Basic and Applied Ecology 92 (2026) 1–12

Contents lists available at ScienceDirect

Basic and Applied Ecology

journal homepage: www.elsevier.com/locate/baae

Accuracy of UAV-based Natura 2000 habitat mapping: seasonal and spectral drivers, with a PlanetScope benchmark

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A R T I C L E I N F O

Keywords:
Habitat classification
Natura 2000
Special areas of conservation
Nature conservation
Unmanned aerial systems
Planetscope
Classification accuracy

A B S T R A C T

Mapping and monitoring of Natura 2000 habitats (Habitat Directive 92/43/EEC) is essential for effective biodiversity protection in Europe. Remote sensing offers promising tools for this task, yet the high number of habitat types and their heterogeneity challenge the achievable classification accuracy. While recent studies demonstrated good results with very-high-resolution satellite data (e.g. Sentinel-2, RapidEye), spatial resolution in the decimetre range may be required for small patches in fine-scale mosaics. This study primarily investigates the potential of UAV-based mapping to distinguish ten Natura 2000 forest, wetland, and grassland habitats within a ~20 km^2 landscape in Central Europe. Using Random Forest classification, we evaluated producer, user, and overall accuracies depending on phenological season (spring, summer), sensor type (multispectral, RGB), predictor type (spectral, textural, object-based), and classification scheme (detailed vs. aggregated habitats). The highest classification accuracy (Cohen's Kappa 0.71–0.77) was achieved using multispectral UAV data from both seasons. Comparable results (0.67–0.76) were obtained from spring data alone, whereas summer-only data yielded substantially lower accuracy (0.46–0.56). RGB-only imagery also produced satisfactory results (0.65–0.75) when combining spring and summer. Spectral predictors were the most important, yet the inclusion of textural and object-based metrics further improved classification. Non-forest habitats were generally classified more accurately than forests. To explore the usability of alternative data sources, we also compared UAV results with classification using PlanetScope satellite imagery. While UAV mapping outperformed PlanetScope overall, several habitat types reached comparable or even better classification accuracy with satellite data. We conclude that UAV mapping can provide high-accuracy habitat classification when multispectral data from multiple seasons are available. If flight capacity is limited, acquiring multispectral imagery in spring should be prioritized. If only RGB data are available, combining spring and summer can still yield satisfactory results. PlanetScope data offer complementary potential, particularly for some forest and grassland habitat types.

Introduction

Natura 2000 is a pan-European network of protected areas (Special Areas of Conservation, SAC) serving the long-term protection of the European most valuable natural and near-natural habitats (Corbane et al., 2015; Jarocińska et al., 2022; Vanden Borre et al., 2011). Successful protection of habitats should be supported, together with a legislative framework given by the European Habitats Directive 92/43/EEC, by spatially explicit habitat mapping and regular monitoring of habitat conservation status. Annex I to the Habitats Directive lists 233 European natural habitats, including 71 priority habitats in danger of disappearance. As the Habitats Directive imposes an obligation on EU members to report the habitats' conservation status every six years, and as the EU Biodiversity Strategy has asked EU members to map biodiversity and ecosystem services digitally (Corbane et al., 2015), individual countries adopted strategies to meet these mapping and reporting obligations. Guidance on the definition of the habitats is given in the European Interpretation Manual (European Commission, 2013) and in national interpretation guidelines adjusting the European manual to the conditions of particular countries and regions (Chytrý et al., 2010; Vanden Borre et al., 2011).

The first Natura 2000 habitat mapping activities and reports were often based on ground mapping or ground mapping supported by visual interpretation of remote sensing data (Vanden Borre et al., 2011).

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https://doi.org/10.1016/j.baae.2026.02.004
Received 26 February 2024; Accepted 24 February 2026
Available online 24 February 2026

Testing of advanced remote sensing techniques for distinguishing (groups of) Natura 2000 habitats soon followed (Díaz Varela et al., 2008) and since then, many studies have demonstrated the potential of remote sensing for Natura 2000 habitat mapping and/or monitoring their conservational status (Čahojová et al., 2022; Corbane et al., 2015; Demarchi et al., 2020; Feilhauer et al., 2014; Jarocińska et al., 2022; Le Dez et al., 2021; Marcinkowska-Ochtyra et al., 2019; Moravec et al., 2023; Schmidt et al., 2017, 2018; Stenzel et al., 2014). However, only some of the studies focus directly on the distinguishability of detailed habitats according to the most detailed level of the Natura 2000 classification scheme, and report achieved classification accuracies. Although we can see encouraging results in the sense of achievable classification accuracies for some habitats (e. g. F1 accuracies for individual grassland habitats of 0.70–0.85 (Demarchi et al., 2020; Marcinkowska-Ochtyra et al., 2019)), only a few of the 233 European natural habitats were explored so far. Hence, acquiring habitat maps that would include all habitats within an area at the thematic resolution of European natural habitats or national catalogues remains a challenging goal.

Moreover, the issue of detailed thematic resolution is often combined with the need for very high spatial resolution, particularly in fine-grain near-natural landscapes or anthropogenic landscapes with residues of near-natural habitats, which are typical of Central Europe (Billeter et al., 2008; Sklenicka et al., 2014). Although many recent studies have brought encouraging results with the classification of very-high-resolution satellite data such as Sentinel-2 or Rapid-Eye (Feilhauer et al., 2014; Schmidt et al., 2018), spatial resolution in the order of several decimetres achievable with UAVs can be needed for distinguishing individual habitat patches in fine-grain landscape mosaics (Prošek & Šímová, 2019; Prošek et al., 2020).

Although UAV mapping is frequently considered a relatively cheap technique to obtain habitat data at a detailed spatial and thematic resolution, such mapping is still non-trivial and time-consuming (Komárek et al., 2018; Kupková et al., 2023; Müllerová et al., 2017; Prošek & Šímová, 2019). This is mainly true when mapping larger areas (e.g., tens of square kilometres) or when multiple phenological phases are needed for distinguishing thematically detailed classes, such as Natura 2000 habitats. Covering multiple phenological seasons across large areas can be prohibitively expensive. On the other hand, it is necessary to capture the habitat in the optimal phenological phase(s), i.e., time point(s) most suitable for high classification accuracy and reliability, which can be difficult without prior screening in multiple time points (Kopeć et al., 2016; Marcinkowska-Ochtyra et al., 2019; Müllerová et al., 2017; Wakulińska & Marcinkowska-Ochtyra, 2020). The spectral resolution needed for such detailed habitat mapping and, therefore, the price of the UAV camera, is another issue that needs to be considered. Hence, it is essential to know which habitats are distinguishable in which season and which habitats require multiseasonal UAV data and/or more expensive equipment (e.g. multispectral camera with near-infrared bands compared to a cheap RGB camera) to achieve sufficient accuracy.

While UAVs offer high spatial and temporal flexibility, their applicability is often limited by legal and logistical constraints. In contrast, satellite systems such as PlanetScope deliver wall-to-wall multispectral imagery at 3–4 m spatial resolution with near-daily revisit frequency, enabling detailed characterisation of vegetation. Recent studies have demonstrated that PlanetScope can discriminate fine-scale land-cover and habitat types, including successful detection and classification of small patches (Khan et al., 2025; Rodrigues et al., 2025; Räsänen & Virtanen, 2019). In this context, PlanetScope offers a complementary observation scale to UAV-based mapping, providing temporally frequent and spatially continuous data that may partially substitute for repeated UAV acquisitions.

In this study, we describe the potential of UAVs for distinguishing several types of Natura 2000 forests, wetlands and grasslands at the thematic level of the European Habitat Classification (10 habitats according to Habitat Directive) and of the Habitat Catalogue of the Czech Republic (14 habitats; Chytrý et al., 2010). Specifically, we aimed to (i) describe the overall accuracy achievable in this combination of habitats, and producer/user accuracy for individual habitats, and to compare the effect of (ii) phenological season and (iii) spectral resolution of the camera on the resulting accuracy. In addition, we included PlanetScope multispectral imagery to (iv) assess how well habitat separability observed at UAV resolution is reflected in satellite data, and to compare achievable classification accuracy between UAV- and PlanetScope-based mapping. Finally, we (v) evaluated how alternative processing workflows influence classification results — testing object-, spectral- and texture-based predictors for UAV data, and assessing the performance of pixel- versus object-based classification for PlanetScope imagery.

Methods

Study area

The study area (~ 20 km^2) is situated in the Žďárské vrchy Protected Landscape Area (PLA) in the heart of the Czech Republic, Central Europe. This highland area (500–800 m a.s.l.), consists of a mosaic dominated by coniferous forests (especially spruce) and patches of agricultural land combined with smaller patches of near-natural forests, wet meadows, peat-bogs, tree and shrubby vegetation (groves, tree-lines, hedgerows), small fishponds and small villages (80–600 inhabitants). Our study area includes seven SACs: CZ0614053 Dářská rašeliniště (390.51 ha), CZ0610412 Ransko (263.97 ha), CZ0614059 Štíří důl – Řeka (92.62 ha), CZ0610517 Niva Doubravy (84.95 ha), CZ0610519 Ranská jezírka (29.61 ha), CZ0612139 Pod Kamenným vrchem (12.13 ha) and CZ0610514 Doubravníček (5.23 ha). Most of the area is covered by a diverse mosaic of small habitat patches. In all, there are 10 Natura 2000 habitats (forests, grasslands and wetlands) within the study area, of which three are the priority habitats according to the Habitats Directive (Table 1). These correspond to 14 habitat types in the more detailed national classification used in the Czech Republic (Chytrý et al., 2010) and mapped in the Habitat Layer of the Czech Republic (Fig. 1), with the crosswalk between both systems provided in Table 2.

Ground truth data

The National Habitat Catalogue of the Czech Republic (Chytrý et al., 2010) was created to meet the Directive obligations. At the same time, a detailed guideline for ground mapping and GIS data processing was prepared by the Nature Conservation Agency (NCA) of the Czech Republic. In 2000, the project Mapping of Habitats of the Czech Republic was launched by NCA and the result of this effort, the Habitat Layer of the Czech Republic (hereinafter referred to as Habitat Layer), provides detailed countrywide information on the occurrence and status of natural habitats. It includes all habitats of the Czech Republic (not only those defined in the Annex I of the Habitats Directive), and therefore it covers the whole country. The Habitat Layer is available as an ESRI

Table 1
Natura 2000 habitats within the study area. The priority habitats are marked with an asterisk*.

ID	Habitat
6230*	Species-rich *Nardus* grasslands on siliceous substrates in mountain areas
6430	Hydrophilous tall herb fringe communities of plains and of the montane to alpine levels
6510	Lowland hay meadows (*Alopecurus pratensis, Sanguisorba officinalis*)
91E0*	Alluvial forests with *Alnus glutinosa* and *Fraxinus excelsior*
9130	*Asperulo-Fagetum* beech forests
9110	*Luzulo-Fagetum* beech forests
9410	Acidophilous *Picea* forests of the montane to alpine levels (*Vaccinio-Piceetea*)
91D0*	Bog woodland
7140	Transition mires and quaking bogs
3150	Natural eutrophic lakes with *Magnopotamion* or *Hydrocharition*-type vegetation

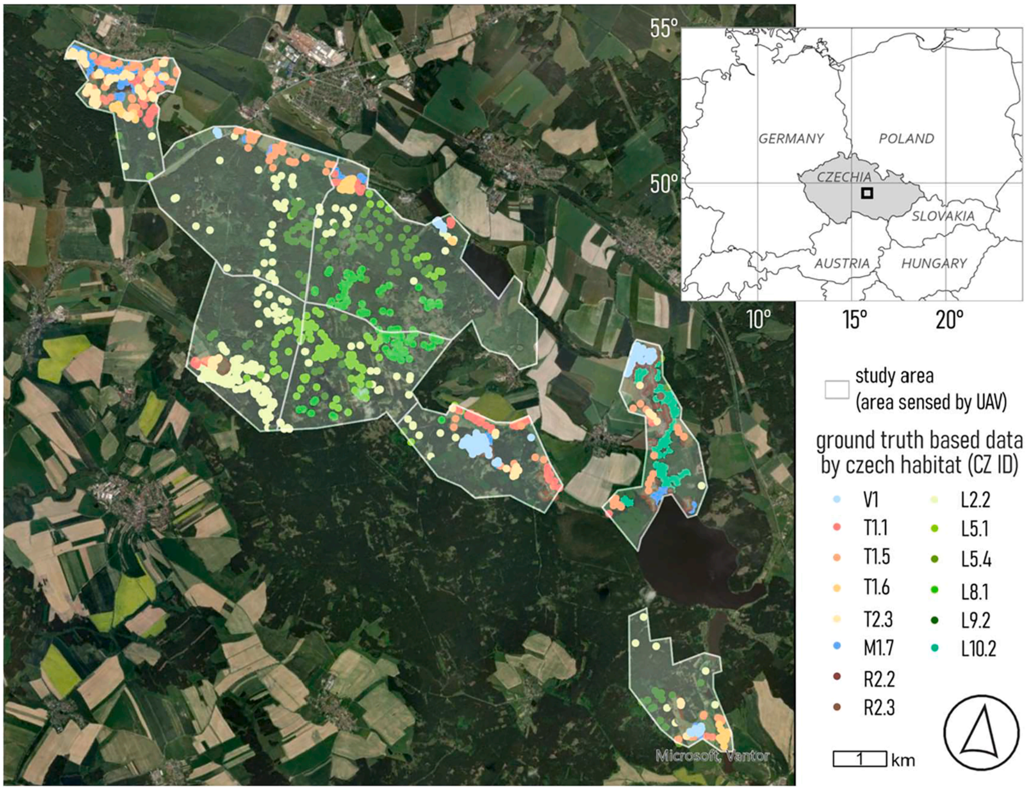

Fig. 1. Study area with locations of ground truth points. Ground truth points are positioned in the centres of habitat patches as mapped in the Habitat Layer of the Czech Republic. The meaning of the habitat codes shown in the map legend is provided in Table 2. Grey polygons delineate the individual UAV flight blocks and do not represent habitat boundaries. The mapped habitat patches are small features embedded within a broader matrix of non-Natura forest and grassland.

Table 2
Conversion of Natura 2000 Habitats to Czech habitats (Chytrý et al., 2010) and five classification schemes used in this study: Czech habitats, three experimental schemes aggregating similar ones (Agg. #1, #2, #3) and European habitats (where the habitat compatible with Czech habitat does not exist, the Czech habitats are used). Cells with the same colour and number within the same column indicate habitats that have been aggregated into one in the respective aggregation scheme. It can be seen that the Agg. #1, #2, and #3 schemes combine moss and fen habitats with wet meadows or forest habitats in different ways because moss and fens in the study area are partly covered with herbs and partly with woody plants. CZ ID = identifier of Czech habitat; EU ID = identifier of European habitat; Agg. = aggregation.

CZ ID	Czech habitat	Agg. #1	Agg. #2	Agg. #3	EU ID
V.1	Macrophyte vegetation of naturally eutrophic and mesotrophic still waters	1	1	1	3150
T2.3	Submontane and montane *Nardus* grasslands	2	2	2	6230
T1.1	Mesic *Arrhenatherum* meadows	2	2	2	6510
T1.5	Wet *Cirsium* meadows	3	3	3	T1.5 + M1.7
T1.6	Wet *Filipendula* grasslands	3	3	3	6430
M1.7	Tall-sedge beds	3	3	3	T1.5 + M1.7
R2.2	Acidic moss-rich fens	4	4	9	7140
R2.3	Transitional mires	4	3	3	7140
L2.2	Ash-alder alluvial forests	5	5	5	91E0*
L5.1	Herb-rich beech forests	6	6	6	9130
L5.4	Acidophilous beech forests	6	6	6	9110
L8.1	Boreo-continental pine forests	7	7	7	L8.1
L9.2	Bog and waterlogged spruce forests	4	4	4	91D0*+9410
L10.2	Pine mire forests with *Vaccinium*	8	8	4	91D0*

shapefile at a cartographic reference scale of 1:10,000 with a relational database of habitats and taxa (NCA Habitat Layer).

The system of the Czech habitat types defined in the Habitat Catalogue is compatible with those defined in the Annex I of the Habitat Directive. In some cases, however, the definition of habitat types within Natura 2000 does not reflect the actual patterns observed in the Czech Republic. Therefore, the habitat classification presented in the Catalogue (and, therefore, in the Habitat Layer) has been developed as a compromise between the Natura 2000 system and the Czech reality allowing adequate description of Czech habitat types (see the conversion of both systems for the study area in Table 2) as was common in national habitats catalogues across Europe (Evans, 2010). The Habitat Catalogue distinguishes nine basic groups of habitats, namely: V – Streams and water bodies, M – Wetlands and riverine vegetation, R – Springs and mires, S – Cliffs and boulder screes, A – Alpine treeless habitats, T – Secondary grasslands and heathlands, K – Scrub, L – Forests, X – Habitats strongly influenced or created by man. These groups are further subdivided into units (coded, e.g., T1) and subunits (e.g. T1.6), totalling 140 habitats (Chytrý et al., 2010).

In this study, we used the Habitat Layer as the source of ground truth data for the classification of UAV multispectral data. 14 near-natural (i.e. except the X category) Catalogue/Habitats Layer habitat types can be found within the study area. We created five classification schemes (Table 2) to cover both Czech and European classifications and test the effect of aggregation of (probably) spectrally similar habitats, namely according to the (a) Czech Habitat Catalogue (CzHab), (b) three different aggregations of classes from the Czech Habitat Catalogue – Agg. #1, #2, and #3) and (c) European Natura 2000 habitats (EUHab).

UAV

We used the eBee fixed-wing vehicle (senseFly, Switzerland; take-off weight 1.3–1.6 kg, wingspan of 116 cm) equipped with the RedEdge-MX 5-band multispectral camera (see Table 3 for details) for the acquisition

Table 3
Internal parameters and spectral characteristics of the multispectral camera (RedEdge-MX).

Spectral band	λ (nm)	Bandwidth (nm)	Focal length (mm) * Crop f.	Sensor resolution (MPx)
Blue	475	20		
Green	560	20		
Red	668	10	5.4 * 7.2	1.2
Red Edge (RE)	717	10		
Near Infra-Red (NIR)	840	40		

of multispectral data. Depending on the weight of the payload (especially the camera) and required resolution (flight altitude), the UAV can acquire images covering hundreds of hectares in a single flight. One flight takes 60–90 min.

We acquired UAV images during flight campaigns in spring (15th to 17th of May) and summer (27th to 29th of August) to cover different phenological phases of the habitats. The flights were conducted between 9 am and 6 pm to cover the entire study area within a minimal number of days and, hence, to make the phenological span as narrow as possible.

The flights were performed with direct pilot supervision using an autopilot controlled by eMotion software. The UAV flight altitude ranged between 250 and 300 m above the ground level. The flight parameters were designed to ensure a lateral overlap of images of at least 75 % and a longitudinal overlap of at least 85 %. We used such a high image overlap to address the elevation variability and diverse height of observed objects, particularly the differences between forested and non-forested areas. The combination of all flight parameters provided images with a spatial resolution (ground sampling distance) of <20 cm/pixel. In total, we performed eighteen flights and acquired over 15,000 individual images in each flight campaign/season.

Photogrammetry (SfM) data processing

We processed the UAV images using the photogrammetric range imaging technique (Structure from Motion, SfM) in Agisoft PhotoScan (Agisoft LLC, Russia) version 1.6.4 software. In the initial step, radiometric calibration was performed on individual images. Surface reflectance values were calculated using the values from the onboard irradiance sensor and a grayscale calibration target with known reflectance values captured before each individual flight. Initial camera calibration parameters (namely principal point coordinates, affinity and skew radial distortion and tangential distortion coefficients) were used to eliminate the influence of lens distortions (image residuals).

In batch processing, the following steps were applied to each of the individual flights: Alignment of the photos (detection of identical points), construction of a dense point cloud (creation of a densified point cloud and automatic noise points filtering), construction of a digital elevation model, and construction of an orthorectified multispectral mosaic (hereafter ortho-mosaic).

The resulting mosaics were built with ground sampling distances ranging from 20 to 25 cm/pixel and georeferenced using the onboard UAV GPS module (Štroner et al., 2021). The positional accuracy of each mosaic was verified based on 8 to 12 points with known coordinates (Ground Control Points). The achieved RMSEs (Root Mean Square Errors) on the X and Y axes were below 0.5 m (<2 pixels) for each mosaic.

Classification

We used object-based random forest (RF) classification to distinguish individual Natura 2000 habitats according to the Czech, European and aggregated classification schemes (Table 2) and to evaluate the importance of the individual UAV-based predictors (bands and indices) as well as that of camera spectral resolution in combination with the phenological season for the classification accuracy (see Fig. 2).

First, we ran segmentation by the 'Segment Mean Shift function' (ArcGIS Pro 2.7), which groups neighbouring pixels with similar spectral characteristics together into segments. To create segments that best describe the boundaries of the observed objects, we iteratively tested different combinations of input parameters (spectral detail, spatial detail and minimum segment size). After a visual inspection, we used the spectral detail value ranging from 16 to 18.5 and the spatial detail value between 15 and 18, depending on the study site. The minimum segment size was set identically for all study sites to 100 pixels (representing objects with a minimum area of 5 m^2). For the resulting segments, we computed (i) spectral characteristics represented by the mean reflectances of individual bands in each segment, (ii) textural (spectral variability) characteristics represented by the standard deviations of the individual bands in each segment, and (iii) object characteristics represented by compactness, rectangularity and pixel count for each segment.

Second, we implemented supervised RF classification using the 'randomForest' (version 4.7–1.2) and 'caret' (version 7.0–1) R packages (Liaw and Wiener, 2002; Kuhn, 2008). For each classification scheme and each set of predictors (see Table 2 and Fig. 2 for a full list of classification schemes and predictor sets), we first tuned RF hyperparameters on an independent training subset using the `train` function

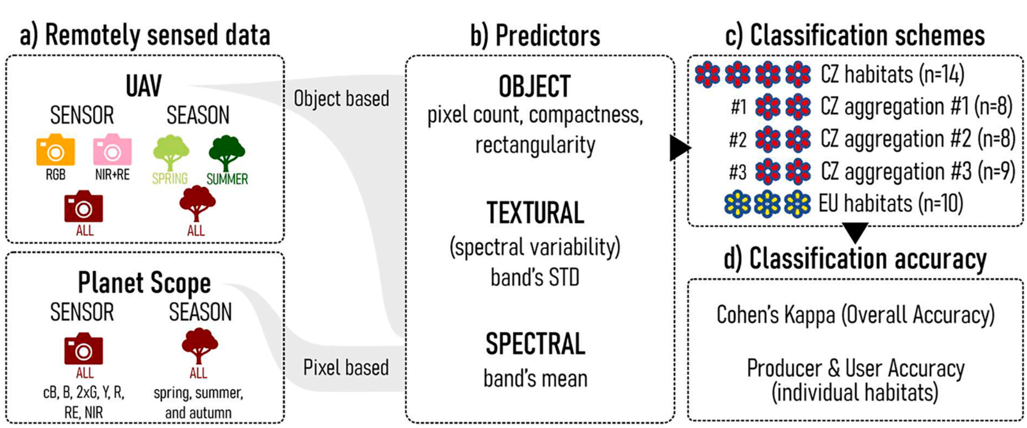

Fig. 2. Workflow for UAV- and PlanetScope-based habitat classification. UAV data were analysed across spectral resolutions (RGB, multispectral), seasons (spring, summer) and object-based segmentation, from which spectral, textural and object-level predictors (e.g., pixel count, compactness, rectangularity) were derived. PlanetScope imagery was classified using both pixel-based and object-based approaches for spring, summer and autumn acquisitions. All classifications were performed for multiple classification schemes: Czech habitats (Chytrý et al., 2010), three aggregated versions of this scheme, and European Natura 2000 habitat types. Classification accuracy was assessed using Cohen's Kappa and producer/user accuracy. CZ = Czech, EU = European.

from the 'caret' package with method = "rf" and 100-fold cross-validation. We searched over values of `mtry` (number of variables available for splitting at each tree node), `maxnodes` (maximum number of terminal nodes per tree), and `ntree` (number of trees to grow) within predefined ranges (approximately `mtry` = 1–100, `maxnodes` = 2–200, `ntree` = 500–2500)(Liaw and Wiener, 2002). The combination yielding the highest cross-validated overall accuracy on the training subset was selected. Using these optimal hyperparameters, we then fitted the final RF model for each classification task with the `randomForest` function and used this model to derive variable importance and predictions.

Accuracy assessment

To evaluate the classification accuracy, we used user accuracy (UA; the probability that the habitat shown on the map will match the reality, i.e. 1-commission error), producer accuracy (PA; the probability that the habitat is classified as such, i.e. 1-omission error), Out of Bag error rate (OOB; the number of misclassified segments from the out-of-bag sample, or, in other words, the number of misclassified segments in the training set obtained by bootstrapping divided by the total number of observations), and Cohen's Kappa (Kappa; how the classification performed in comparison with assigning the classes randomly). All results are based on cross-validation with $n = 100$ replications, and data proportion $p = 0.10$ (by 'crossValidation' function from R - package 'rfUtilities' (version 2.1–5); Evans & Cushman, 2009; Murphy et al., 2010). The summary characteristics are reported as the median of the values obtained in each repetition.

Moreover, we estimated the importance of camera types, phenological seasons, and object-based, spectral and textural predictors for RF performance. Reported importance values of individual variables and combinations of variables are based on the Mean Decrease Gini – the decrease of Gini impurity when a variable is chosen to split an RF node (for more information about this characteristic, see Liaw and Wiener, 2002). We used a variation partitioning procedure to divide the importance of phenological seasons and camera types for the resulting overall accuracy.

Planet scope data and analysis

To compare the performance of UAV data with a globally available alternative, we classified the same area using PlanetScope (Planet Labs, Inc., San Francisco, CA, USA) imagery acquired in the same year. For this purpose, we used three PlanetScope scenes representing spring (May 2021), summer (July 2021) and autumn (October 2021). These three acquisitions together reflect the full range of easily obtainable observations from this sensor, without the logistical constraints associated with additional UAV flights. Because our goal was not to replicate the UAV seasonal design, but rather to evaluate how PlanetScope performs when all readily available scenes are used, we did not analyse seasonal effects for PlanetScope. Instead, we compared two methodological approaches: object-based classification (using image segmentation analogous to the UAV workflow) and pixel-based classification.

We used bottom-of-atmosphere reflectance Ortho Scene products acquired by the Super Dove instrument with a spatial resolution of 3 m. The spring scene was affected by sensor striping artifacts, particularly visible in the coastal blue and blue bands. To mitigate this, we generated a three-day composite (May 9–11, 2021) by selecting the minimum pixel values of the coastal blue band across consecutive dates. This was implemented using a custom R script developed in RStudio. All scenes were selected based on minimal cloud coverage and seasonal relevance. The data comprised eight spectral bands ranging from visible to near-infrared wavelengths (coastal blue: 431–452 nm, blue: 465–515 nm, green I: 513–549 nm, green II: 547–583 nm, yellow: 600–620 nm, red: 650–680 nm, red-edge: 697–713 nm, and NIR: 845–885 nm), delivered as 16-bit GeoTIFFs. The classification schemes, vegetation classes, and analytical workflows were kept identical to those applied in the UAV-based analysis.

Results

Effect of the phenological season and camera spectral resolution on the overall accuracy

Overall accuracy depended on the combination of phenological seasons and camera spectral resolution. Cohen's Kappa values achieved using both phenological seasons (SPRING, SUMMER) and full spectral resolution (RGB+RE+NIR) ranged among classification schemes between 0.71 (European Habitats) and 0.77 (Czech habitats, aggregation #3).

Classification based only on the spring season and multispectral resolution reached very similar values (0.67–0.76) as that obtained using both seasons combined (0.71–0.77); conversely, the classification based only on the summer data produced markedly worse results (0.46–0.56). In other words, when full spectral resolution (RGB+RE+NIR camera) was used, the spring flight mission was crucial, while the summer data contributed only slightly (0.009–0.032) to the overall classification accuracy (Fig. 3).

Classification using data from both seasons and RGB bands only yielded Kappa values ranging from 0.65 (European habitats) to 0.75 (Czech habitats, aggregation #3). This is similar to the values obtained using multispectral resolution and only spring season (see previous paragraph), which implies that the effects of the phenological season and camera spectral resolution on overall classification accuracy were similar and that when using data from both seasons, the contribution of RE+NIR bands to the overall accuracy was low. This was particularly obvious for the aggregated schemes of Czech habitats #1–3 (0.022, 0.014, 0.019, respectively). The lower spectral resolution appeared to be compensable with two seasonal mappings, and vice versa, spring flight campaign with a multispectral camera comprising RE and NIR bands can substitute the summer season image acquisition. Such behaviour of Kappa values and values of overlaps (SPRING vs. SUMMER; RGB vs. multispectral) was consistent through all classification schemes (Fig. 3).

Importance of spectral, textural and object predictors

When looking at the importance of predictors in detail (Fig. 4), variables derived from multispectral spring data were more important for classifications than those derived from the summer acquisition, regardless of the predictor group (spectral, i.e. individual bands; textural, i.e. spectral variability of individual bands; and object, i.e. pixel count, compactness and rectangularity). Within the spring season, spectral predictors appeared to be more important than the object and textural ones. Similarly, spectral predictors (particularly NIR, red and blue bands) were the most important when evaluating both seasons together.

The importance of individual predictors slightly differed among classification schemes (Fig. 5); however, the essential predictors remained the same. The mean values of spring bands are ranked as the most important, with only the pixel count and mean summer NIR being of comparable importance. In the order of importance, they were followed by some of the textural (spectral variability) spring predictors; this was especially pronounced when classifying European habitats. Thus, although the mean band values appeared crucial for the habitats classification, inclusion of the object properties and spectral variability was worthwhile.

Effect of phenological season and camera spectral resolution on the classification accuracy of individual habitats

Producer (PA) and user (UA) accuracy of individual habitats (Table 4) depended on the classification scheme and, similarly to overall

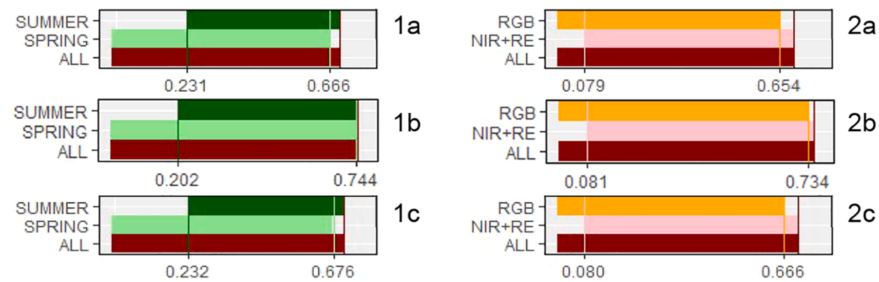

Fig. 3. Variation partitioning of Cohen's Kappa accuracies for phenological seasons (1) and camera spectral resolution (2). The effect of (selected) classification schemes is shown vertically (a–c). (a) Czech habitats (Kappa = 0.696); (b) the most successful aggregation of the Czech habitats (#3, Kappa = 0.769); (c) Europen habitats (Kappa = 0.708). We can see the dominant effect of the SPRING season (1) on overall accuracy and the contribution of the multitemporal use of an RGB camera (2).

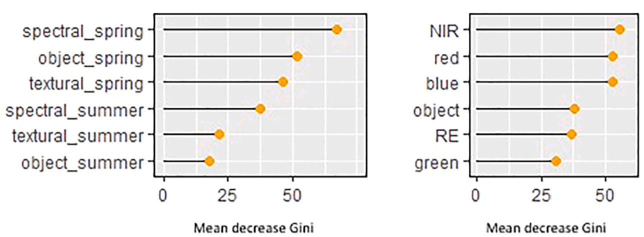

Fig. 4. Importance of predictor groups expressed as mean decrease in Gini. Left: Combined influence of phenological season and predictor group; labels indicate predictor group (spectral, textural, object) and season (spring, summer). Right: Importance of individual predictors when both seasons are combined; NIR = near-infrared band and RE = red-edge band. All spring predictors were more important than the summer ones. Spectral predictors were the most important for the classification, although the object group also contributed considerably.

accuracy, on the season and camera spectral resolution (Fig. 6). Natural Eutrophic lakes 3150 (V1) were the only habitat classified with the absolute accuracy of 100 % independently of the classification scheme.

The most detailed classification schemes, i.e. Czech habitats and European habitats, were classified relatively successfully. 8 out of 14 Czech habitats and 7 out of 10 European habitats were classified with both producer and user accuracies higher than 70 %, despite the similarities between some classes. Grassland habitats such as *Nardus* grasslands 6230 (T2.3), Hydrophilous tall herb fringe communities 6430 (T1.6) and Lowland hay meadows 6510 (T1.1) were successfully distinguished from woody habitats and even from each other (PA 70.0–88.4, UA 73.1–86.9). The tall sedge beds (M1.7) and wet *Cirsium* meadows (T1.5) (Czech habitats that do not have European equivalents) were the only grassland/herbaceous classes that did not reach 70 % PA and UA. Transition mires and quaking bogs 7140 (R2.2 and R2.3) were distinguished very well not only as a combined class 7140 but even as two separate classes in the Czech Habitat Catalogue (acidic moss-rich fens, transitional mires). Compared with grasslands and mires, distinguishing between individual forest habitats appeared problematic in these two most detailed schemes. The alluvial forest with *Alnus glutinosa* and *Fraxinus excelsior* 91E0 (L2.2) was the only well-distinguishable forest type (see Table 4 for PA and UA values).

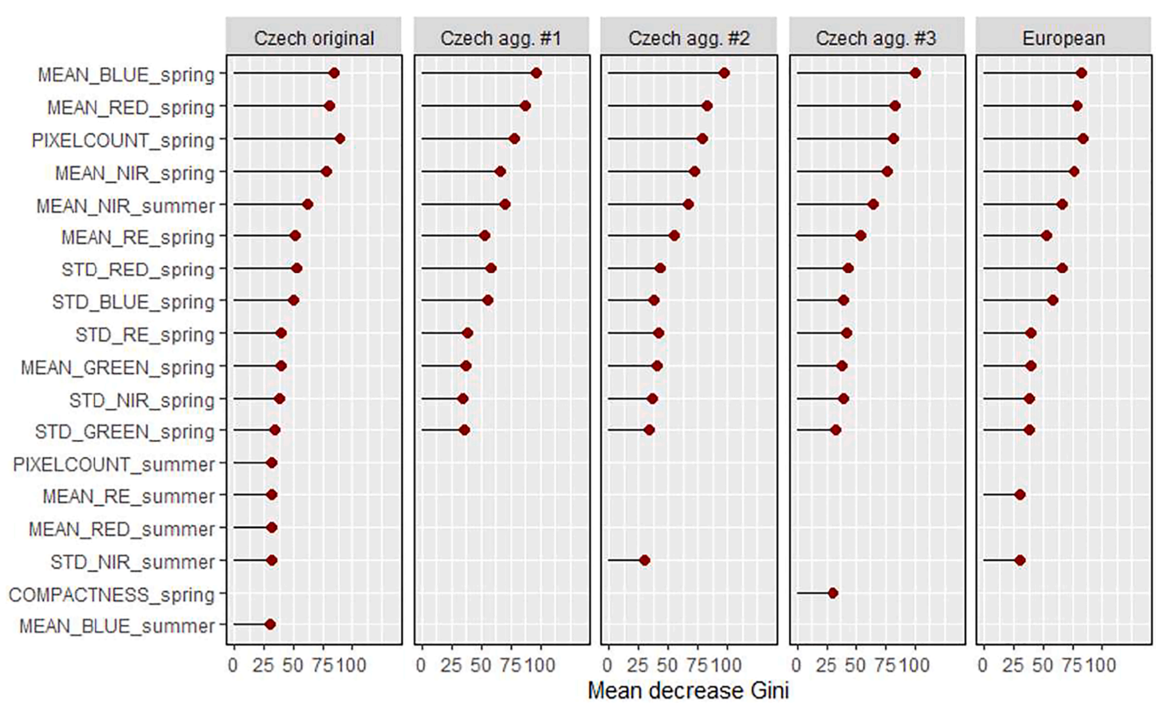

Fig. 5. Variable importance (mean decrease in Gini) across the five classification schemes. Y-axis labels encode predictor type and season: MEAN_/STD_ are the mean/standard deviation of band reflectance (BLUE, GREEN, RED, NIR = near-infrared, RE = red-edge) and _spring/_summer indicates season. PIXELCOUNT, COMPACTNESS and RECTANGULARITY are object-level predictors.

Table 4
The highest producer and user accuracies of individual Czech (CZ) habitats, aggregated Czech habitats (Agg.#number of aggregation scheme) and European (EU) habitats. Only accuracies higher than 70 % are shown. Values in italics indicate combinations yielding worse accuracies after aggregation compared with the original habitats. See Appendix B for all producer and user accuracies and F1 scores.

CZ ID	CZ habitat	Agg. #1	Agg. #2	Agg. #3	EU ID	EU habitat
			producer/user accuracy			
V1	100/100	100/100	100/100	100/100	3150	100/100
T2.3	88.4/80.8	85.6/86.4	86.0/84.3	84.8/-	6230	75.0/75.8
T1.1	83.5/76.8			75.0/-	6510	85.0/73.3
T1.5	71.1/-	80.0/86.1	80.1/91.4	76.5/93.4	T1.5 + M1.7	70.5/73.2
T1.6	70.0/86.9				6430	73.1/81.8
M1.7	-/-				T1.5 + M1.7	70.5/73.2
R2.2	92.0/73.7	*83.5/-*	*79.8/-*	98.3/-	7140	91.0/84.3
R2.3	88.4/80.8		80.1/91.4	76.5/93.4		
L2.2	71.8/89.3	76.1/85.8	77.0/85.5	76.1/85.8	91E0*	74.0/88.3
L5.1	84.3/71.7	79.4/80.2	80.2/82.3	79.1/81.8	9130	84.0/-
L5.4	-/-				9110	-/-
L8.1	73.5/-	75.4/-	76.3/-	75.8/-	L8.1	74.7/-
L9.2	-/-	83.5/-	79.8/-	92.0/84.8	91D0*+9410	72.2/-
L10.2	-/-	-/79.8	-/83.8		91D0*	-/84.8

Aggregations #1–3 were beneficial for some habitat combinations but were associated with poorer detection of others. In the case of grasslands, combining habitats 6230 and 6510 improved the accuracies, as did combining T1.5, T1.6 (6130) and M1.7 habitats. However, this improvement was accompanied by a decrease in user accuracies of the mires (R) habitat. In forests, combining both beech habitats was beneficial, as was combining bog/waterlogged spruce forests (L9.2) with Pine mire forests (L10.2).

The effect of the phenological season and spectral resolution of the camera on the classification accuracy of individual habitats follows a similar pattern as in the case of overall accuracy. As Fig. 6 shows for European habitats, PA/UA of individual habitats differ across habitats, seasons and camera bands. The highest PA/UA values were (not surprisingly) achieved when combining both seasons and all spectral bands (the panel ALL). However, the accuracies obtained using only spring values with all bands (the SPRING panel) and those using values from both seasons with RGB bands only (RGB panel) were only slightly lower. This implies that the effects of the season and spectral resolution were generally similar. However, we can see differences in individual habitats. For example, the classification of 6430 Hydrophilous tall herb fringe communities was more successful when using both seasons than when employing better spectral resolution (as the PA/UA values are lower for the spring than for both-seasonal RGB). These patterns were consistent across all classification schemes. See Appendix A for all classification schemes.

Comparison with planetscope data

Across the evaluated Natura 2000 habitats, UAV-based classifications generally yielded higher maximum F1-scores than those derived from PlanetScope imagery. Nevertheless, for several habitats, PlanetScope reached F1 values above 75, indicating that for these types, the coarser spatial resolution did not preclude usable mapping results.

Specifically, ash-alder forests (91E0, L2.2), pine mires (L10.2, 91D0 + 9410), and bog/waterlogged spruce (L9.2) reached maximum F1-scores above 75 with PlanetScope data. These habitats are typically structurally distinct or spatially extensive, which may explain their successful classification even from satellite data. For example, ash-alder achieved F1 values exceeding 86 with both PlanetScope and UAV, showing that this habitat can be reliably mapped from either platform.

In addition, several grassland habitats also reached F1 scores above 75, including T1.1 Mesic *Arrhenatherum* meadows, 6510 Lowland hay meadows, and the aggregated class M1.7 + T1.5 + T1.6 + R2.3 Wet grasslands. Although the highest F1 values for these habitats were generally achieved using UAV data (especially in multispectral spring or combined seasonal settings), the fact that PlanetScope also provided high accuracy suggests that these relatively homogeneous open habitats may be distinguishable even with coarser spatial detail.

Most remaining habitats performed best with UAV, particularly when combining both seasons and multispectral imagery. These included wet *Filipendula* grasslands (T1.6), *Nardus* grasslands (6230, T2.3), and herbaceous bogs (M1.7, T1.5) — all with F1 values above 80 in UAV results. The fine-scale mosaic character of these habitats likely benefits from UAV's higher spatial resolution.

Only one habitat — R2.2 Spruce bog — showed consistently low F1-scores (below 50) across all schemes and both sources, suggesting it is difficult to map with the available input data due to spectral similarity with surrounding vegetation or limited sample representation.

Object-based vs. pixel-based classification

For PlanetScope data, object-based classification consistently outperformed per-pixel classification. The median F1-score was significantly higher for the object-based approach (63.2 vs. 59.4), and this difference was statistically supported by a Wilcoxon rank-sum test ($p < 0.001$). These results suggest that spatial context and object-level features enhance habitat classification performance even with coarser satellite imagery.

Discussion

In this study, we analysed the detection accuracy of a wide range of habitats over a (in terms of UAV use) large area. The study area covered about 20 km^2, which is almost the limiting extent for UAV habitat mapping when the same lighting and phenological conditions are to be maintained. Various lighting conditions caused by different times of acquisition during the day or partial shading within a single flight can significantly affect radiometric accuracy and the interpretability of acquired multispectral images (Daniels et al., 2023; Jenerowicz et al., 2023; Zhou et al., 2022). Another challenge associated with the classification of imagery data lies in the increased occurrence of shadows, which leads to misclassification (Movia et al., 2016; Weil et al., 2017; Wu et al., 2014). The presence and extent of shadows are the more pronounced, the further the acquisition time is from solar noon. This presents a trade-off between (i) the desire to process as large an area as possible within a single day (or a single flight campaign) to cover the same phenological phase of plants and (ii) the effort to ensure consistent lighting conditions and minimize shadows. Consequently, this poses a significant limitation for UAV applications in terms of the manageable coverage area, which needs to be considered. In our study, flights were conducted throughout the whole day (specifically from 9 AM to 6 PM). Radiometric correction is an essential step in such cases. After standardized radiometric corrections within the Agisoft software, the resulting classification does not exhibit noticeable artefacts caused by different times of day or shading from cloud cover. However, one flight conducted between 6 and 7 PM had to be excluded from the processed dataset due to poor lighting conditions.

Many authors emphasize the importance of the data acquisition season (and thus the phenological phase of plants) and spectral resolution of the data for classification accuracy (Cruz et al., 2023; Demarchi

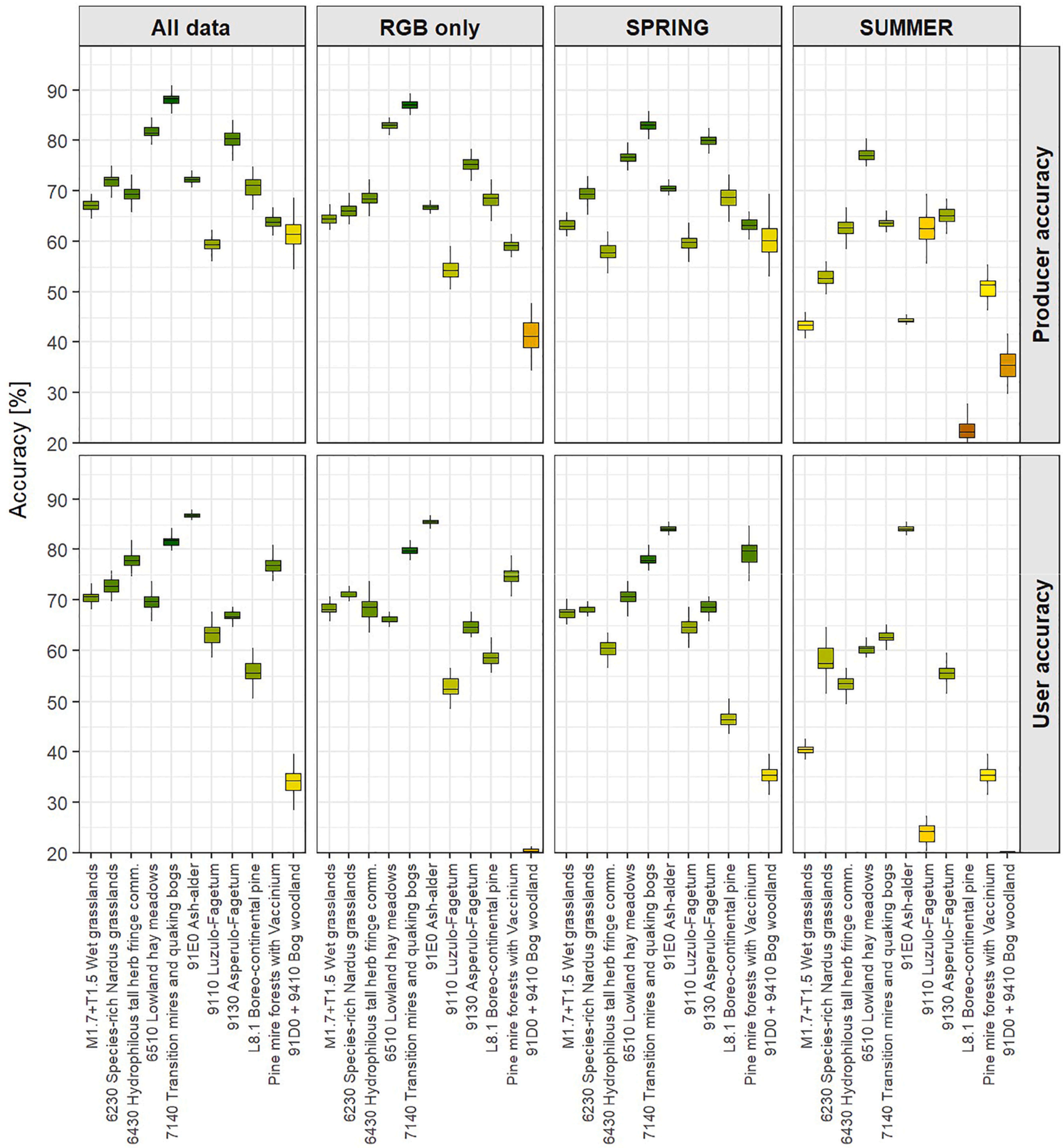

Fig. 6. UAV-based classification: Producer and user accuracies of European habitats and the effect of the camera spectral resolution and phenological season (spring, summer). ALL – both seasons and all bands, RGB – both seasons and RGB bands. SPRING – all bands and spring season only, SUMMER – all bands and summer season only. Box colors represent F1-scores using a gradient from dark green (highest values), through yellow (intermediate), to dark red (lowest values). See Appendix A for all classification schemes and the full comparison with PlanetScope-based classification.

et al., 2020; Jarocińska et al., 2022; Marcinkowska-Ochtyra et al., 2019, 2018; Müllerová et al., 2017; Wakulińska & Marcinkowska-Ochtyra, 2020). This is consistent with our results. Similar to (Cruz et al., 2023), the highest accuracies were achieved in our study when using multitemporal data. However, when only a single date is available, the optimal timing appears to be habitat-specific. Cruz et al. (2023) recommend peak-season imagery for coastal dune vegetation, whereas Keränen et al. (2024) found early-season data to perform best for boreal mire systems, which are structurally and functionally more comparable to the peatbog–meadow–forest mosaic of our study area. Likewise, our highest accuracies were obtained in mid-May, suggesting that early growth stages provide strong spectral contrast among habitats. This is especially relevant for temperate forests, where freshly flushed beech and alder stands differ markedly from evergreen conifers, improving separability in fine-grained mosaics. Together, these studies highlight that there is no single universally optimal acquisition date for habitat mapping and that phenological responses must be understood at the habitat-group level. For effective monitoring and conservation planning, further work should therefore identify which phenophases maximize discriminability for each habitat type.

In the study area, forests, meadows, and wetlands were represented, including several Natura 2000 habitats of each of these main categories. This is a significant improvement brought by our study compared to studies dealing with fewer habitats as the accuracy of the classification and importance of spectral bands for distinguishing individual habitats can be significantly affected by habitats present in the study area (Jarocińska et al., 2022; Stenzel et al., 2014). Therefore, a combination of multiple habitats can bring more reliable resulting producer and user accuracies. With this in mind, we selected the study area to include habitats that are (viewed from above) both structurally and optically very different (e.g. herb-rich beech forests vs. mesic *Arrhenatherum* meadows) and very similar (e.g. herb-rich beech forests and acidophilous beech forests). There were also habitats that, although dominated by different woody species when viewed from above, allow a good view into the understory that is optically similar (e.g. bog/waterlogged spruce forests vs pine mire forests).

Thanks to this design and the aggregation schemes that grouped individual (potentially similar in their reflectance) habitats into joint classes, we showed similarities and differences between several Natura 2000 habitats as viewed by multispectral or RGB sensors. It is not surprising that habitats dominated by the same tree species while differing in their herbaceous understories, such as herb-rich beech forests and acidophilous beech forests, were not distinguishable individually, but reached good producer and user accuracies (both of approx. 80 %) when they were combined. Interestingly, the combined category "beech forests" yielded these accuracies despite the particular aggregation scheme, hence that near-natural beech forest can be considered as well distinguishable from other Natura 2000 forests habitats (pine, spruce, and ash-alder forests) under study. The aggregation schemes also showed similarities of forest habitats dominated by different coniferous species, such as bog/mire spruce and pine forests. This is probably because tree cover is sparse in such habitats with high groundwater levels, whereas the herbaceous and moss cover of these habitats visible from the above is very similar in species composition and reflectance. The classification of herbaceous Natura 2000 habitats can also be tricky. Although their visibility from above is not confused by tree cover, the same group of herb species can dominate in different habitats. This is shown on the example of tall-sedge beds and wet *Filipendula* grasslands, both of which can be optically influenced by tall sedge species.

Based on the results and classification accuracies achieved in our study, it is clear that the classification of UAV data cannot yet fully replace field mapping. While the accuracies achieved are relatively high, it is important to consider whether this level of accuracy is acceptable for specific conservation purposes. For example, if we wanted to monitor changes in the health of a particular habitat in selected patches, we would need to know that the patch represents the habitat. Thus, we need the highest possible user accuracy. If we aim to find as many as possible occurrences of a given habitat in an unmapped area, we need the highest possible producer accuracy. Of course, it is optimal to achieve high values for both UA and PA. Simultaneously high (80 % or more) UA and PA were achieved mainly for non-forest habitats (grasslands and wetlands V, T, M and partly R), especially for the Czech classification scheme or for aggregation of certain grassland habitats into one. For forest habitats, UA of 80 % or more was rarely achieved, mostly ranging between 70 and 80 %. These UA values were compensated by low PA for most forest habitats (except aggregated beech forests). In general, therefore, non-forest habitats performed better than forest habitats in the classification. A number of pixels of forest habitats were probably not found by the classification in the study area. For practical conservation use, it would, therefore, be possible to identify patches of forest suitable for ongoing monitoring rather than, for example, determining the total area of individual forest habitats in the study area.

Direct comparison of the accuracies obtained for individual habitats with other papers is difficult because habitats used in our study were only rarely studied. Moreover, none of the studies focusing on the same Natura 2000 habitats as ours report producer and user accuracies achieved by UAVs. In comparison with Natura 2000 habitat classifications based on multispectral satellite data (e.g. Feilhauer et al. (2014), Stenzel et al. (2014)), the UAV-based classification yielded higher overall accuracy even though we worked with a higher number of habitats. This can be attributed to the higher spatial resolution of UAVs, but also to the specific appearance and pattern of habitats in areas under study.

Incorporating PlanetScope data into the analysis provided valuable context for evaluating the relative performance of UAV-based mapping. As expected, the coarser spatial resolution (3 m) of satellite imagery generally resulted in lower classification accuracy compared to UAV imagery with sub-decimetre resolution. However, several Natura 2000 habitats – notably ash-alder forests (91E0, L2.2), pine mires (L10.2, 91D0 + 9410), and bog spruce forests (L9.2) – were mapped with maximum F1-scores exceeding 75 using PlanetScope data. These habitats tend to be either spatially extensive or structurally distinct, which likely explains their successful detection even at lower spatial resolution. In contrast, fine-scale mosaic habitats such as wet grasslands (T1.5, T1.6, T2.3) benefited strongly from the higher resolution of UAV data, particularly when multispectral sensors and both spring and summer acquisitions were combined.

From a practical perspective, the inclusion of PlanetScope imagery allowed us to explore classification performance unconstrained by seasonal limitations typical of UAV campaigns. Although we did not explicitly analyse the effect of season for satellite data, the use of multiseasonal (spring to autumn) composites ensured that phenological variability was captured. Instead, we compared object-based and per-pixel approaches using PlanetScope data and found that object-based classification yielded significantly better F1-scores than the per-pixel alternative. This result emphasizes the importance of spatial context and texture in medium-resolution satellite data and supports the broader remote sensing trend of incorporating object-level features to improve classification outcomes (Blaschke, 2010; Drăguţ & Eisank, 2012). Together, these findings suggest that PlanetScope can serve as a viable alternative for selected habitats where spatial extent or spectral uniqueness compensate for limited resolution—while UAVs remain the preferred option for detailed mapping of small, heterogeneous patches (Fig. 7).

Conclusions

Our findings highlight the importance of timing of data acquisition and suggest that using a multispectral camera in the spring season (in the latitude of the Czech Republic) may be a cost-effective way to classify Natura 2000 habitats based on UAV data. A combination of an RGB camera and two seasons of mapping gave similar results. The highest accuracies can be achieved, not surprisingly, by combining a multispectral camera and multiple seasons. To increase the effect of multiple seasons, it could be fruitful for further studies to replace summer with autumn, when the spectral signatures of herbaceous habitats and deciduous forests can differ more than in the summer.

Moreover, the study highlights variations in classification accuracy for individual Natura 2000 habitats within different classification schemes. The most detailed schemes, such as Czech and European habitats, achieved relatively successful classification results, particularly in distinguishing individual non-forest habitats. Aggregating certain habitats into a combined class can improve accuracy in some cases but may lead to impaired detection capability in others. In general, we recommend testing multiple classification schemes with different aggregations of habitats that are potentially spectrally similar due to dominant woody or herbaceous species. This can provide a reliable UAV-based classification that can be refined to the level of individual Natura 2000 habitats by additional field mapping.

Finally, our comparison with PlanetScope satellite data shows that despite its lower spatial resolution, it enabled successful classification ($F1 > 75$) of several Natura 2000 habitat types, particularly spatially extensive or structurally distinct ones such as ash-alder forests, pine mires, and bog spruce forests. These results suggest that satellite-based mapping can provide a viable alternative for selected habitats, especially where UAV use is limited by flight capacity, accessibility, or regulatory restrictions. In contrast, herbaceous habitats with fine-scale heterogeneity (e.g. *Filipendula* grasslands, *Nardus* grasslands) achieved higher accuracy with UAV data, benefiting from its finer spatial detail. We therefore recommend prioritizing UAV mapping for heterogeneous grassland and wetland habitats or when fine-scale delineation is essential (as is the case in our study area, where grasslands and wetlands are more heterogeneous and fragmented than most forest habitats). For

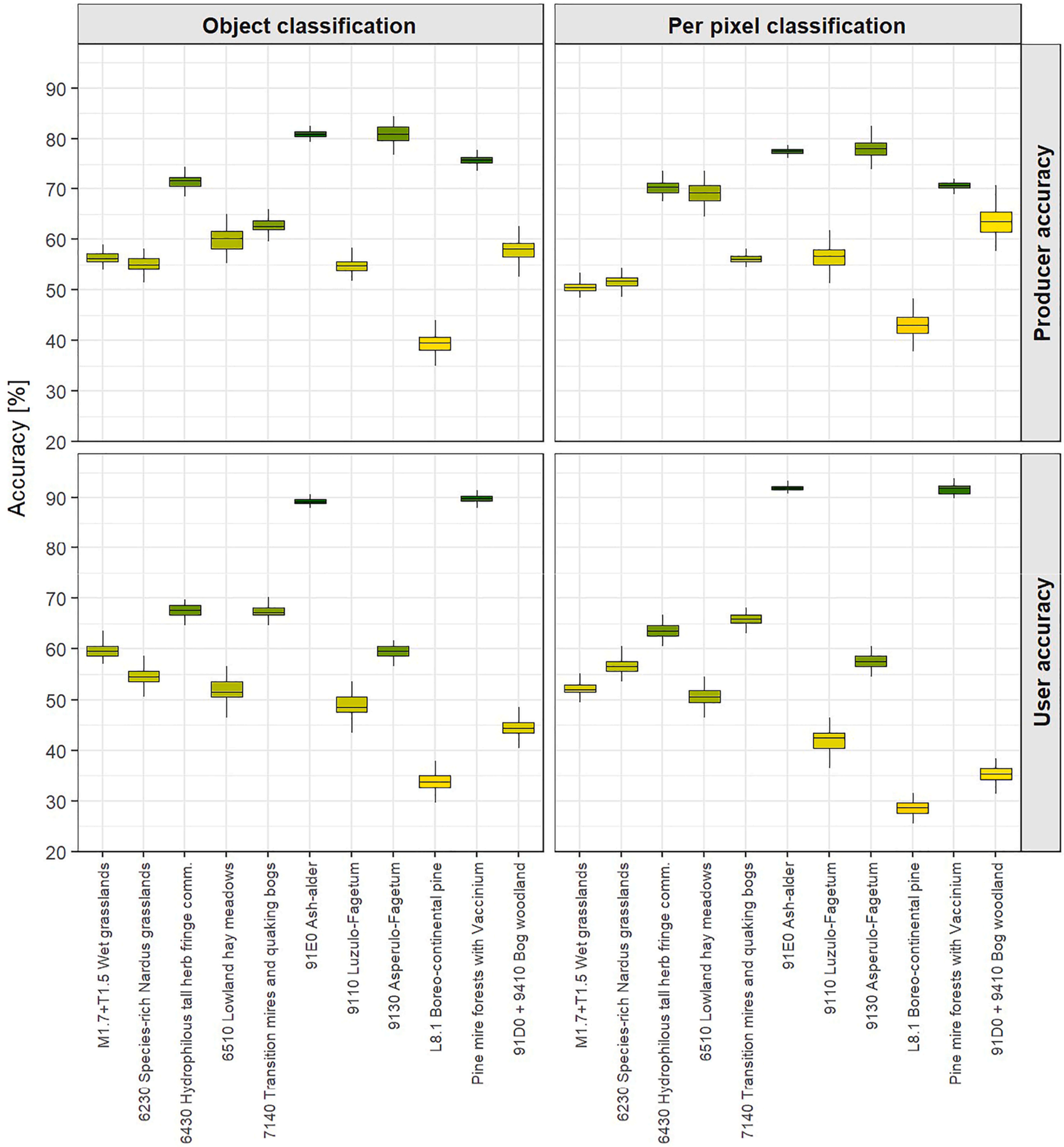

Fig. 7. PlanetScope-based classification: Producer and user accuracies of European habitats and the effect of object-based and pixel-based approaches. Box colors represent F1-scores using a gradient from dark green (highest values), through yellow (intermediate), to dark red (lowest values). See Appendix A for all classification schemes and the full comparison with UAV-based classification.

more homogeneous forest habitats, satellite imagery such as PlanetScope can serve as an efficient and scalable alternative, particularly for broader-scale assessments or when UAV deployment is limited by regulatory, temporal, or logistical constraints. An integrated approach combining both platforms may further enhance mapping efficiency by tailoring data sources to habitat characteristics and conservation objectives.

Funding

This research was funded by the Technology Agency of the Czech Republic (Environment for Life program), project Possibilities for updating map layers of NATURA 2000 habitats using advanced remote sensing methods, grant number: SS01010046, 2021–2023.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT (OpenAI) in order to assist with R script debugging and local language editing during manuscript revision. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Data availability

The habitat mapping layer used to train and validate the models (Habitat Layer of the Czech Republic) is publicly available via the Nature Conservation Agency of the Czech Republic data portal (registration required; website in Czech). PlanetScope imagery was accessed under a Planet Labs licence and cannot be redistributed by the authors. The UAV imagery is large (tens of GB) and is therefore not deposited in a public repository; it can be made available from the authors upon reasonable request, subject to storage and sharing constraints. All predictor variables derived from the UAV data and used for model training and validation are provided as CSV files with metadata in supplementary material.

CRediT authorship contribution statement

Petra Šímová: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Jiří Prošek:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation. **Duccio Rocchini:** Writing – review & editing, Supervision, Methodology. **Richard Bittman:** Writing – review & editing, Methodology. **Vítězslav Moudrý:** Writing – review & editing, Writing – original draft, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors are grateful to the Nature Conservation Agency of the Czech Republic for their consultations during the project and Milan Chytrý for his valuable comments and improving suggestions on the manuscript. We also thank Jaroslav Janošek for his valuable comments.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.baae.2026.02.004.

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