and spectral resolution, while reducing costs and time associated with data acquisition process (Sothe et al., 2019; Abdollahnejad & Panagiotidis, 2020; Xu et al., 2020).

In the last decades, the advancements in measurement techniques brought significant increase in computational power of mobile devices that have changed the traditional forest inventory methods and approaches (Mokroš et al., 2021). Recent developments in remote sensing technology, particularly in multispectral imaging sensors, have significantly improved the accuracy and ease of detecting tree species (Yel & Gormus, 2023). Table 1 presents a compilation of common approaches found in recent literature using multispectral data for tree species mapping and classification.

Among all new measurement techniques, the Unmanned Aerial System (UAS) serves as a versatile platform, operating at low altitudes to acquire ultra-high spatial resolution data, thereby offering a solution for enhanced forestry inventory tasks, including tree species classification (Xu et al., 2020). At the same time, UAS is inherently limited in terms of the area that can be covered single platform. To use UAS for large-area mapping, covering thousands of square kilometers through coordinated, autonomous missions, and the integration of multiple platforms must be utilised.

UAV-based data acquisition offers numerous advantages compared to satellite and airborne methods. These include the ability to collect data regardless of cloud cover, the flexibility to acquire data at desired spatial and temporal resolutions while minimizing costs, and the capability to capture high-resolution images. Moreover, UAVs are not reliant on airports or satellite availability in the target area. However, UAVs also have limitations, such as limited payload capacity, short flight durations, and susceptibility to windy conditions, among others (Sothe et al., 2019). Recently, small multispectral and hyperspectral cameras on-board unmanned aerial vehicles (UAVs) have been widely applied to forestry inventories and tree species classification (Sothe et al., 2019; Briechle et al., 2021; Sivanandam & Lucieer, 2022). Table 1 presents a summary of selected features of several studies using UAV ultra-high resolution multispectral images to classify tree species.

Despite all advancements in data acquisition, the challenges in extracting relevant information from all these data persist. Efficient and robust supervised learning approaches have been developed and enhanced in the last decades (Nasteski, 2017; Yel & Gormus, 2023). New strategies, such as deep learning, have achieved outstanding results in computer vision tasks such as image segmentation and classification (Briechle et al., 2021). However, the reliance on vast amounts of labelled training data and the high complexity of machine learning models present barriers to their implementation for many real-world applications (Schmarje et al., 2021).

Paper	Tree species	Sensor	Input Variables*	Resolution [cm]	Classifier	Accuracy [%]
Gini et al. (2014)	Tree of Heaven, Horn-beam, Elm, Black Locust	Pentax Optio A40 Sigma DP1 with Foveon X3	R, G, B, NIR, NDVI, GR, IHS	5	ISO-DATA	50,1
					Max. Likeli -hood	79,1
Franklin (2018)	Cedar, Pine, Spruce, Sugar, Maple, Red, Maple, Aspen, Ash, Birch, Bass-wood	Tetracam Mini Cam MCA6Son y DSC-WX220, Parrot Sequoia NIR	R, G, B, NIR, TV	3 - 12	ISO-DATA	50,5
					Max. Likeli hood	61,3
					Rand. Forest	80,0
Abdollahnejad & Panagiotidis (2020)	Broadleave s, Norway Spruce, Scots Pine	MicaSense RedEdge-M	R, G, B, NIR, RE, TV, VI	5	SVM	81,2
Briechle et al. (2021)	Scots Pine, Silver Birch, Black Alder	MicaSense RedEdge, Yellow-Scan Mapper I	R, G, B, NIR, RE, point cloud	10	CNN	96,1
Sivanandam & Lucieer (2022)	Acacia, Allocasuari na, Callitris, Eucalyp. pulchella,E ucalyp. viminalis	MicaSense RedEdge-MX	R, G, B, NIR, RE, VI, TV	5	Rand. Forest	84,0
Liu (2023)	32 typical tree species of Luoyan, China	RedEdge-MX	R, G, B, NIR, RE, DSM, TV, TC, HSV, PCA, MNF, VI	15	Max. Likeli hood	87,6
					Rand. Forest	87,9

*) Input Variables key: R – red; G – green; B – Blue; RE – Red-Edge, NIR – near infrared; NDVI – Normalized Difference Vegetation Index; GR – green ratio; HIS – Intensity; Hue, Saturation; TV – texture variables; VI –vegetation indexes; DSM – Digital Surface Model; TC – Tasselled caps; HSV – Hue, Saturation and Value; PCA – Principal Component Analysis; MNF – Minimum Noise Fractions.

Tab. 1. Summary of important features of several studies using UAV ultra-high resolution multispectral images to classify tree species

Unsupervised classification methods may offer a compelling solution for tree species classification and mapping, allowing for the automatic categorization of data without the need for a high number of labelled samples (Schäfer et al., 2016, Shahi et al., 2023). Compared to supervised models, unsupervised approaches present some advantages: they can be easily implemented and reproduced, they usually require less computational capacity, and they can be executed without ground truth data that are generally costly and difficult to obtain. However, there are also disadvantages, for example, it is well-known that very often unsupervised models provide lower accuracies than supervised models in image classification tasks (Rozenstein &Karnieli, 2011; Franklin, 2018).

Among unsupervised methods, Iterative Self-Organizing Data Analysis – ISODATA (Ball & Hall, 1965) stands out as a widely used and well-known clustering algorithm of unsupervised classification (Irvin et al., 1997; Theodoridis & Koutroumbas, 2009; Shahi et al., 2023). Its straightforward and machine-based approach, minimizing human intervention, makes it an attractive choice for many research endeavours (Lemenkova, 2021). ISODATA has demonstrated its utility in tree species classification as well (Franklin, 2018).

In this context, this study aims to apply and evaluate the performance of ISODATA clustering for tree species classification using ultra-high resolution multispectral data acquired by airborne mobile mapping platform. The objective of this study also includes:

- to explore various parameters for ISODATA classification, such as different input image dates, data combinations, and number of clusters, to achieve an optimal configuration.
- to assess the inherent potential of the UAV ultra-high resolution multispectral data itself, without introducing secondary variables or utilizing highly intricate models.
- to compare the outcomes of ISODATA unsupervised classification with those of supervised classification, aiming to gauge the proximity or disparity between results.
- to elucidate the strengths, weaknesses and potentials of employing unsupervised models for tree species classification.

The experiments conducted in this study aimed to examine the following research questions:

- is ISODATA unsupervised classification, when applied to UAV multispectral ultrahigh-resolution imagery, a straightforward, viable, and effective method for tree species classification with satisfactory accuracy?
- to what extent is the performance of ISODATA in this context compared to that of more complex supervised models?

2. Methodology and materials

2.1 Methodology of the experiment

The methodology involved several steps: first, tree crowns were delineated using canopy height model analysis, and the resulting polygons were used to mask the orthomosaics to focus only on pixels within tree crowns. The ISODATA clustering algorithm was then applied to identify similar spectral groups, with ground truth data and visual interpretation used to label the clusters into tree species classes. Accuracy metrics like precision, recall, F1 score and OA (overall accuracy) were calculated based on a validation dataset introduced in section 2.3.

The ISODATA clustering was executed using the Iso Cluster Unsupervised Classification tool within ArcGIS Pro 3.1. Initially, the classification input comprised the 10-band dataset masked by tree polygons. Furthermore, various combinations of multiple dates and the Conopy Height Model (CHM) were experimented with as additional inputs. The ISODATA algorithm, implemented in ArcGIS Pro for unsupervised classification, requires several parameters, including the number of clusters, the minimum class size, and the sample interval. Numerous cluster numbers were evaluated, and the detailed results will be presented subsequently.

The methodology is shown in Figure 1. In the research, many classifications were generated, in which the polygons of tree stands were assigned to clusters, and then to collections of specified tree species. Various input parameters were tested, such as the number of clusters and different combinations of inputs.

The classifications in experiments were carried out at two levels of forest detail:

- forest types, considering two classes: 1) Broadleaf and 2) Conifer
- tree species, considering four classes in Study Area 1: 1) SO – pine, 2) SW – spruce, 3) DB – oak, 4) BRZ – birch; and ten classes in Study Area 2: 1) SO – pine, 2) SW – spruce, 3) DB – oak, 4) BRZ – birch, 5) OL – alder, 6) GB – hornbeam, 7) KL – maple, 8) MD – larch, 9) LP – linden, 10) JS – ash.

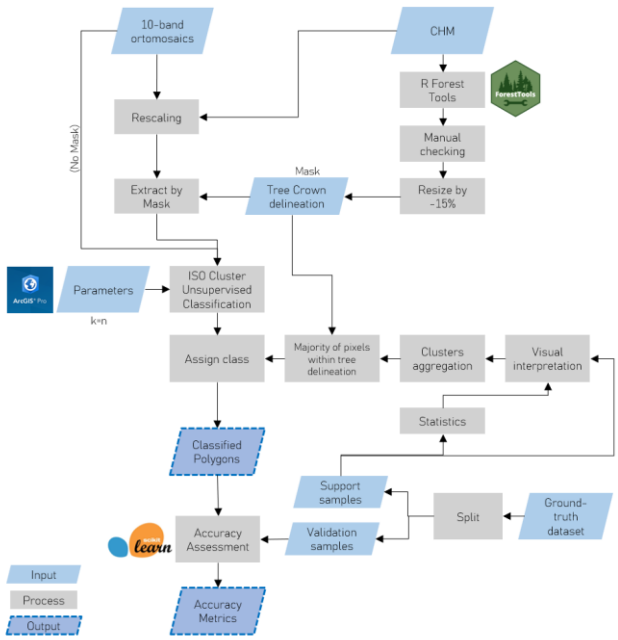

Fig. 1. Workflow of the experiment

2.2 Test studies

The forest site used in this study is located in the Żednia Forest District, near the city of Białystok (approximately 15 km away), in the Podlaskie voivodeship, northeastern Poland (Figure 2). Two experimental sites were established: Study Area 1, with dimensions of 930 x 180 m and an area of 0.169 km², and Study Area 2, with dimensions of 1108 x 1325 m and an area of 1.46 km². Geographically, Study Area 1 central coordinates are 23°23'44" E 53°8'47" N, and Study Site 2 area is 23°25'4"E 53°8'48"N.

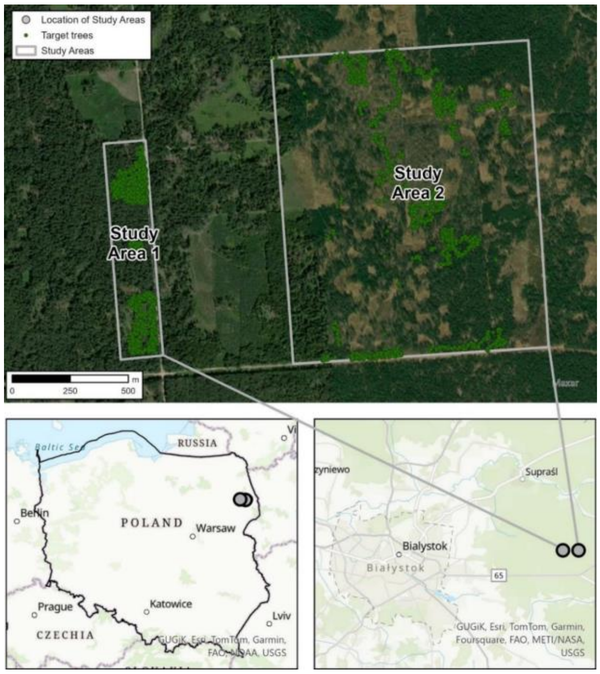

Fig. 2. Location of study areas.

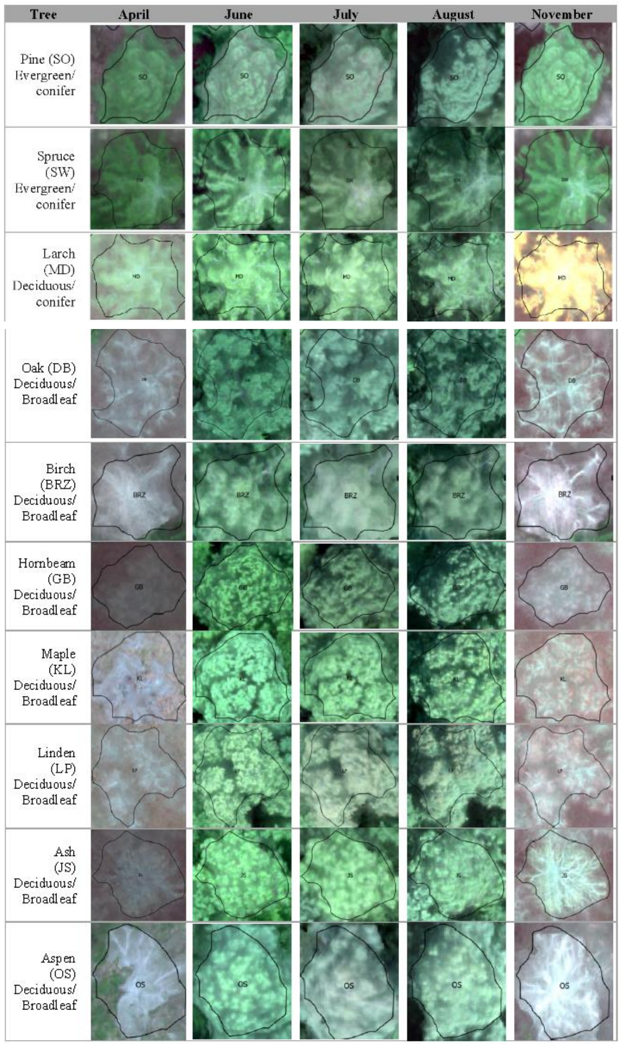

Fig. 3. Example of tree species images visible in images obtained from different dates.

2.3 Analysed and reference datasets

The measurement data are 10-channel multispectral orthomosaics with a spatial resolution of 10 cm, obtained from images from the UAV platform equipped with the MicaSenseRedEdge-MX Dual Camera and from a digital surface model of the tree crowns generated based on an image-matching technique. The images from the UAV were taken on one day, in similar weather conditions, from a height of 100 m above ground level using the DJI Matrice 300 UAV platform in flight at a speed of 7 m/s, delivering images from a GSD of 6 cm with 80% overlap. The spectral lengths of the images used are: Coastal blue 444(28), Blue 475(32), Green 531(14), Green 560(27), Red 650(16), Red 668(14), Red Edge 705(10), Red Edge 717(12), Red Edge 740(18), Near-IR 842(57). Data were obtained for area one in April, November 2022, April, July, September 2023, and for area two in August, November 2022 and April and July 2023. The example of zoomed data is presented in Figure 3. The reference data shown in Figure 4 constituted field measurement data and interpretation results, which in turn were used to designate clusters in tree species classes.

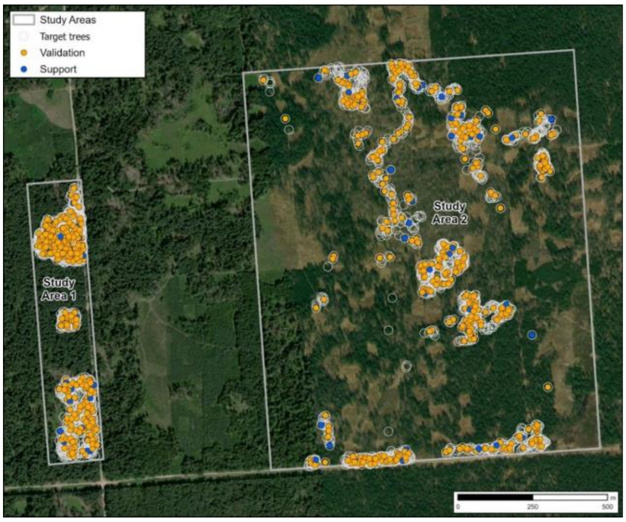

Fig. 4. Reference data for classification including locations and species of trees measured in-situ

3. Results

The first classification level, focusing on forest type, demonstrated satisfactory outcomes, with overall accuracies ranging from 84,09% to 97,57% in Study Area 1 (Tab. 2) and from 82,31% to 92,74% in Study Area 2 (Tab. 3) across all experiments, showing the results referred to different data collection, selected number of classes. These results suggest a strong performance in categorizing forest types across both study areas. Notably, the classification based on the July 2023 (classification 5) orthomosaic achieved the highest accuracy of 97,57% in Study Area 1. The metrics revealed a high level of accuracy in classifying coniferous trees, with precision, recall, and F1-score surpassing 0,980. However, the classification performance for broadleaf trees is less consistent, with an F1-score value of 0,810. In Study Area 2, the most accurate classification was derived from the November 2023 orthomosaic (classification 1), achieving an overall accuracy of 92,74%. In this area, the accuracy metrics for the broadleaf class surpassed those for the conifer class. For the broadleaf class, the precision, recall, and F1-score were 0,920, 0,976, and 0,948, respectively. Conversely, for the conifer class, metrics values were 0,945, 0,828, and 0,882 for precision, recall, and F1-score, respectively.

Cl.	Input data	Date	Clusters	OA [%]	F1-score	
					Conifer	Broadleaf
01	10-band	Apr’23	4	84,09	0,911	0,257
02	10-band	Apr’23	10	96,65	0,982	0,718
03	10-band	Apr’23	20	96,97	0,984	0,772
04	10-band	Nov’22	20	90,88	0,951	0,348
05	10-band	Jul’23	20	97,57	0,987	0,809

Tab. 2. Results of ISODATA forest type classification in Study Area 1

Cl.	Input data	Date	Clusters	OA [%]	F1-score	
					Conifer	Broadleaf
01	10-band	Nov’22	10	92,74	0,882	0,947
02	10-band	Jul’23	10	82,31	0,761	0,860
03	10-band	Apr’23	10	89,79	0,823	0,928
04	10-band	Jul’23	20	86,84	0,788	0,905
05	10-band	Nov’22	20	92,52	0,879	0,946
06	10-band	Apr’23	20	90,93	0,846	0,936

Tab. 3. Results of ISODATA forest type classification in Study Area 2

For the second level of classification, focusing on tree species, the overall accuracies ranged from 70,73% to 91,77% in Study Area 1 (Tab. 4). In Study Area 1, the optimal result was achieved in classification 14 (Fig. 5), utilizing a combination of orthomosaics from April and July 2023 as input. Classification 14 stood out not only for its high overall accuracy of 91,46% but also for superior precision, recall, and F1-score for individual classes. Particularly, class SO exhibited a robust performance F1-score of 0,955. Class SW also demonstrated good performance, with an F1-score of 0,899, albeit slightly lower compared to Class SO. On the other hand, Classes DB and BRZ displayed relatively lower overall performance compared to the other classes, possibly due to their limited representation in the test site, with occurrences of 4% and 3% among all target trees, respectively.

Cl.	Input data	Date	Clusters	OA [%]
01	10-band	Apr’22	12	86,47
02	10-band	Apr’22	40	88,71
03	10-band	Apr’22	60	91,46
04	10-band	Apr’23	20	86,59
05	10-band	Apr’23	40	87,81
06	10-band	Jul’23	12	70,73
07	10-band	Jul’23	24	89,63
08	10-band	Jul’23	36	89,64
09	10-band	Jul’23	40	91,77
10	10-band	Jul’23	60	91,77
11	10-band	Sept’23	40	90,24
12	10-band	Nov’22	40	86,58
13	10-band	Apr’23+Jul’23	40	91,77
14	10-band	Apr’23+Jul’23	60	91,46
15	10-band	Nov’22+Apr’23+Jul’23+Sept’23	40	82,01
16	10-band	Nov’22+Apr’23+Jul’23+Sept’23	60	86,28
17	10-band + CHM	Jul’23	40	76,21

Tab. 4. Results of ISODATA tree species classification in Study Area 1

The most favourable outcome achieved in Classification 14, distinguished not only by its high overall accuracy of 91,46% but also by superior precision, recall, and F1-score for individual classes. Figure 6 presents the corresponding confusion matrix and Table 5 shows classification report, providing a comprehensive view of the classification performance.

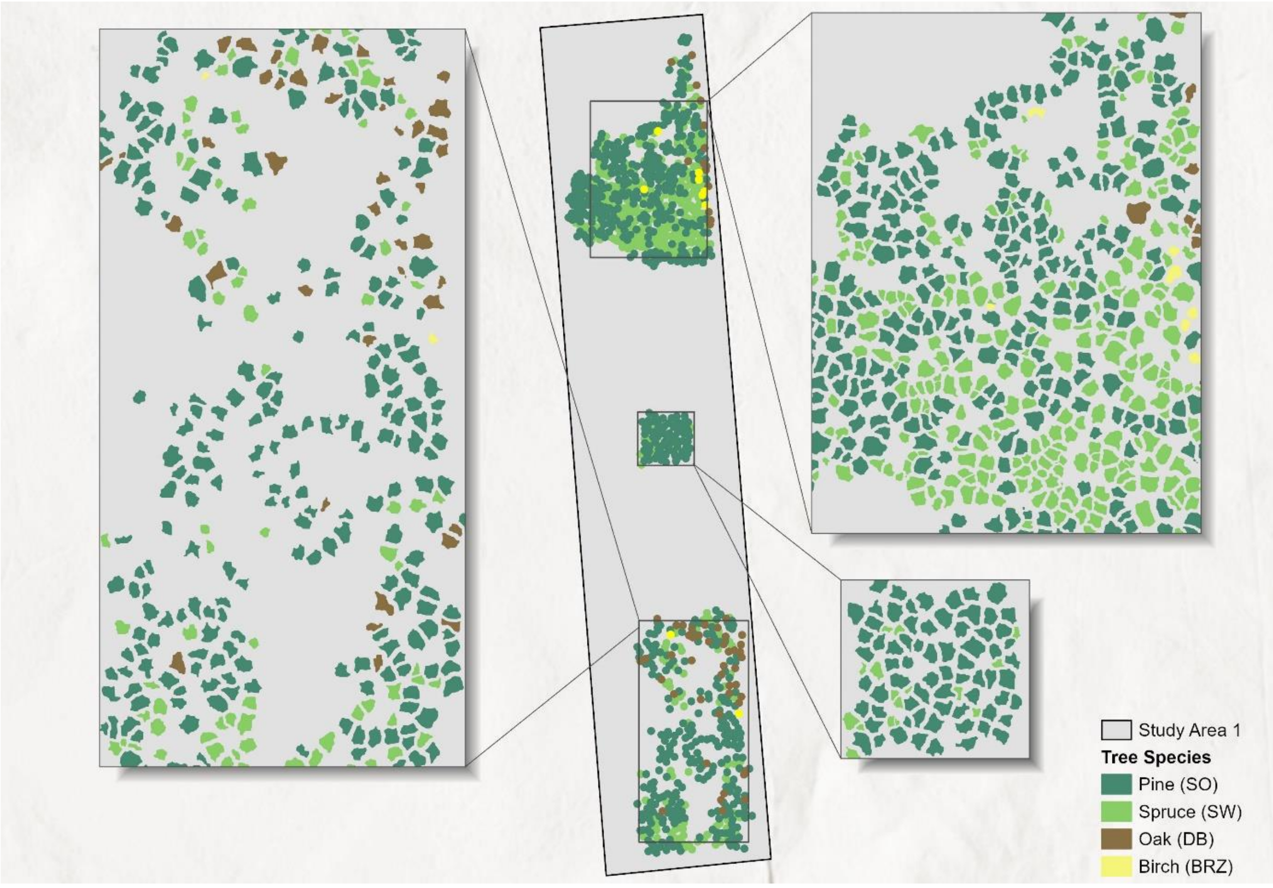

Fig. 5. Visualization of example ISODATA classification results of tree species in Study Area 1

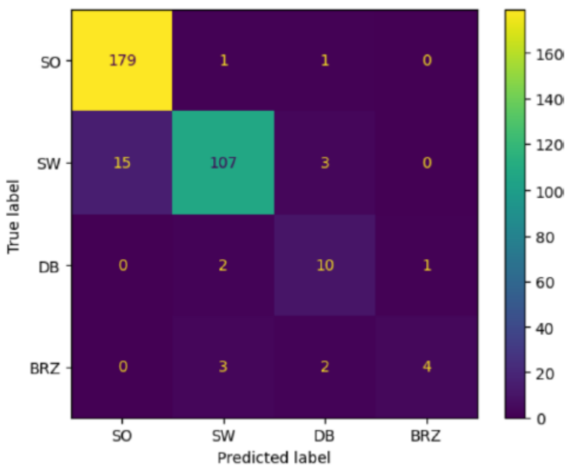

Fig. 6. Confusion matrix of the classification 14 in Study Area 1

Cl.	Precision	Recall	F1-score	Support
SO	0,923	0,989	0,955	181
SW	0,947	0,856	0,899	125
DB	0,625	0,769	0,690	13
BRZ	0,800	0,444	0,571	9
Accuracy			0,915	328

Tab. 5. Detailed results of the classification 14 in Study Area 1

In the second level of classification, focusing on tree species for the Study Area 2, the overall accuracies ranged from 36,51% to 72,33% in Study Area 2 (Tab. 6). Despite numerous tests, the highest accuracy achieved for tree species classification was 72,33% (classification 08) (Fig. 7). While the overall accuracy of 72,33% indicates reasonably good performance, a closer examination of precision, recall, and F1-score for individual classes reveals variations in performance across different species. Classes SO, DB, and MD demonstrated F1-scores of 0,860, 0,796, and 0,787, respectively, suggesting that the classifier performs well in identifying these species. Conversely, certain classes presented low F1-Scores, such as 0,080 for LP, 0,154 for JS, and 0,381 for OS, indicating challenges in accurately classifying these species, possibly due to their lower occurrence within the dataset.

Cl.	Input data	Date	Clusters	OA [%]
01	10-band	Nov’22	40	63,73
02	10-band	Nov’22	60	62,81
03	10-band	Apr’23	40	53,62
04	10-band	Jul’23	40	64,17
05	10-band	Nov’22+Jul’23	40	59,86
06	10-band	Nov’22	80	64,85
07	10-band	Nov’22	100	65,30
08	10-band	Jul’23	100	72,33
09	10-band	Jul’23	120	70,52
10	10-band	Aug’22	100	36,51
11	10-band + CHM	Jul’23	100	66,17
12	10-band	Nov’22+Apr’23+Jul’23Nov’22	100	70,98

Tab. 6. Results of ISODATA tree species classification in Study Area 2

Figure 8 presents its confusion matrix and Table 5 shows classification report, providing a comprehensive view of the classification performance.

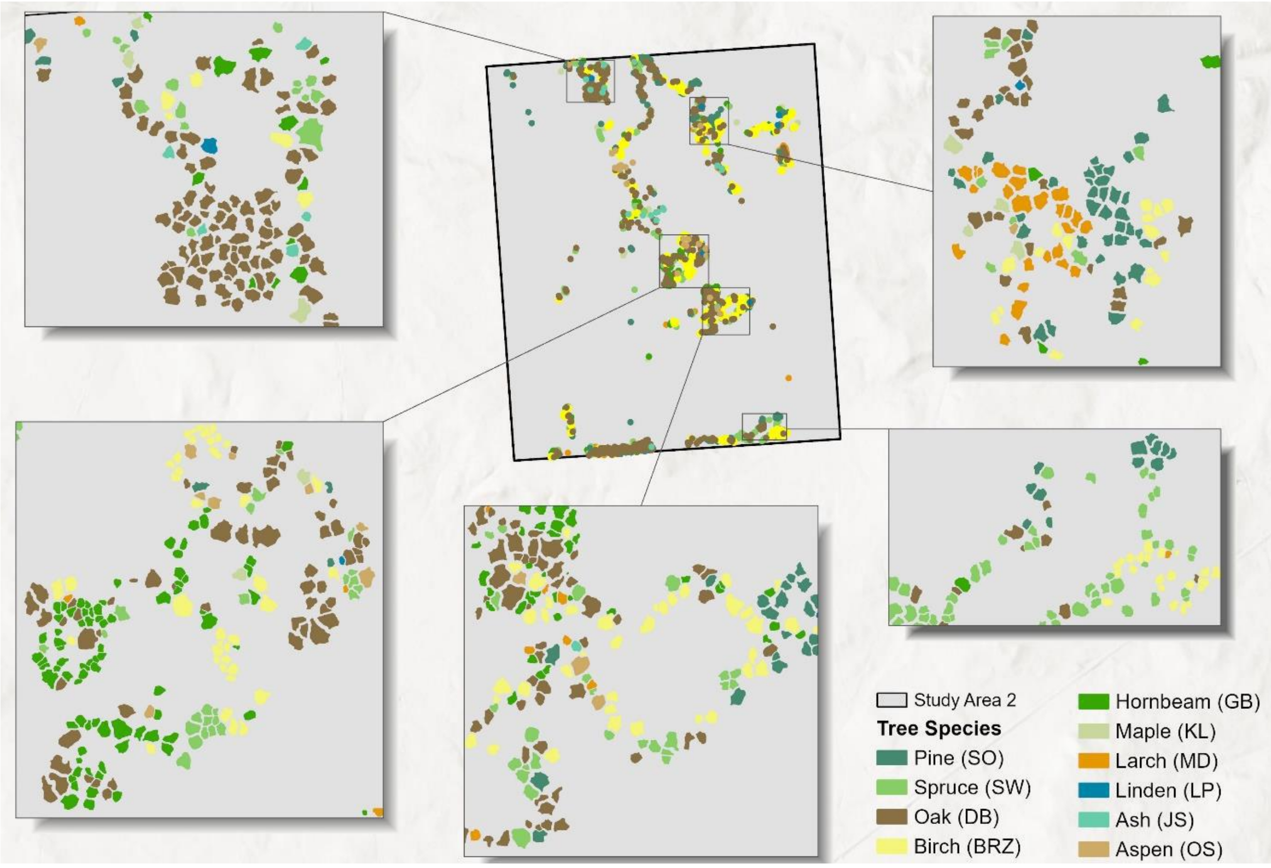

Fig. 7. Visualization of example ISODATA classification results of tree species in Study Area 2

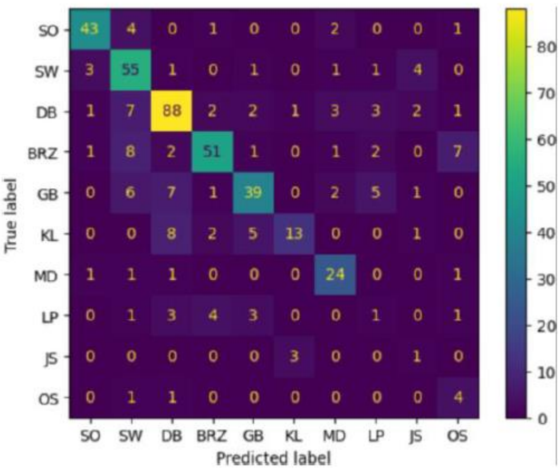

Fig. 6. Confusion matrix of the classification 08 in Study Area 2

Cl.	Precision	Recall	F1-score	Support
SO	0,878	0,843	0,860	51
SW	0,663	0,833	0,738	66
DB	0,793	0,800	0,796	110
BRZ	0,836	0,699	0,761	73
GB	0,765	0,639	0,696	61
KL	0,765	0,448	0,565	29
MD	0,727	0,857	0,787	28
LP	0,083	0,077	0,080	13
JS	0,111	0,250	0,154	4
OS	0,267	0,667	0,381	6
Accuracy			0,723	441

Tab. 5. Detailed results of the classification 08 in Study Area 2

3.1 Comparison to supervised methods results

The results of the unsupervised classification were compared with the results of the supervised classification of Random Trees, and Support Vector Machine classifiers in both study areas (Figure 9). The F1 and OA coefficients were used in the assessment of the classification.

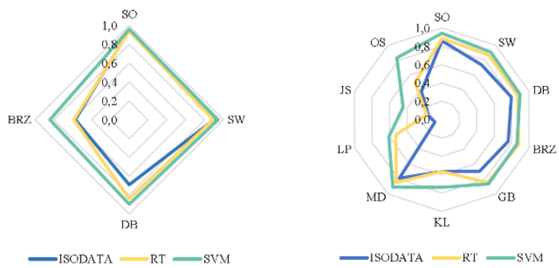

Fig. 9. Comparative analysis of tree species F1-scores across various classifiers in Study Areas 1 and 2

In Study Area 1, across all classifications, SO and SW classes consistently demonstrate high F1-scores, indicating robust classification performance for this species regardless of the algorithm employed. Notably, the SVM classifier achieves the highest F1-scores for all classes, indicating its effectiveness in accurately classifying various tree species. DB appeared to be the most challenging class to classify, with lower F1-scores across all classifiers, indicating difficulties in distinguishing this species from others based on the available features, as previously discussed.

Comparing ISODATA, an unsupervised clustering algorithm, with supervised algorithms like RT and SVM that benefit from labelled training data, its performance in this Study Area 1, as indicated by the F1-scores, is commendable. Unsupervised algorithms like ISODATA rely solely on the intrinsic structure of the data without the use of labelled samples. And despite this inherent limitation, ISODATA demonstrates competitive performance, especially for classes such as SW and SO, which have presented high F1-scores, outperforming RT results. In Study Area 2, ISODATA shows varying performance across different classes, with relatively high scores for SO, DB, MD, and BRZ, while achieving lower scores for LP, JS, and OS. RT demonstrates consistent and generally high performance across all classes, with particularly strong F1-scores for SO, DB, and BRZ, while also demonstrating lower performance for JS and OS. SVM exhibits outstanding performance for most classes, achieving the highest F1-scores among the three classifiers.

The results from Study Area 2 generally exhibit lower accuracies compared to those from Study Area 1. This trend is evident across both supervised and unsupervised algorithms and proves a general statement that classification of coniferous is less demanding. It is worth noting that ISODATA demonstrated also competitive performance, particularly for classes such as SO, DB, and MD.

4. Discussion

Several studies have demonstrated that UAV images captured by modern multispectral sensors are a suitable tool for tree species recognition at tree-level, offering high fidelity in their results (Abdollahnejad & Panagiotidis, 2020; Liu, 2023). Sivanandam & Lucieer (2022) used UAV multispectral images from MicaSense RedEdge-MX and Random Forest (RF) classifier for tree detection and species classification in Australia, achieving an accuracy of 84,0% within all tree species and 93,0% within Eucalyptus species. Such a high result is attributed to the detection of a single tree species. Another example of good results was achieved by Briechle et al. (2021) in which a new approach is proposed for classifying tree species and standing dead trees based on Convolutional Neural Networks (CNN). In this approach, airborne lidar data and multispectral images were combined, providing an accuracy of 91,5%. Abdollahnejad & Panagiotidis (2020) performed tree species classification and tree health assessment using ultrahigh resolution 5-band UAS bi-temporal aerial imagery acquired by MicaSense in the Czech Republic, using Support Vector Machine (SVM) classifier. The overall accuracy was 81,18%. All the studies mentioned above utilized UAV ultra-high resolution multispectral images as input for supervised learning models for tree species classification, achieving impressive accuracies. This raises the question: what level of accuracy can be achieved using a well-known, less intricate, readily implementable method such as unsupervised clustering, particularly when applied to novel multispectral ultra-high-resolution data?

Franklin (2018) in a study on multispectral classification utilizing pixel-based and object-based approaches for nine coniferous and deciduous tree species in a forest situated in central Ontario, Canada. The tree species examined included cedar, pine, spruce, sugar maple, red maple, aspen, ash, birch, and basswood. Franklin (2018) implemented three classification models being two pixel-based models, ISODATA unsupervised clustering and maximum-likelihood supervised statistical classifier, and one object-based model, Random Forest machine learning classifier. The best overall accuracies in each classifier were 50,5% for ISODATA, 61,3% for Maximum Likelihood, and 80,0% for OBIA Random Forest, all obtained using a combination of RGB and NIR multispectral data, texture, and shape variables. ISODATA accuracies varied from 45% to 50%. The results were not as good as those obtained in the experiment shown in this paper. In general, the classification of conifer trees had better performance than deciduous trees, which was also noticed in our experiment.

5. Conclusion

Throughout all experiments, it is possible to observe that the tree species with larger occurrences were better distinguished by ISODATA in both study areas, indicating that the algorithm tends to form clusters that are larger and more representative of the majority classes in the dataset. As a result, the majority classes may receive a more accurate representation in the clustering results compared to minority classes. It became evident that the selection of input data, particularly orthomosaics, and their acquisition dates had a significant influence on classification accuracy. Overall, the most favourable outcomes were attained using orthomosaics acquired during the summer months of June and July. Additionally, orthomosaics captured in April and November also yielded good results, particularly aiding in the distinction between broadleaf and conifer species. August orthomosaic produced the lowest accuracy among all experiments, potentially attributed not only to seasonal variations but also to other factors such as imaging quality. Experiments combining data from multiple dates showed promising results, achieving accuracy comparable to or even higher than some tests using single-date data. This suggests that integrating information from different time points may enhance classification accuracy by capturing complementary aspects of tree species variation, especially when including leaf-in and leaf-off images.

To sum up, the method's great potential for unsupervised classification of ultra-high-resolution multispectral data from UAVs was confirmed by the results, which demonstrated the effectiveness of the approach based on UAV images and the ISODATA algorithm for classifying tree species. Better results were obtained for the dominant species in unsupervised classification. The algorithm is more effective at recognizing species that are more abundant, resulting in larger and more representative clusters for dominant classes. In the analysis of the impact of the data acquisition date, the highest accuracy was achieved for orthomosaics from June and July, and good results were also achieved for April and November (easier differentiation between deciduous and coniferous trees). Advantages of combining data from different dates: Combining images from different dates improves classification accuracy by capturing seasonal changes in tree cover.

Looking at cluster count vs. accuracy: a larger number of clusters increased accuracy to a certain level (e.g., from 70.7% to 91.8% with an increase from 12 to 40 clusters), but once this threshold was exceeded, accuracy did not increase, which can also be observed for lower resolution data for which unsupervised classification techniques were studied.

Future research can compare results with other supervised classification approaches and modern deep-learning-based classification approaches to better contextualize the reported accuracies and highlight the strengths and limitations of the ISODATA algorithm. The further research is also needed to assess the transferability of the proposed approach to other forest environments, as this would enhance the robustness of the methodology and improve its practical applicability across diverse ecological conditions.

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