Accuracy of UAV mapping of Natura 2000 forest, wetland and grassland habitats: Do we need more seasons or more spectral bands?

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ABSTRACT

Mapping and monitoring of Natura 2000 habitats (Habitat Directive 92/43/EEC) is one of the key activities to ensure the protection of natural habitats in Europe. Remote sensing can help to acquire high-quality maps of the distribution and conservation status of Natura 2000 habitats, for example through classifying multispectral data. However, due to the high number of habitats (classes) distinguished in the Habitat Directive, achievable classification accuracies for individual habitats in the context of a given landscape remain unknown. Moreover, although many recent studies have brought encouraging results in the classification of very-high-resolution satellite data such as Sentinel-2 or Rapid-Eye, spatial resolution in the order of several decimetres achievable with UAVs can be needed for distinguishing individual habitat patches in fine-grain landscape mosaics. In this study, we investigated the potential of UAVs for distinguishing eleven Natura 2000 forests, wetlands and grasslands. The study area (~ 20 km^2) is situated in the heart of the Czech Republic, Central Europe. We aimed to assess the producer, user and overall accuracy of Random Forest classification, considering the importance of different phenological seasons (spring, summer), spectral resolutions of the camera (multispectral and RGB), predictor types (spectral, textural and object) and classification scheme (detailed habitats vs their aggregations). The highest achieved overall classification accuracy (Cohen's Kappa) ranged from 0.71 to 0.77 and resulted from classifying multispectral data from both seasons. We obtained similar results from the spring season (0.67-0.76), whereas the isolated data from summer provided poor distinguishing capacities. Relatively good accuracies (0.65 to 0.75) were achievable even using a simple RGB camera when combining both seasons. In general, the classification of non-forest habitats was better than that of forest habitats. Spectral predictors (mean band values) played a crucial role in the classification, but including the object properties and texture (spectral variability) also improved the distinguishing capabilities.

KEYWORDS

Habitat classification, Natura 2000, Special Areas of Conservation, nature conservation, Unmanned aerial systems, classification accuracy

1. 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 earlier versions) and in national interpretation guidelines adjusting the European manual to the conditions of particular countries and regions (Vanden Borre et al. 2011, Chytrý et al., 2010).

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). 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 and Moravec, 2023; Schmidt et al., 2018, 2017; 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 et al., 2020; Prošek and Šímová, 2019).

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 and 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 and 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-red bands compared to a cheap RGB camera) to achieve sufficient accuracy.

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 (11 habitats according to Habitat Directive) and of the Habitat Catalogue of the Czech Republic (14 habitats; Chytrý et al., 2010). We aimed to (i) describe the overall accuracy achievable in this combination of habitats and producer/ user accuracy achievable for each of the habitats and define and compare the effect of (ii) the phenological season and (iii) the spectral resolution of the camera on the resulting accuracy. In other words, we aimed to answer the practical question of whether and how much multiseasonal mapping can be compensated for by using a camera with a higher spectral resolution and vice versa. Last but not least, we (iv) aimed to evaluate the effect of object-based, spectral and textural predictors on the resulting accuracy, i.e. the contribution of more demanding data processing, on the quality of results.

2. Methods

2. 1. 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 11 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, Fig. 1).

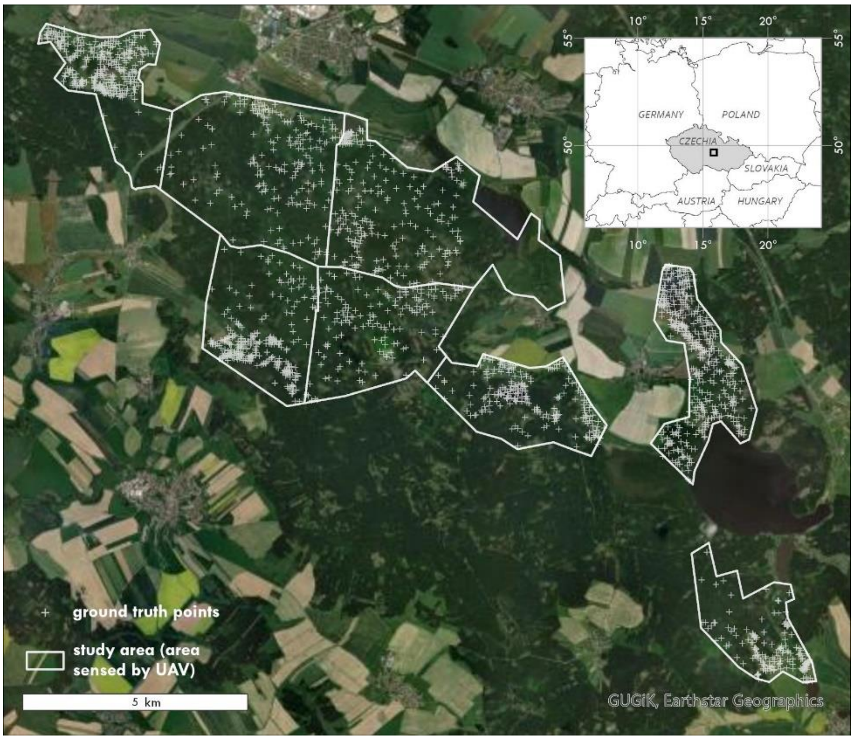

Fig. 1. Study area with locations of ground truth points. Ground truth points are in the centres of habitat patches; the density of these points, therefore, indicates the size of habitat patches as mapped for the Habitat Layer of the Czech Republic.

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

2.2. 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 (Härtel et al. 2009). 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 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).

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 Agg 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	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*

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).

2.3. UAV data

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

We acquired UAV images during flight campaigns in the 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 the eMotion software. The UAV flight altitude ranged between 250–300 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/pix. In total, we performed eighteen flights and acquired over 15,000 individual images in each flight campaign/season.

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 (MPix)
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		

2.3. Photogrammetry (SfM) data processing

We processed the UAV images using the photogrammetric range imaging technique (Structure from Motion, SfM) in PhotoScan 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 on the X and Y axes were below 0.5 m (<2 pixels) for each mosaic.

2. 4. 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).

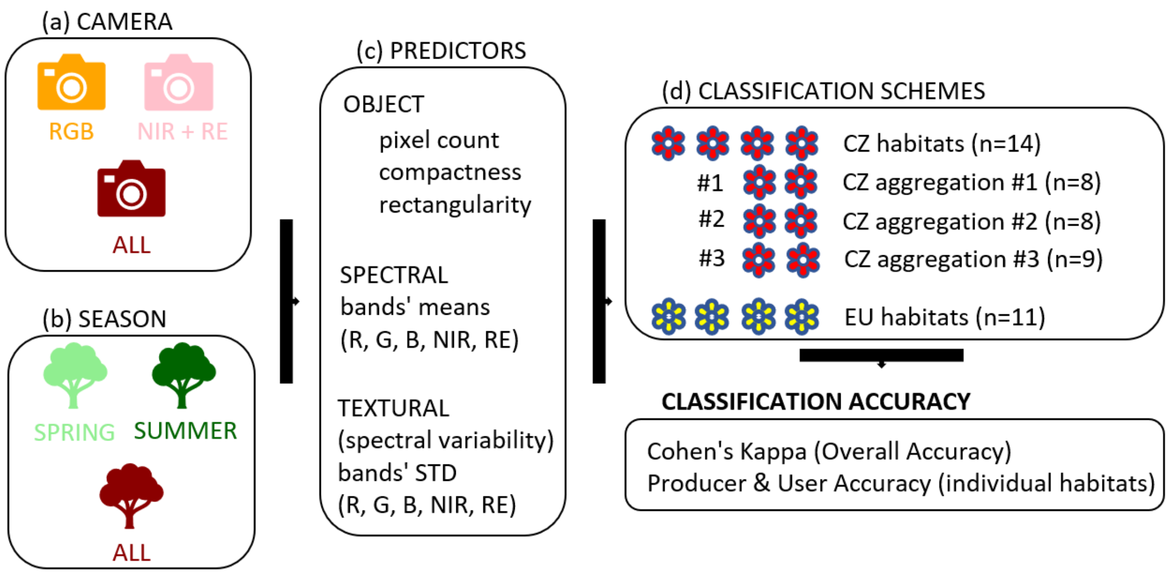

Fig. 2. Classification diagram. We evaluated the influence of (a) camera spectral resolution, (b) phenological season (spring, summer, multitemporal), and (c) predictors used in the RF algorithm, and

different classification schemes (Czech habitats according to Chytrý et al. 2010, three aggregations of this original scheme, and European NATURA 2000 habitats) on the overall classification accuracy (Cohen's Kappa) and producer/user accuracy of individual classes.

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 used supervised RF classification ('*randomForest*' R package) independently for (i) each classification scheme and (ii) each set of predictors (see Table 2 and Fig. 2 for a full list of classification schemes and used sets of predictors). We tuned RF classification parameters using the '*train*' function from the '*caret*' R package. The '*mtry*' parameter (number of variables available for splitting at each tree node) was iterated from 1 to 60, '*maxnodes*' (maximum number of terminal nodes that trees in the forest can have) from 5 to 200, with a step of 5, and '*ntree*' (number of trees to grow) from 500 to 2,500, with a step of 500 (Liaw and Wiener, 2002). We selected the best parameters according to the RF accuracy score.

2. 5. 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*'). 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.

3. Results

3.1. 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).

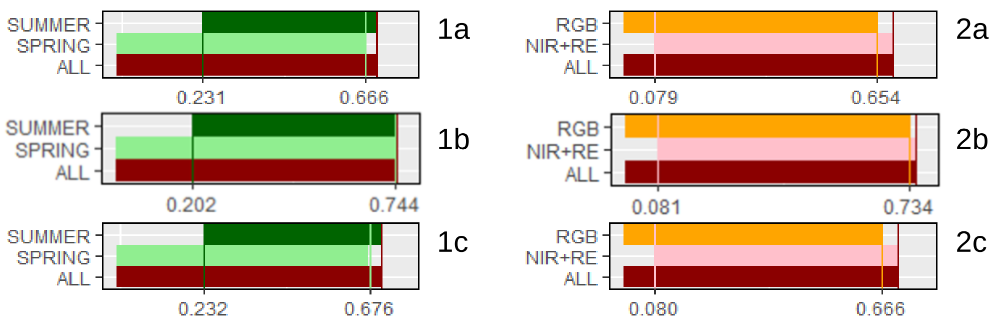

Fig. 3. Variation partitioning of Cohen's Kappa accuracies for phenological seasons (1) and camera spectral resolution (2). The effect of (selected) classification schemes is shown vertically (a–c). (a) Czech habitats (Kappa = 0.696); (b) the most successful aggregation of the Czech habitats (#3, Kappa = 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).

3.2. *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.

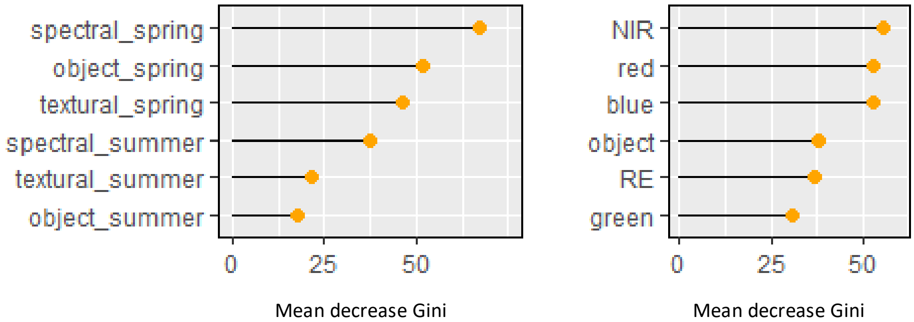

Fig. 4. Importance of predictor groups expressed as Mean decrease Gini. Left: Combined influence of the phenological season and the group of predictors. All spring predictors were more important than the summer ones. Right: Importance of individual predictor groups when both seasons are combined. Spectral predictors were the most important for the classification, although the object group also contributed considerably.

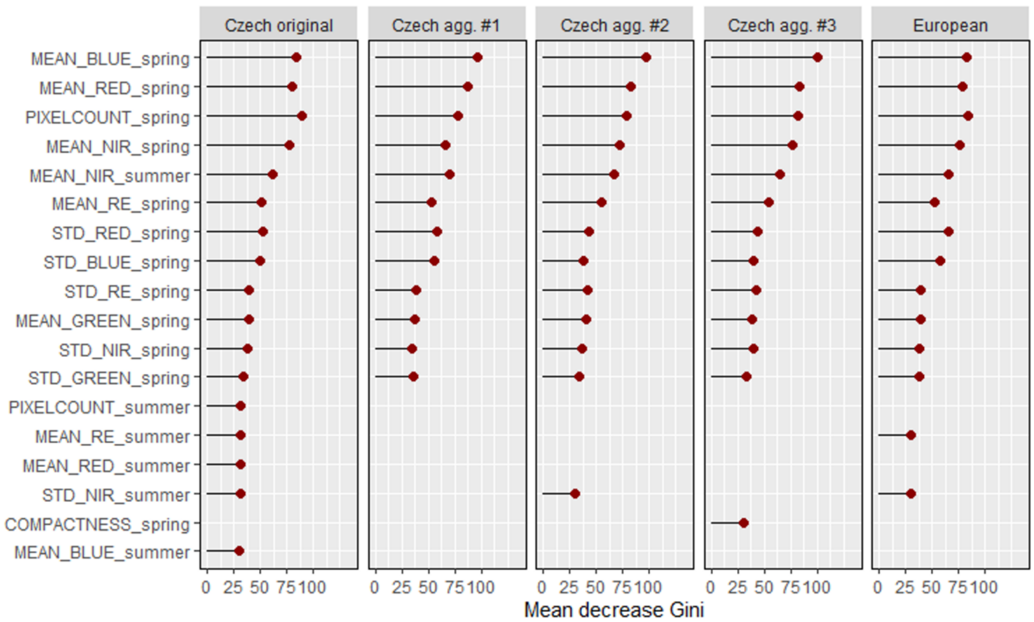

Fig. 5. Importance of individual predictors expressed as Mean decrease Gini.

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.

3.2. 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 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 12 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).

Table 4
The highest producer and user accuracies of individual Czech habitats, aggregated Czech habitats and European habitats. Only accuracies higher than 70% are shown. Red values indicate combinations yielding worse accuracies after aggregation compared with the original habitats.

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/-				T1.5+M1.7	70.5/73.2
T1.6	70.0/86.9	80.0/86.1	80.1/91.4	76.5/93.4	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

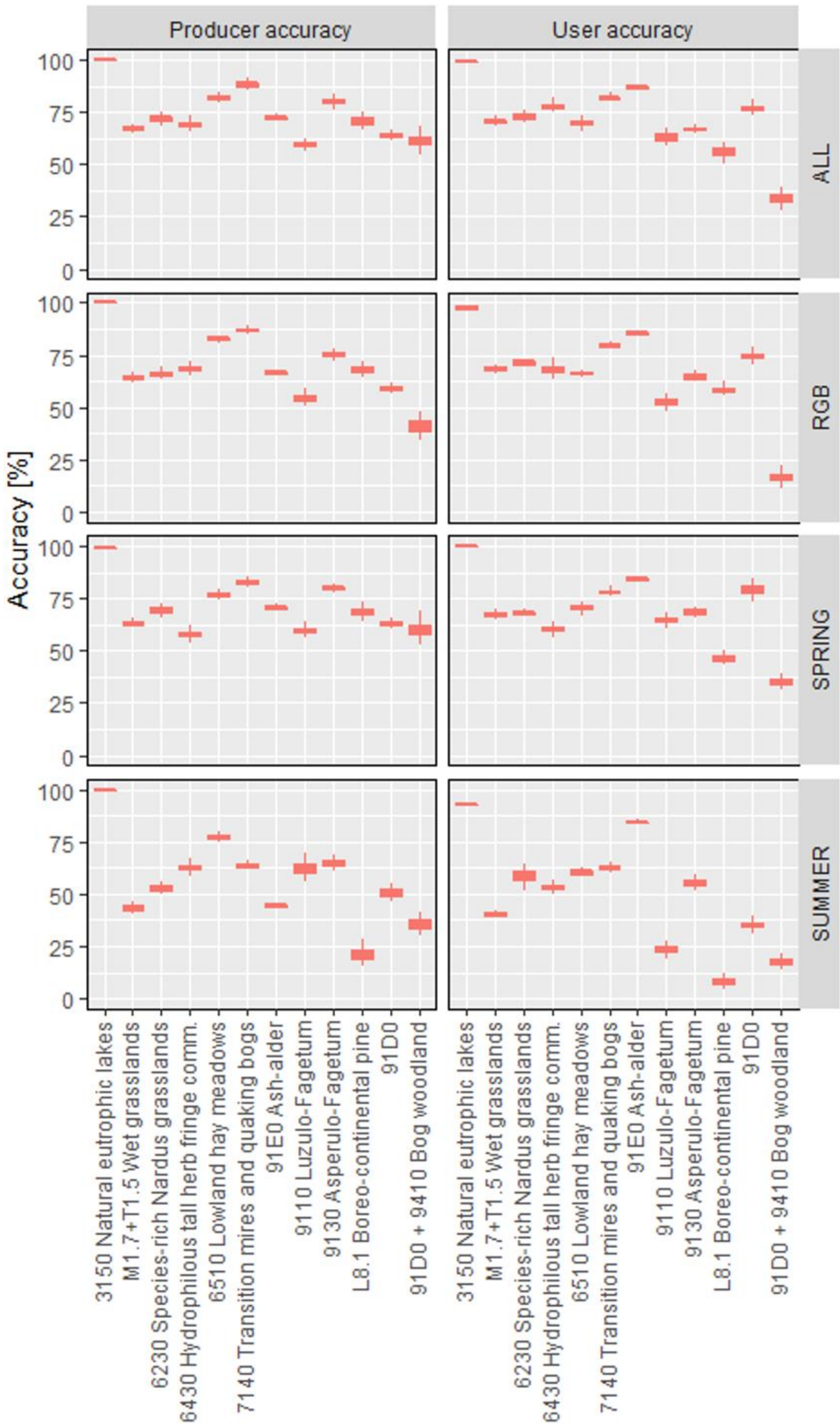

Fig. 6. Producer and user accuracies of European habitats and the effect of the camera spectral resolution and phenological season (spring, summer). ALL – both seasons and all bands, RGB – both seasons and RGB bands. SPRING – all bands and spring season only, SUMMER – all bands and summer season only. See Appendix A for all classification schemes.

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.

4. 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 to 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 et al., 2020; Jarocińska et al., 2022; Marcinkowska-Ochtyra et al., 2019, 2018; Müllerová et al., 2017; Wakulińska and 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 one time point is to be selected for the flight campaign, the results of the studies differ. For example, (Cruz et al., 2023) recommend the middle of the growing season for coastal dune habitats, while in our study, the best results for our habitats were achieved at the beginning of the growing season. This shows that it is not possible to recommend one optimal data acquisition time that would be universally valid for all habitats. For the purpose of mapping and, hence, protecting Natura 2000 habitats, it is, therefore, necessary to further test in which phenological phases habitats are spectrally best distinguishable.

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.

5. 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.

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References

Billeter, R., Liira, J., Bailey, D., Bugter, R., Arens, P., Augenstein, I., Aviron, S., Baudry, J., Bukacek, R., Burel, F., Cerny, M., De Blust, G., De Cock, R., Diekötter, T., Dietz, H., Dirksen, J., Dormann, C., Durka, W., Frenzel, M., Hamersky, R., Hendrickx, F., Herzog, F., Klotz, S., Koolstra, B., Lausch, A., Le Coeur, D., Maelfait, J.P.P., Opdam, P., Roubalova, M., Schermann, A., Schermann, N., Schmidt, T., Schweiger, O., Smulders, M.J.M.J.M., Speelmans, M., Simova, P., Verboom, J., Van Wingerden, W.K.R.E.K.R.E., Zobel, M., Edwards, P.J.J., 2008. Indicators for biodiversity in agricultural landscapes: A pan-European study. J. Appl. Ecol. 45, 141–150. https://doi.org/10.1111/j.1365-2664.2007.01393.x

Čahojová, L., Ambroz, M., Jarolímek, I., Kollár, M., Mikula, K., Šibík, J., Šibíková, M., 2022. Exploring Natura 2000 habitats by satellite image segmentation combined with phytosociological data: a case study from the Čierny Balog area (Central Slovakia). Sci. Rep. 12, 1–14. https://doi.org/10.1038/s41598-022-23066-3

Chytrý M., Kučera T., Koči M., Grulich V. & Lustyk P. (eds) (2010): *Katalog biotopů České republiky.* Ed. 2. Agentura ochrany přírody a krajiny ČR, Praha.

Corbane, C., Lang, S., Pipkins, K., Alleaume, S., Deshayes, M., García Millán, V.E., Strasser, T., Vanden Borre, J., Toon, S., Michael, F., 2015. Remote sensing for mapping natural habitats and their conservation status – New opportunities and challenges. Int. J. Appl. Earth Obs. Geoinf. 37, 7–16. https://doi.org/10.1016/j.jag.2014.11.005

Cruz, C., O'Connell, J., McGuinness, K., Martin, J.R., Perrin, P.M., Connolly, J., 2023. Assessing the effectiveness of UAV data for accurate coastal dune habitat mapping. Eur. J. Remote Sens. 56. https://doi.org/10.1080/22797254.2023.2191870

Daniels, L., Eeckhout, E., Wieme, J., Dejaegher, Y., Audenaert, K., Maes, W.H., 2023.

Identifying the Optimal Radiometric Calibration Method for UAV-Based Multispectral Imaging. Remote Sens. 15, 1–22. https://doi.org/10.3390/rs15112909

Demarchi, L., Kania, A., Ciezkowski, W., Piórkowski, H., Oświecimska-Piasko, Z., Chormański, J., 2020. Recursive feature elimination and random forest classification of natura 2000 grasslands in lowland river valleys of poland based on airborne hyperspectral and LiDAR data fusion. Remote Sens. 12. https://doi.org/10.3390/RS12111842

Díaz Varela, R.A., Ramil Rego, P., Calvo Iglesias, S., Muñoz Sobrino, C., 2008. Automatic habitat classification methods based on satellite images: A practical assessment in the NW Iberia coastal mountains. Environ. Monit. Assess. 144, 229–250. https://doi.org/10.1007/s10661-007-9981-y

Evans, D., 2010. Interpreting the habitats of Annex I: Past, present and future. Acta Bot. Gall. 157, 677–686. https://doi.org/10.1080/12538078.2010.10516241

Feilhauer, H., Dahlke, C., Doktor, D., Lausch, A., Schmidtlein, S., Schulz, G., Stenzel, S., 2014. Mapping the local variability of Natura 2000 habitats with remote sensing. Appl. Veg. Sci. 17, 765–779. https://doi.org/10.1111/avsc.12115

Härtel, H.; Lonˇcáková, J.; Hošek, M. Mapování Biotopů v České Republice. Východiska, Výsledky, Perspektivy; Agentura Ochrany Pˇrírody a Krajiny ˇCR: Praha, Czech Republic, 2009; ISBN 9788087051368.

Jarocińska, A., Kopeć, D., Kycko, M., Piórkowski, H., Błońska, A., 2022. Hyperspectral vs. Multispectral data: Comparison of the spectral differentiation capabilities of Natura 2000 non-forest habitats. ISPRS J. Photogramm. Remote Sens. 184, 148–164. https://doi.org/10.1016/J.ISPRSJPRS.2021.12.010

Jenerowicz, A., Wierzbicki, D., Kedzierski, M., 2023. Radiometric Correction with Topography Influence of Multispectral Imagery Obtained from Unmanned Aerial Vehicles. Remote Sens. 15. https://doi.org/10.3390/rs15082059

Komárek, J., Klouček, T., Prošek, J., 2018. The potential of Unmanned Aerial Systems: A tool towards precision classification of hard-to-distinguish vegetation types? Int. J. Appl. Earth Obs. Geoinf. 71, 9–19. https://doi.org/10.1016/j.jag.2018.05.003

Kopeć, D., Michalska-Hejduk, D., Sławik, Ł., Berezowski, T., Borowski, M., Rosadziński, S., Chormański, J., 2016. Application of multisensoral remote sensing data in the mapping of alkaline fens Natura 2000 habitat. Ecol. Indic. 70, 196–208. https://doi.org/10.1016/j.ecolind.2016.06.001

Kupková, L., Červená, L., Potůčková, M., Lysák, J., Roubalová, M., Hrázský, Z., Březina, S., Epstein, H.E., Müllerová, J., 2023. Towards reliable monitoring of grass species in nature conservation: Evaluation of the potential of UAV and PlanetScope multi-temporal data in the Central European tundra. Remote Sens. Environ. 294. https://doi.org/10.1016/j.rse.2023.113645

Le Dez, M., Robin, M., Launeau, P., 2021. Contribution of Sentinel-2 satellite images for habitat mapping of the Natura 2000 site 'Estuaire de la Loire' (France). Remote Sens. Appl. Soc. Environ. 24, 100637. https://doi.org/10.1016/j.rsase.2021.100637

Marcinkowska-Ochtyra, A., Gryguc, K., Ochtyra, A., Kopeć, D., Jarocińska, A., Sławik, Ł.,

2019. Multitemporal hyperspectral data fusion with topographic indices'improving classification of natura 2000 grassland habitats. Remote Sens. 11, 1–22. https://doi.org/10.3390/rs11192264

Marcinkowska-Ochtyra, A., Jarocińska, A., Bzdęga, K., Tokarska-Guzik, B., 2018. Classification of expansive grassland species in different growth stages based on hyperspectral and LiDAR data. Remote Sens. 10. https://doi.org/10.3390/rs10122019

Moravec, D., Moravec, D., 2023. Finding Misclassi fi ed Natura Finding Habitats Misclassi by Applying fi ed Natura 20 Finding Misclassified Habitats Applying Outlier Detection to Sentinel-1 and Outlier Detection to Sentinel-1 Detection Data Data.

Movia, A., Beinat, A., Crosilla, F., 2016. Shadow detection and removal in RGB VHR images for land use unsupervised classification. ISPRS J. Photogramm. Remote Sens. 119, 485–495. https://doi.org/10.1016/j.isprsjprs.2016.05.004

Müllerová, J., Josef, B., Bartaloš, T., Dvořák, P., Vítková, M., Pyšek, P., 2017. Timing Is Important : Unmanned Aircraft vs . Satellite Imagery in Plant Invasion Monitoring. Front. Plant Sci. 8. https://doi.org/10.3389/fpls.2017.00887

NCO VMB https://portal.nature.cz/publik_syst/ctihtmlpage.php?what=1035

Prošek, J., Gdulová, K., Barták, V., Vojar, J., Solský, M., Rocchini, D., Moudrý, V., 2020. Integration of hyperspectral and LiDAR data for mapping small water bodies. Int. J. Appl. Earth Obs. Geoinf. 92. https://doi.org/10.1016/j.jag.2020.102181

Prošek, J., Šímová, P., 2019. UAV for mapping shrubland vegetation: Does fusion of spectral and vertical information derived from a single sensor increase the classification accuracy? Int. J. Appl. Earth Obs. Geoinf. 75, 151–162. https://doi.org/10.1016/j.jag.2018.10.009

Schmidt, J., Fassnacht, F.E., Förster, M., Schmidtlein, S., 2018. Synergetic use of Sentinel-1 and Sentinel-2 for assessments of heathland conservation status. Remote Sens. Ecol. Conserv. 4, 225–239. https://doi.org/10.1002/rse2.68

Schmidt, J., Fassnacht, F.E., Neff, C., Lausch, A., Kleinschmit, B., Förster, M., Schmidtlein, S., 2017. Adapting a Natura 2000 field guideline for a remote sensing-based assessment of heathland conservation status. Int. J. Appl. Earth Obs. Geoinf. 60, 61–71. https://doi.org/10.1016/j.jag.2017.04.005

Sklenicka, P., Šímová, P., Hrdinová, K., Salek, M., 2014. Changing rural landscapes along the border of Austria and the Czech republic between 1952 and 2009: Roles of political, socioeconomic and environmental factors. Appl. Geogr. 47, 89–98. https://doi.org/10.1016/j.apgeog.2013.12.006

Stenzel, S., Feilhauer, H., Mack, B., Metz, A., Schmidtlein, S., 2014. Remote sensing of scattered natura 2000 habitats using a one-class classifier. Int. J. Appl. Earth Obs. Geoinf. 33, 211–217. https://doi.org/10.1016/j.jag.2014.05.012

Štroner, M., Urban, R., Seidl, J., Reindl, T., Brouček, J., 2021. Photogrammetry using UAV-mounted GNSS RTK: Georeferencing strategies without GCPs. Remote Sens. 13. https://doi.org/10.3390/rs13071336

Vanden Borre, J., Paelinckx, D., Mücher, C.A., Kooistra, L., Haest, B., De Blust, G., Schmidt, A.M., 2011. Integrating remote sensing in Natura 2000 habitat monitoring: Prospects on the way forward. J. Nat. Conserv. 19, 116–125. https://doi.org/10.1016/J.JNC.2010.07.003

Wakulinśka, M., Marcinkowska-Ochtyra, A., 2020. Multi-temporal sentinel-2 data in classification of mountain vegetation. Remote Sens. 12. https://doi.org/10.3390/RS12172696

Weil, G., Lensky, I.M., Resheff, Y.S., Levin, N., 2017. Optimizing the timing of unmanned aerial vehicle image acquisition for applied mapping ofwoody vegetation species using feature selection. Remote Sens. 9. https://doi.org/10.3390/rs9111130

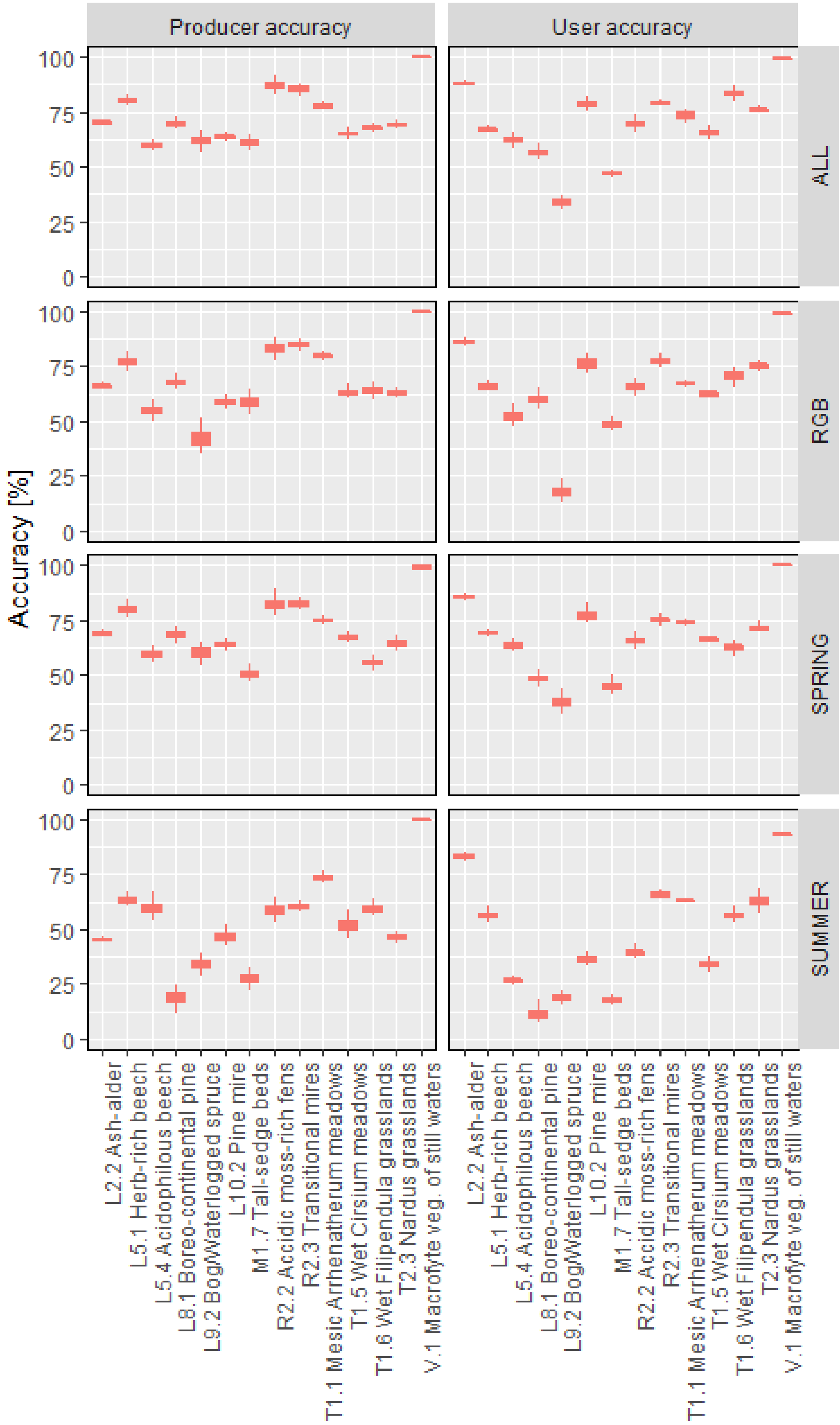
Wu, S.T., Hsieh, Y.T., Chen, C.T., Chen, J.C., 2014. A comparison of 4 shadow compensation techniques for land cover classification of shaded areas from high radiometric resolution aerial images. Can. J. Remote Sens. 40, 315–326. https://doi.org/10.1080/07038992.2014.979488

Zhou, X., Liu, C., Xue, Y., Akbar, A., Jia, S., Zhou, Y., Zeng, D., 2022. Radiometric calibration of a large-array commodity CMOS multispectral camera for UAV-borne remote sensing. Int. J. Appl. Earth Obs. Geoinf. 112, 102968. https://doi.org/10.1016/j.jag.2022.102968

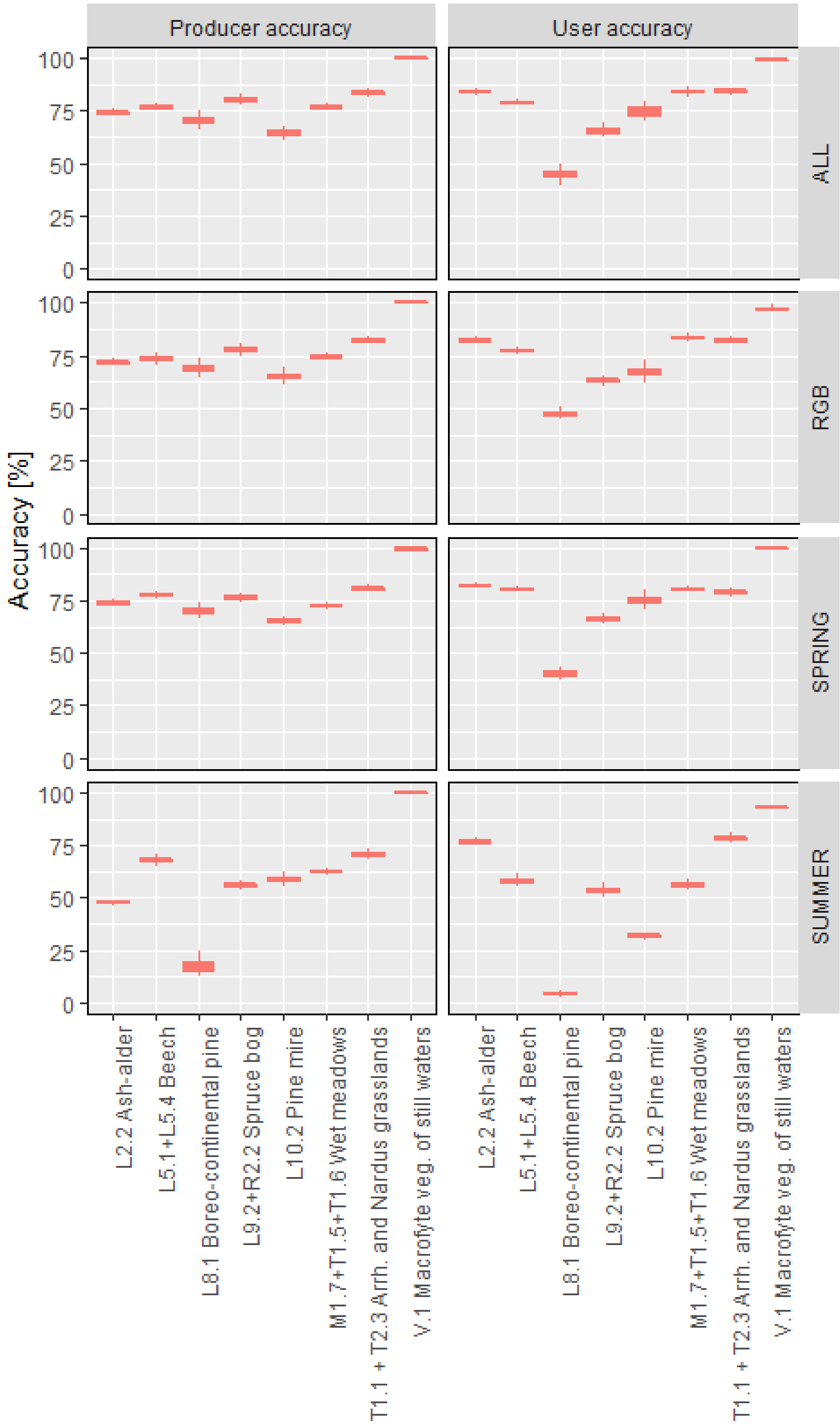
APPENDIX A

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

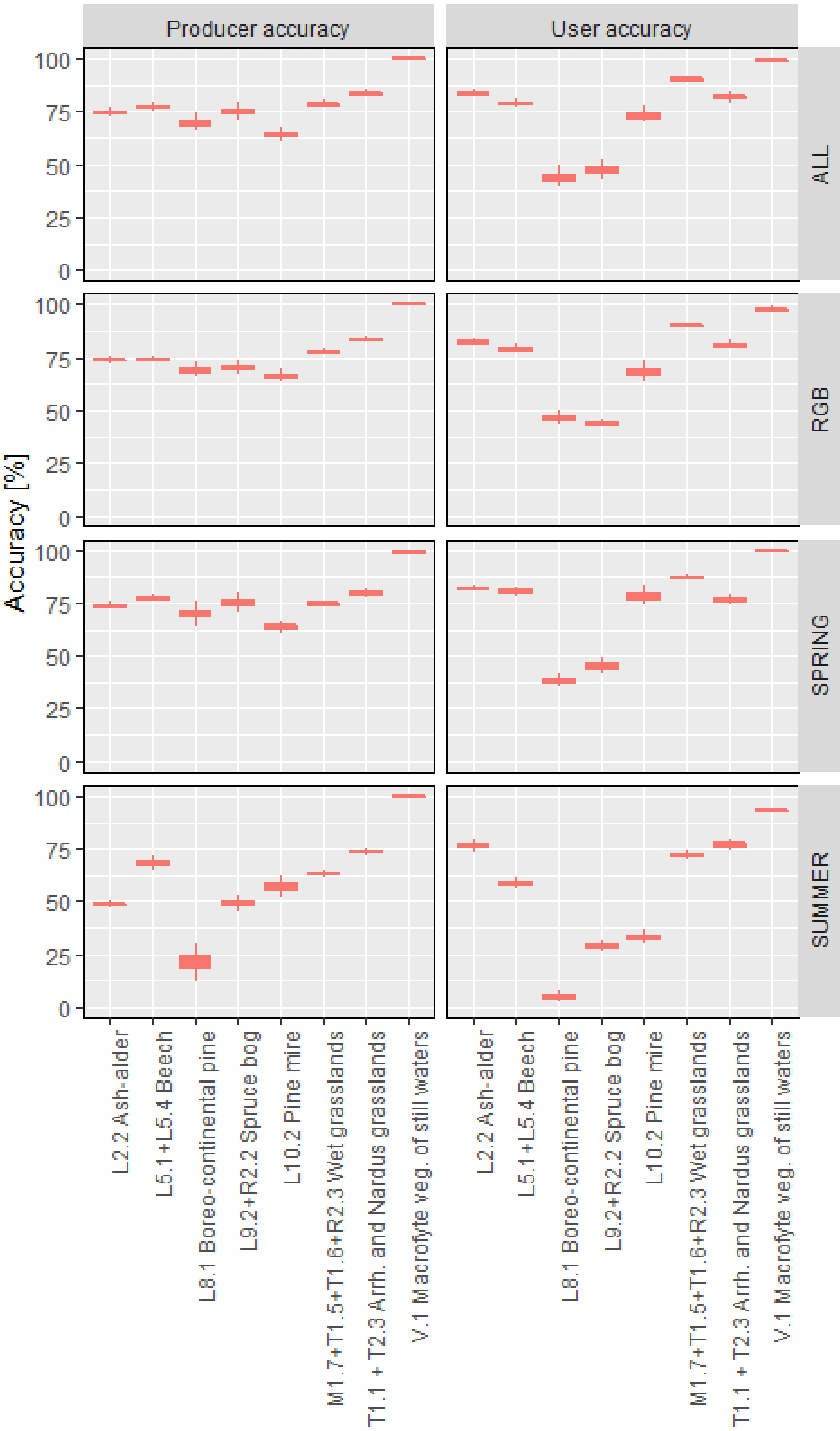
Scheme 1: Czech habitats according to Chytrý et al. (2010)



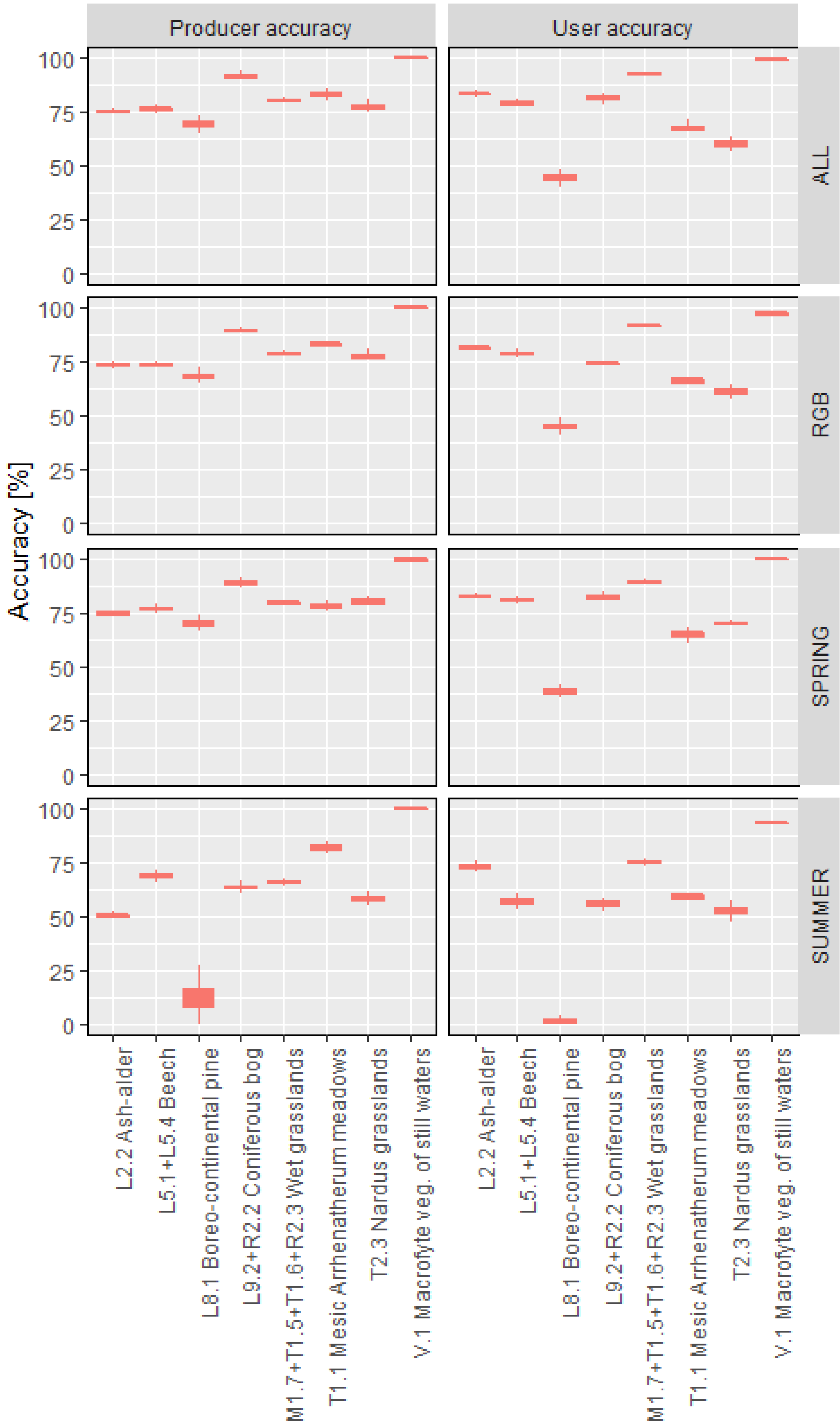
Scheme 2: Czech habitats, Aggregation #1



Scheme 3: Czech habitats, Aggregation #2



Scheme 4: Czech habitats, Aggregation #3



Scheme 5: European habitats