The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-M-7-2025
44th EARSeL Symposium, 26–29 May 2025, Prague, Czech Republic

Advancing the Monitoring of Traditional Meadow Orchards: Current Approaches and Future Directions

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Keywords: Cultural landscapes, meadow orchards, remote sensing, UAV-imaging.

Abstract

Meadow orchards represent critical components of European cultural landscapes and biodiversity, yet face significant threats from land-use intensification and management abandonment. Current studies show that the number of meadow orchards in Baden-Württemberg; Germany has declined sharply in recent decades and that existing trees are inadequately maintained. In this context, the aim of this study is to present an integrated remote sensing approach to monitor the ecological condition and management intensity of these cultural landscapes. Using high-resolution unmanned aerial system (UAS) imagery, we identified and assessed around 5,000 fruit trees in our study area near Bad Schönborn, Germany. Metrics such as canopy structure and spectral information such as NDVI were extracted, indicating high vitality (99%) but low maintenance (only 28% well maintained). Tree species classification accuracies ranged from 56% to 85%. The approach also emphasises stakeholder engagement and capacity building, embedding digital geo-information tools in community-based conservation. By combining UAS data with satellite imagery, the workflow is likely to be scalable across Baden-Württemberg to enable cost-effective, large-scale monitoring. Our findings highlight the role of advanced geospatial methods in meadow orchard conservation, bridging ecological knowledge with actionable landscape management.

1. Introduction

Central European cultural landscapes have been continuously altered by human activities for thousands of years, shaped by different economic and social systems (Job and Knies, 2001). Over time, many of these extensively used landscapes – such as alpine meadows, planter forests or meadow orchards – have evolved into ecologically valuable habitats, providing a wide range of niches for flora and fauna.

Traditional meadow orchards, comprised of extensively cultivated fruit trees and meadows, are among the most biodiverse of these cultural landscapes, providing a habitat for more than 5,000 plant and animal species (Zehnder, 2020).
These ecosystems provide numerous ecosystem services, including soil and groundwater conservation through the lack of pesticide use. Furthermore, they serve as recreational and tourism areas, contributing to the economic and social value of the local region (Heiland, 2017; Tengberg et al., 2012).

Despite their ecological and socio-cultural value, traditional orchards have been subject to massive transformations in the last decades, driven by institutional, technological and economic changes (Gömann and Weingarten, 2018). Many traditional orchard areas were cleared during the second half of the 20th century, due to low economic profitability and agricultural modernization. The remaining meadow orchards increasingly compete with expanding settlement areas and intensively used agricultural land (Zehnder, 2020).

One of the largest remaining traditional orchard areas in Europe is found in Germany, covering about 250,000 to 300,000 hectares, with approximately 40% of them located in Baden-Württemberg. Here, an estimated 7.1 million trees are still standing (Borngraeber et al., 2020). Yet even in this region, meadow orchard vitality and maintenance conditions are declining. Trees are dying without being replaced, insufficient meadow maintenance leads to bush encroachment, and mistletoe infestations are often ignored. These dynamics lead to a general loss of habitat quality (Henle et al., 2024).

These developments are further amplified by demographic changes: Many owners of meadow orchards are elderly or have moved to other regions. As a result, maintenance is neglected, particularly given the lack of economic incentives (Bürckmann et al., 2022). Climate change, invasive species, and emerging diseases demand more intensive care, yet the number of people able or willing to provide it is declining (Henle et al., 2024; Zehnder, 2020).

Although conservation efforts have increased over the past 15 years (Borngraeber et al., 2020), they remain insufficient. Institutions such as NABU call for stronger political action, more training for caretakers, and integrated strategies to preserve these landscapes. Ultimately, the preservation of meadow orchards depends on socio-economic and political decisions, not solely on agricultural land use (Michlmayr-Gomenyuk, 2016).

Accurate, high-resolution data on the location, number, vitality and tree species composition of meadow orchards is essential for targeted conservation and landscape planning. While Baden-Württemberg maintains a dataset on tree numbers within meadow orchards, the last larger survey was conducted in 2018 (Borngraeber et al., 2020) and lacks information on species, vitality or maintenance conditions

Remote sensing technologies, particularly those involving unmanned aerial systems (UAS), offer significant potential for improving the monitoring and management of traditional orchards. UAS-derived data can meet the high spatial and temporal resolution required for single-tree detection and vitality assessments (Pleșoianu et al., 2020). RGB and multispectral imagery can support object-based image classification to distinguish between fruit trees and other species, assess vitality and infer maintenance status. These approaches are already widely used in forestry and precision agriculture (Eltner et al. 2022; Shen et al., 2019).

Combining UAS imagery with existing geodata enables a comprehensive analysis of meadow orchard conditions, tree structure, and landscape dynamics. This approach also allows for the evaluation of potential replanting areas and supports adaptive landscape management strategies in light of climate change (Davis et al., 2020; Plieninger et al., 2015).

Thus, the objective of this study was to establish a robust and cost-efficient UAS-based workflow to assess and monitor tree species composition, tree vitality and care needs of individual trees on meadow orchards. By developing such a monitoring concept, reliable and detailed information on the state of meadow orchards in Baden-Württemberg can be gained.

2. Study Area and Methods

2.1 Study Area

For establishing the workflow, a pilot study was conducted in the municipality of Bad Schönborn, which is located in the Kraichgau region of Baden-Württemberg, Germany. The study area covers approximately 500 hectares within the cadastral districts of Bad Mingolsheim and Bad Langenbrücken. The region is distinguished by a mild climate with minimal ground frost and an extended growing season of around 240 days. The annual precipitation range is from 750 to 850 mm (Weber et al., 2022).

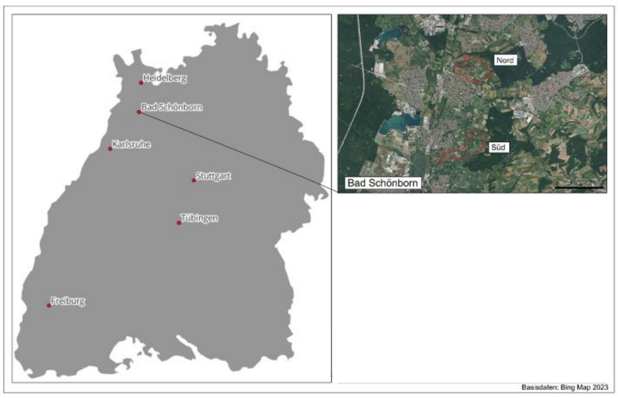

Figure 1: Study area Bad Schönborn in the North of Baden-Württemberg, Germany

The region's soil composition is predominantly characterised by decalcified, loess-covered sediments. These conditions provide a favourable environment for traditional orchard cultivation (Weber et al., 2022). which remains a prominent land-use form in this part of the Kraichgau. The highest concentrations of meadow orchards are found in the north-eastern part of Bad Mingolsheim and the south-eastern part of Bad Langenbrücken, where they often appear alongside vineyards. The municipality of Bad Schönborn is of particular significance for the preservation of orchard landscapes due to its favourable climatic and geological setting.

2.2 Methods

In order to monitor and evaluate the meadow orchards within the study area, a combination of UAS- and satellite-based remote sensing was used. Additionally, field data was collected for training and validation.

2.2.1 UAV-based Data Acquisition: In the municipality of Bad Schönborn, a total of 20 representative sites were monitored throughout 2019 and 2020, with four flight missions per year. The acquisition followed a multi-phase flight campaign that was timed to match the phenological development stages of the meadow-orchard tree species (Figure 2). The selection of plots was guided by diversity in species composition, tree density, and management status.

Figure 2: Images of the same patch of a meadow orchard taken at different dates in 2019.

UAS equipped with optical and multispectral sensors were used to capture high-resolution aerial images of selected test sites. The routes were arranged in overlapping parallel strips to ensure stereoscopic coverage, with typical longitudinal and lateral overlaps of 90% and 70% respectively. Flight altitude was adjusted to the local terrain. The total amount of raw data collected was approximately 400 GB, comprising over 120,000 individual images.

For imagery in the visible spectrum, a *ZENMUSE X5S* camera was used, achieving a spatial resolution of 1.8 cm for the surface model (Orthomosaic, OM) and 3.6 cm for the digital elevation model (DEM). To capture reflectance in the RedEdge (~717 nm) and near-infrared (NIR, ~840 nm) wavelength ranges, a *MicaSense RedEdge 3* multispectral camera with a downwelling light sensor (DLS) was installed. However, the multispectral data quality was found insufficient due to calibration issues and spatial misalignments between sensors, and further use was discontinued.

Ground control points (GCPs) were established using high-precision GNSS measurements. These permanent, visually distinguishable markers enabled accurate spatial referencing and alignment of multi-temporal datasets. Through the integration of these GCPs, consistent and location-specific datasets were produced across various surface models, elevation models and spectral layers.

The image data were processed via Structure from Motion (SfM) methods using *Agisoft Metashape* to reconstruct three-dimensional surface structures and produce orthomosaics corrected for geometric distortions. This workflow allowed for detailed terrain modelling and surface analysis at single-tree-level.

https://doi.org/10.5194/isprs-archives-XLVIII-M-7-2025-133-2025

2.2.2 Satellite-Based Data Acquisition: To supplement the UAS data and to compensate the calibration issues encountered with the multispectral camera, satellite imagery from WorldView-3 (acquisition data: June 4th, 2019) was used. These data offer a panchromatic resolution of 31 cm and a multispectral resolution of 1.24 m, covering key spectral bands such as RedEdge (705–745 nm), Near-IR1 (770–895 nm), and Near-IR2 (860–1040 nm).

2.2.3 Field Data: To allow for automated classification and enable a reliable interpretation of the UAS-based data, comprehensive field data were collected. On several designated test sites, structural condition and vitality data were recorded for existing fruit trees. This reference dataset, gathered at different times between autumn 2020 and 2021 by various surveyors, encompassed a total of 1,352 individual trees across the selected areas. Each mapped tree was assigned a unique ID and characterized by key attributes, including species, vitality, and maintenance condition.

The vitality assessment employed a three-class system, adapted from (Weihs, 2017), to categorize tree health consistently. Class 1 ('vital') represented trees exhibiting good growth, a typical crown structure and leaf condition, minimal damage, and evidence of strong compensatory mechanisms. Class 2 ('ailing') denoted trees with noticeably reduced vigour, an increase in deadwood, or visible signs of damage or disease. Class 3 ('dying') included trees essentially lacking vitality indicators and showing no signs of compensatory growth. This classification scheme provided a repeatable framework, facilitating the reliable linkage of subjective field-assessed vitality with objectively derived data from the UAS imagery analysis.

2.2.4 Object Based Analysis: To detect and classify individual fruit trees within the study areas, object-based image analysis (OBIA) was applied using the software *eCognition 10.2.* as well as *ArcGIS Pro.* Unlike pixel-based approaches, OBIA analyses spatial data in the form of image objects that reflect contextual relationships within the landscape. High-resolution orthomosaics and digital elevation models derived from UAS imagery as described earlier in section 2.2.1 provide the necessary data basis, offering spatial resolutions in the sub-centimeter range and several centimeters, respectively.

Initially, the datasets were segmented using the normalized digital surface model (nDSM) to delineate potential objects like tree crowns as shown in Figure 3.

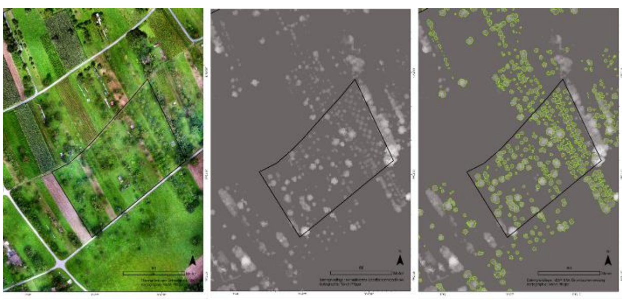

Figure 3: Example results for delineated objects: Information from the Orthomosaic (left) as well as the nDSM (middle) are used to delineate tree crowns (right) to identify single fruit trees

The resulting tree polygons formed the basis for subsequent object-based attribute extraction. Subsequently, geometric and spectral attributes were calculated for each segmented object (Table 1). Geometric parameters included height (applying a minimum threshold of two meters to exclude shrubs), area, perimeter, roundness, and compactness. Spectral characteristics encompassed the mean and standard deviation of RGB values, offering information on object reflectance properties. Additionally, texture measures were derived for each spectral band to further characterize the objects. Finally, vegetation indices, notably the NDVI (Normalized Difference Vegetation Index), were integrated to assess photosynthetic activity and general vitality. Table 1 provides an overview of the spectral and geometric attributes of the single polygons which have been extracted via *eCognition* and *ArcGIS*.

<table>
<tr><th colspan="2">Attribute</th><th>Description</th></tr>
<tr><td rowspan="8">Geometry</td><td>Height</td><td>Max. pixel value nDSM</td></tr>
<tr><td>Shape (pixels)</td><td>Perimeter</td></tr>
<tr><td>Shape (polygons)</td><td>Shape Length</td></tr>
<tr><td>Area (polygons)</td><td>Shape Area</td></tr>
<tr><td>Roundness</td><td>Radius (smallest ellipse) – Radius (largest ellipse)
[0,∞] ; 0 = ideal</td></tr>
<tr><td>Compactness</td><td>(Length*Width) / number of pixels
[0,∞] ; 1 = ideal</td></tr>
<tr><td>Mean nDSM</td><td>The average intensity of all the pixels within the object</td></tr>
<tr><td>σ nDSM</td><td>Dispersion around the arithmetic mean value for each object</td></tr>
<tr><td rowspan="11">Spectral Information</td><td>Brightness</td><td>Arithmetic mean of the combined pixel values for each band as implemented in eCognition</td></tr>
<tr><td>Max. Difference</td><td>Max. Difference</td></tr>
<tr><td>NDVI</td><td>$\frac{\mathrm{NIR}-\mathrm{R}}{\mathrm{NIR}+\mathrm{R}}$</td></tr>
<tr><td>Green NDVI</td><td>$\frac{\mathrm{NIR}-\mathrm{G}}{\mathrm{NIR}+\mathrm{G}}$</td></tr>
<tr><td>MTVI2[1]</td><td>$\frac{1.5*(1.2*(\mathrm{NIR}-\mathrm{G})-2.5*(\mathrm{R}-\mathrm{G}))}{\sqrt{(2*NIR+1)^2-\left(6*NIR-\sqrt[5]{R}\right)-0.5}}$</td></tr>
<tr><td>Mean blue</td><td rowspan="3">Average intensity of all the pixels within the object</td></tr>
<tr><td>Mean green</td></tr>
<tr><td>Mean red</td></tr>
<tr><td>σ blue</td><td rowspan="3">Dispersion around the arithmetic mean value for each object</td></tr>
<tr><td>σ green</td></tr>
<tr><td>σ red</td></tr>
</table>

Table 1: parameters extracted from the dataset and used in the classification

[1] MTVI2 as defined by ArcGIS

For evaluating tree species, vitality, and maintenance condition, ground-truth data were collected within selected test sites as explained in section 2.2.3. These reference data subsequently guided the development of a classification model utilizing the previously extracted object attributes. Several classification algorithms were then tested to determine the most effective approach. Following this comparison, the most suitable algorithm was selected and applied to the entire dataset of segmented tree objects (Figure 4).

As automated classification faced limitations, particularly with overlapping crowns and ambiguous spectral signals, a subsequent validation and correction process was necessary. This involved field verification to assess the accuracy of the classification results, including categories like 'fruit trees', 'other trees', and 'buildings'. Identified misclassifications were then manually corrected. This correction was particularly relevant in areas of dense vegetation where the automated algorithm had difficulty separating adjacent tree crowns distinctly.

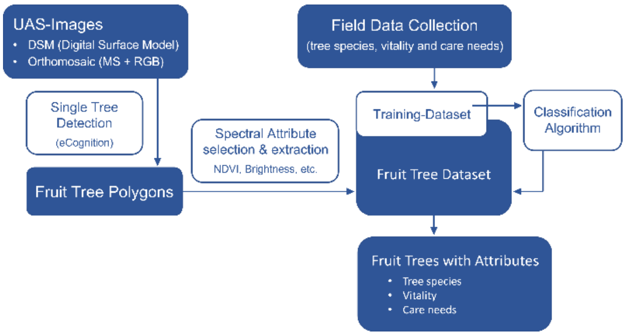

Figure 4: Workflow of the study starting with image collection, a single-tree detection and a subsequent object-based classification

3. Results

Applying the single tree detection approach across the study area resulted in the identification of approximately 5,000 potential fruit trees. Based on the model's classification of these detected trees, apple was the predominant species identified (68%), followed by pear (16%) and plum (7%). The assessment indicated high overall vitality across the detected trees, with 99% classified as vital. However, the maintenance status assessment revealed different results: only 19% of trees were classified as well-maintained without immediate care needs. A majority (53%) were assessed as requiring at least a low amount of care, while the remaining trees were identified as potentially needing urgent interventions (Figure *5*).

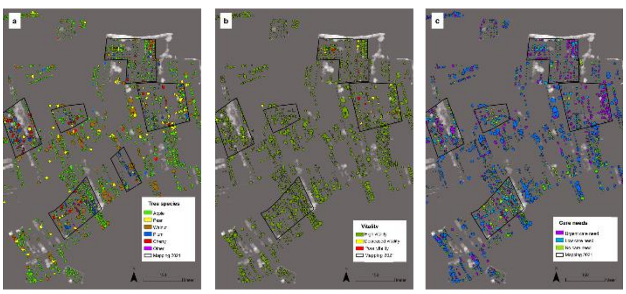

Figure 5: Results of the classification of a) tree species, b) vitality and c) care needs.

The Random Forest classifier yielded the best performance for tree species classification based on the tested algorithms. The classification models for 'tree species', 'vitality', and 'care need' were trained and validated using the reference dataset of 1,352 manually assessed trees. Comparison with this reference data showed an overall accuracy of 51.15% for species identification (Figure *6*), 88,97% for vitality assessment (Figure *7*), and 51,92% for the care-need classification (Figure *8*).

Further analysis of the species classification performance using a confusion matrix revealed variations between classes. For example, apple trees achieved a high Producer's Accuracy (recall) of 0.85, meaning most reference apple trees were correctly identified by the model. However, the User's Accuracy (precision) for apples was lower at 0.56, indicating that a considerable number of trees classified as apples belonged to other species in reality. Other species, such as cherry, showed considerably lower detection rates (e.g., Producer's Accuracy of 0.03).

		Survey									
		N.A.	apple	pear	walnut	plum	cherry	other	Sum (k)	Producer's Accuracy = $\frac{Classification}{Sum\ (a)}$ (error of exclusion)	User's Accuracy = $\frac{Classification}{Sum\ (k)}$ (errors of inclusion)
Classification	apple	6	522	124	62	149	61	16	**940**	0,85	0,56
	pear	3	40	89	11	23	8	1	**175**	0,36	0,51
	walnut	1	13	8	31	9	11	0	**73**	0,25	0,42
	plum	0	37	22	15	45	14	0	**133**	0,19	0,33
	cherry	0	5	6	7	8	3	0	**29**	0,03	0,10
	other	0	0	0	0	0	0	0	**0**	0	0
	Sum (a)	**10**	**617**	**249**	**126**	**234**	**97**	**16**	**1349**		

Figure 6: Confusion matrix for the classification of tree species. Classifier: Random Forest, Cross-validation, Folds: 10. Overall Accuracy: 51,15 % and Kappa coefficient: 0,23

For the prediction of the vitality by the Random Forest classifier, only class 'vital' was classified with a True Positive Rate of over 0.9 whereas the algorithm performed poorly in predicting the other classes. The Kappa coefficient indicates the quality of the algorithm, which can be considered low for values below 0.01. With such a dominant class within the training data, this is hardly surprising.

		Survey					
		vital	ailing	dying	Sum (k)	Producer's Accuracy = $\frac{Classification}{Sum\ (a)}$ (error of exclusion)	User's Accuracy = $\frac{Classification}{Sum\ (k)}$ (errors of inclusion)
Classification	vital	1201	115	28	1344	0,99	0,89
	ailing	6	1	0	7	0,009	0,14
	dying	0	0	0	0	0	0
	Sum (a)	1207	116	28	1351		

Figure 7: Confusion matrix for the classification of vitality. Classifier: Random Forest, Cross Validation, Folds: 10. Overall Accuracy: 88,97% and Kappa coefficient: 0,0044

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		Survey					
		Well maintained	Low demand	High demand	Sum (k)	Producer's Accuracy = $\frac{Classification}{Sum\ (a)}$ (error of exclusion)	User's Accuracy = $\frac{Classification}{Sum\ (k)}$ (errors of inclusion)
Classification	Well maintained	141	91	33	665	0,38	0,21
	Low demand	166	330	153	649	0,6	0,51
	High demand	61	130	244	626	0,57	0,39
	Sum (a)	368	551	430	1349		

Figure 8: Confusion matrix for the classification of care need. Classifier: Random Forest, Cross Validation, Folds: 10. Overall Accuracy: 51,92% and Kappa coefficient: 0,27

The Random Forest classification of tree care need, evaluated using 10-fold cross-validation, yielded limited predictive power, achieving an overall accuracy of 51.9% and a Kappa coefficient of 0.27, indicating only fair agreement. Analysis of the confusion matrix (Figure 8) revealed varying performance across the three categories ('Well maintained', 'Low demand', 'High demand').

The 'low demand' class performed best relatively, with the highest Producer's Accuracy (0.60) and User's Accuracy (0.51). Conversely, both the 'well maintained' (User's Accuracy: 0.21) and 'high demand' (User's Accuracy: 0.39) classes suffered from low precision, indicating that many trees predicted to be in these categories actually belonged elsewhere. Overall, the model demonstrated limited reliability in accurately classifying specific care needs based on the employed features.

4. Discussion

This pilot study aimed to extend the common practice of single tree detection via UAS data by including the assessment of tree species, vitality, and care need — the latter two being considered particularly complex (Fraser und Congalton, 2021; Johnstone et al., 2013). The results indicated no direct correlation between the assessed vitality and care-need parameters; trees classified with high vitality could still exhibit characteristics indicating an urgent need for care interventions. These discrepancies between vitality and care needs could stem from the different parameters which are relevant here. While vitality is primarily measured and assessed through spectral parameters such as the NDVI, care need might also depend more on structural parameters such as crown shape. Although the spectral information might be linked to the 3D-structure of the tree itself (Jurado et al., 2020), structural parameters such as tree height and diameter are still considered important sources for assessing stand condition and potential maintenance needs (Eltner et al., 2022).

However, given the overall low classification accuracies, several factors may have contributed to this outcome. The malfunction of the multispectral camera mounted on the UAS and the resulting use of WorldView-3 data likely introduced additional sources of error into the classification process.

The biggest issue is likely related to the training data and tree structure in the study area, resulting in a strong imbalance within the training dataset. This mainly affects both vitality and species representation. Specifically, the vitality assessment was compromised, as approximately 90% of the reference trees were labelled 'vital'. This strong skew likely biased the classifier towards the majority class, significantly limiting its utility for reliably identifying trees in 'ailing' or 'dying' states (Chabalala et al., 2023). The resulting Kappa coefficient of approximately 0.004 suggests performance no better than random chance for this specific task. Similarly, the dominance of apple trees in the training set (Figure *6*) restricts the model's generalizability. This overrepresentation is likely to produce overfitting to apple-specific features, potentially reducing classification accuracy for other fruit tree species and application in more heterogeneous orchard settings. These imbalances underscore the critical need for representative and balanced training datasets to develop robust ecological monitoring models, as skewed data can obscure underlying patterns.

Another issue is likely related to the difference between data acquisition and field data collection. Comparison of the field data for same trees from different years showed that the collected parameters can differ at different points in time. It cannot be ruled out that in the time between differing dates, trees had been maintained or changed in their status of vitality.

Adding to this, a decisive factor for the accuracy of the reference data is the subjectivity of the assessment of, e.g., maintenance requirements and especially vitality in the field. If, for example, the assessment of tree vitality is based on the length of new shoots, this can only be reliably evaluated if the same tree species is considered in a specific development phase at a similar location (Roloff, 2018). Even when assessing the proportion of deadwood, the subjectivity of the survey can strongly influence the classification (Johnstone et al., 2013; Tilly et al., 2020). An attempt was made to use an objective catalogue of criteria to estimate vitality using a set of parameters. However, significant inconsistency was observed between different surveyors, which led to reverting to a purely subjective assessment of vitality. This lack of uniformity, stemming from the involvement of different project staff and the absence of a single decisive factor for classifying a tree as 'dead', reduced comparability in the reference data on tree vitality. For instance, if the proportion of deadwood exceeded 75%, trees were sometimes classified as 'dead' and sometimes as 'ailing' if living parts showed signs of vitality, such as new shoot growth. Given these inconsistencies in human assessment, an algorithm is unlikely to achieve significantly better performance in predicting tree vitality.

Finally, the automatic tree detection process offers potential for further optimization, as indicated by necessary corrections identified in random verification samples. In some areas, trees were found during field verification that the detection algorithm did not recognize; the majority of these were very young trees. Several factors may explain these detection errors (Mohan et al., 2017). It is possible that some trees were planted after the UAS survey and therefore do not appear in the drone image. Furthermore, the automatic recognition relies on surface structure to identify taller objects, meaning the less distinct crown structure of very small trees may not always be clearly detected. It is also possible that tall ground vegetation, such as high grassland present at the time of the survey, obscured small trees, preventing their recognition as distinct objects. Comparative studies by (Borngraeber et al., 2020) report similar difficulties with tree detection and subsequent classification using such methods.

5. Conclusion

The aim of this pilot study was to develop a cost-effective UAS-based workflow for the assessment and monitoring of tree species, vitality and maintenance needs in traditional meadow orchards in Bad Schönborn, Germany. While a complete workflow from data acquisition to classification was established, the study encountered significant challenges that limited the reliability of the initial results. Key issues included technical problems with the multispectral sensor of the UAS, forcing the use of alternative satellite data, pronounced imbalances within the training dataset especially, in terms of vitality and species distribution, temporal mismatches between image acquisition and field surveys, as well as inherent subjectivity in the tree assessment leading to inconsistencies in the ground truth data. These factors led to low overall classification accuracies, particularly for tree species and care needs, and questionable performance in vitality assessment.

Despite these limitations encountered in the pilot phase, the results indicate that the designed UAS-based workflow has considerable potential as a valuable tool for meadow orchard assessment and conservation efforts. The lessons learnt from this study are already being incorporated into a follow-up project focusing on targeted improvements to the methodology.
These improvements include the use of a modern UAS with a reliable, high quality multispectral camera that provides more accurate data, synchronisation of field data collection with image acquisition to minimise temporal discrepancies, implementation of more sophisticated classification algorithms that are readily available, and a concentrated effort to create more balanced training datasets in terms of tree species and care need. These advancements are expected to address the primary limitations identified here, paving the way for a more robust and reliable UAS-based approach to support meadow orchard monitoring and management.

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