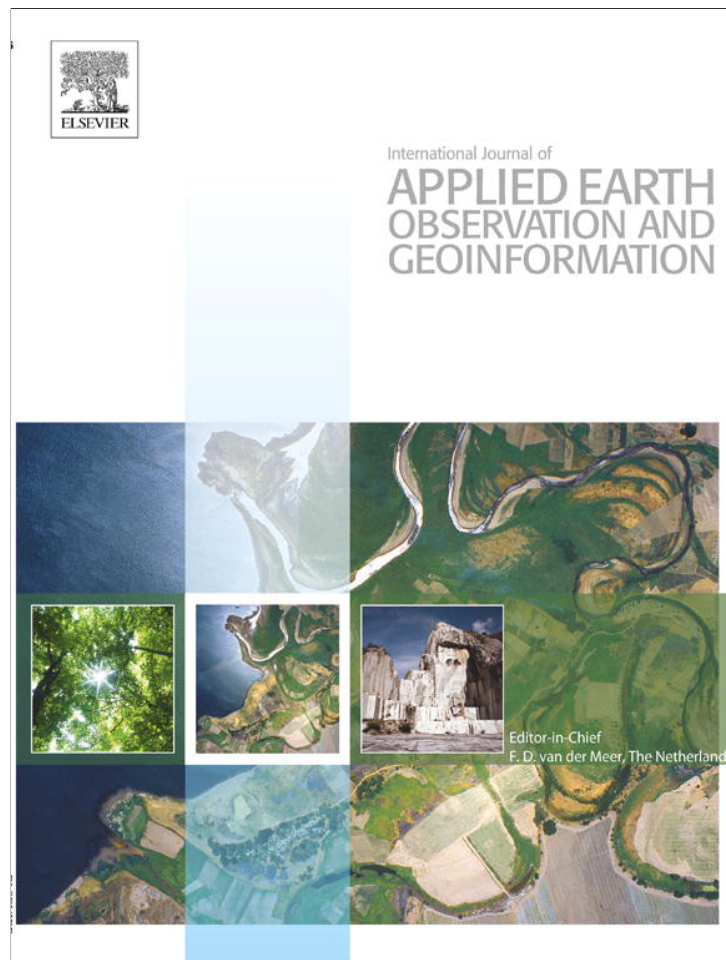


Provided for non-commercial research and education use.
Not for reproduction, distribution or commercial use.



This article appeared in a journal published by Elsevier. The attached copy is furnished to the author for internal non-commercial research and education use, including for instruction at the authors institution and sharing with colleagues.

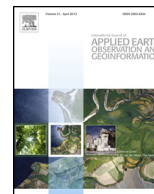
Other uses, including reproduction and distribution, or selling or licensing copies, or posting to personal, institutional or third party websites are prohibited.

In most cases authors are permitted to post their version of the article (e.g. in Word or Tex form) to their personal website or institutional repository. Authors requiring further information regarding Elsevier's archiving and manuscript policies are encouraged to visit:

<http://www.elsevier.com/authorsrights>

Contents lists available at [SciVerse ScienceDirect](http://www.sciencedirect.com)

International Journal of Applied Earth Observation and Geoinformation

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

Remote sensing as a tool for monitoring plant invasions: Testing the effects of data resolution and image classification approach on the detection of a model plant species *Heracleum mantegazzianum* (giant hogweed)

Jana Müllerová^{a,*}, Jan Pergl^a, Petr Pyšek^{a,b,c}^a Institute of Botany, Academy of Sciences of the Czech Republic, CZ-252 43 Průhonice, Czech Republic¹^b Department of Ecology, Faculty of Science, Charles University, Viničná 7, CZ-128 01 Praha, Czech Republic^c Centre for Invasion Biology, Department of Botany & Zoology, Stellenbosch University, Matieland 7602, South Africa

ARTICLE INFO

Article history:

Received 10 January 2013

Accepted 12 March 2013

Keywords:

Accuracy assessment

Historical aerial VHR photography

Invasion progress

Object-based

Pixel-based classification

Rapid Eye

ABSTRACT

Plant invasions represent a threat not only to biodiversity and ecosystem functioning but also to the character of traditional landscapes. Despite the worldwide efforts to control and eradicate invasive species, their menace grows. New techniques enabling fast and precise monitoring and providing information on spatial structure of invasions are needed for efficient management strategies to be implemented. We present remote sensing assessment of a noxious invasive species *Heracleum mantegazzianum* (giant hogweed) that integrates different data sources, spatial and spectral resolutions, and image processing techniques. Panchromatic, multispectral and color very high spatial resolution (VHR) aerial photography (1947–2006, resolution 0.5 m), and medium spatial resolution satellite data (Rapid Eye 2010, resolution 5 m) were analyzed to assess their potential for hogweed monitoring by using pixel- (both supervised and unsupervised) and object-based image analysis (OBIA, automated hierarchical, iterative, and rule-based). Both point and grid based accuracy assessment was carried out. Described methods of object-based image analysis of VHR data enabled monitoring of hogweed at high classification accuracies measured by various means, regardless of the spectral resolution of the data provided that the data came from the species flowering period. Although the proposed automated processing of VHR data is relatively time-effective and standardized, application over large areas would be rather demanding due to the size of datasets, and multispectral satellite data of medium spatial resolution (lower than the size of individuals) was therefore tested. On such imagery, only larger stands could be identified but still the pixel-based supervised classification achieved moderate accuracy. Depending on the size of the area of interest and the detail needed the very high or medium spatial resolution data (acquired at the species flowering period) are to be used. High accuracies achieved for VHR data indicate the possible application of described methodology for monitoring invasions and their long-term dynamics elsewhere, making management measures comparable precise, fast and efficient.

© 2013 Elsevier B.V. All rights reserved.

1. Introduction

Alien plants represent a serious threat to modern changing landscapes that suffer from intensive exploitation by humans, or on the other hand, land abandonment (Millennium Ecosystem Assessment, 2005). They not only have devastating economic impacts, affect human health, and threaten biodiversity and ecosystem functioning (Ehrenfeld, 2010; Pyšek and Richardson, 2010;

Vilà and Ibáñez, 2011; Pyšek et al., 2012b), but also dramatically change the character of traditional landscapes (With, 2002; Chytrý et al., 2012). Regardless of growing eradication and management efforts the abundance of invasive species and their impact on biodiversity worldwide is increasing (Hulme et al., 2010). Invasion is a dynamic process that can be fast, and after the species has spread over the landscape and achieved a high abundance it can be difficult or even impossible to stop or slow down the invasion (Rejmánek and Pitcairn, 2002; Pluess et al., 2012). Early and fast detection is needed to make the management cost-effective (Nielsen et al., 2005; Pyšek and Hulme, 2005; Wittenberg and Cock, 2005; Vilà and Ibáñez, 2011). More information on the invasion process itself, and on the role environmental conditions and landscape structures play in the course of invasion is important for efficient protective

* Corresponding author. Tel.: +420 271015207; fax: +420 271015105.

E-mail addresses: jana.mullerova@ibot.cas.cz (J. Müllerová),jan.pergl@ibot.cas.cz (J. Pergl), petr.pysek@ibot.cas.cz (P. Pyšek).¹ <http://www.ibot.cas.cz/en/oddeleni.gis>.

measures to be implemented (Andrew and Ustin, 2010; Minor and Gardner, 2011).

To efficiently manage ongoing invasions it is necessary to monitor the species spread regularly, and there is an urgent need for new techniques enabling timely, fast and precise monitoring (European Commission, 2008; Hulme et al., 2009). Semi-automated, computer-assisted approaches of remotely sensed (RS) data are cost-effective and permit fast and frequent mapping (Kokaly et al., 2003; Underwood et al., 2003). RS was successfully used in invasion studies (for reviews see Huang and Asner, 2009), mostly for shrubs and trees (Costello et al., 2000; Fuller, 2005; Hamada et al., 2007; Asner et al., 2008; Lawes and Wallace, 2008; Walsh et al., 2008). RS of herb species is possible only if the data provide enough spectral and/or spatial detail, the species is distinct from surrounding species and background, forms dense and uniform stands, and/or is large enough to be detected (Maheu-Giroux and de Blois, 2004; Müllerová et al., 2005; Peterson, 2005; Bradley and Mustard, 2006; Jones et al., 2011). Due to the difficulties of herb species recognition on RS imagery, hyperspectral data are often used (for reviews see Huang and Asner, 2009; He et al., 2011), and multispectral or even panchromatic data applications focusing on herb species invasions are not common (but see Müllerová et al., 2005; Laba et al., 2010; Jones et al., 2011).

Historical very high spatial resolution (VHR) aerial photography provides an excellent source of information on changing landscapes over time (Laliberte et al., 2004; Brook and Bowman, 2006), and under certain circumstances (appropriate time of acquisition, good recognizability of target, good time series) it can be used for studying invasion process in detail. Due to the low spectral resolution of historical aerial photography, traditional pixel-based approaches of computer-assisted classification are not successful, and in the past, photographs were usually processed manually (Costello et al., 2000; Maheu-Giroux and de Blois, 2004; Müllerová et al., 2005; Morgan et al., 2010). With the development of the object-based image analysis (OBIA) new possibilities of automated or semi-automated processing of such high spatial and low spectral resolution data arose (Laliberte et al., 2004; Pringle et al., 2009). While OBIA is increasingly applied in studies of ecological patterns and processes, few studies have so far used OBIA for herbaceous or invasive species classification (but see Walsh et al., 2008; Jones et al., 2011; Ouyang et al., 2011). In our previous study dealing with RS mapping of giant hogweed, we used manual interpretation, i.e. on-screen digitizing of historical panchromatic VHR aerial imagery (Müllerová et al., 2005). The mapped hogweed invasion history enabled us to assess rates of invasion (Müllerová et al., 2005; Pyšek et al., 2007c, 2008) as well as to address more general ecological questions on the role of long-distance dispersal in population dynamics of plant species (Pergl et al., 2011; Nehrbass et al., 2007). However, manual processing is laborious, time consuming, and not feasible for larger areas. Therefore, it was important to develop automatic or semi-automatic image processing techniques to classify VHR imagery that would enable us to study the patterns at larger scales.

In this paper, we present RS assessment of a noxious invasive species *Heracleum mantegazzianum* (giant hogweed). This well-known invasive herb species introduced from Asia occupies large areas in central and northern Europe and continues to spread. The rate of its invasions is comparable to some of the most dramatic invasions globally (Müllerová et al., 2005; Pyšek and Hulme, 2005). Invading populations not only change the character of ecosystems by forming dense uniform stands (Page et al., 2006; Thiele and Otte, 2006; Hejda et al., 2009) but also pose danger to humans due to toxins that cause skin injuries (Nielsen et al., 2005).

The objectives of our study were to test and evaluate the potential of spectrally and spatially different RS data for automatic detection of giant hogweed, and establish methods that could be

used to monitor invasions at larger spatial scales. Invasions are typically expressed at regional scales as species disperse over long distances, and therefore need to be managed at a landscape level (Lawes and Wallace, 2008). Although recent VHR data are readily available in digital and georeferenced form, their application over large areas is costly and laborious (Chen et al., 2012). Therefore, in addition to the VHR data we also decided to test satellite imagery at a coarser spatial resolution (5 m) in order to address invasions at the landscape scale. Further, we used the results obtained for this particular model invasive species to outline best mapping strategies and management recommendations that can be applied to plant invasions in general.

2. Methods

2.1. Study species

Giant hogweed (*H. mantegazzianum* Sommier and Levier, Apiaceae) is the tallest herbaceous species in Europe, reaching 2–5 m in height during flowering period, with leaves up to 2.5 m long and large white inflorescences of compound umbels up to 80 cm wide (Page et al., 2006; Perglová et al., 2006, Fig. 1). The species is monocarpic, and usually lives 3–5 years, although a 12-year-old individual was recorded (Pergl et al., 2006). It reproduces entirely by seed and can produce enormous numbers of fruits, on average 20,000 per plant (Perglová et al., 2006). In the study area, the species flowers from late June to early August (Perglová et al., 2006).

The species is native to the western Greater Caucasus (Jahodová et al., 2007) where it grows on wet and nutrient-rich soils on mountain slopes, and following its introduction as an ornamental in the beginning of the 19th century it became one of the most serious plant invaders in Europe (DAISIE, 2012), including Czech Republic (Pyšek et al., 2012a). In central Europe, it invades mainly unmanaged semi-natural grassland communities, nutrient-rich sites, forest edges and anthropogenic habitats (Pyšek and Pyšek, 1995; Thiele and Otte, 2006) forming large homogenous populations, although small groups of plants scattered along linear landscape structures such as roadsides and water streams are frequently observed (Thiele et al., 2007). In once invaded sites, it may persist in for a long time, up to many decades (Pergl et al., 2012). Eradication and control of the species is difficult (Pyšek et al., 2007a). On recently infested sites eradication is cheaper and more likely to be successful because it targets small and young populations where the seed bank has not yet established. Early detection of the species and rapid management response is therefore important (Nielsen et al., 2005; Page et al., 2006).

2.2. Study area

The study region is located in the Slavkovský les Protected Landscape Area (PLA), West Bohemia, Czech Republic (Fig. 1). Here, the species was first introduced to the country in 1862 (Pyšek, 1991). After World War II, the region experienced profound changes in settlement and land use. Local German inhabitants were expelled from the country, and the area became a military zone and later uranium mining area with restricted access (until the 1960s). In that time, many villages were destroyed and never restored. After the army and mining industry left, the sparsely inhabited area with extensive agriculture was declared as the PLA in 1973. Natural vegetation of beech and spruce forests, peat bogs and pine forests on serpentine (Neuhäuslová and Moravec, 1997) was largely replaced by spruce plantations (covering 53% of the area), extensive wet grasslands with high species diversity, and pastures. The absence of regular management combined with historical disturbances increased the suitability of the landscape

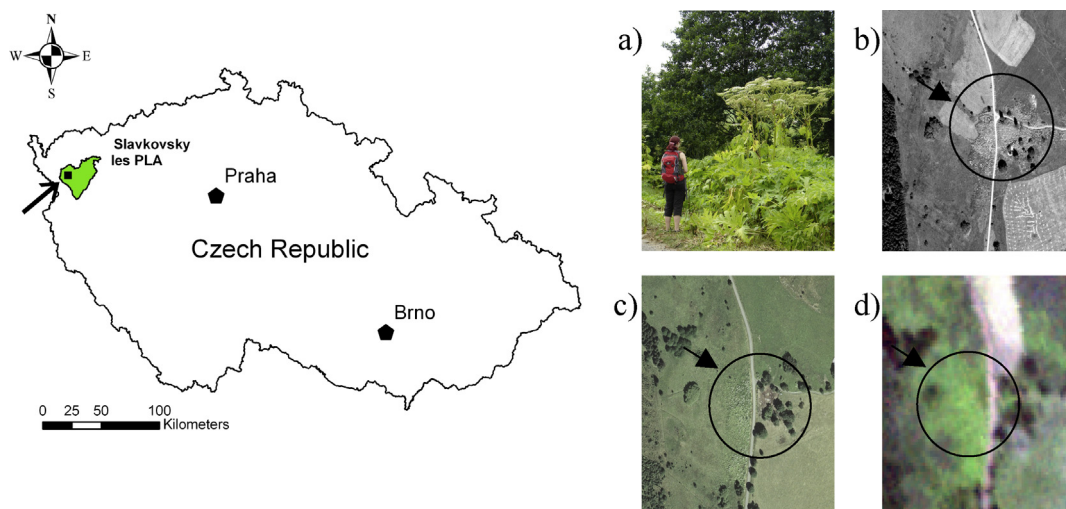


Fig. 1. Location of the study site. *Heracleum mantegazzianum* (giant hogweed) from the ground (a), and from the air: (b) panchromatic photography (1962, Military Topographic Institute, Dobruška); (c) color photography (2006, GEODIS, Prague); (d) multispectral satellite imagery (2010, Rapid Eye AG). Available in color online.

to the invasion (Pyšek, 1991). The invasion started in the 1950s and today the region is heavily infested (Müllerová et al., 2005). The start of the invasion in PLA corresponds to the beginning of the rapid spread of the species over the country, with the Western Bohemian region serving as a source (Pyšek, 1991; Pyšek et al., 2007c). For the purposes of this methodological study we chose a test site of 100 hectares within the study region of PLA (Fig. 1) that has been infested for more than 50 years, and is covered by various RS data sources acquired at the giant hogweed flowering season.

2.3. Data processing

Data of different origin (aerial and satellite, archival and current), spatial (VHR and medium), and spectral (panchromatic, color, and multispectral) resolution (Table 1) were assessed for automatic detection of hogweed. Historical aerial photographs were scanned in 1200 dpi and orthorectified using 2006 orthophotographs with 40–60 ground control points distributed along the whole area of the rectified photograph (2nd order of transformation and nearest neighbor rectification method) at a final pixel size of 0.5 meters. Aerial photographs (panchromatic, color, and multispectral) and satellite imagery (Rapid Eye, resolution 5 m) were analyzed by both pixel- and object-based approaches.

The pixel-based approach classifies individual pixels by similarities in their spectral characteristics. Both unsupervised (ISODATA, *K*-means and Fuzzy *K*-means) and supervised (maximum likelihood and minimum distance) classifications (Jensen, 2004) were tested using software *Geomatica 10* (2005). Training areas for supervised classification were selected from visual interpretation of historical data and field observation (2010).

The object-based approach (OBIA) relies on both spectral and spatial information (texture, spatial characteristics, context, and topology; Benz et al., 2004), and is therefore ideal for low spectral resolution imagery such as historical panchromatic photography (Laliberte et al., 2004). In OBIA, the image is segmented into groups of contiguous pixels (image objects) that are then classified according to spectral variables, shape, texture, size, thematic data, and spatial relationship (contiguity) and the distance between objects. In our study, a combination of automated hierarchical, iterative, and ruled-based classification (for description of the terms, see Blaschke et al., 2008) was applied using the software *Definiens Developer 8* (Definiens AG, 2009). Only the hogweed objects were classified. Multiresolution segmentation was applied with parameters (scale,

color, and shape) determined using a systematic trial-and-error approach. Various scales were tested and segmentation outputs were visually evaluated to identify the best parameters to extract the targets of interest (i.e. hogweed). Rule-based classification (Fig. 2) was applied on the segmented objects using conditions related to spectrum (brightness, mean layer, maximum pixel values, standard deviation, hue, saturation, intensity transformation for RGB), shape (area, length/width), texture (compactness, GLCM homogeneity, GLCM dissimilarity, and GLCM contrast), and context (existence of thematic layer, relative border, contrast and edge contrast of neighbor pixels, existence of super-object, growth region in certain conditions). To speed up the classification process two hierarchical levels of multiresolution segmentation were performed. Coarser segmentation objects with a high probability of giant hogweed presence (indicated by spectral characteristics and texture) were classified as “Hogweed candidate class”. This candidate class was further segmented by fine segmentation and classified to extract “Hogweed class” (Fig. 3).

Analyzed imagery was acquired at different times during the season, mostly in July, except for the 1973 panchromatic VHR data and 1987 multispectral VHR data (August). Since the species appearance differs markedly in vegetation season (having distinct white rounded umbels in flowering), we considered the timing of the data acquisition as an important factor in the success of the species mapping. Phenophases of hogweed captured on the analyzed RS data were derived from detailed analysis of the course of hogweed phenophases in the study area, carried by Perglová et al. (2006). To eliminate the inter-year differences, the phenological stages in analyzed years were calibrated using long-term phenological observations of summer flowering herbs at nearby phenological stations (Oracle Phenodata database; Czech Hydrometeorological Institute, CHMI; Hájková et al., 2012; Table 2).

2.4. Accuracy assessment

Ground truthing of historical images was obviously impossible, and visual photo-interpretation was therefore used to assess their accuracy. Recent imagery was field verified. In pixel-based assessment (further called “point assessment”), a total of 500 randomly located verification points (distinct from the training areas of supervised classification) were used to create error matrices (Congalton, 1991). To ensure sufficient coverage of hogweed class, the points were stratified (300 points located inside and 200 points outside manually classified hogweed area).

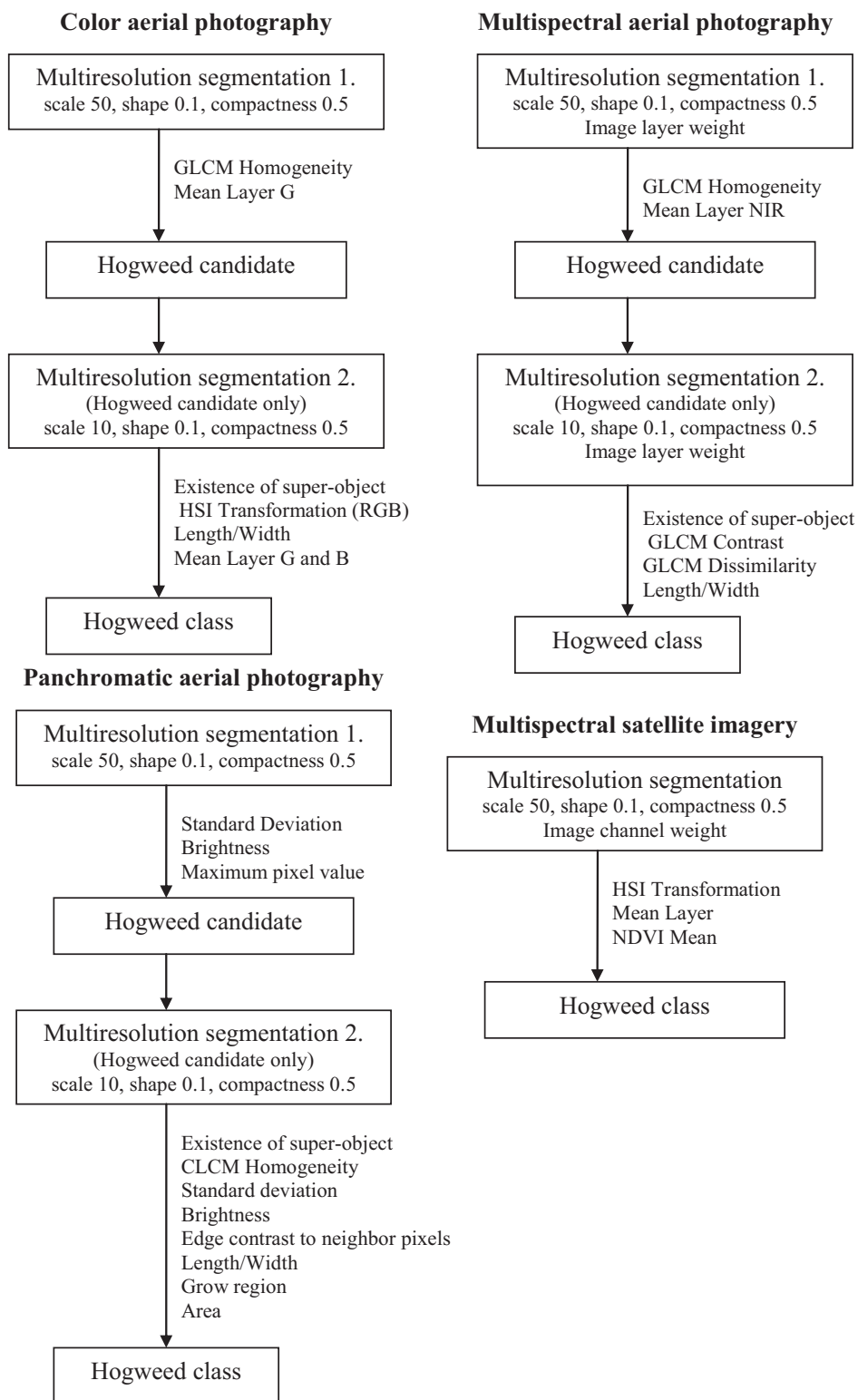


Fig. 2. OBIA classification schemes for the four types of data tested.

Although many authors state that for evaluation and comparison of classification results the accuracy assessment is crucial (Foody, 2010; Chen et al., 2012), there are many methodological uncertainties, especially in object-based approach (Foody, 2002; Morgan et al., 2010). It has been argued that traditional pixel-based accuracy assessment (i.e. points) tends to underestimate object-based image accuracy mainly due to allocation inaccuracies

(Hamada et al., 2007). To verify OBIA classification, some authors used random polygons (Jobin et al., 2008; Mallinis et al., 2008). We rejected this approach because it suffers from several problems: (i) polygon complex borders are difficult to locate exactly in the field and thus verify, especially when working with VHR imagery (in sub-meter resolution it comes to the limits of field GPS instruments); (ii) polygons are not perfectly homogenous

Table 1
Technical parameters of analyzed data.

Year	Date	Scale	Source	Spectral resolution	Channels (in nm)	Camera	Focal length	Film material	Provided by
1962	25 July	1:12,000	Aerial	Panchromatic		WILD 328	209.73	Unknown	Military Topographic Institute, Dobruška
1973	11–16 August	1:27,000	Aerial	Panchromatic		WILD 328	114.36	Unknown	Military Topographic Institute, Dobruška
1987	21–23 August	1:25,000	Aerial	Multispectral	448, 540, 660, 840	MSK-4	125	FOMA (visible), I-840 (NIR)	Nature Conservation Agency of the CR in Prague
1991	23 July	1:13,400	Aerial	Panchromatic		LMK 269152B	152.2	FOMA	Military Topographic Institute, Dobruška
2006	18 July	1:5000	Aerial	Color orthophoto		ZEISS RMK TOP 300	300	AGFA AVICOLOR NP 200	GEODIS s.r.o.
2010	8 July	5 m/res.	Satellite	Multispectral	440–510, 520–590, 630–685, 690–730, 760–850	Rapid Eye			RapidEye AG

so it is difficult to evaluate their “correctness” (thus subjective thresholds are needed); and (iii) different sizes of polygons (or segments) make the comparison difficult. Some authors compare OBIA results to manually classified plots (Laliberte et al., 2004; Laba et al., 2010). This approach could work for simple landscapes but for a complex patchy mosaic on VHR data manual delineation is very difficult and subjective (Corcoran and Winstanley, 2008; Hofmann et al., 2008), making the bias caused by inaccuracies in manual classification too great to make relevant assessment (being more manual/digital comparison than the accuracy assessment). After thorough search in the literature, we modified approach from Hamada et al. (2012). We established 20 random quadrates of 40 to 40 m, and to reduce subjectivity of visual photo-interpretation of historical photography overlaid the quadrates by a 1 m² grid assigned onscreen by hogweed presence/absence (further called “grid assessment”; sort of pixelization of the VHR results).

From the error matrices, standard accuracy measures were calculated, such as user's accuracy (UA; ratio of the correctly classified and the number of total classified, evaluating reliability of the results for the user), producer's accuracy (PA; ratio of the number of correctly classified and the number of observed), and Kappa analysis (conditional Kappa index evaluating the statistical significance of the classifications, considers the actual agreement of the class in relation with chance agreement, Congalton and Green, 1999; Foody, 2002). We used the Kappa statistics even though it has recently come under strong criticism due to the randomness used as a baseline (Pontius and Millones, 2011), because it is a widely used mean of the accuracy measure providing an opportunity for comparison with previous studies. Yet, because these classic accuracy measures were developed for pixel-based approach and their application on OBIA results is questioned (Möller et al., 2007; Blaschke, 2010), we also searched the literature for other accuracy indices, tested them for correlation to reduce their number, and finally chose allocation disagreement (AD; Winter, 2000; Pontius and Millones, 2011), calculated as a sum of false positives and false negatives divided by a sum of true positives and all false; and quantity disagreement (QD; Pontius and Millones, 2011), calculated as false positives minus false negatives divided by a sum of true positives and all false. Values of acceptable classification accuracy presented in the literature differ considerably. Pringle et al. (2009) consider accuracy over 70% as adequate, whereas Foody (2002) recommends values over 85%. Landis and Koch (1977) proposed categories for assessment of the classification performance measured by Kappa value as poor (<0.41), moderate (0.41–0.61), good (0.61–0.81), and excellent (>0.81).

We were also interested in comparing the results of manual and computer interpretation of the imagery. Hogweed polygons in 20 randomly located circles of 20 m radius were manually on-screen digitized and fragmentation analysis carried out, counting sets of patch metrics such as class area, number of patches, mean patch size, standard deviation, and coefficient of variance, total length of edge and mean patch edge reflecting the complexity of the polygons. Since we were interested in hogweed class only, other land cover types were not classified in OBIA approach, and the overall accuracy was therefore not relevant. All accuracy values account solely for the hogweed class.

GIS analyses were performed using ArcGIS 9.2 (ESRI, 2006), landscape metrics calculated using Patch Analyst 5.0 for ArcGIS (Rempel et al., 2012) and FRAGSTAT 3.3 (McGarigal et al., 2002), and statistical analysis using Statistica 10 (StatSoft Inc., 2011).

3. Results

The analyses showed rapid invasion of the test site over the 50 years covered (Fig. 4). From the primary dispersal foci in the

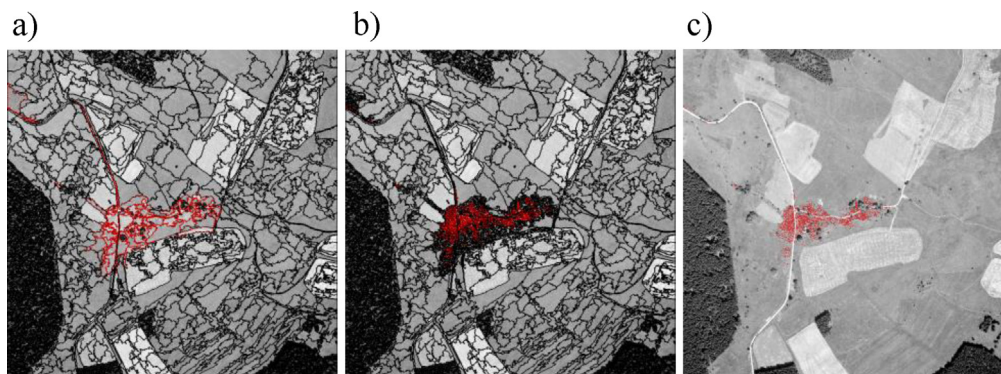


Fig. 3. Example of hierarchical coarse (a) and fine (b) image segmentation, and rule-based classification process (OBIA; c). Panchromatic aerial photography of 1962 (Military Topographic Institute, Dobruška) was analyzed in Definiens software. Giant hogweed candidate in segmentation process and resulting hogweed class are marked in red. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

center of the study site in 1962 the species spread exponentially into the surroundings. For most of the data, good efficiency in hogweed classification was achieved (assessed by both point and grid approach; Table 2). The appropriate classification methods depended on the character of RS data (its spectral and spatial resolution), and on the projection of giant hogweed on different imagery (Tables 3 and 4). For panchromatic as well as color VHR (spatial) imagery, the best results were provided by OBIA approach with average accuracies (by both assessment methods) of UA 81%, PA 87%, conditional Kappa 0.77, QD 0.12, and AD 0.28. Pixel-based methods gave very poor results for such low spectral resolution data and were excluded from further analysis. For multispectral VHR aerial data, acquired at the time of the species fruiting, the OBIA approach yielded better results but the accuracy was still lower compared to the previously mentioned results. Average accuracies (both assessment methods) of multispectral VHR imagery were: UA 71%, PA 65%, conditional Kappa 0.61, QD 0.36, and AD 0.51. The medium resolution satellite data showed comparably higher accuracies for pixel-based methods, with supervised (maximum likelihood) classification achieving the best results (average UA 66%, PA 79%, conditional Kappa 0.5, QD 0.22, and AD 0.45; Tables 2 and 3) but still much lower compared to VHR data.

In our study, we used both grid and point accuracy assessment. Both methods agreed in choosing the best classification methods for the hogweed classification; however, their results differed. The pattern of differences in the two accuracy assessments could be related to the type of classification approach (Table 2). In OBIA,

grid accuracies were usually higher compared to the point assessment, and the opposite was true for the pixel-based classification. This pattern was most pronounced for Kappa coefficient and AD and for other indices the response was more complex. For both types of assessment, UA was significantly positively correlated with the Kappa value and negatively with both disagreement measures whereas PA was only correlated to AD. AD and QD were also significantly correlated, with AD values in all cases higher than QD.

On the imagery, plants were captured in different phenological phases from early flowering to ripe fruiting (Table 2). Classification success was influenced by the phenological stage of the species. The best classification results (VHR imagery – average UA 84%, PA 87%, conditional Kappa 0.8, QD 0.11, and AD 0.26) were obtained during the mid-flowering phase (July) due to the distinct white color of inflorescences, whereas at later stages (end of flowering – early fruiting) hogweed stands were not so distinct, and the detection of stands with ripe fruits was problematic (case of 1973 panchromatic and 1987 multispectral aerial data, Table 2).

The results of automated classification were compared to the manual on-screen digitizing of hogweed polygons (Table 5). The results of manual interpretation were less complex with multiple lower numbers of polygons, significantly higher standard deviation, higher mean size of patches, larger area, lower patch size coefficient of variance, and significantly lower total length of edge compared to the digital classification. This was especially true for the later stages of invasion where a larger area was invaded.

Table 2
Classification results of different data sources and classification approaches. Both point and grid accuracy assessments are included. Accuracy indices were: user's accuracy (UA), producer's accuracy (PA), quantity disagreement (QD), and allocation disagreement (AD). Phenological phases of *H. mantegazzianum* (giant hogweed) on the data were calibrated using detail phenological study of Perglová et al. (2006), and CHMI long-term phenological database (Hájková et al., 2012).

Year	Resolution (in m)	Source	Type of data	Phenological phases (after calibration)	Processing	UA (in %)		PA (in %)		Conditional Kappa		QD		AD	
						Point	Grid	Point	Grid	Point	Grid	Point	Grid	Point	Grid
1962	0.5	Aerial	Panchromatic	Middle flowering	OBIA	80.53	74.29	88.95	98.65	0.70	0.74	0.09	0.24	0.27	0.26
1973	0.5	Aerial	Panchromatic	Final-size/ripe fruiting	OBIA	68.87	78.91	86.39	85.60	0.53	0.78	0.18	0.07	0.38	0.30
1987	0.5	Aerial	Multispectral	Ripe fruiting	OBIA	74.23	67.70	36.55	94.08	0.57	0.65	0.45	0.27	0.68	0.36
1987	0.5	Aerial	Multispectral	Ripe fruiting	MaxLike	57.20	17.43	68.53	64.95	0.29	0.12	0.13	0.67	0.54	0.84
1987	0.5	Aerial	Multispectral	Ripe fruiting	ISO	65.47	26.98	46.19	55.86	0.43	0.22	0.24	0.43	0.63	0.78
1991	0.5	Aerial	Panchromatic	Middle flowering	OBIA	82.39	81.39	82.98	91.13	0.75	0.81	0.01	0.10	0.30	0.25
2006	0.2	Aerial	Color	Middle flowering	OBIA	88.98	95.50	67.26	94.49	0.83	0.95	0.23	0.01	0.38	0.10
2010	5	Satellite	Multispectral	Early flowering	OBIA	39.13	44.07	97.06	87.96	0.24	0.29	0.59	0.47	0.61	0.58
2010	5	Satellite	Multispectral	Early flowering	MaxLike	64.50	67.21	99.50	58.77	0.41	0.58	0.35	0.10	0.36	0.54
2010	5	Satellite	Multispectral	Early flowering	ISO	63.03	39.08	75.38	58.73	0.39	0.26	0.14	0.69	0.48	0.22

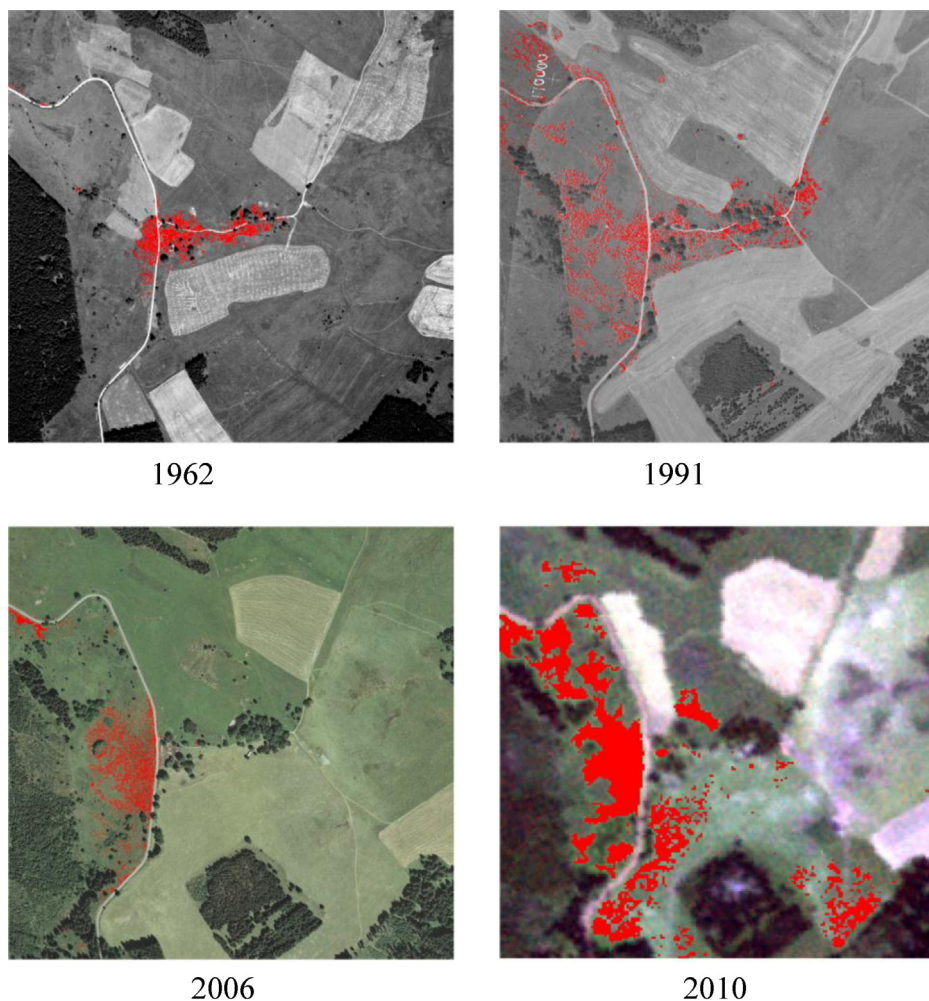


Fig. 4. 50 years of invasion on the study site (giant hogweed class in red). In 2006 protective measures against invasion were implemented, and the area occupied by giant hogweed is therefore temporarily reduced. The imagery comes from Military Topographic Institute, Dobruška (1962, 1991), GEODIS, Prague (2006), and Rapid Eye AG (2010). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Discussion

4.1. Trade-off between accuracy and scale: choosing the most suitable monitoring method

Our study established efficient automatic methods for monitoring of the invasive herb giant hogweed from remote sensing data. VHR (spatial) imagery with pixel size smaller than individual plant enabled reliable detection of individuals with good to excellent results according to Landis and Koch (1977) if classified by object-based methods and acquired at the right phenological stage of the species. The success of classification did not depend on the spectral resolution of data; even historical panchromatic imagery provided good results.

Although at peak flowering hogweed flowers have distinct round shape and white color, they form large compound umbels that flower successively, hence the inflorescences are composed of buds, flowers and ripening seed at the same time (Perglová et al., 2006), and the inflorescences are therefore not spectrally homogeneous on VHR imagery. Such high spectral variability within objects reduced accuracy of pixel-based classification (so called H-resolution problem and salt-and-pepper effect; Yu et al., 2006; Chen et al., 2012) whereas OBIA employing additional information such as shape, texture, and the context of mapped objects (hogweed individuals) reached comparably higher accuracies

(c.f. Cleve et al., 2008; Pringle et al., 2009; and Ouyang et al., 2011).

Mapping of hogweed was generally precise, but under the tree canopy or if grazed or mown, the hogweed could not be detected. On managed sites it could be present in a form of short individuals with few small leaves in ground rosettes, sometimes even manage to flower late in the season producing short stems with and small inflorescences (ca. up to 20 cm in diameter) with a few seeds. Together with a seed bank that persist for up to 3 years (Moravcová et al., 2006; Gioria et al., 2012) this not only ensures regeneration of the populations, but also indicates that such stands are not suitable for giant hogweed in a long-term. However, if the stand is not managed regularly during the whole vegetation season, the species might return quickly to its previous abundance (Pyšek et al., 2007b). Despite such limitations, the overall distribution in the target area could be obtained with a high accuracy.

Even though the proposed automated processing of VHR data is relatively efficient, for large areas it would be rather demanding because of the enormous amount of data to be analyzed and associated high costs (Chen et al., 2012). As shown in our study, satellite data of medium resolution such as Rapid Eye can provide an effective alternative on a coarser level, serving as a useful tool for nature protection to mitigate the large-scale impacts of plant invasions.

Comparing automated and manual interpretation of data, the automated approach captured very small patches as well as gaps

Table 3

Processing approaches for data of different spatial and spectral resolution and their performance illustrated by conditional Kappa coefficient (Congalton and Green, 1999). The measure of classification performance (poor to excellent) follows Landis and Koch (1977).

Low spectral/very high spatial resolution data
Our type of data

- color/panchromatic aerial data
- very high spatial resolution (<0.5 m)
- low to very low spectral resolution

Pixel-based image processing

- not suitable – not enough spectral information

Object-based image processing

- applied semi-automated hierarchical, iterative, and rule-based classification approach
- additional information on shape, texture and context of mapped objects enhance classification considerably
- moderate to excellent classification performance (conditional Kappa – 0.53–0.95)

High spectral/very high spatial resolution data
Our type of data

- multispectral aerial photographs
- very high spatial resolution (<0.5 m)
- high spectral resolution (5 channels including NIR)
- wrong timing of the data acquisition (after flowering) ► poor classification results

Pixel-based image processing

- unsupervised classification – ISODATA: moderate classification accuracy (conditional Kappa – 0.43)
- supervised classification – maximum likelihood: poor classification accuracy (conditional Kappa – 0.29)

Object-based image processing

- semi-automated hierarchical, iterative, and rule-based classification approach
- moderate classification accuracy (conditional Kappa – 0.57)

High spectral/medium spatial resolution data
Our type of data

- multispectral satellite imagery (Rapid Eye)
- medium/high spatial resolution – lower than the size of individuals but enabling to map homogeneous stands (5 m)
- high spectral resolution (5 channels including NIR)

Pixel-based image processing

- unsupervised classification – ISODATA: poor classification performance (conditional Kappa – 0.39)
- supervised classification – maximum likelihood: moderate classification performance (conditional Kappa – 0.41)

Object-based image processing

- poor classification performance (conditional Kappa – 0.24)
-

in hogweed stands that were often omitted by manual delineation. This was especially true for images from the latter stages of invasion when larger areas were infested. Hogweed structures became more complex and therefore difficult and laborious to delineate manually and so the interpreter tended to omit small patches and generalize (cf. Corcoran and Winstanley, 2008; Morgan et al., 2010). Thus the advantage of automatic classification of RS imagery over the manual one increased with the growing size and complexity of the landscape mapped. The direct use of manually classified maps of hogweed presence as a reference would therefore bring about many inaccuracies.

Overall, there is a trade-off between the accuracy necessary for studies at the ecological scale, and large-scale applicability needed for efficient management. The most suitable method to be applied to monitor a particular plant invasion thus depends on the purpose of the study. As different data types and processing methods can capture different features of plant morphology and structure and different aspects of the ecological dynamics of invasion, follow up studies on monitoring invasive plant species are encouraged to find out the best methods for their purposes by conducting pilot studies.

Table 4

Consequences of different spatial resolution of data for vegetation detection.

Spatial resolution higher than the size of mapped individuals (very high resolution data)
Conditions for the species detected

- unique spatial (spectral) patterns
- recognizable on the images (by eye)

Conditions for the RS data

- availability of images acquired in the right season

Advantages

- very high spatial resolution
- small patches and individuals can be recognized ► helps in monitoring onset of invasion and dispersal foci
- historical datasets enabling reconstruction of invasion progress

Disadvantages

- spectral resolution often low (panchromatic historical photographs)
- data often not standardized (historical datasets) ► difficulties in automatic processing
- timing of the data acquisition often not ideal (historical dataset) ► shifts in phenological stage of invasive species
- small areal extent of images ► large amount of data ► processing is labor and time intensive

Data used in our study

Sensor: aerial photography

Spatial resolution: <0.5 m

Temporal resolution: app. every decade since 1940s

Spectral resolution: mostly panchromatic

Spatial resolution lower than the size of mapped individuals (high/medium resolution data)
Conditions for the species detected

- large homogeneous stands
- unique spectral characteristics
- possibility of ground truth (by field work or aerial imagery with the species clearly visible)

Conditions for the RS data

- availability of images acquired in the right season
- sufficient spectral detail to recognize the species
- spatial resolution enabling to capture larger patches

Advantages

- larger area covered by a single image ► faster processing compared to VHR data
- standardized datasets ► possibility to apply automatic processing techniques
- repeated temporal coverage for regular monitoring
- high spectral resolution

Disadvantages

- lower spatial resolution compared to VHR data ► impossible to extract small patches or individuals
- short temporal resolution compared to aerial photography

Data used in our study

Sensor: Rapid Eye

Spatial resolution: 5 m

Temporal resolution: daily (off-nadir)/5.5 days (at nadir) since 2008

Spectral resolution: 5 bands incl. NIR

4.2. Accuracy assessment: an important issue

Sources of error in our study were the image mis-registration, and the inability to ground truth historical imagery in the field. At early stages of invasion grid accuracy assessment could be biased by the fact that the extent of hogweed was limited.

Although in our study the results of both pixel and object based accuracy assessment generally agreed (the same methods were selected as the best), the differences in accuracies derived by the two assessment types and different accuracy measures illustrate that the choice of classification accuracy assessment method has a great influence on results (especially true for OBIA). Lower values of AD (as well as conditional Kappa) in grid compared to the point assessment for OBIA (unlike the pixel-one) agree with statement of underestimation of OBIA accuracy by pixel assessment (Hamada et al., 2007). UA and conditional Kappa values derived from the two assessments were strongly correlated. Values of PA were usually higher compared to UA. Although the UA (expressing the commission error) seems important for natural protection applications,

Table 5

Comparison of automated classification (D) and manual on-screen digitizing (M) of hogweed polygons. Significant differences on level $\alpha = 0.05$ are marked by *. Classification approach providing the best results was analyzed, i.e. maximum likelihood in 2010 and OBIA in other cases.

Year	Class area		Number of patches		Mean patch size		Patch size standard deviation ¹		Patch size coefficient of variance		Total length of edge [*]		Mean patch edge	
	D	M	D	M	D	M	D	M	D	M	D	M	D	M
1962	7633.4	9002.3	334	285	22.9	31.6	117.4	131.5	792.0	439.7	10620.2	5810.2	31.8	20.4
1973	17085.7	15242.0	134	47	127.5	324.3	486.6	894.5	381.7	318.2	14063.9	3566.2	105.0	75.9
1987	26642.1	33254.9	204	59	130.6	563.6	582.5	1411.0	774.1	292.7	18766.4	6347.8	92.0	107.6
1991	12679.2	24498.3	3162	823	4.0	29.8	12.0	173.6	800.9	600.9	33825.6	16648.7	10.7	20.2
2006	7811.2	33267.1	3167	50	2.5	665.3	22.3	1941.3	904.4	253.7	32334.0	4454.6	10.2	89.1
2010	24362.9	34474.3	43	14	566.6	2462.4	1626.3	3257.4	287.0	132.3	4318.8	3042.6	100.4	217.3

the PA (omission error) is important for efficient control measures because it reflects the error of omitting of some plants that can later serve as a source of diaspores. An acceptable level of accuracy depends on the map purpose; it should be maximized if the goal is to locate infestation hotspots, but can be lower if all possible locations of the invasive species are to be addressed (Hamada et al., 2007).

4.3. Implications for mapping strategy: the role of phenological stage

We found that timing data acquisition to coincide with flowering and early fruiting was important for successful detection of invading populations because only at these stages were they distinct enough to be accurately distinguished (for other plant species see Huang and Asner, 2009; Somodi et al., 2012). While RS detection of flowering hogweed plants was relatively easy, detection of fruiting or non-flowering plants was limited, and the data capturing the species in fruiting period (1973 panchromatic and 1987 multispectral aerial photography) showed significantly lower recognition success.

In general, the best mapping strategy needs to reflect the morphological and structural features of the plant under study and chose the phenological stage at which individuals are most efficiently captured by monitoring. For invasive plant species with conspicuous flowering appearance it is crucial to collect data at the peak of the flowering period and take the temporal pattern of flowering into account; in case of giant hogweed it is concentrated into relatively short period (Perglová et al., 2006) but other plant species can have the flowering spread over longer periods of time, and for others there can be vegetative features such as the structure of the canopy or spectral signature especially in the NIR part of spectrum that may be effectively used for recognition (Everitt et al., 2005; Laba et al., 2010; Jones et al., 2011; Dorigo et al., 2012; Somodi et al., 2012). Overall, it points again to usefulness of a pilot analysis before a large-scale monitoring is started.

4.4. Lessons learned: implications for management of plant invasions

Our study, using giant hogweed as a model species, established a comparably fast method of detecting and capturing the spread of an invasive plant provided that the imagery is acquired at the time of the species flowering. Medium spatial resolution image analysis gives a fast overview of regional infestation whereas VHR data provide details on invasion progress and serves for early detection at the beginning of invasion. Presented results also underline that RS is important not only for analyses of past invasion dynamics and related issues (e.g. Müllerová et al., 2005; Nehrbass et al., 2007; Pergl et al., 2011) but also for rapid response and eradication of detected invasion foci (Pluess et al., 2012).

The described methodology developed on the test site has been successfully applied over the study region (175 km²) to monitor and manage the hogweed invasion in the PLA Slavkovský les in cooperation with Mariánské Lázně Municipality Office, and to analyze the patterns of invasion process at landscape scale in order to relate the dynamics of hogweed invasion (dispersal foci, maximum infestation, spatial structure, and rate of spread) to the landscape patterns (land cover, land use, fragmentation, connectivity, disturbance, and invisible habitat availability), and study mechanism of the species spread, habitat preferences and driving forces in the landscape. This knowledge helps us to understand why certain habitats are more susceptible to invasions than others and find optimum management strategies (Müllerová et al., 2005).

The high classification accuracies indicate that the method is potentially applicable to other areas and/or other invasive plants, despite the possible biases encountered in managed habitats or under forest canopies where identification by RS is somewhat restricted. For other regions or species with similar characteristics, namely well-recognizable inflorescences, the method is directly transferable; for other species a pilot analysis is advisable to identify features that can be efficiently used in the identification process. If adapted to the purpose of a particular study, the methodology presented here is potentially broadly applicable, enabling (i) early detection, (ii) identification of the foci to be targeted for eradication at the early stages of invasion, and (iii) regular monitoring of the sites. The proposed automated RS detection can make control measures more effective, faster, and less expensive than traditional monitoring methods based on ground mapping of invasive populations.

Acknowledgements

The study was supported by the project IAA600050811 from the Academy of Sciences of the Czech Republic, long-term research development project no. RVO 67985939 and Institutional Resources of Ministry of Education, Youth and Sports of the Czech Republic. P.P. acknowledges support by the Praemium Academiae award from the Academy of Sciences of the Czech Republic. We thank Martin Adámek for technical assistance, and Kirsty McGregor for improving our English.

References

- Andrew, M.E., Ustin, S.L., 2010. The effects of temporally variable dispersal and landscape structure on invasive species spread. *Ecological Applications* 20, 593–608.
- Asner, G.P., Jones, M.O., Martin, R.E., Knapp, D.E., Hughes, R.F., 2008. Remote sensing of native and invasive species in Hawaiian forests. *Remote Sensing of Environment* 112, 1912–1926.
- Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I., Heynen, M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing* 58, 239–258.
- Blaschke, T., 2010. Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing* 65, 2–16.

- Blaschke, T., Lang, S., Hay, G.J. (Eds.), 2008. Object-based Image Analysis: Spatial Concepts for Knowledge-driven Remote Sensing Applications. Springer, Berlin.
- Bradley, B.A., Mustard, J.F., 2006. Characterizing the landscape dynamics of an invasive plant and risk of invasion using remote sensing. *Ecological Applications* 16, 1132–1147.
- Brook, B.W., Bowman, D.M.J.S., 2006. Postcards from the past: charting the landscape scale conversion of tropical Australian savanna to closed forest during the 20th century. *Landscape Ecology* 21, 1253–1266.
- Chen, G., Hay, G.J., Carvalho, L.M.T., Wulder, M.A., 2012. Object-based change detection. *International Journal of Remote Sensing* 33, 4434–4457.
- Chytrý, M., Wild, J., Pyšek, P., Jarošík, V., Dendoncker, N., Reginster, I.L., Pino, J., Maskell, L., Vilà, M., Pergl, J., Kühn, I., Spangenberg, J., Settele, J., 2012. Projecting trends in plant invasions in Europe under different scenarios of future land-use change. *Global Ecology and Biogeography* 21, 75–87.
- Cleve, C., Kelly, M., Kearns, F.R., Moritz, M., 2008. Classification of the wildland-urban interface: a comparison of pixel- and object-based classifications using high-resolution aerial photography. *Computers, Environment and Urban Systems* 32, 317–326.
- Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remotely-sensed data. *Remote Sensing of Environment* 37, 35–46.
- Congalton, R.G., Green, K., 1999. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. Lewis Publishers, New York.
- Corcoran, P., Winstanley, A., 2008. Using texture to tackle the problem of scale in land-cover classification. In: Blaschke, T., Lang, S., Hay, G.J. (Eds.), Object-based Image Analysis: Spatial Concepts for Knowledge-driven Remote Sensing Applications. Springer, Berlin, pp. 113–132.
- Costello, D.A., Lunt, I.D., Williams, J.E., 2000. Effects of invasion by the indigenous shrub *Acacia sophorae* on plant composition of coastal grasslands in south-eastern Australia. *Biological Conservation* 96, 113–121.
- DAISIE, 2012. European Invasive Alien Species Gateway. <http://www.europe-alien.org/>
- Definiens AG, 2009. Definiens eCognition Developer 8 User Guide. Definiens AG, München, Germany.
- Dorigo, W., Lucieer, A., Podobnikar, T., Čarni, A., 2012. Mapping invasive *Fallopia japonica* by combined spectral, spatial, and temporal analysis of digital orthophotos. *International Journal of Applied Earth Observation and Geoinformation* 19, 185–195.
- Ehrenfeld, J.G., 2010. Ecosystem consequences of biological invasions. *Annual Review of Ecology, Evolution and Systematics* 41, 59–80.
- ESRI, 2006. ArcGIS 9.2. ESRI, Redlands, California, USA (Environmental Systems Research Institute).
- Everitt, J.H., Yang, C., Deloach, C.J., 2005. Remote sensing of giant reed with QuickBird satellite imagery. *Journal of Aquatic Plant Management* 43, 81–85.
- European Commission, 2008. Towards an EU strategy on invasive species. In: COM, 789, EC, Brussels.
- Foody, G.M., 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment* 80, 185–201.
- Foody, G.M., 2010. Assessing the accuracy of land cover change with imperfect ground data. *Remote Sensing of Environment* 114, 2271–2285.
- Fuller, D.O., 2005. Remote detection of invasive *Melaleuca trees (Melaleuca quinquenervia)* in South Florida with multispectral IKONOS imagery. *International Journal of Remote Sensing* 26, 1057–1063.
- Geomatica 10, 2005. Focus User Guide. Geomatics Enterprises, Ontario.
- Gioria, M., Pyšek, P., Moravcová, L., 2012. Soil seed banks in plant invasions: promoting species invasiveness and long-term impact on plant community dynamics. *Preslia* 84, 327–350.
- Hájková, L., Nekovář, J., Richterová, D., Koznarová, V., Sulovská, S., Vávra, A., Vondráková, A., Voženílek, V., 2012. Phenological observation in the Czech Republic: history and present. In: Zhang, X. (Ed.), Phenology and Climate Change. InTech, pp. 71–100 <http://www.intechopen.com/books/phenology-and-climate-change/phenological-observation-in-the-czech-republic-history-and-present>
- Hamada, Y., Stow, D.A., Coulter, L.L., Jafolla, J.C., Hendricks, L.W., 2007. Detecting Tamarisk species (*Tamarix* spp.) in riparian habitats of Southern California using high spatial resolution hyperspectral imagery. *Remote Sensing of Environment* 109, 237–248.
- Hamada, Y., Stow, D.A., Roberts, D.A., Franklin, J., Kyriakidis, P.C., 2012. Assessing and monitoring semi-arid shrublands using object-based image analysis and multiple endmember spectral mixture analysis. *Environmental Monitoring and Assessment*, <http://dx.doi.org/10.1007/s10661-012-2781-z>.
- He, K.S., Rocchini, D., Neteler, M., Nagendra, H., 2011. Benefits of hyperspectral remote sensing for tracking plant invasions. *Diversity and Distributions* 17, 381–392.
- Hejda, M., Pyšek, P., Jarošík, V., 2009. Impact of invasive plants on the species richness, diversity and composition of invaded communities. *Journal of Ecology* 97, 393–403.
- Hofmann, P., Strobl, J., Blaschke, T., Kux, H., 2008. Detecting informal settlements from QuickBird data in Rio de Janeiro using an object-based approach. In: Blaschke, T., Lang, S., Hay, G.J. (Eds.), Object-based Image Analysis: Spatial Concepts for Knowledge-driven Remote Sensing Applications. Springer, Berlin, pp. 531–553.
- Huang, Ch., Asner, G.P., 2009. Applications of remote sensing to alien invasive plant studies. *Sensors* 9, 4869–4889.
- Hulme, P.E., Pyšek, P., Nentwig, W., Vilà, M., 2009. Will threat of biological invasions unite the European Union? *Science* 324, 40–41.
- Hulme, P.E., Nentwig, W., Pyšek, P., Vilà, M., 2010. Are the aliens taking over? Invasive species and their increasing impact on biodiversity. In: Settele, J., Penev, L., Georgiev, T., Grabau, R., Grobelenik, V., Hammen, V., Klotz, S., Kotarac, M., Kühn, I. (Eds.), Atlas of Biodiversity Risk. Pensoft, Sofia and Moscow, pp. 132–133.
- Jahodová, S., Trybush, S., Pyšek, P., Wade, M., Karp, A., 2007. Invasive species of *Heracleum* in Europe: an insight into genetic relationships and invasion history. *Diversity and Distributions* 13, 99–114.
- Jensen, J.R., 2004. Introductory Digital Image Processing: A Remote Sensing Perspective, 3rd ed. Prentice Hall, London.
- Jobin, B., Labrecque, S., Grenier, M., Falardeau, G., 2008. Object-based classification as an alternative approach to the traditional pixel-based classification to identify potential habitat of the Grasshopper Sparrow. *Environmental Management* 41, 20–31.
- Jones, D., Pike, S., Thomas, M., Murphy, D., 2011. Object-based image analysis for detection of Japanese Knotweed *s.l.* taxa (Polygonaceae) in Wales (UK). *Remote Sensing* 3, 319–342.
- Kokaly, R.F., Despain, D.G., Clark, R.N., Livo, K.E., 2003. Mapping vegetation in Yellowstone N.P. using spectral feature analysis of AVIRIS data. *Remote Sensing of Environment* 84, 437–456.
- Laba, M., Blair, B., Downs, R., Monger, B., Philpot, W., Smith, S., Sullivan, P., Baveye, P., 2010. Use of textural measurements to map invasive wetland plants in the Hudson River National Estuarine Research Reserve with IKONOS satellite imagery. *Remote Sensing of Environment* 114, 876–886.
- Laliberte, A.S., Rango, A., Havstad, K.M., Paris, J.F., Beck, R.F., McNeely, R., Mathieu, R., Freeman, C., Aryal, J., 2004. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. *Remote Sensing of Environment* 93, 198–210.
- Landis, J., Koch, G., 1977. The measurement of observer agreement for categorical data. *Biometrics* 33, 159–174.
- Lawes, R.A., Wallace, J.F., 2008. Monitoring an invasive perennial at the landscape scale with remote sensing. *Ecological Management and Restoration* 9, 53–59.
- Maheu-Giroux, M., de Blois, S., 2004. Mapping the invasive species *Phragmites australis* in linear wetland corridors. *Aquatic Botany* 83, 310–320.
- Mallinis, G., Koutsias, N., Tsakiri-Strati, M., Karteris, M., 2008. Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site. *ISPRS Journal of Photogrammetry and Remote Sensing* 63, 237–250.
- McGarigal, K., Cushman, S.A., Neel, M.C., Ene, E., 2002. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. Computer software program. University of Massachusetts, Amherst.
- Millennium Ecosystem Assessment, 2005. Ecosystems and Human Well-being: Synthesis. Island Press, Washington, DC.
- Minor, E.S., Gardner, R.H., 2011. Landscape connectivity and seed dispersal characteristics inform the best management strategy for exotic plants. *Ecological Applications* 21, 739–749.
- Möller, M., Lymburner, L., Volk, M., 2007. The comparison index: a tool for assessing the accuracy of image segmentation. *International Journal of Applied Earth Observation and Geoinformation* 9, 311–321.
- Moravcová, L., Pyšek, P., Pergl, P., Perglová, I., 2006. Seasonal pattern of germination and seed longevity in the invasive species *Heracleum mantegazzianum*. *Preslia* 78, 287–301.
- Morgan, J.L., Gergel, S.E., Coops, N.C., 2010. Aerial photography: a rapidly evolving tool for ecological management. *BioScience* 60, 47–59.
- Müllerová, J., Pyšek, P., Jarošík, V., Pergl, J., 2005. Aerial photographs as a tool for assessing the regional dynamics of the invasive plant species *Heracleum mantegazzianum*. *Journal of Applied Ecology* 42, 1–12.
- Nehrbass, N., Winkler, E., Müllerová, J., Pergl, J., Pyšek, P., Perglová, I., 2007. A simulation model of plant invasion: long-distance dispersal determines the pattern of spread. *Biological Invasions* 9, 383–395.
- Neuhäuslová, Z., Moravec, J., 1997. Map of potential natural vegetation of the Czech Republic. Academia, Praha.
- Nielsen, C., Ravn, H.P., Nentwig, W., Wade, M. (Eds.), 2005. The Giant Hogweed Best Practice Manual. Guidelines for the Management and Control of an Invasive Weed in EUROPE. Forest and Landscape Denmark, Hoersholm.
- Ouyang, Z., Zhang, M., Xie, X., Shen, Q., Guo, H., Zhao, B., 2011. A comparison of pixel-based and object-oriented approaches to VHR imagery for mapping saltmarsh plants. *Ecological Informatics* 6, 136–146.
- Page, N.A., Wall, R.E., Darbyshire, S.J., Mulligan, G.A., 2006. The biology of invasive alien plants in Canada, 4. *Heracleum mantegazzianum* Sommier and Levier. *Canadian Journal of Plant Science* 85, 569–589.
- Pergl, J., Perglová, I., Pyšek, P., Dietz, H., 2006. Population age structure and reproductive behavior of the monocarpic perennial *Heracleum mantegazzianum* (Apiaceae) in its native and invaded distribution ranges. *American Journal of Botany* 93, 1018–1028.
- Pergl, P., Müllerová, J., Perglová, I., Herben, T., Pyšek, P., 2011. The role of long-distance seed dispersal in the local population dynamics of an invasive plant species. *Diversity and Distribution* 17, 725–738.
- Pergl, J., Pyšek, P., Perglová, I., Jarošík, V., 2012. Low persistence of a monocarpic invasive plant in historical sites biases our perception of its actual distribution. *Journal of Biogeography* 39, 1293–1302.
- Perglová, I., Pergl, J., Pyšek, P., 2006. Flowering phenology and reproductive effort of the invasive alien plant *Heracleum mantegazzianum*. *Preslia* 78, 265–285.
- Peterson, E.B., 2005. Estimating cover of an invasive grass *Bromus tectorum* using tobit regression and phenology derived from two dates of Landsat ETM+ data. *International Journal of Remote Sensing* 26, 2491–2507.

- Pluess, T., Cannon, R., Jarošík, V., Pergl, J., Pyšek, P., Bacher, S., 2012. When are eradication campaigns successful? A test of common assumptions. *Biological Invasions* 14, 1365–1378.
- Pontius, R.G., Millones, M., 2011. Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing* 32, 4407–4429.
- Pringle, R.M., Syfert, M., Webb, J.K., Shine, R., 2009. Quantifying historical changes in habitat availability for endangered species: use of pixel- and object-based remote sensing. *Journal of Applied Ecology* 46, 544–553.
- Pyšek, P., 1991. *Heracleum mantegazzianum* in the Czech Republic: dynamics of spreading from the historical-perspective. *Folia Geobotanica and Phytotaxonomica* 26, 439–454.
- Pyšek, P., Hulme, P.E., 2005. Spatio-temporal dynamics of plant invasions: linking patterns to process. *Ecoscience* 12, 302–315.
- Pyšek, P., Pyšek, A., 1995. Invasion by *Heracleum mantegazzianum* in different habitats in the Czech Republic. *Journal of Vegetation Science* 6, 711–718.
- Pyšek, P., Cock, M.J.W., Netwing, W., Ravn, H.P., 2007a. Master of all traits: can we successfully fight giant hogweed? In: Pyšek, P., Cock, M.J.W., Nentwig, W., Ravn, H.P. (Eds.), *Ecology and Management of Giant Hogweed (Heracleum mantegazzianum)*. CAB International, Wallingford, pp. 297–312.
- Pyšek, P., Krinke, L., Jarošík, V., Perglová, I., Pergl, J., Moravcová, L., 2007b. Timing and extent of tissue removal affect reproduction characteristics of an invasive species *Heracleum mantegazzianum*. *Biological Invasions* 9, 335–351.
- Pyšek, P., Müllerová, J., Jarošík, V., 2007c. Historical dynamics of *Heracleum mantegazzianum* invasion on regional and local scales. In: Pyšek, P., Cock, M.J.W., Nentwig, W., Ravn, H.P. (Eds.), *Ecology and Management of Giant Hogweed (Heracleum mantegazzianum)*. CAB International, Wallingford, pp. 42–54.
- Pyšek, P., Jarošík, V., Müllerová, J., Pergl, J., Wild, J., 2008. Comparing the rate of invasion by *Heracleum mantegazzianum* at continental, regional, and local scales. *Diversity and Distribution* 14, 355–363.
- Pyšek, P., Richardson, D.M., 2010. Invasive species, environmental change and management, and health. *Annual Review of Environment and Resources* 35, 25–55.
- Pyšek, P., Chytrý, M., Pergl, J., Sádlo, J., Wild, J., 2012a. Plant invasions in the Czech Republic: current state, introduction dynamics, invasive species and invaded habitats. *Preslia* 84, 576–630.
- Pyšek, P., Jarošík, V., Hulme, P.E., Pergl, J., Hejda, M., Schaffner, U., Vilà, M., 2012b. A global assessment of invasive plant impacts on resident species, communities and ecosystems: the interaction of impact measures, invading species' traits and environment. *Global Change Biology* 18, 1725–1737.
- Rejmánek, M., Pitcairn, M.J., 2002. When is eradication of exotic pest plants a realistic goal? In: Veitch, C.R., Clout, M.N. (Eds.), *Turning the Tide: The Eradication of Invasive Species*. IUCN, Gland and Cambridge, pp. 249–253.
- Rempel, R.S., Kaukinen, D., Carr, A.P., 2012. Patch Analyst and Patch Grid. Ontario Ministry of Natural Resources. Centre for Northern Forest Ecosystem Research, Thunder Bay, Ontario.
- Somodi, I., Čarni, A., Ribeiro, D., Podobnikar, T., 2012. Recognition of the invasive species *Robinia pseudacacia* from combined remote sensing and GIS sources. *Biological Conservation* 150, 59–67.
- StatSoft, 2011. STATISTICA (Data Analysis Software System) Version 10. StatSoft, Tulsa.
- Thiele, J., Otte, A., 2006. Analysis of habitats and communities invaded by *Heracleum mantegazzianum* Somm. et Lev. (Giant Hogweed) in Germany. *Phytocoenologia* 36, 281–320.
- Thiele, J., Otte, A., Eckstein, R.L., 2007. Ecological needs, habitat preferences and plant communities invaded by *Heracleum mantegazzianum*. In: Pyšek, P., Cock, M.J.W., Nentwig, W., Ravn, H.P. (Eds.), *Ecology and Management of Giant Hogweed*. CAB International, Wallingford, UK, pp. 144–156.
- Underwood, E., Ustin, S., DiPietro, D., 2003. Mapping nonnative plants using hyperspectral imagery. *Remote Sensing of Environment* 86, 150–161.
- Vilà, M., Ibáñez, I., 2011. Plant invasions in the landscape. *Landscape Ecology* 26, 461–472.
- Walsh, S.J., McCleary, A.L., Mena, C.F., Shao, Y., Tuttle, J.P., González, A., Atkinson, R., 2008. QuickBird and Hyperion data analysis of an invasive plant species in the Galapagos Islands of Ecuador: implications for control and land use management. *Remote Sensing of Environment* 112, 1927–1941.
- Winter, S., 2000. Location similarity of regions. *ISPRS Journal of Photogrammetry and Remote Sensing* 55, 189–200.
- With, K.A., 2002. The landscape ecology of invasive spread. *Conservation Biology* 16, 1192–1203.
- Wittenberg, R., Cock, J.W., 2005. Best practices for the prevention and management of invasive alien species. In: Mooney, H.A., Mack, R.N., McNeely, J.A., Neville, L.E., Schei, P.J., Waage, J.K. (Eds.), *Invasive Alien Species*. Island Press, Washington, DC, pp. 209–232.
- Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M., Schirokauer, D., 2006. Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery. *Photogrammetric Engineering and Remote Sensing* 72, 799–811.