Synergistic Use of LiDAR and Hyperspectral Data in Vineyard Classification: A Case Study from the Tokaj Region, Slovakia

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Abstract: *Hyperspectral (HS) and LiDAR sensing provide complementary information for vineyard monitoring. HS imagery captures detailed spectral signals related to canopy physiology and biochemistry but is often affected by contamination from inter-row soil and weeds. LiDAR offers precise measurements of canopy structure yet lacks biochemical sensitivity. Their integration has the potential to overcome these limitations, and remotely piloted (unpiloted) aerial vehicles (UAVs) provide the flexible platform needed to collect both datasets at very high resolution over vineyards. In this study, UAV-based hyperspectral and laser scanning data were collected in the Slovak part of the Tokaj wine region to evaluate their combined potential for distinguishing vine from non-vine areas, producing dense point clouds with more than 600 points per square metre and hyperspectral imagery consisting of 172 bands at 0.1 m spatial resolution. Four datasets were prepared: hyperspectral imagery alone, hyperspectral imagery combined with canopy height, simulated natural colour imagery alone, and simulated natural colour imagery combined with canopy height. All datasets were transformed using principal component analysis, and the resulting features were classified with a supervised maximum likelihood classifier. Accuracy was evaluated using 1,000 field-validated reference points. The classification based only on the hyperspectral data reached 89% overall accuracy but performed poorly for vine detection, with a producer's accuracy of 48.9% and an F1-score of 0.61. When canopy height information was included, performance improved to 96% overall accuracy, a Kappa coefficient of 0.85, and an F1-score of 0.88. Simulated natural-colour imagery combined with canopy height achieved intermediate results, with 93% overall accuracy and an F1-score of 0.79. These findings confirm that integrating spectral and structural information enhances vineyard mapping and provides a reliable basis for precision viticulture applications.*

Keywords: *vineyard mapping, hyperspectral imaging, laser scanning, UAV, precision viticulture*

Introduction

For precision viticulture, high-resolution, timely information on vine presence and condition is essential for pruning, fertilization, irrigation, disease monitoring, and harvest planning. Remotely piloted (i.e. unpiloted) aerial platforms (UAV) equipped with dedicated remote sensing sensors allow flexible, sub-meter-scale data acquisition, enabling targeted management decisions in individual vineyard parcels (Matese et al. 2015, 2022, Sofia et al. 2025). Among UAV sensors, hyperspectral (HS) and airborne laser scanning (LiDAR) are highly complementary: HS captures contiguous spectral signatures sensitive to pigments, water content, and soil chemical properties, while LiDAR provides detailed three-dimensional structural information and terrain data, enabling the derivation of canopy height models (CHM) and related metrics (Chu et al. 2016, Matese et al. 2022, Sousa et al. 2022).

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Individually, each modality has limitations when applied in vineyards. HS classifications are often affected by inter-row background contamination (soil, weeds, residues), which biases vegetation metrics and class labels, whereas LiDAR lacks direct biochemical sensitivity. Previous vineyard research demonstrates that accurate separation of canopy from inter-rows is crucial, as leaf area index and other vegetation estimates tend to be overestimated in sparse or stressed vines (Kalisperakis et al. 2015). Combining structural and spectral information can mitigate these errors (Chu et al. 2016, Pádua et al. 2022).

These capabilities are particularly relevant in the Tokaj wine region ─ a transboundary viticultural landscape in Central Europe, shared by Hungary (≈58 km²) and Slovakia (≈9.29 km²). In Slovakia it lies in the southeast; in Hungary it occupies the northeastern Bodrog basin. The exceptional quality of Tokaj wines is attributed to soils formed on volcanic rocks and the favourable local climate shaped by the Zemplén Mountains (Hungary) and Zemplínske vrchy (Slovakia). The Hungarian part is inscribed as a UNESCO World Heritage cultural landscape, while the Slovak part is on the country's UNESCO Tentative List (UNESCO World Heritage Centre 2002). Tokaj is among the world's earliest legally delimited wine regions, formally established in the 18th century, underpinning its long viticultural tradition and international reputation for distinctive wines (Marcinčák et al. 2022). Microclimatic variation, slope-aspect differences, and heterogeneous vine vigour across parcels further highlight the value of fine-scale structural and spectral mapping for vineyard management and conservation, as shown in UAV-based studies where spatial variability in vine vigour influenced grape and wine composition (Romboli et al. 2017).

Multi-spectral and hyperspectral sensors on-board UAVs and satellites have been widely used in viticulture to estimate canopy architecture, leaf area index, and biochemical traits (Zarco-Tejada et al. 2005, Weiss and Baret 2017). In situ RGB, multispectral, and hyperspectral systems have further enabled detailed phenotyping, from predicting leaf area and fruit load to assessing NDVI and water stress (Diago et al. 2022). In Italian vineyards, Matese and Di Gennaro (2018) demonstrated the potential of a multisensor UAV platform carrying RGB (visible spectral range), multispectral, and thermal cameras simultaneously, enabling the assessment of vine vigor with normalized difference vegattion index, canopy water stress, and missing plant detection with high accuracy. This highlighted the multipurpose monitoring capabilities of UAV platforms for precision viticulture. At the leaf scale, spectral indices have been linked to plant water status or biotic stress (Tosin 2020), whereas recent computer vision approaches have been used to detect disease symptoms on leaves (Gangl et al. 2021). LiDAR sensing has also become an important tool for vineyard characterization, offering detailed 3D reconstructions of canopy structure that support estimates of light interception, photosynthesis, and evapotranspiration (Arnó et al. 2012, Jin et al. 2021). Across Europe, hyperspectral data have supported canopy detection, stress assessment, and yield modelling (Zarco-Tejada et al. 2005, Sofia et al. 2025). In Hungary, UAV-based multispectral sensing validated against field measurements proved effective for describing canopy vigour or disease mapping (Bálo et al. 2019, Székely et al. 2024). Yet, while hyperspectral and LiDAR methods are individually established in viticulture, their integrated use remains rare – unlike in urban vegetation, forests, or riparian zones, where such synergies enhance structural and spectral analysis (e.g., Prošek et al. 2020, Kim et al. 2025).

Despite the prominence of Tokaj and other vine-growing areas in Slovakia, vineyard remote-sensing studies remain sparse. Existing work has focused on object-based mapping of vineyard rows and utilization from airborne optical imagery in Modra (Karlík et al. 2017), UAV-based detection of row gaps in vineyards in Jelenec and Topoľčianky (Šupčík and Matečný 2021), and vine canopy morphology analysis from 3D UAV-derived point clouds for grape yield prediction (Šupčík et al. 2024). Broader surveys have examined precision-agriculture technology adoption without vineyard-specific analytics (Petrovič et al. 2024), and a state-of-the-art review highlighted weaker institutional support and adoption barriers for agricultural RS in Slovakia compared with Hungary (Pélissier et al. 2023). More recent applications emphasize multispectral satellite monitoring of arable crops (Košánová et al. 2025), with no published examples of UAV hyperspectral – LiDAR fusion for vineyards in the Slovak Tokaj region.

The first step toward applying UAV-based remote sensing in the Slovak Tokaj vineyards was taken within the cross-border TOKAJGIS project (INTERREG SKHU 2017), implemented Eszterházy Károly University in Eger and by Pavol Jozef Šafárik University in Košice This initiative developed a modular WebGIS platform for the Tokaj wine region, integrating UAV-derived multispectral imagery, orthophotos, and other geospatial datasets to support sustainable vineyard management, spatial planning, and cross-border collaboration (INTERREG SKHU 2019). Data collected within this project form the basis for the present study, in which we extend the scope from multispectral UAV mapping to HS–LiDAR integration for precision viticulture. The precision mapping of vine canopy structure and condition that HS–LiDAR fusion enables has strong potential to support sustainable vineyard management and preserve this unique cultural landscape.

This study aims to assess the potential of integrating UAV-based LiDAR-derived CHM with hyperspectral imagery for vine-versus-non-vine classification in the Slovak part of the Tokaj wine Region. We compare hyperspectral-only classifications with approaches that incorporate LiDAR-derived canopy structure and further evaluate a simplified scenario using simulated natural colour composites combined with CHM. To our knowledge, this is the first UAV-based study in the Tokaj region applying LiDAR–hyperspectral integration specifically for vineyard mapping. Building on earlier UAV sensing research in Central Europe (Gallay et al. 2016, Kaňuk et al. 2018, Gallay et al. 2023), the study demonstrates how multimodal UAV data can enhance precision viticulture in Slovakia.

Study area

The experimental site is situated in the Slovak part of the Tokaj wine-growing region, located in the southeastern part of Slovakia on the border with Hungary (fig. 1). The area of interest (AOI) lies between the villages of Malá Tŕňa and Bara (48.4403° N, 21.7038° E) on a south-facing slope, with elevations ranging from 174 to 179 m above sea level.

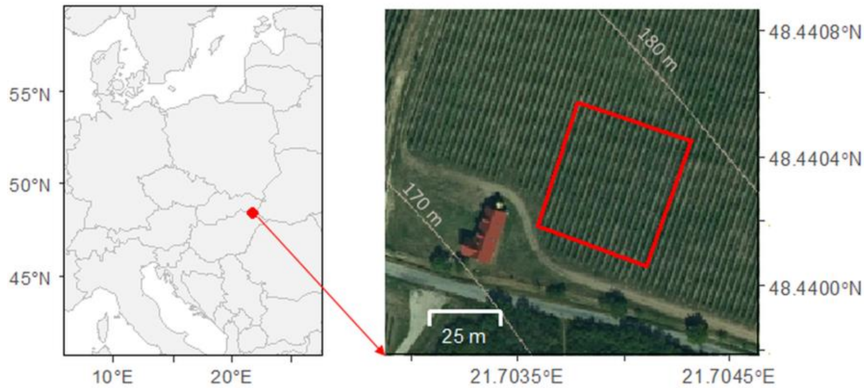

Fig. 1. *Location of the study area in the Slovak Tokaj region (left) and orthophoto of the vineyard site as marked by red rectangle; Source: orthophoto © Photomap 2018, the European basemap is derived from the "world" dataset in R (maps package, version 3.4.3)*

The geological bedrock consists mainly of Permian to Carboniferous conglomerates, sandstones, and shales, which form the substrate of the local soils. According to the official Slovak soil coding (BPEJ 0377265) in Džatko et al. (2009), the climate of the region is classified as warm, very dry, and lowland continental. The soils are predominantly Cambisols, characterized by shallow profiles with high skeletal content. The texture corresponds to medium-heavy soils with a tendency toward lighter fractions.

Methods and Data

Data collection

Data acquisition in the vineyard was conducted using the Scout B1-100 UAV, an autonomous helicopter platform developed by Aeroscout (fig. 2). The aircraft, with a 3.2 m rotor diameter and 100 ccm gasoline engine, supports payloads of up to 30 kg, offering long endurance (up to 90 minutes) and stability superior to multirotor systems (Gallay et al. 2016, Kaňuk et al. 2018). The mission was carried out on 3 July 2018 between 11:00 to 13:00 under favourable conditions: sunny skies and mild wind up to 2 m/s, which ensured smooth flight lines and consistent data quality. Two complementary payloads were employed to capture both structural and spectral characteristics of the vineyard canopy. Both payloads were tightly integrated with a dual-antenna GPS/IMU navigation system (OXTS xNAV550) and supported by a GPS reference station, enabling centimetre-level accuracy of the resulting datasets through differential post-processing. For three-dimensional vineyard structure mapping, the UAV was equipped with a RIEGL VUX-1 laser scanner. Lidar data collection was conducted at a 30 m altitude above ground with a forward speed of 5 m/s. Under these parameters, the laser operated at 550 kHz, producing point densities exceeding 600 points/m² with an average spacing of just 4 cm (fig. 3). To capture spectral properties of the vineyard canopy, the platform carried an AISA KESTREL 10 hyperspectral camera manufactured by SPECIM. The sensor provides fine sampling and high radiometric stability operating across the 400–1000 nm spectral range. Flights were carried out at a 100 m altitude above ground with a forward speed of 5 m/s, resulting in a ground sampling distance of ~0.1 m in 172 spectral bands of 3.5 nm width of each band. These data allow for the detection of subtle variations in leaf reflectance related to stress, growth stage, or nutrient status, offering a valuable complement to the structural LiDAR outputs.

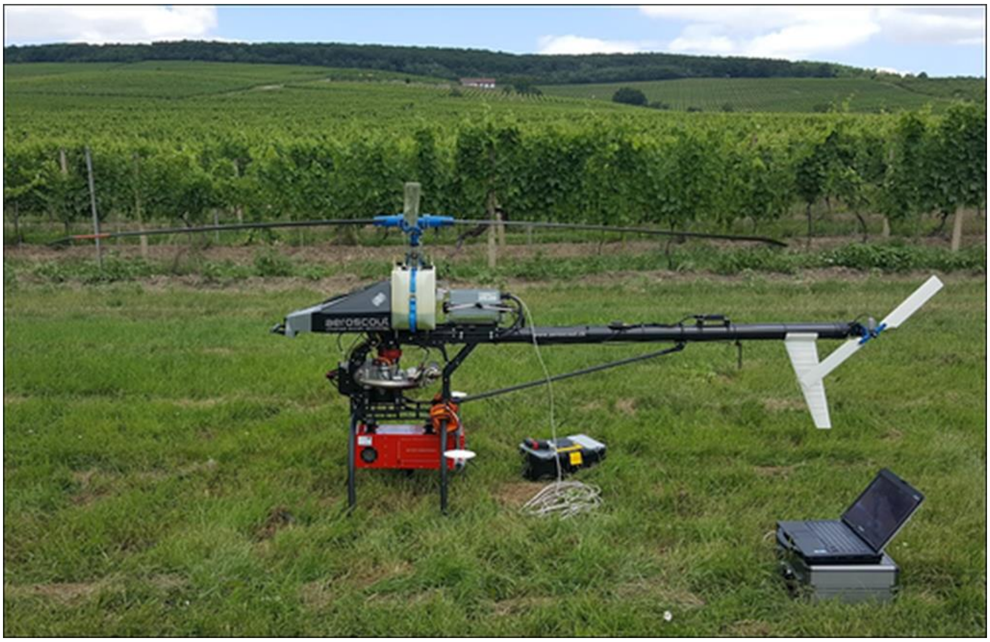

Fig. 2. *The Scout B1-100 remotely piloted helicopter powered by a gasoline two-stroke engine with the hyperspectral payload in the red box coupled with a dual GPS antenna during data download in the vineyard of "Hon Makovisko", Malá Tŕňa owned by Ostrožovič s.r.o.,*

The photo was taken on 3 July 2018.

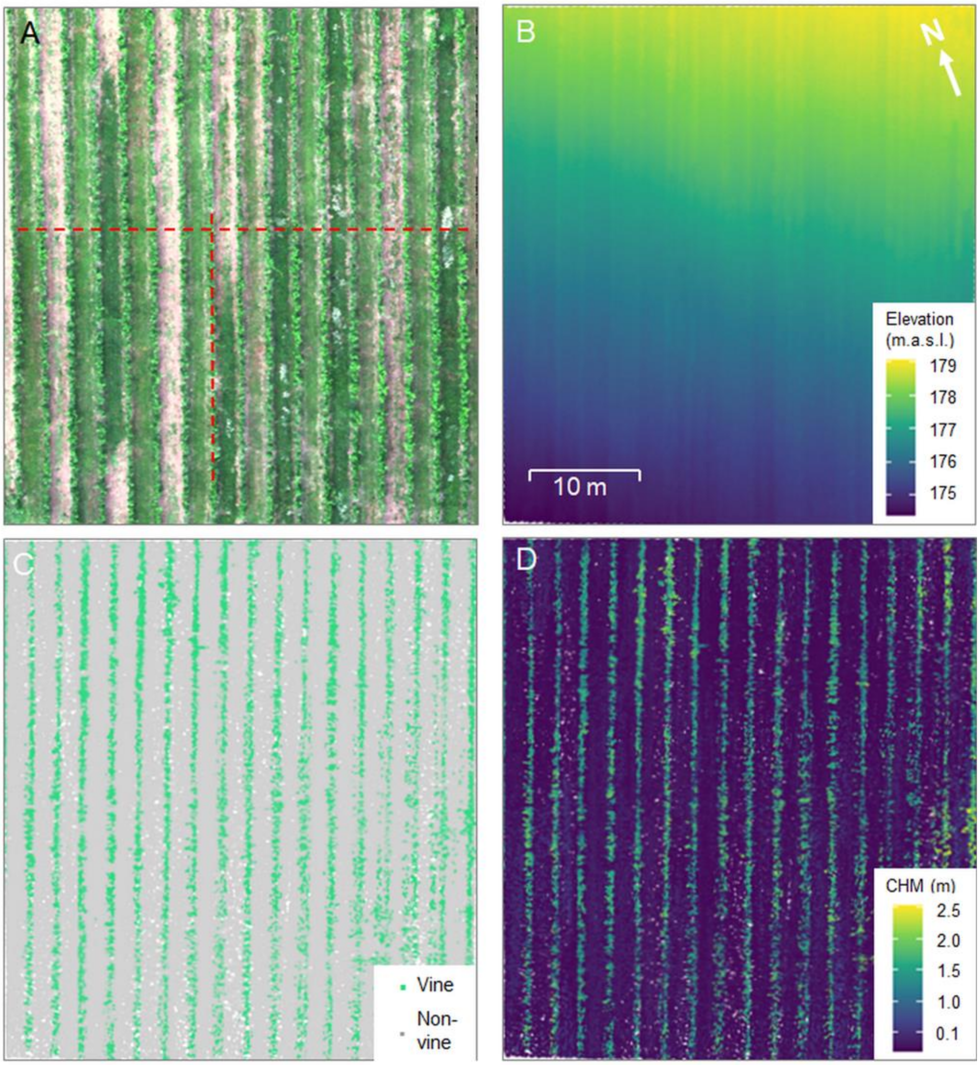

Fig. 3. *Visualization of multi-source remote sensing data of the vineyard study site:*
(A) Natural-colour composite from hyperspectral data with transect profiles indicated (fig. 4);
(B) digital terrain model (DTM) interpolated from ground-classified LiDAR points;
(C) classified LiDAR point cloud distinguishing vine points (green) from non-vine points (grey);
(D) Canopy height model (CHM) showing heights normalized with respect to the terrain elevation.

LIDAR data processing

The raw LiDAR data were first co-registered and georeferenced in RiPROCESS (RIEGL), which integrates laser returns with position and orientation data from the on-board GPS/IMU system (Gallay et al. 2016). The resulting point clouds were exported in LAZ format and subsequently processed in LAStools (version 220107, rapidlasso GmbH). Point clouds were quality-checked and processed as follows. First, obvious outliers were flagged using lasnoise (isolated returns) and excluded from subsequent steps. Ground points were then classified with lasground_new using fine settings suitable for vineyard micro-relief (row interspaces and wheel ruts), producing ASPRS class 2 (ground). Heights were normalized relative to the classified ground with lasheight, which writes each point's height above ground. To isolate vine foliage, we leveraged the known canopy height (~2 m) and classified returns in the 0.5–3.0 m band (above ground) as class 4 (medium vegetation) while ignoring ground (class 2) and prohibiting extrapolation into areas lacking ground support. This tagged the vine rows consistently while leaving non-vegetated structures unaltered. Raster products were generated at 0.20 m resolution. The DTM was interpolated from ground points (class 2), and the DSM from the highest returns after excluding ground. The CHM was computed from the normalized point cloud as the per-cell maximum height (i.e., the highest normalized return within each 0.20 m cell), which yields a pit-free canopy surface consistent with the approach of Khosravipour et al. (2014) for dense, row-structured vegetation such as vineyards. These layers (DTM, DSM, CHM) were used for subsequent canopy-structure analysis.

Hyperspectral data processing

The hyperspectral raw data were first pre-processed in CaliGeoPRO (SPECIM). During this stage, the raw digital numbers (DNs) were converted to at-sensor radiance using factory calibration coefficients, and the dark current effect was subtracted to remove sensor-related bias. Additional corrections included compensation for spectral smile and stray light, while noisy bands at both extremes of the spectral range were excluded. The images were georectified using the on-board GPS/IMU position and attitude data combined with sensor geometry information and resampled to a ground sampling distance of 0.10 m. Radiometric and atmospheric corrections were subsequently applied in ENVI 5.3 (NV5 Geospatial Software) using the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) module. The processing used a mid-latitude summer atmospheric model with rural aerosol type, and atmospheric visibility was set to 40 km according to local meteorological conditions. Water vapor retrieval was performed using the 940 nm absorption band, and sensor-specific parameters (band centers, spectral response functions, flight altitude) were provided to FLAASH. This step transformed radiance into surface reflectance, minimizing atmospheric absorption and scattering. The resulting reflectance cube with 10 cm spatial resolution formed the basis for classification experiments.

Data classification experiment

Four input datasets were prepared and analyzed in MultiSpec (version 2025.02.19; Biehl and Landgrebe 2025). In the first case, the full hyperspectral cube was imported into MultiSpec and its dimensionality was reduced using the program's principal component analysis (PCA) function. The first three components, which explained the highest proportion of variance, were retained and used for classification. To evaluate the effect of structural information, the PCA features were also combined with the LiDAR-derived CHM. In the second case, a simulated natural-colour composite was generated from the hyperspectral data by averaging the spectral bands corresponding to the visible blue (430–500 nm), green (520–600 nm), and red (630–690 nm) regions. This three-band RGB dataset was likewise transformed by PCA and analysed both directly and in combination with the CHM to assess the added value of canopy structure. This design resulted in four classification scenarios: (i) PCA-transformed hyperspectral data only, (ii) PCA-transformed hyperspectral data combined with the LiDAR-derived CHM, (iii) PCA-transformed simulated RGB composite only, and (iv) PCA-transformed simulated RGB composite combined with the LiDAR-derived CHM.

PCA was performed on each dataset using the covariance matrix. For hyperspectral inputs, the first three components were retained, explaining over 99% of the spectral variance (96–97% in PC1, 3–4% in PC2, <0.2% in PC3). For the simulated RGB and RGB+CHM datasets, PCA likewise reduced dimensionality while maintaining consistency of pre-processing.

Across all cases, the retained components captured at least 99.4% of the variance, providing a compact but representative feature set for classification. Although PCA was not strictly necessary for the 3-band RGB composite, it was applied to maintain methodological consistency across all datasets. This ensured that performance differences reflect the input data (RGB, HS, with or without CHM) rather than variations in the analytical procedure.

PCA was performed on the hyperspectral data (185 bands, 400–1000 nm) using the covariance matrix. For each scenario, the first three principal components were retained, which together explained 99.5% of the total spectral variance, and were used as input features for supervised maximum likelihood classification. To ensure comparability, the same PCA pre-processing was applied across all datasets, including the simulated RGB composites.

For all four scenarios, a supervised maximum likelihood classifier was applied. Where CHM was included, it was treated as an additional predictor variable alongside the spectral features. The classification scheme was restricted to two classes (vine rows and non-vine areas), reflecting the primary distinction relevant to vineyard monitoring.

Classification accuracy was evaluated using 1,000 independent reference points, of which 141 (14.1%) fell within vine rows and 859 (85.9%) within non-vine areas. This distribution closely reflected the areal proportions of the AOI (~16% vine). The 95% confidence interval for the sample proportion (11.9-16.3%) includes the AOI estimate, indicating that the reference set (141 points, i.e. 14.1%) reflects the actual class distribution. The points were randomly sampled from the natural-colour orthophoto generated from the hyperspectral composite and classified into vine and non-vine categories by visual interpretation. The labelling procedure was supported and validated by field observations. Performance was quantified using a confusion matrix, reporting user's and producer's accuracies (UA, PA), overall accuracy (OA), the Kappa coefficient (κ), and the F1 score for the vineyard class.

Results

Data processing produced a CHM from the LiDAR dataset and a hyperspectral reflectance cube from the HS imagery, providing complementary information on the vineyard structure and terrain conditions. Figure 3 illustrates the multi-source data products derived for the study site. The natural-colour composite generated from the hyperspectral cube (fig. 3A) offers detailed spatial context, with the positions of transect profiles indicated. The LiDAR data enabled the derivation of a high-resolution digital terrain model (fig. 3B) and classification of returns into vine and non-vine categories (fig. 3C), forming the basis for canopy structure analysis.

Transect profiles extracted from the LiDAR point cloud further illustrate the three-dimensional arrangement of vineyard vegetation (fig. 4). Cross-row and along-row sections reveal clear differentiation between vine canopy returns and ground or inter-row points. Vine points are concentrated in distinct row structures, while non-vine returns occupy the inter-row spaces.

The smoothed 99th-percentile profile of vine points provides a reliable approximation of the upper canopy envelope, highlighting variation in canopy height along and across the vineyard rows. Together, these visualizations demonstrate the capacity of UAV-based hyperspectral and LiDAR data to capture both spectral and structural characteristics of the vineyard, forming the foundation for subsequent classification experiments.

Building on these data products, the classification experiments assessed the ability of different input datasets to distinguish vine rows from non-vine areas. The first three principal components explained over 99% of the spectral variance in both hyperspectral scenarios, while in the RGB dataset all variance was necessarily captured by its three input bands. In the RGB+CHM dataset, which included three spectral bands and one structural variable, the first three components already accounted for essentially 100% of the variance, reflecting the limited dimensionality of the input data (tab. 1).

The classification accuracy varied depending on the spectral input and the inclusion of structural (geometric) information from the CHM. A summary of key metrics is provided in tab. 2. The best performance was obtained when the full hyperspectral cube was combined with the CHM (HS+CHM), reaching an overall accuracy (OA) of 96.0%, a Kappa coefficient of 0.85, a vineyard F1-score of 0.88, and the highest balanced accuracy (90.3%).

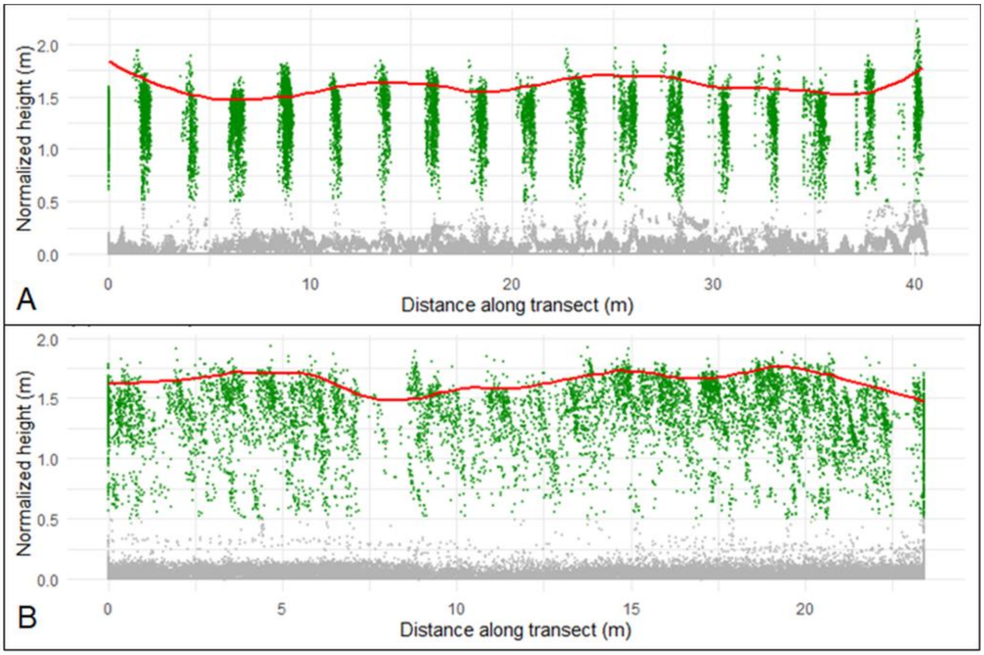

Fig. 4. *Transect profiles across vineyard rows (A) and along (B) a vineyard row showing LiDAR points height above ground. Grey points represent non-vine returns, and green points represent vine returns. The red line indicates the smoothed 99th-percentile of vine heights along the transect, approximating the upper canopy envelope. The position of the profiles is shown in fig. 3A.*

Tab. 1. *Variance explained by the first three principal components for each dataset.*

Dataset	PC1 (%)	PC2 (%)	PC3 (%)	Cumulative variance (%)
HS + CHM (185 bands)	96.35	3.02	0.10	99.47
HS only (184 bands)	95.82	3.45	0.11	99.38
RGB (3 bands)	93.11	5.72	1.18	100.00
RGB + CHM (4 bands)	96.48	3.31	0.21	100.00

Tab. 2. *Summary of accuracy assessment for vineyard classification using PCA and the maximum likelihood classifier with different input datasets*

Input dataset	OA (%)	Kappa	PA Vine (%)	PA Non-vine (%)	UA Vine (%)	UA Non-vine (%)	F1-score	BA (%)
HS + CHM	96.0	0.85	81.6	99.0	94.7	96.2	0.88	90.3
RGB + CHM	93.0	0.75	71.3	97.9	87.9	94.2	0.79	84.6
HS	89.0	0.55	48.9	97.6	81.0	90.1	0.61	73.2
RGB	89.0	0.60	58.6	95.9	75.0	91.7	0.66	77.3

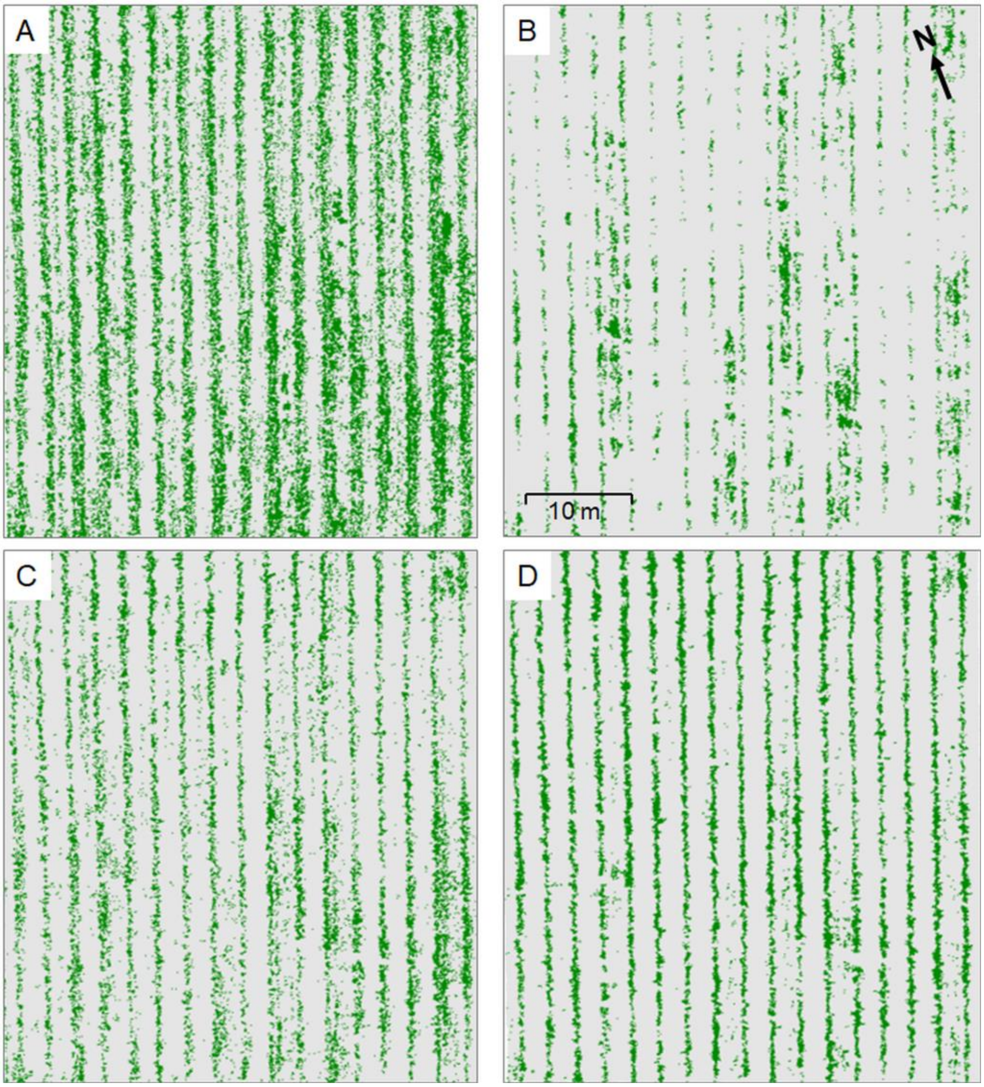

Fig. 5*. Results of binary maximum likelihood classification of vineyard structure: (A) simulated natural-colour composite (3-band RGB) image, (B) complete hyperspectral (HS) image, (C) simulated natural-colour composite combined with the canopy height model (CHM), and (D) complete HS image combined with CHM*

Vine area user's and producer's accuracies were also high (94.7% and 81.6%, respectively), confirming the added value of structural information for detecting the vine canopy. The simulated natural composite combined with CHM (RGB+CHM) achieved intermediate performance with an overall accuracy of 93.0%, an F1 score of 0.79, and a balanced accuracy of 84.6%, showing that structural features substantially enhance vineyard detection even with limited spectral input. In contrast, HS data alone produced a comparable overall accuracy of 89.0%, but much weaker vineyard detection, with a producer's accuracy of 48.9%, an F1 score of 0.61, and a balanced accuracy of 73.2%. This underscores the limitations of spectral information without canopy structure. The simulated natural colour composite (RGB) performed slightly better, reaching a producer's accuracy of 58.6%, an F1 score of 0.66, and a balanced accuracy of 77.3%, but it still showed limitations in separating vine rows from the inter-row background.

Since the reference dataset is unbalanced (141 vine vs. 859 non-vine points), the overall accuracy is biased toward the majority class. Balanced accuracy, therefore, provides a more representative measure of vineyard detection, showing that the integration of CHM consistently improved performance across both classes. Overall, HS + CHM offered the most accurate mapping, while RGB + CHM provided a practical alternative when hyperspectral data were not available. The spatial patterns of the four classification outputs are shown in fig. 5, comparing the vineyard mapping results from RGB, HS, and their combinations with CHM.

To better understand the spectral separability of classes, we examined mean reflectance profiles of vine canopies and inter-row areas (Fig. 6) based on the classification of complete HS image combined with CHM (Fig. 5D). Both classes exhibited low reflectance in the visible range, with considerable overlap in the blue (430–500 nm), green (520–600 nm), and red (630–690 nm) regions. A sharp increase occurred at the red edge (700–740 nm), followed by a plateau in the near-infrared (760–1000 nm), where vine canopies reached approximately 0.75 reflectance compared to approximately 0.55 for inter-row areas.

Although hyperspectral data captured these differences, the overlap observed in the visible range partly explains the misclassification of inter-row soil and vegetation as vine canopy in HS-only classifications. The inclusion of LiDAR-derived CHM reduced this ambiguity by adding structural information that clearly distinguished vines from background elements. The profiles also show that RGB bands alone provide limited class separability, underscoring why their combination with CHM yielded intermediate but still useful results for vineyard delineation.

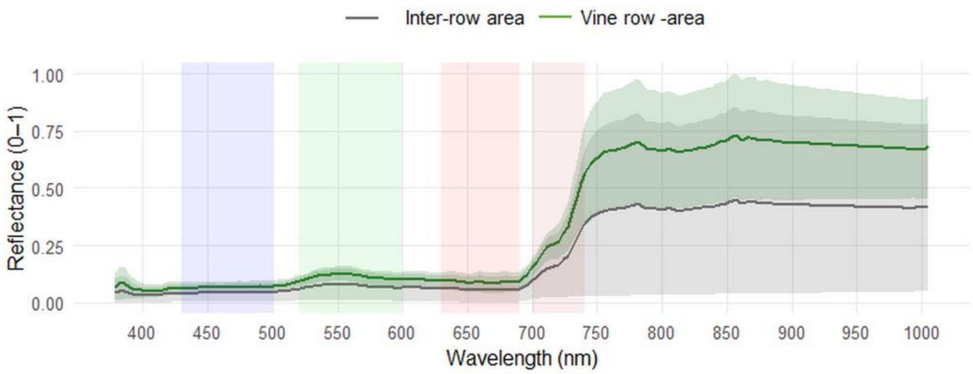

Fig. 6. *Mean spectral reflectance curves (solid lines) of vine canopies (green) and inter-row areas (dark grey), derived from the classification results shown in Figure 5D, with ribbons indicating ±1 standard deviation. Coloured regions denote key spectral intervals: Blue (430–500 nm), Green (520–600 nm), Red (630–690 nm), Red edge (700–740 nm), and Near-infrared (760–1000 nm). Spectral separation between vine and inter-row areas is most pronounced in the red-edge and NIR domains, which are widely used for vegetation monitoring*

Discussion

The results demonstrate that integrating hyperspectral imagery with LiDAR-derived canopy height models (CHM) improves vineyard classification in the Tokaj Region. Hyperspectral data alone led to frequent misclassification between vine canopies and inter-row soil or vegetation, a limitation noted in earlier vineyard remote sensing research (Zarco-Tejada et al. 2005, Kalisperakis et al. 2015). By incorporating CHM, these ambiguities were reduced, as structural differences between vines and background vegetation were captured, leading to a marked improvement in accuracy. The simulated RGB composite combined with CHM achieved intermediate results. Although limited to three visible bands, the inclusion of structural information still enabled reasonable vineyard delineation. This has practical significance since RGB sensors are widely available on commercial UAVs and have been used successfully for row detection and vigour mapping (Bálo et al. 2019, Šupčík and Matečný 2021, Matese and Di Gennaro 2018). Nevertheless, the superior performance of the hyperspectral and LiDAR integration underlines the added value of spectral detail when precise canopy characterization is required. Similar benefits of multimodal data fusion have been reported in agricultural and forestry applications (Chu et al. 2016, Prošek et al. 2020). Compared to previous Slovak studies, which mostly relied on multispectral UAV imagery for row-gap detection or canopy morphology (Šupčík and Matečný 2021, Šupčík et al. 2024), this work represents a new application of LiDAR–hyperspectral integration. The results align with international studies in Italy and Spain, where UAV hyperspectral and LiDAR technologies have been utilized for vigour assessment and yield estimation (Matese et al. 2015, Romboli et al. 2017). This places our study within the growing body of evidence that multimodal UAV sensing can support precision viticulture.

Although canopy height models (CHM) derived from LiDAR clearly delineate vine rows, relying exclusively on structural information would restrict the analysis to geometric separation of vegetation and inter-rows. PCA-reduced hyperspectral data provide complementary information on canopy biochemical and physiological traits, enabling classification beyond simple row delineation. Furthermore, PCA reduces redundancy and noise in the hyperspectral dataset, yielding compact features that integrate efficiently with CHM. This fusion is particularly relevant in heterogeneous vineyards where canopy height alone may be insufficient (e.g., gaps, stressed vines, or irregular training systems). Our results, therefore, highlight the advantage of combining CHM with hyperspectral features rather than relying on structural data alone.

Although PCA was not strictly required for the 3-band RGB composite, applying it uniformly across all datasets ensured a consistent pre-processing and classification workflow. This methodological consistency strengthens the comparison by attributing observed accuracy differences to the data sources (spectral versus structural) rather than to variations in analytical procedure.

Some limitations must be acknowledged. First, the study used data from a single survey date, which does not account for seasonal variability in canopy vigour or phenology (Zarco-Tejada et al. 2005). Second, the classification was limited to a binary vineyard/non-vineyard distinction. For operational management, more detailed classes such as vigour levels, weeds, or disease presence would be desirable (Gangl et al. 2021). Finally, although reference points were validated in the field, their distribution was unbalanced: 141 vine points (14.1%) compared to 859 non-vine points (85.9%). This closely reflects the actual areal proportions of the AOI (≈16% vine), but it means that overall accuracy is weighted toward the majority class and should be interpreted with caution. More balanced insights are provided by class-specific metrics such as user's and producer's accuracies and F1-scores, which directly capture vineyard detection performance. Importantly, even under this class imbalance, the inclusion of CHM consistently improved vineyard metrics, underscoring its value as a complementary data source to both hyperspectral and RGB inputs. Despite these constraints, the observed improvements consistently highlight the practical relevance of multimodal UAV sensing in viticulture.

Even with these limitations, the study shows that UAV-based LiDAR–hyperspectral integration can deliver accurate vineyard mapping in the Tokaj Region. Reliable delineation of vine rows is a crucial first step toward applications such as vigour monitoring, yield prediction, or linking canopy characteristics with grape quality (Arnó et al. 2012, Romboli et al. 2017). Future research should focus on multi-temporal acquisitions and testing advanced classification methods, including machine learning, to further improve robustness and scalability (Sousa et al. 2022).

Conclusions

This study demonstrates the value of integrating UAV-based LiDAR and hyperspectral data for vineyard mapping in the Slovak part of the Tokaj Region. Hyperspectral imagery alone was prone to misclassification of vine and non-vine areas due to spectral confusion with soil and inter-row vegetation. Incorporating LiDAR-derived canopy height models (CHM) reduced these ambiguities and substantially improved classification, yielding an overall accuracy of 96% and a Kappa of 0.85. Natural colour composites combined with a CHM also produced reasonable results, highlighting the practical relevance of structural information even when only broadband imagery is available. Nevertheless, the highest accuracies were achieved by fusing full hyperspectral data with LiDAR, confirming the complementary strengths of spectral and structural cues.

Accurate delineation of vine rows provides a crucial foundation for precision viticulture, enabling applications such as vigour monitoring, yield estimation, and site-specific canopy management. From a practical standpoint, UAV-based hyperspectral–LiDAR integration offers vineyard managers reliable maps for decision-making, while a 3-band natural colour images with LiDAR CHM could serve as a cost-effective alternative in case hyperspectral sensors are unavailable.

Future research should extend this work to multi-temporal surveys capturing canopy phenology, include more detailed classes such as vigour levels or disease presence, and adopt advanced machine-learning approaches. Such efforts will enhance robustness and scalability, supporting the operational use of multimodal UAV sensing in vineyard management and the preservation of culturally significant viticultural landscapes such as Tokaj.

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