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Integration of ground-based and remote sensing data with deep learning algorithms for mapping habitats in Natura 2000 protected oak forests

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ABSTRACT

Landscape changes caused by climate change require new methods for forest research, analysis, mapping, and monitoring. This study aims to combine ground-based and remote sensing data utilising deep learning techniques to map protected forest habitats and communities within the Natura 2000 network. The study also seeks to evaluate the accuracy of this approach, specifically in oak-dominated forests, as well as identify the optimal time period within a year for effective habitat identification.

Using the specialised software NaturaSat, automated segmentations were performed based on the coordinates of phytosociological relevés and forest strands defined in database. Oak-dominated forest habitats were differentiated solely through multispectral data obtained from Sentinel-2 satellites. A dataset was selected for the training of a deep learning algorithm called the Natural Numerical Network on the basis of the analysis results. This algorithm aims to create a prediction map of habitats dominated by *Quercus cerris*, which is also known as the relevancy map.

Through the utilisation of the Natural Numerical Network, a training accuracy of 95.24% was achieved. Field validation, which was conducted at randomly generated locations within the relevancy map, yielded an accuracy of 98.33%. The most distinguishing differences in band characteristics between the two oak-dominated habitats were observed during the autumn months.

This study presents a framework that integrates terrestrial and remote sensing data. This method can serve as a basis for mapping forest habitats and observing changes related to climate change. Moreover, it contributes to the documentation of nature conservation and the mapping of landscapes.

Introduction

The oak genus (Filizzola et al., 2022; Rita et al., 2020) is considered one of the most dominant groups of woody angiosperms in the Northern Hemisphere (Tantray et al., 2017). Moreover, it is highly valuable due to the typically high species diversity found in oak habitats, as well as its economic importance (Najib et al., 2021). In Central Europe, two deciduous oak species dominate the majority of broad-leaved forests in the lowlands and at low elevations: *Quercus petraea* [Matt.] Liebl. (sessile oak) and *Quercus robur* L. (pedunculate oak) (Mészáros et al., 2022). Another oak species in Central Europe is *Quercus cerris* L. (Turkey oak), whose northern distribution limit passes through Slovakia (Praciak et al., 2013). These oak habitats are categorised under Natura 2000 habitat types (European Commission, 2013), including Quercus cerris-dominated habitats (91M0 Pannonian-Balkanic turkey oak-sessile oak forests and 91I0 Euro-Siberian steppic woods with Quercus spp.) and Quercus petraea-dominated habitats (91G0* - Pannonic woods with *Quercus petraea* and *Carpinus betulus*), which are relevant for understanding the ecological significance and conservation of these forests.

Future climate scenarios predict increased temperatures and

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frequency of major droughts across Europe (Change, 2013; Karl & Trenberth, 2003). Climate change is likely to affect forests and tree species differently, depending on local conditions and physiological thresholds (Allen et al., 2010). Droughts caused by the climate result in shifts in the boundaries of forest habitats and changes in species composition, as observed in Europe (Rita et al., 2020) and in different areas of the world (Andrus et al., 2021; Luo & Chen, 2015; McDowell et al., 2020). Weiss et al. (2023) also investigated the shift in forest habitat boundaries in favour of deciduous-dominated landscapes. In Slovakia and many other countries, data from botanists and foresters provide insights into forest areas and their species composition (and sometimes quality). Nevertheless, given the rapid transformation of forest ecosystems, relying solely on established field-based procedures for assessing forest conditions is challenging (Rigling et al., 2015; Zürcher-Gasser et al., 2016). This highlights the growing necessity for effective monitoring systems to assess habitat quality (Vaz et al., 2015). While Ivits et al. (2014) focused on the responses of European ecosystems to drought (according to vegetation phenology and productivity) using remote sensing (RS) techniques, Vincente-Serrano et al. assessed the impact of drought in a Mediterranean, semi-arid region (Vicente-Serrano, 2007), as well as the vegetation responses to droughts across global terrestrial biomes (Vicente-Serrano et al., 2013). They also analysed the diverse relationships between forest growth and the normalised difference vegetation index (NDVI) on a global scale (Vicente-Serrano et al., 2016).

Despite wide distribution in Europe (Barbati et al., 2014; Portoghesi, 2006), mixed deciduous oak forests have received relatively little attention in the context of climate change. Climate warming is expected to cause changes in the species composition and distribution of oak forests (Hlásny et al., 2011; Petritan et al., 2021). *Quercus cerris* has great potential because of its high resilience to adverse environmental factors and good adaptability to different site conditions, heat, and drought tolerance (Majer, 1984; Praciak et al., 2013), including resistance to environmental pollution (Bozzano & Turok, 2003; Tzvetkova & Kolarov, 1996). It is the only Central European oak species that rejuvenates well, even under a relatively closed canopy (Savill, 2019; Úradníček et al., 2001).

The forests of habitats dominated by *Quercus cerris* (91M0 Pannonian-Balkanic turkey oak-sessile oak forests and 91I0 Euro-Siberian steppic woods with *Quercus* spp.) are highly endangered in Slovakia because the wood of the turkey oak is considered of lower quality than that of other oak species in the country, thus leading to its frequent removal in favour of the other species. Consequently, it is imperative to understand the present occurrence of oak habitats and ensure their ongoing monitoring and steadfast protection of remnants. Furthermore, the speed and extent of the impacts of climate change pose a growing problem in the fields of forest management, landscape analysis, and modelling. The demand for timely, spatially, and thematically accurate information about these changes is constantly increasing (Burkhard et al., 2012; Gebhardt et al., 2014; Nguyen et al., 2018; Nguyen et al., 2020; Tomppo et al., 2021). Even the quantification, mapping, and monitoring methods for landscapes and forests are changing (Dettwiler, 2022). At present, there is a need for innovating these methods. RS and satellite data have proven effective in tracking the spatiotemporal dynamics of vegetation (e.g. Castellaneta et al., 2022; Imanyfar et al., 2019), as well as recognising, mapping, and monitoring forest/tree species (e.g., Cavender-Bares et al., 2016; Fassnacht et al., 2016; Puletti et al., 2018), including their diversity (Immitzer & Atzberger, 2023). Moreover, Filizzola et al. (2022) presented satellite data analyses to evaluate the effects of drought and the potential climatic impact on the oak forests of Southern Italy.

Researchers have also combined RS and deep learning to develop maps and tree detection/identification systems (Beloiu et al., 2023; Kattenborn et al., 2021), which may also be used for plant disease detection and classification (Saleem et al., 2019). As stated by Kerry et al. (2022), automation systems have improved so much in recent years that the monitoring of plants, animals or even insects has become less demanding, and the need to solve problematic methods and rely on field experts has also decreased (Bergslien, 2013; Buxton et al., 2018; Willi et al., 2018). RS and computer-based simulation techniques also play key roles in predicting and modelling anthropogenic activities, habitats, and land use, as well as in monitoring biodiversity over time (Bae et al., 2019; Bakx et al., 2019; Bouvier et al., 2017) and applying of deep learning algorithms (Mosebo Fernandes et al., 2020). These systems not only are reliable in the monitoring of habitats and biodiversity worldwide, but can also help prevent their further loss and contribute to the proper establishment of conservation measures.

The monitoring of habitats based on Natura 2000, as outlined in the Habitats Directive 92/43/EEC (92/43/EEC), presents significant challenges due to the complex nature of these habitats, defined by their species composition. According to the Habitats Directive's reporting guidelines, techniques such as the one used in this study are still under development and require further testing or adaptation for operational use for most Annex I habitats. Recently, a supervised deep-learning method based on a nonlinear, forward-backward diffusion model (the so-called Natural Numerical Network) was successfully used in the case of several forest habitats (riparian forests, oak-hornbeam, and beech forests (Mikula et al., 2023)). In this study, the application of the Natural Numerical Network for the classification of oak- and turkey oak-dominated habitats was tested. While in this study we use freely available multispectral satellite data, which we consider to be one of the main advantages of our approach, many recent studies have used hyperspectral imagery, which provides more detailed spectral information but is often limited in its availability (Huang et al., 2022; Liu et al., 2022; Sun et al., 2021; Sun et al., 2022). Nevertheless, advanced deep learning methods applied to hyperspectral data can serve as an inspiration for further development of classification techniques when dealing with multispectral data.

This study aims to (i) test the feasibility and find a suitable period of the year to distinguish similar forest habitats of the Natura 2000 system dominated by oaks (habitats dominated by *Quercus cerris* (QC) and habitats dominated by *Quercus petraea* (QP)) based only on optical information from Sentinel-2 satellite data; **(ii)** create a relevancy map of habitats dominated by *Quercus cerris* in the test area with the occurrence of the target habitat; and **(iii)** perform validation based on the Natural Numerical Network.

Materials and methods

Study area

The forest polygons in this study are located in the southwestern part of the Slovak Republic and are spread over a square area of approximately 2420 km^2 (Fig. 1). The edge coordinates for the westernmost polygon, are 48°9′37.47″ N, 17°3′18.06″ E; for the northernmost polygon, they are 48°32′33.7″ N, 17°31′27.15″ E; and for the easternmost polygon, they are 48°23′46.63″ N, 17°47′27.4″ E. The territory belongs to the Alpine and Pannonian bioregions (Cervellini et al. 2020). The polygons are located in the Podunajská Nížina Lowland and the Malé Karpaty Mts. (The Little Carpathians). The geological bedrock in the Podunajská Nížina Lowland consists mainly of clay, whereas in the Malé Karpaty Mts., the bedrock is more heterogeneous and includes limestone, granite, and quartzite (Asch, 2003, https://macrostrat.org). The mean values for altitudinal gradient, annual temperature, and annual precipitation characteristics are summarised for both groups of habitats in Table 1.

Data sampling

Phytosociological approach

To distinguish the specific habitats, relevés/polygons located in one square covered by Sentinel-2 data (Sentinel-2 square tile number 33UXP

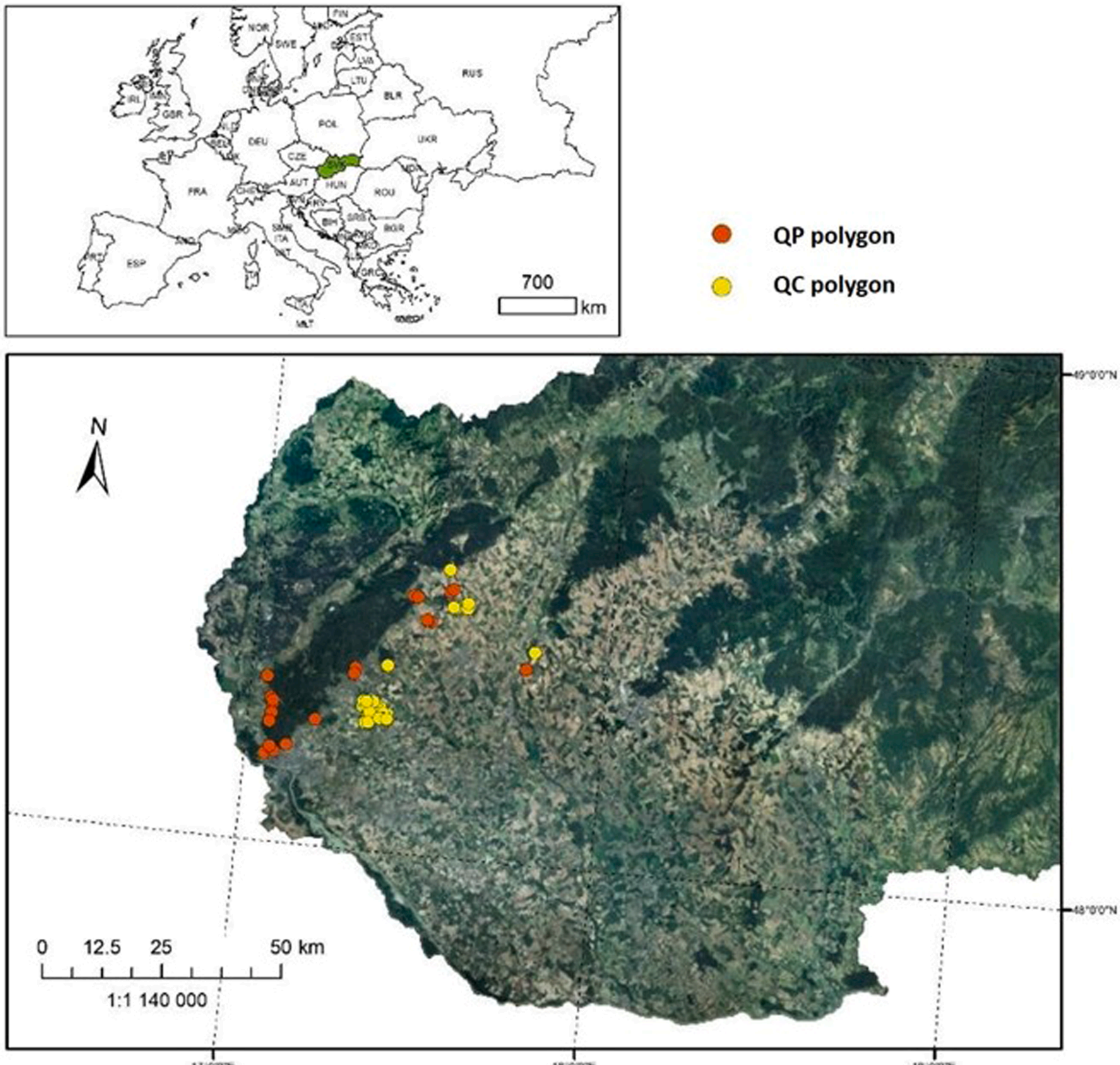

Fig. 1. Map of the location of all polygons from the case study (created by software ArcGIS 10.8.2 (ESRI, 2011), using orthoimage data from the State Geological Institute of Slovakia (GKÚ Bratislava) and National Forest Centre (NLC), Ortofotomozaika SR – ÚGKK ZBGIS 2023 https://zbgisws.skgeodesy.sk/zbgis_ortofoto_wmts/service.svc/get; data source (Geoportal, 2023).

Table 1
Descriptive statistics of mean altitudinal gradient and climatic data for the study area. The localities are displayed in Fig. 1: 'Map of the location of all polygons from the case study. The climatic variables were extracted from WorldClim version 2 ((Fick & Hijmans, 2017); http://www.worldclim.org)).

	Mean	Std	Min	Max
Altitude [m]				
Polygons dominated by *Quercus petraea* (habitat 91G0)	262	48	201	360
Polygons dominated by *Quercus cerris* (habitats 91M0, 91I0)	216	50	146	338
Mean **Annual Temperature [°C]**				
Polygons dominated by *Quercus petraea* (habitat 91G0)	9.3	0.3	8.8	9.8
Polygons dominated by *Quercus cerris* (habitats 91M0, 91I0)	9.4	0.5	8.5	9.9
Mean ***Annual Precipitation*** **[mm]**				
Polygons dominated by *Quercus petraea* (habitat 91G0)	683.4	38.8	590	751
Polygons dominated by *Quercus cerris* (habitats 91M0, 91I0)	637.8	57.7	538	707

covers eastern Slovakia and, the spatial resolution of Sentinel-2 data is up to 10 to 10 m, shown in Fig. 2) were included. Phytosociological relevés (31) sampled in the vegetation seasons of 2015, 2016, and 2021 (each on a plot of 400 m^2 via the Braun-Blanquet approach (Braun-Blanquet, 1964)) were supplemented with polygons on the basis of data from the LGIS forestry database (LGIS, 2020), where botanists confirmed the presence of target oak species in the tree layer (A table of phytosociological relevés for cluster analysis (see Appendix A) and a table of tree layer species and coverage for all polygons (see Appendix B) are available in the Supplementary.).

The NaturaSat software

The NaturaSat software is designed as a specialised tool for habitat identification, monitoring, and assessment, utilising advanced remote sensing techniques (Mikula, et al., 2021a). The software integrates a comprehensive set of tools for preprocessing satellite imagery, implementing classification algorithms, detecting temporal changes in habitat features, visualising habitat distributions, and facilitating interactions with geographic information systems (GIS).

By comparing satellite images captured at different time intervals, NaturaSat supports multitemporal analysis. Accurate segmentation

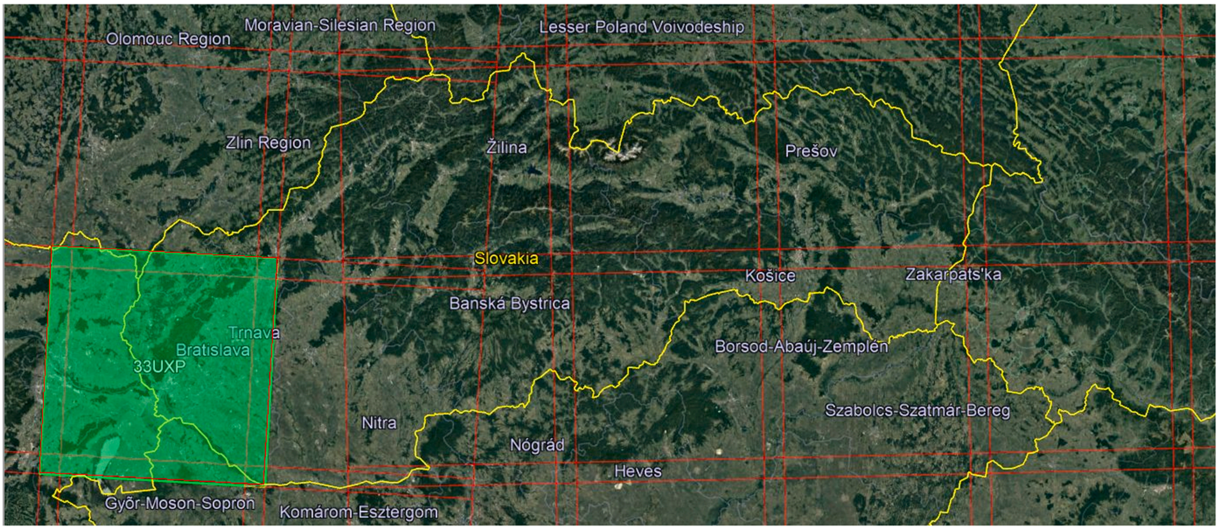

Fig. 2. Part of the map in the Remote Satellite Data Manager in NaturaSat focussed on the territory of Slovakia with red parallel lines indicating the boundaries of the Senitnel-2 tiles. The green square is the selected square with tile number 33UXP.

methods in NaturaSat are essential for delineating habitat boundaries and extracting spatial information for further analysis. Segmentation involves dividing an image into meaningful regions, each representing a distinct object. Object-based segmentation techniques commonly group pixels into homogeneous regions on the basis of spectral, spatial, and contextual data. To achieve precise image segmentation, the semi-automatic segmentation method evolves open polygons (discrete curves) in a Lagrangian formulation (Mikula et al. 2021b). Alternatively, an automatic segmentation method is available, which also utilises a Lagrangian formulation involving the evolution of closed plane polygons to segment the images (Mikula et al., 2021c). Following segmentation, feature extraction is conducted to compute various attributes for each polygon, characterising its spectral, textural, and geometric properties. These extracted features are then used as inputs for classification algorithms to distinguish between different habitat types on the basis of spectral information (Mikula et al. 2023). By integrating segmentation with classification, remote sensing specialists can efficiently map habitat types and monitor changes in habitat distribution over time.

The NaturaSat software is developed using the C++ programming language and is specifically designed for deployment on the Windows

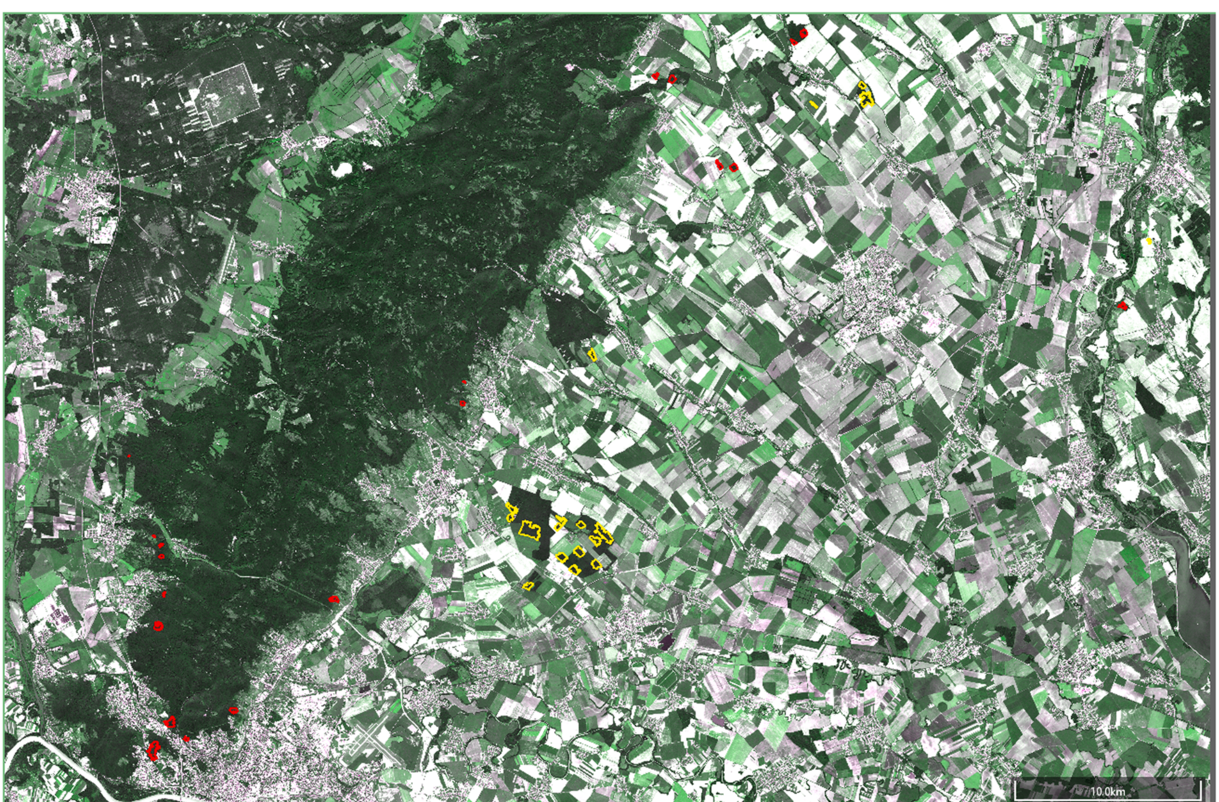

Fig. 3. Details of Sentinel-2 tiles with QC polygons (yellow) and QP polygons (red) (created with NaturaSat v2.1 software (Mikula et al., 2021a), data from October 15, 2019, Level-2A, sensing time 2019–10–15T09:50:31.024Z).

operating system, which targets the 64-bit architecture. The graphical user interface (GUI) is implemented using the Qt widget toolkit, version 6.5.2, distributed under the LGPL v3 and GPL v3 open-source licenses. The European Space Agency funds the development of NaturaSat and allows the trial version to be on the web page of the NaturaSat software (*NaturaSat*, 2024).

Segmentation methods

In the present study, automatic segmentation (Mikula et al., 2021c) methods are used to identify the habitat areas of 42 polygons, representing two oak-dominated habitats (21 polygons of QC and 21 polygons of QP habitats) (Fig. 3). The segmentations are performed on cloud-free Sentinel-2 datasets from 2018 to 2021 from locations representing the coordinates of phytosociological relevés or from the centre of a homogeneous area of forest stands in the case of areas supplemented by the forestry database (see Fig. 4). The Sentinel-2 datasets are downloaded directly via the NaturaSat component, the Remote Satellite Data Manager, which allows remote satellite data to be downloaded from the Copernicus Data Space Ecosystem (CDSE) by sending the URL request to the CDSE. Automatic segmentation is mathematically based on the use of partial differential equations (PDEs) for polygon evolution. In automatic segmentation, the polygons evolve via a function that incorporates both edge detection and smoothness constraints, enabling them to adapt precisely to the image's structure. This function typically includes terms for the image gradient and curvature, which help the evolving polygon align accurately with the boundaries of the objects of interest. Automatic segmentation has the advantage of being based solely on a high-quality estimation of the parameters of the entire segmented area from the inside of the initial circle (e.g., around a phytosociological relevé); therefore, it is not burdened by the "subjective" factor of the user (expert). This method preserves spatial coherence and can effectively capture complex habitat structures. Therefore, we consider its results to be objective, especially when relevés or initial circles are made in a representative location of the area where the botany experts confirmed the appearance of the target forests.

Computing of the multispectral characteristics

The monitoring tool in the NaturaSat component, allows the spectral characteristics inside the segmented habitat areas to be calculated via standard mathematical statistics formulations. All 17 optical bands which can be extracted from the Level-2A product of the Sentinel-2 satellite are used, namely B01-B08, B8A, B9, B11, B12, AOT, SCL, WVP, CLD, and SNW (for details and definitions, see Copernicus (2024)). Together with the NDVI, these indices contribute to the construction of the featured space. All optical bands are included in the final datasets in the PERMANOVA analyses, (see Data analyses section) which works with multidimensional data and tests the significance of differences between defined groups of relevés. The images with pixel resolutions of 20 m and 60 m were interpolated to a resolution of 10 m for all optical bands; in each forest polygon, we calculate the following statistical characteristics for all bands: the mean value, the minimum value, the maximum value, and the standard deviation. This set of calculated values creates a spectral characteristic of the habitat, which can be used for its identification.

Statistical analyses are performed on all cloudless available Sentinel-2 Level-2A datasets covering the area of all polygons during the vegetation season (from April to October) of 2018–2021. The characteristics of all the available band values are computed using NaturaSat tools.

In addition to testing the distinguishability of the QC habitats from the QP habitat, we are interested in determining the period of the year when differences in the spectral characteristics of habitats are most significant. Commonly in this type of research, time-series of datasets are used; however, in terms of very similar habitats dominated by the same tree genus (*Quercus*), the mean spectral values from a longer time period could conceal some important time-specific differences. The characteristics are calculated for datasets recorded in different parts of the year, namely, spring – April 21, 2019; April 22, 2020; June 16, 2021; summer–August 31, 2019; September 9, 2020; September 9, 2021; autumn–October 15, 2018; October 15, 2019; and October 24, 2021, and analysed separately. The seasonal classification (spring, summer, autumn) used in this study follows the astronomical calendar. This approach was chosen to reflect the specific climatic conditions, phenological stages, and environmental characteristics of the study area.

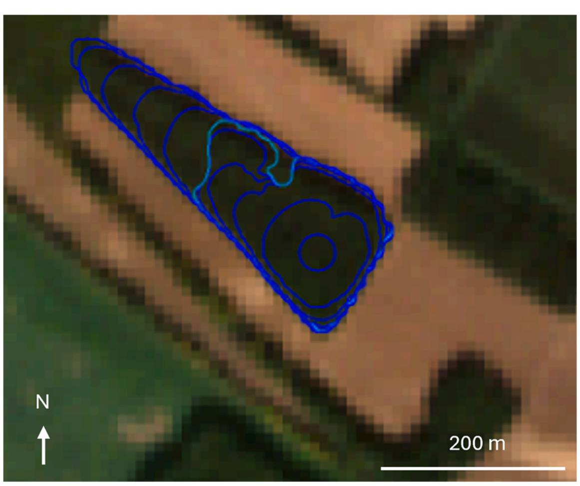

Fig. 4. Automatic segmentation of the QC habitat (polygon QC_senkvice2_733,845). The initial circle is placed around the location of the phytosociological relevé; the turquoise line indicates the fifth step of the automatic segmentation. The final polygon is created in the tenth step (in the software NaturaSat v2.1 (Mikula, et al., 2021a), data from October 15, 2019, Level-2A, sensing time 2019–10–15T09:50:31.024Z).

Data analyses

Cluster analyses

Available phytosociological relevés (31) are stored in the TURBOVEG (Hennekens & Schaminée, 2001) and exported to the JUICE (Tichý, 2002). Data for the species composition of relevés were processed via the hierarchical clustering method (with a beta-flexible algorithm (β= –0.25) and a Ruzicka coefficient similarity). The results are applied to the synoptic table to create differential groups of species of target relevés. The nomenclature of vascular plants is derived from the Euro+Med PlantBase, which is an information resource for Euro-Mediterranean plant diversity (Euro+Med, 2006).

PERMANOVA analyses

The spectral values inside the habitat areas are processed for each date separately and prepared for testing via PERMANOVA analyses, which are implemented in R- software (R Core Team, 2021) (package vegan (Oksanen J, 2022)) with Bray−Curtis indices, and 999,999 permutations. The significance of the difference between two sets of habitat areas (QP and QC) is tested, and the season with the most significant differences (lower p-value) was chosen as the best date for distinguishing habitats . Bray−Curtis dissimilarity, as an asymmetric index, is chosen over the symmetric Euclidean distance because it is more sensitive to relatively small differences, which is crucial for distinguishing between similar habitats in our spectral data.

Training of the natural numerical network and creation of the relevancy map

On the basis of the analysis results, the Sentinel-2 dataset, which was best for distinguishing habitats, is used for training the supervised deep-learning method on the basis of a nonlinear, forward-backward diffusion model, the Natural Numerical Network. The mathematical model of the method and algorithms was described in our previous work and published in journals focussed on mathematical modelling (Mikula et al., 2023). PCA analyses are used to find a combination of bands with the highest data variance, thereby automatically avoiding the bands without any significant contribution to data variability. The Natural Numerical Network classification output is given together with the cluster membership of any pixel of the satellite image via a relevancy map. The relevancy map is a greyscale image, with values between 0 and 1, which provides information on the relevancy of cluster membership to any given analysed habitat for every pixel. It has the same dimension as the satellite image. A total of 42 polygons from the dataset were used for the training of the Natural Numerical Network. This trained network was then imported into the NaturaSat software, and relevancy maps for both habitats were created for the areas of interest, i.e., Martinský Les (Martin Woods) protected area and surroundings.

Validation

Polygons representing QP and QC habitats were used for training, and the remaining polygons in the Martinský Les protected area outside these polygons were chosen for validation. On the basis of the training of the Natural Numerical Network and the created relevancy map, validation locations representing four neighbouring pixels (20×20 m area with GPS coordinates) were randomly selected using the NaturaSat software, providing 30 locations in the area with high relevancy (greater than 0.9) for the QC habitat (the target habitat occurs there) and 30 locations with the lowest relevancy, where the target habitat does not occur. All locations were verified by botanists in the field to confirm the presence/absence of the target habitat (Fig. 5). At the locations in the area with high relevancy, phytosociological relevés were sampled using the same method as those used for cluster analyses (each on a plot of 400 m^2etres using the Braun–Blanquet approach (Braun–Blanquet, 1964). Phytosociological relevés sampled at locations with high relevancy (see Appendix C) can be found in the Supplementary). The results of the validation were subsequently processed and evaluated by percentage accuracy, which refers to the identification accuracy of the target habitat (QC) at validation locations with high and low relevancy.

Results

Habitat classification

Habitat classification based on species composition confirmed the affiliation of the segmented areas with the QC and QP habitats in the case of all plant species, including those from undergrowth layers that are hidden from satellite data. The table created in JUICE (Tichý, 2002) using fidelity (< 25) shows the differential species pools for the analysed forests (the table is available in the supplementary materials). For the first group, which was dominated by *Quercus petraea* agg. in the tree layer, the differential species are: *Carex muricata* agg., *Carpinus betulus, Euphorbia amygdaloides, Euphorbia cyparissias, Fagus sylvatica, Fraxinus excelsior, Galium odoratum, Galium aparine, Hedera helix, Hypericum perforatum, Impatiens parviflora, Loranthus europaeus, Moehringia trinervia, Mycelis muralis, Prunus avium, Quercus petraea* agg., *Rubus hirtus* s. lat., *Tilia cordata*, and *Vincetoxicum hirundinaria*, all of which represent typical mesophilous forest species at lower elevations.

The second group, dominated by *Quercus cerris* in the tree layer contains more thermophilous differential species: *Cornus mas* and *Polygonatum latifolium*. Among the species occurring with similar frequency in the entire dataset, the grove grass *Melica uniflora* prevails. They are accompanied by the deciduous forest species *Acer campestre, Fallopia convolvulus, Ligustrum vulgare*, and *Prunus spinosa*.

According to the list of Slovak habitats, the training dataset was divided into two groups of habitats: i) QP oak-hornbeam forests (Ls2) and ii) QC oak-turkey oak forests/oak or mixed oak forests (Ls3) (Stanová & Valachovič, 2002). According to the EUNIS habitat classification, the first group, dominated by *Quercus petraea* agg., fits into *Carpinus* and the *Quercus* mesic deciduous forest (= 91G0* Pannonic woods with *Quercus petraea* and *Carpinus betulus* in Natura2000), which belongs to the alliance *Carpinion betuli* Issler 1931, whereas the second group, dominated by *Quercus cerris*, fits into the temperate and sub-mediterranean thermophilous deciduous forest (= 91M0

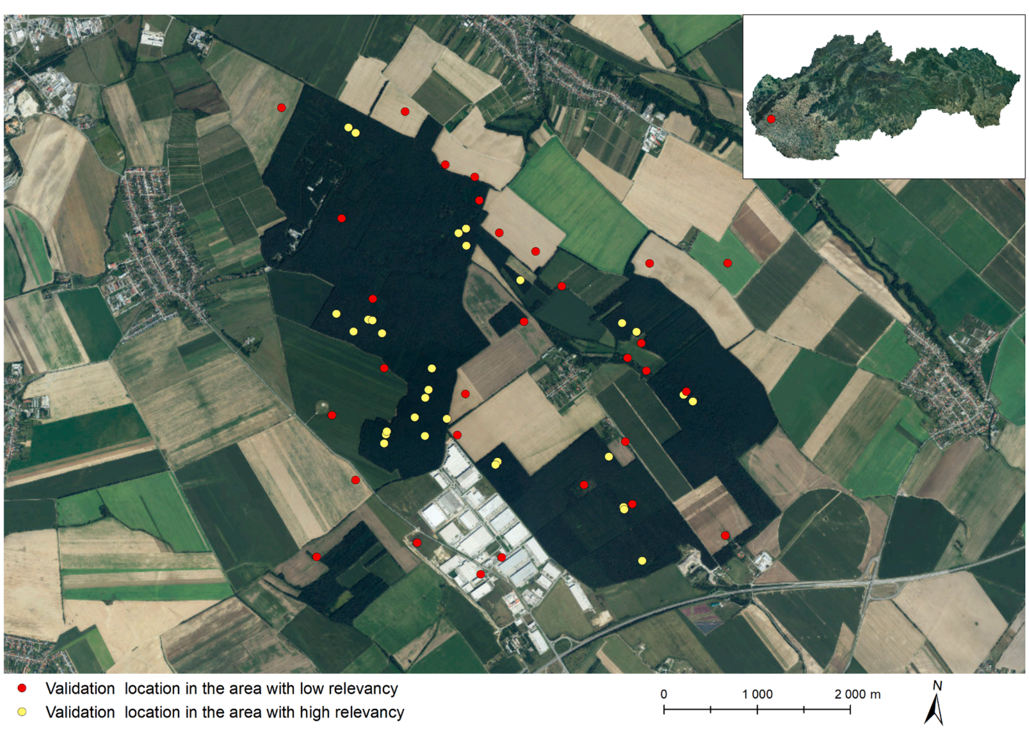

Fig. 5. Map with validation locations in the areas of Martinský Les SPA, Šenkvický Háj, and the surrounding forest. The locations in the area with high relevancy (30 yellow points) represent a locality where the QC habitat is located. A location in the area with low relevancy (30 red points) means that the target habitat does not occur there (created by ArcGIS 10.8.2 software (ESRI, 2011), with orthoimage data from the State Geological Institute of Slovakia (GKÚ Bratislava) and the National Forest Centre (NLC), 2023).

Pannonian-Balcanic turkey oak-sessile oak forests in Natura2000), which belongs to the alliance *Quercion petraeo-cerridis* Lakušić et B. Jovanović in B. Jovanović et al. ex Čarni et Mucina 2015 (Chytrý et al., 2020). According to the newest syntaxonomical Slovak revision of forest and shrub vegetation (Valachovič et al., 2021), the first group, with *Quercus petraea* agg. dominant, can be included in the alliance *Carpinion betuli* Issler 1931, whereas the second group, with *Quercus cerris* dominant, can be included in the alliance *Quercion petraeae* Issler 1931, as well as the association *Quercetum petraeo-cerridis* Soó ex Máthé et Kovács 1962.

Distinction of habitat types

When considering the distinction of habitat types, the most significant differences in the composition of band characteristics between the two oak-dominated habitats were obtained in the autumn season via PERMANOVA tests on the Sentinel-2 dataset from October 15, 2019 (Fig. 6). The optical band input data table (see Appendix D: Table 1) for all polygons, R-script (see Appendix D: Table 2), and results from PERMANOVA tests for other seasons (see Appendix D: Tables 2 and 3) are provided in the Supplementary.

Training of natural numerical network and the relevancy map

The results from the PERMANOVA analysis determines the most appropriate season for the classification and training of the Natural Numerical Network. The dataset from October 15, 2019 (Sentinel-2 Level-2A, sensing time 2019–10–15T09:50:31.024Z) is utalised. The training success rate is 95.24%, which represents only 1 misclassified polygon and 1 outlier from all polygons. A relevancy map is subsequently created for the QC habitats (Fig. 7B) in the areas of Martinský Les SPA, Šenkvický Háj, and surrounding forest fragments.

The relevancy map corresponds correctly to the areas of training polygons of the target habitat since they contain pixels of high relevancy represented by the white colour.

Table 2
Validation results of 60 randomly generated localities using software NaturaSat v2.1, where locations with high relevancy represent pixels, where the habitat dominated by *Quercus cerris* is present and locations with low relevancy represent pixels where the target habitat should not occur.

	Correct classification	Dubious classification	Incorrect classification
30 locations in the area with high relevancy	30	0	0
30 locations in the area with low relevancy	29	1	0
Summary	59	1	0
Evaluation [%]	**98.33**	**1.67**	**0**

Validation

The validation accuracy is 98.33% (Table 2). The occurrence of the QC habitats is confirmed at all 30 validation locations in the area, with high relevancy expressed in white in the relevancy map. Roads, buildings, fields, grasslands, plantations of *Robinia pseudoacacia*, and other forest habitats (e.g., riparian forests) were confirmed in 29 locations in the area with low relevancy (expressed in black in the relevancy map). In one location of the area with low relevancy, there was one QC tree surrounded by bushes, a road, and a field; thus, it cannot be classified as a habitat. In addition, the pixel resolution is 10×10 m, and the crown of the tree was relatively small; the software evaluated this pixel as not meeting the parameters of the target habitat.

Discussion

Our study integrates ground-based data and RS with deep-learning methods. Although such techniques are still developing (European

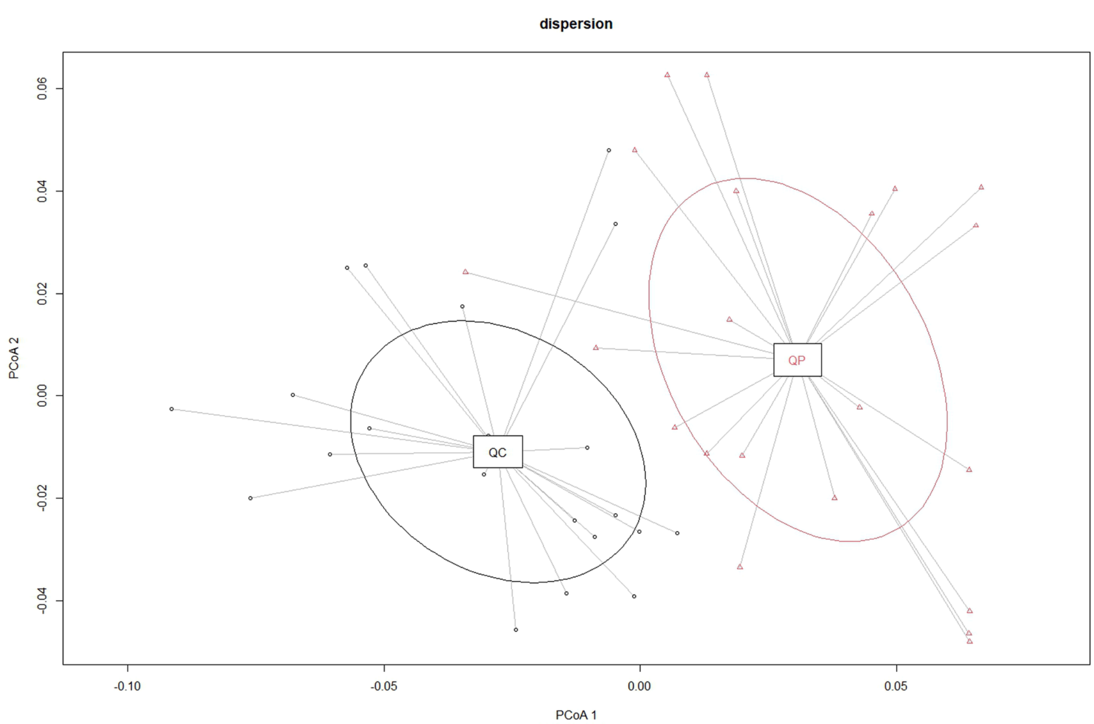

Fig. 6. Principal coordinates analysis (PCoA) of the data, which visualises the results of the PERMANOVA. PCoA is used to represent the multivariate distances and group differences identified by PERMANOVA. The target forest types were significantly differentiated on the basis of combinations of all optical bands extracted from Sentinel-2 data (Sentinel-2 Level-2A data from October 15, 2019, sensing time 2019–10–15T09:50:31.024Z), where the p-value is less than 0.001. Abbreviations: QC - polygons dominated by *Quercus cerris*, QP - polygons dominated by *Quercus petraea*.

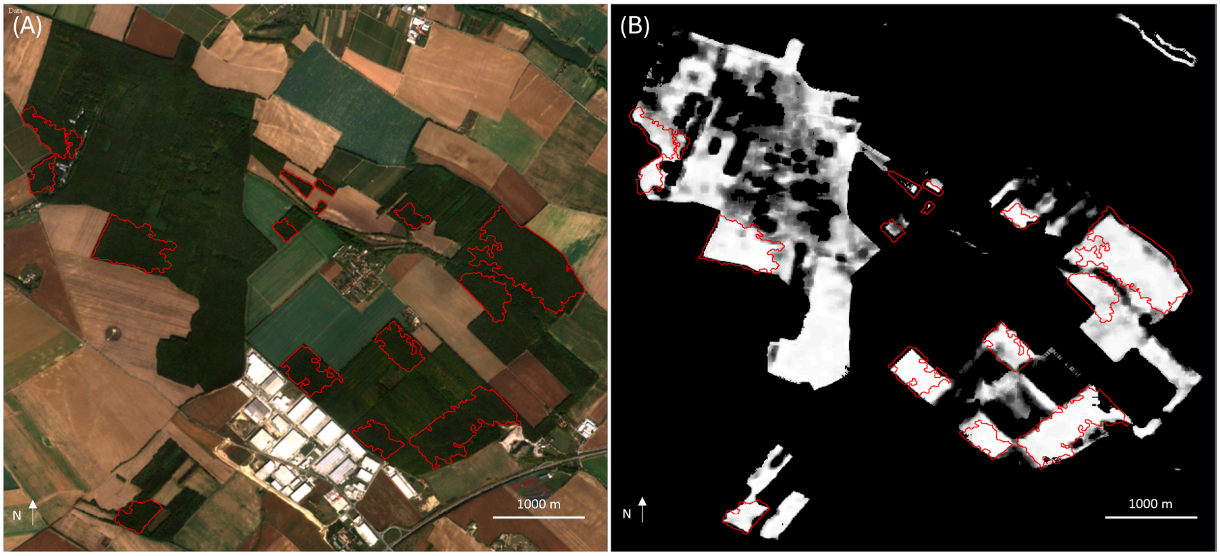

Fig. 7. Map showing (A) the location Martinský Les SPA, Šenkvický Háj and surrounding forest fragments. Relevancy map (B) of the QC habitats in the same location (created by NaturaSat v2.1 software (Mikula et al., 2021a), Sentinel-2, Level-2A data from October 15, 2019, sensing time 2019–10–15T09:50:31.024Z). The red line marks the QC polygons.

Commission, 2018), our approach shows considerable promise for effective habitat mapping, addressing the impacts of climate change (Allen et al., 2010; Gazol et al., 2018; Hlásny et al., 2011) and improving habitat map accuracy through advanced modelling (Dalle Fratte et al., 2019; Mucher et al., 2009).

Our findings demonstrate the efficacy of using only multispectral data from Sentinel-2 satellites to distinguish habitats, even those with similar species compositions. The accuracy assessment was performed on oak-dominated forests, which encompass habitats dominated by *Quercus cerris* (QC) and *Quercus petraea* (QP) on a fine spatial scale. We achieved a 95.24% training success rate and a 98.33% validation accuracy. Validation is conducted across randomly generated locations within the relevancy map created by the NaturaSat software. Our approach correctly identified QC habitats in all 30 expected locations and accurately indicated the absence of a QC in 29 out of 30 locations where the habitat was not expected. Only one location, which contained a solitary QC tree surrounded by fields, bushes, and a road, raised some uncertainty. However, as this location did not conform to the defined habitat parameters, it was classified as dubious rather than incorrectly identified. For comparison, our results correspond with, and in certain cases, even surpass results from previous studies (e.g., Adam et al., 2014; Fagan et al., 2015; Imbrenda et al., 2022; Laurin et al., 2016; Le Dez et al., 2021; Liu et al., 2018; Rapinel et al., 2020; Sittaro et al., 2022; Vaz et al., 2015). These studies employed diverse combinations of classifiers and methods for obtaining multitemporal, multispectral, and hyperspectral data. Their investigations, which involved basic land cover classification (e.g., bare soil, coastal habitats, forest types, grasslands, and wetlands) via a combination of different data sources (e.g., digital terrain model, Landsat, RapidEye, and Sentinel-2) and classifiers that achieved accuracy values above 90%, were common. However, when relying solely on information from the Sentinel-2 optical bands, the classification accuracy decreased to approximately 80%.

The accuracy of habitat classification is influenced by several factors, including training sample size, sample design, the spatial, spectral, and temporal resolutions of remote sensing data, the algorithm used, and the characteristics and complexity of the study area (Corbane et al., 2015; Phinzi, Ngetar, Pham, Chakilu, & Szabó, 2023; Phinzi & Szabó, 2024). The lower accuracy observed in other studies compared to our study may result from the classification of a larger number of habitat types or land-use categories. For example, Fagan et al. (2015) classified 20 land-use categories (e.g., urban, water, pasture, swamp forest) with a validation accuracy of 88.5%, whereas Rapinel et al. (2020) classified 18 plant communities with a validation accuracy of 72%. In contrast, our study focussed on distinguishing only two habitats.

In our study, we used 42 polygons representing QC and QP habitats to train the Natural Numerical Network and validated the model using 30 locations with QC presence and 30 without QC presence. Most studies used larger ground-based datasets, particularly for testing, which may have contributed to their lower accuracy. For example, Fagan et al. (2015) used 1287 training points and 1086 testing points, whereas Liu et al. (2018) used 603 reference samples, with one-fourth randomly selected for validation. However, QC and QP habitats are relatively rare in our study area, making it challenging to create a larger, evenly distributed ground-based dataset. A notable advantage of our study is the use of precise ground-based vegetation data collected between 2015 and 2021, which approximately aligns with the Sentinel-2 data (2018–2022) used. Additionally, the exact segmentation methods used during the training phase provided detailed insights, which are not always feasible in larger study areas.

Zhu and Liu (2014) and Turlej et al. (2022) employed Landsat data to identify forest types in Ohio (overall accuracy (OA) = 90.52%), as well as in northern Wisconsin and Australia (OA > 70%). However, their validation accuracy was lower than in our study, likely because the spatial resolution of Sentinel-2 images is greater than that of Landsat images (Liu et al., 2018). According to Xu et al. (2021) and Kwong et al. (2022), high spatial resolution is essential for the detailed classification of forest types or even individual tree species. Additionally, it enables the detection of small habitat patches even in heterogeneous landscapes.

Although we classified forest types in detail, the resulting accuracy was significantly greater than that of previous studies that focussed on more generalised landscape structures or broadly defined forest types (Dostálová et al., 2021; Erinjery et al., 2018; Thanh Noi & Kappas, 2018; Waśniewski et al., 2020) and used additional data such as DTM, hyperspectral data, or Lidar. The higher accuracy in our study may be attributed to the smaller study area, which provided more uniform conditions, as well as the selection of homogeneous forest stands and clear habitat transitions during the training phase. Future research should focus on the extrapolation of these methods to larger areas with more heterogeneous environmental conditions.

Our study also suggests that while time-series data can be beneficial, the results from Grabska et al. (2019) indicate that, compared with single-date imagery, Sentinel-2 time -series data could improve species mapping accuracy by approximately 5–10%. Despite Grabska et al.'s high accuracy with their time-series approach, our results with a single Sentinel-2 image were comparable, suggesting that high classification accuracy can be achieved even without time-series data. This underscores the effectiveness of our approach in distinguishing habitats with a single carefully chosen image, although incorporating time-series data could further refine the results in future research.

Axelsson et al. (2021) demonstrated that sequential Bayesian inference improves classification accuracy in cases of partial cloud cover, achieving an overall accuracy of 87% for tree species classification. Our results, with a validation accuracy of 98.33%, suggest that our method is highly effective, even surpassing some previous studies that relied on multitemporal data.

The most suitable period within the year to distinguish between the QC and QP habitats is the autumn season, which corresponds to the findings of Turlej et al. (2022) and Zhu and Liu (2014). This suggests that differences in the leaf colours between the QC and QP samples during this season lead to noticeable changes in spectral information, with the greatest variations occurring in autumn. Statistically significant differences between the spectral values of QC and QP were observed in the bands related to the vegetation red edge (B05, B06, B07, B8A), near-infrared band (B08) and mean NDVI in autumn. These differences suggest that QC and QP vary in terms of biomass, and the amount of chlorophyll and water in their leaves during this time of year (Filella et al.,1992). Additionally, QC and QP can be distinguished in the summer periods, although the differences are not as pronounced as they are in October. This variation may be related to the greater sap flow and water content in the trunks of QC compared to QP, as demonstrated by Tognetti et al. (1996), which can influence spectral signatures in the near-infrared bands and contribute to differentiation between the species across different seasons.

Bolyn et al. (2018) demonstrated the potential of Sentinel-2 for mapping forests in the Belgian Ardenne ecoregion, achieving high classification accuracies with spectral indices and classifiers. Their findings align with the results in our study, highlighting the importance of selecting the correct spectral bands and data periods for accurate mapping.

Overall, while our study focussed on a single Sentinel-2 image, the high accuracy achieved suggests that similar approaches could be expanded to other areas and incorporated into future software developments, potentially integrating time-series data for further enhancement.

Conclusions

RS can make botanical research and vegetation mapping more efficient. Our research emphasises connecting RS with data directly in the field, whether during data collection or validation. We demonstrated that we can use the automatic segmentation of NaturaSat data to determine the more accurate area of Natura 2000 habitat fragments dominated by *Quercus cerris*. We also confirmed that distinguishing target habitats is possible using only optical information from Sentinel-2 satellite data without any a priori information. In addition, our study achieved high accuracy when a single dataset of one day was used, without the need for time-series data, despite focussing on a smaller area. This approach can serve as a basis for future studies, with the potential to expand the study area. As we assumed for differentiation, but especially for training deep learning models, selecting the right period remains crucial.

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Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

Lucia Čahojová: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ivan Jarolímek:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis. **Barbora Klímová:** Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis. **Michal Kollár:** Writing – review & editing, Software. **Michaela Michalková:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Karol Mikula:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Funding acquisition, Formal analysis. **Aneta A. Ožvat:** Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Data curation. **Denisa Slabejová:** Writing – original draft, Formal analysis, Data curation. **Mária Šibíková:** Writing – review & editing, Software, Supervision, Resources, Methodology, Funding acquisition.

Declaration of competing interests

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.

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Supplementary materials

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