

Unmanned aircraft in nature conservation – an example from plant invasions

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Abstract:

To successfully fight plant invasions, new methods enabling fast and efficient monitoring are needed, and remote sensing can make their management more efficient and less expensive. However, the data resolution, cost and availability can be limiting. Optimal solution depends on the species characteristics, where the spectral and spatial resolution can compensate each other to some extent, and phenology plays an important role. Available high spatial resolution satellite data are sufficient for recognition of species that are distinct and either large or form uniform patches at size comparable to the data pixel size. For other species, higher spatial resolution is needed, and unmanned aircraft (UAV) provide data of extremely high spatial resolution (cm) at low cost and high flexibility. We assess its potential to map invasive black locust (*Robinia pseudoaccacia*), testing imagery of different origin (satellite, UAV), spectral (MSS, RGB+NIR) and spatial resolution, and various technical approaches to choose the best strategy for the species monitoring balancing between precision of detection and economic feasibility. Using purposely designed low-cost UAV with tailless fixed wing design for two consumer cameras (RGB and modified NIR) ensures robustness and repeatable field performance while maintaining high aerodynamic efficiency, with resulting mapping capacity over 10 km² per day. Several challenges exist in UAV application, such as lower spectral resolution, geometrical and radiometric distortions, and significant amount of data (necessity of automatic processing). In our study we tested different options of UAV data processing and present comparison of resulting orthomosaic accuracies. For repeated measurements it is extremely important to ensure spatial co-registration of pixels/objects from different phenological phases. Investment in GPS receiver in the UAV and GPS post-processing eliminated laborious collection of ground control points, while maintaining the co-registration of objects across multiple flights. In our study we provide evidence of benefit of the low cost unmanned system for species monitoring with high classification accuracies of target species from UAV orthomosaic outcompeting WorldView-2 satellite data, and describe methodology that can be used for practical management of invasions.

Keywords: environmental monitoring; geometric accuracy; invasive species; orthorectification; Structure from Motion; UAV

Introduction

Plant invasions impose increasing impacts not only on biodiversity and ecosystem functioning, but also economy and human health (Pimentel, Zuniga and Morrison 2005; Hulme et al. 2009; Ehrenfeld 2010; Pyšek and Richardson 2010). They can be fast and very dynamic, and this makes the control measures difficult especially at the later stages of invasion (Pluess et al. 2012). Eradication should therefore focus first on recently infested sites (Müllerová et al. 2005; Pluess et al. 2012). Hence early and regular detection of the invading species and rapid management response on both local and landscape level is crucial (Rejmánek 2000; Vilà and Ibáñez, 2011), and new techniques enabling timely, fast and precise monitoring are urgently needed (European Commission 2008, 2014; van Kleunen et al. 2015).

Remote sensing (RS) represents a promising option, potentially reducing the needs for extensive field campaigns and connected costs (Lawes and Wallace 2008, Buchanan et al. 2015; Marvin et al. 2016). It has been successfully applied for some invasive species (for reviews see Huang and Asner 2009; Bradley 2014; Rocchini et al. 2015), mostly for shrubs and trees (Hamada et al. 2007; Hantson, Kooistra and Slim 2012; Somodi et al. 2012). The potential for invasive species monitoring has still not been fully exploited and detection algorithms are missing for the majority of invasive species. Our species of interest, black locust (BL, *Robinia pseudoaccacia*), an invasive North American tree widely planted in Europe for centuries, is not much exploited although it is very common in Europe. Somodi et al. (2012) explored Landsat and aerial data (RGB and RGB+NIR) potential for the species detection, comparing spring and summer imagery. They determined the spring flowering as an important for the species detection. Wang et al. (2015) used combined spectral, spatial and textural information from IKONOS imagery to assess the BL health conditions. By using spectral characteristics combined with texture measures they were able to identify the forest health and characterize the spatial structure of stressed forests.

Data of very-high spatial resolution, such as from unmanned aerial system (UAV), together with semi-automated, computer-assisted processing can enable cost-effective, fast and frequent

monitoring in case of appropriate methodological approach (Müllerová et al. 2016). For plant species detection, the proper timing of the RS data acquisition is important since some species might be better detected at certain phenological stages (Müllerová et al. 2013). UAV can provide flexible data acquisition of very high spatial and temporal resolution data at very low costs, and is also suitable for targeted monitoring (e.g. focus on sites of high natural interest such as NATURA 2000 sites, areas prone to invasion, or those recently managed to check eradication effectivity). Among the main limits are reduced spectral resolution compared to the satellite imagery, and the data degradation by geometrical distortions and other inhomogeneous artefacts (Colomina and Molina 2014; Whitehead and Hugenholtz 2014). The high spatial resolution may also result in ‘salt and pepper’ classification in case of increased within-patch variability (if image resolution does not match the resolution of the studied community texture (Zweig et al. 2015)).

Unmanned platforms are being increasingly utilized in diverse scientific fields including ecology (Whitehead et al. 2014, Zweig et al. 2015). Majority of the used UAV systems are based on multicopter aerial platforms (Whitehead and Hugenholtz 2014). Since such type of platform is able to cover only limited areas due to the inherent energy demands of the rotorcraft concept, fixed wing UAVs are much better suited to the monitoring purpose, and their operational radius is restricted primarily by the legislation (most often requiring visual contact between the UAV and its operator) rather than the capability of the platform itself. This paper aims at describing the cost effective and efficient methodology of invasive plant species monitoring (on example of invasive black locust) using purposely designed unmanned aerial system. Compared to the commercial products, such as Trimble/Gatewing, SenseFly eBee, Aeromapper and others, deployment of in-house developed system brings the advantage of reduced cost, operational experience and most importantly it can be easily adapted for the required payload.

In our research, we seek for optimal low-cost solution of invasive species monitoring, applicable in both plant ecology and practical management. We describe methodology of application of UAV for such purpose, assessing to what extent it can be used to analyse plant invasions (Figure 1).

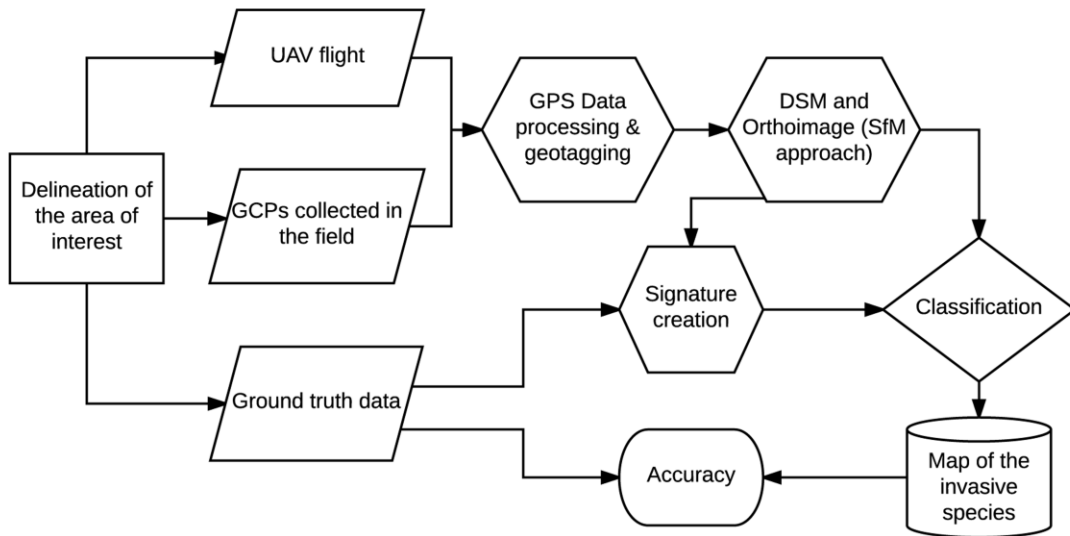





Figure 1. Flow-chart of the presented study.

2. Methods

2.1 The deployed unmanned system

Development of dedicated unmanned platform optimized for invasive species monitoring forms an important part of presented low-cost invasive monitoring solution. During the development, several aerial platforms were tested (Table 1).

Table 1. Summary of small unmanned platforms used for invasive species monitoring in this project.

	VUT 712 	VUT 713 	VUT 720 
Span	2.1 m	2.0m	2.6 m
Length	0.9 m	0.7m	1.3 m
m_{TOW}	3.1 kg	2.7kg	2.2 kg
v_C	17 m/s	18m/s	15 m/s
Battery	LiPo 4S 5000mAh	LiPo 4S 5000mAh	LiPo 3S 5000mAh
Endurance	1 hr	0.7hr	1 hr

Power	650 W	300 W	360 W
Payload	0.8 kg	0.9 kg	0.3 kg
Autopilot	Pixhawk autopilot	DroPix autopilot	APM2.5+ autopilot
Camera	2x Canon S100 stabilized	2x Sony A5100 + E20/2.8	1x Canon S100+ 1x GoPro
Based on	SkyWalker X8	RVJET	Multiplex Cularis

For the initial trials a motorized glider concept was selected (VUT 720, Dvořák et al. 2013, Figure 2a) to take advantage of the low wing loading. Combined with expanded polypropylene, a durable material featuring excellent impact properties, this concept ensures safe landings even in rugged terrain. The platform is hand-launched with no need for additional equipment. However, VUT 720 is able to carry only one camera (Canon PowerShot S100) at a time. The requirement to produce RGB+NIR data for further classification and research meant that two consecutive flights had to be performed at each location. This procedure not only resulted in increased time spent at a single site, but also introduced significant problems during image processing, as the lighting conditions often change during consecutive flights making the radiometric corrections of the captured images more complex. Therefore a platform providing actively stabilized mount for two Canon S100 cameras was devised – VUT 712 (Figure 2b). Data acquired by VUT 712 showed higher quality compared to previous datasets in terms of both radiometric consistency and georeferencing accuracy.

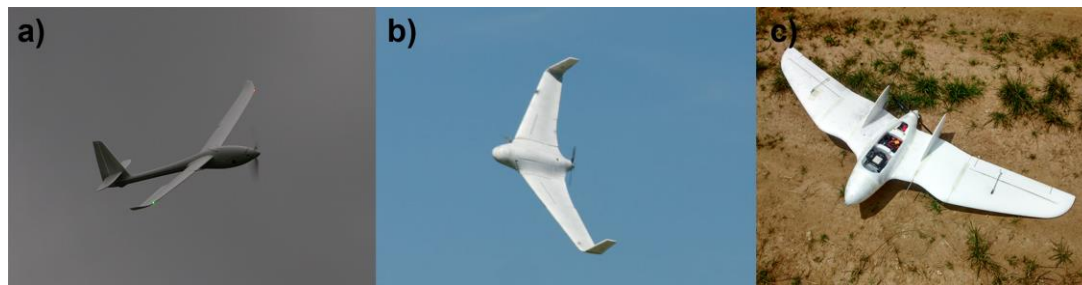


Figure 2. Unmanned systems used in the project - VUT 720 (a), VUT 712 (b), and VUT 713 (c).

Our operational experience clearly shows that consumer point-and-shoot cameras such as Canon S100 are not well suited for the harsh environmental conditions of repeated mapping missions. Retractable zoom lenses of the cameras are inherently prone to (uncommanded) focal length changes, deteriorating the photogrammetric quality of acquired imagery. Dust can easily penetrate the lens during landings, resulting in jammed lens and prolonged down-times of the platform.

Deployment of dedicated multispectral cameras (such as Micasense RedEdge) or an array of industrial grade cameras with spectral filters would overcome mentioned problems; however the costs would limit operational use. As a cost-effective solution, fixed pancake lens (Sony E20/2.8) coupled to a lightweight mirrorless camera (Sony A5100) has been deployed in a new platform – VUT 713 (Figure 2c, Table 2). To save weight, the stabilized mount was substituted by software limited camera triggering based on UAV attitude. Our operational experience confirms the described setup as a reliable and high-performing system. Approximate costs of our solution are 1,000 EUR for the unmanned system and 1,600 EUR for the cameras (NIR and RGB). Men power is not considered in the calculation. To assemble the system no professional expertise is needed. Elementary technical skills and motivation are sufficient (for more information see e. g. <https://conservationdrones.org>).

Table 2. Technical details of an aerial platform VUT 713.

Platform	Range Video RVJET
Remote Control	Graupner MC 22s + Jeti 2,4GHz Tx Modul + JetiBox Profi
RC telemetry	Jeti Duplex Rsat2 + Mvario2EX + MT125EX
Battery	Schweighofer Modster 4S1P 5000mAh
Motor speed controller	Foxy R-65SB 65A SBEC
Motor	Dualsky XM3542EA-6 790RPM/V modified, 140g
Propeller	Aeronaut CAM Carbon folding prop 13/6.5"
Servos	2 x elevon: Hitec Mini Digital Servo HS-5245MG
Autopilot	Drotek Dropix v2.1, 3DR PowerModule, Digital Airspeed sensor
GPS	Drotek u-blox M8T, external magnetometer

Autopilot telemetry	SiK radio V2 433mHz
Ground station	Panasonic Toughbook CF-19
Camera	2xSony A5100 + E20/2.8

2.2 Image acquisition and pre-processing

2.2.1 Camera selection and spectral characteristics

For vegetation classification the NIR band is very important. As mentioned in previous chapter, a set of two consumer cameras (one standard RGB, and one modified to be sensitive in NIR band - built-in IR-cut filter removed and Hoya R72 filter added) was used instead of expensive multispectral camera (Table 3, Figure 3). Two camera types were tested during the project - Canon S100 and Sony A5100 (Table 3). The sensor of Canon S100, size of 1/1.7" (7.44×5.58 mm) resulted in comparably high levels of noise and low dynamic range of the pixels. The NIR modified camera was especially affected by this fact due to the longer wavelength of sensed light. The APS-C (23.5×15.6 mm) sized sensor of Sony A5100 camera provided nearly 8.8 times larger photosensitive area compared to the S100 camera. Fixed lens of Sony A5100 addressed the problems experienced with retractable zoom lens of Canon S100.

Table 3. Comparison of the two cameras setup used for tested unmanned platforms.

Platform	VUT 712	VUT 713	Comparison
Cameras	2x Canon S100 (VIS + NIR)	2x Sony A5100 + E20/2.8 (VIS+NIR)	
Sensor size	1/1.7" (7.44×5.58 mm)	APS-C (23.5×15.6 mm)	~9 times larger; FIXED LENS
Stabilization	External mechanical (2 axis Simple BGC BLDC gimbal) + Internal optical	N/A (autopilot does not trigger if the attitude exceeds preset	OK even without stabilization

limits)			
Georeferencing	<ul style="list-style-type: none"> • Internal GPS • Precise shutter time (CHDK script) synchro with autopilot GPS 	<ul style="list-style-type: none"> • Autopilot DGPS – trigger log • Correction for shutter lag 	Much better precision
Triggering	Intervalometer ~0.5Hz (CHDK scripting)	Distance based – from autopilot system	Efficient – no unnecessary images; maintains overlap
Total Weight	2x192g + 280g gimbal = 664g	2x360g = 720g	Not a significant penalty

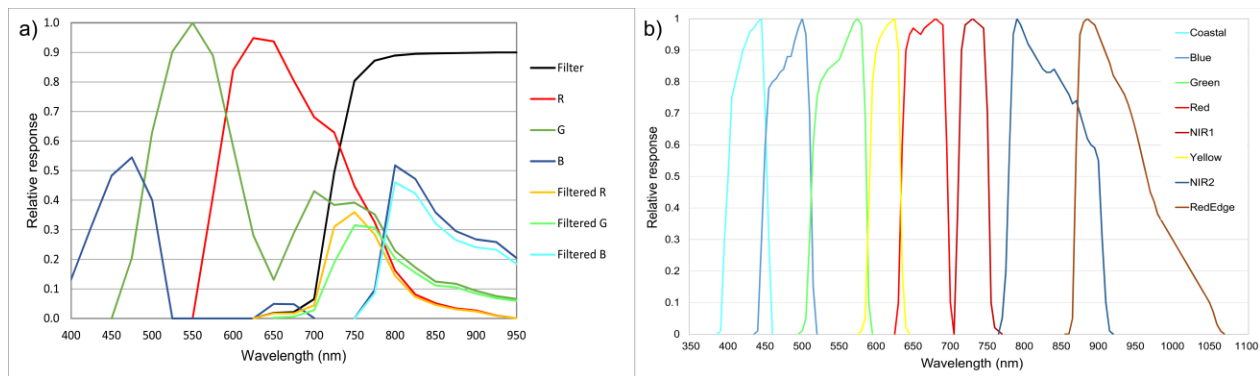


Figure 3. Spectral response of Sony A5100 camera – standard RGB and NIR version without IR-cut filter (a), compared to the spectral sensitivities of the WorldView-2 satellite sensors (b) based on DigitalGlobe datasheet (DigitalGlobe 2016).

2.2.2 Triggering

The sensors were periodically triggered during the flight to cover the area of interest with sufficient image data. Significant overlap was required for robust mosaicking. Typically, the missions were flown with overlap and sidelap ranging between 80% and 85% of the image height and width, respectively.

To achieve homogenous coverage of the area, the following camera triggering strategies were employed:

- Constant time between images (intervalometer). This strategy has been implemented with the S100 cameras by means of modifying firmware (CHDK 2013). The firmware ran an in-house developed script based on KAP 3.4 (KAP 2015). The script triggered the camera in preset intervals (2 s intervals are proven to be the shortest interval the Canon S100 camera is able to maintain for prolonged periods). This approach provided homogenous coverage under ideal conditions. Wind and atmospheric turbulence caused the images to be spaced unevenly in real world application because of the varying ground speed of unmanned platform.
- Constant distance between images. Triggering was performed based on distance travelled by the UAV – a value computed by an autopilot from GPS data. This approach ensured homogenous image coverage even with a strong wind during the mapping flight. The cameras needed to be capable to capture the imagery with sufficient frequency - Sony A5100 cameras achieved 1 s intervals for prolonged periods.

2.2.3 Georeferencing

Structure-from-motion approach (SfM; Dandois and Ellis 2010; Westoby et al. 2012) was used to generate the digital surface model (DSM) and resulting orthomosaic using Agisoft PhotoScan software (Agisoft 2016). The SfM approach identifies similar features in conjugate images, tolerating large variations in scale and image acquisition geometry. Even though PhotoScan has a simple interface with no possibility to control all the parameters, it is able to generate very dense and accurate three-dimensional point cloud (Turner et al. 2012; Whitehead and Hugenholtz 2014).

Using UAV data for monitoring of invasive species brings a principal advantage of very high spatial resolution. On the other hand, this resolution poses significant demand for geometrical accuracy to fit other ancillary or reference data such as aerial orthophoto or satellite VHR imagery or to carry out change detection using repeated data. Since low-cost components are primarily preferred in our project, precise georeferencing of the final image mosaics may be an issue, leading to unacceptable geometrical distortions and/or positional shifts. Several inputs influence the precision of final orthomosaic. Besides quality and type of the GPS receiver and the measurement method itself, further limitations such as shutter lag or availability of GPS corrections have to be considered.

To overcome such deficiencies and for the overall improvement of the final geometrical accuracy, different procedures were tested to evaluate the best setup balancing the accuracy and costs. At the first phase, only GPS built in the camera was used with original EXIF-based GPS information. Accuracy achieved by such low-end camera GPS burdened by high error rate up to several meters resulting in expected shifts of the processed orthomosaic. Influence of random misplacement of GPS coordinates led to local differences up to $\times 10\text{m}$.

Alternatively, an aircraft/autopilot GPS receiver (u-blox LEA 6H) with assumed higher accuracy was considered. All trigger events were recorded by the camera with 10 ms accuracy by means of the in-house CHDK script. The resultant datalog was synchronized with GPS position log from autopilot during post-processing. In this case the proper synchronization of exact GPS position record and the image acquisition time is questionable, since the time coherence of the two independent devices may differ slightly resulting in a varying amount of misplacement.

As an optimal solution, a GPS module capable of RAW data output (u-blox M8T) was added to the autopilot. Triggering of the cameras was performed by the autopilot based on the distance travelled between the two consecutive images. Subsequently an automated approach of image geotagging was developed: the flight log records are used as a base to derive the correct coordinates. The employed SONY A5100 cameras are characterized by a stable 90 ms lag between the trigger event and the instant the shutter is actually released. This lag is accounted for by the post-processing procedure. Besides the time stamp of the camera trigger event, the GPS position is continuously recorded during the flight with a 5Hz frequency. Due to the above mentioned shutter lag effect, a linear interpolation between two closest GPS log records is introduced to the final calculation of each image coordinates. Additionally the GPS coordinates were improved by post-processing using the RTKlib – an open-source package (Takasu 2009) and the respective correction data from the local Czech Reference Station Network (CZEPOS). Different settings were evaluated including the application of ionospheric map. An overview of positional variability is illustrated by Figure 4, comparing original, enhanced and post-processed GPS coordinates of the flight path and geo-tagged images. The overall positional accuracy was evaluated on the resulting orthomosaics only, based on signalized GCP with independently measured coordinates using reference data obtained with Trimble GeoExplorer GeoXH 6000 differential GNSS with post-processing in Trimble Pathfinder Office using CZEPOS correction data (Figure 5).

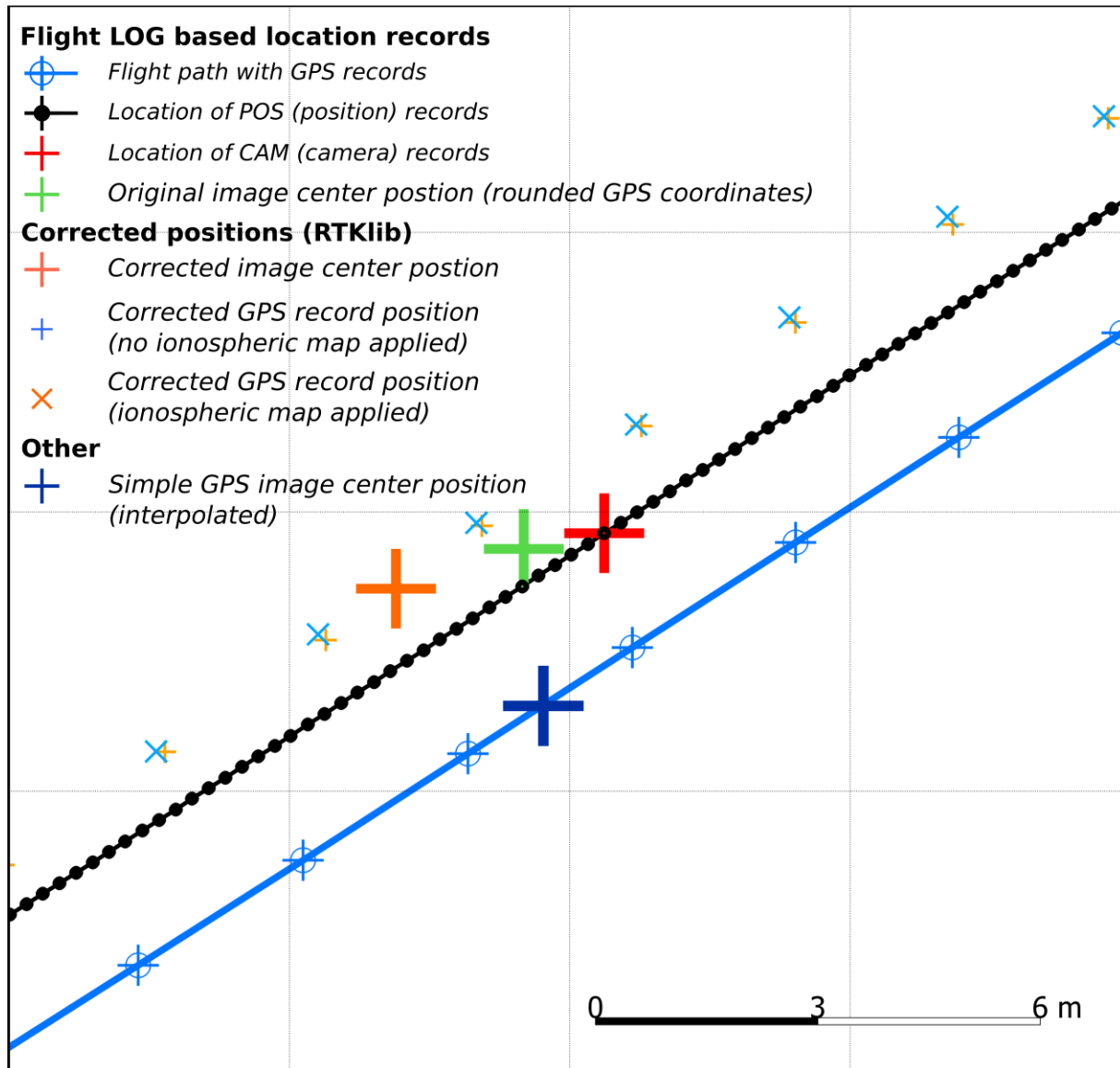


Figure 4. An overview of different settings for correction of GPS data and geotagged images.

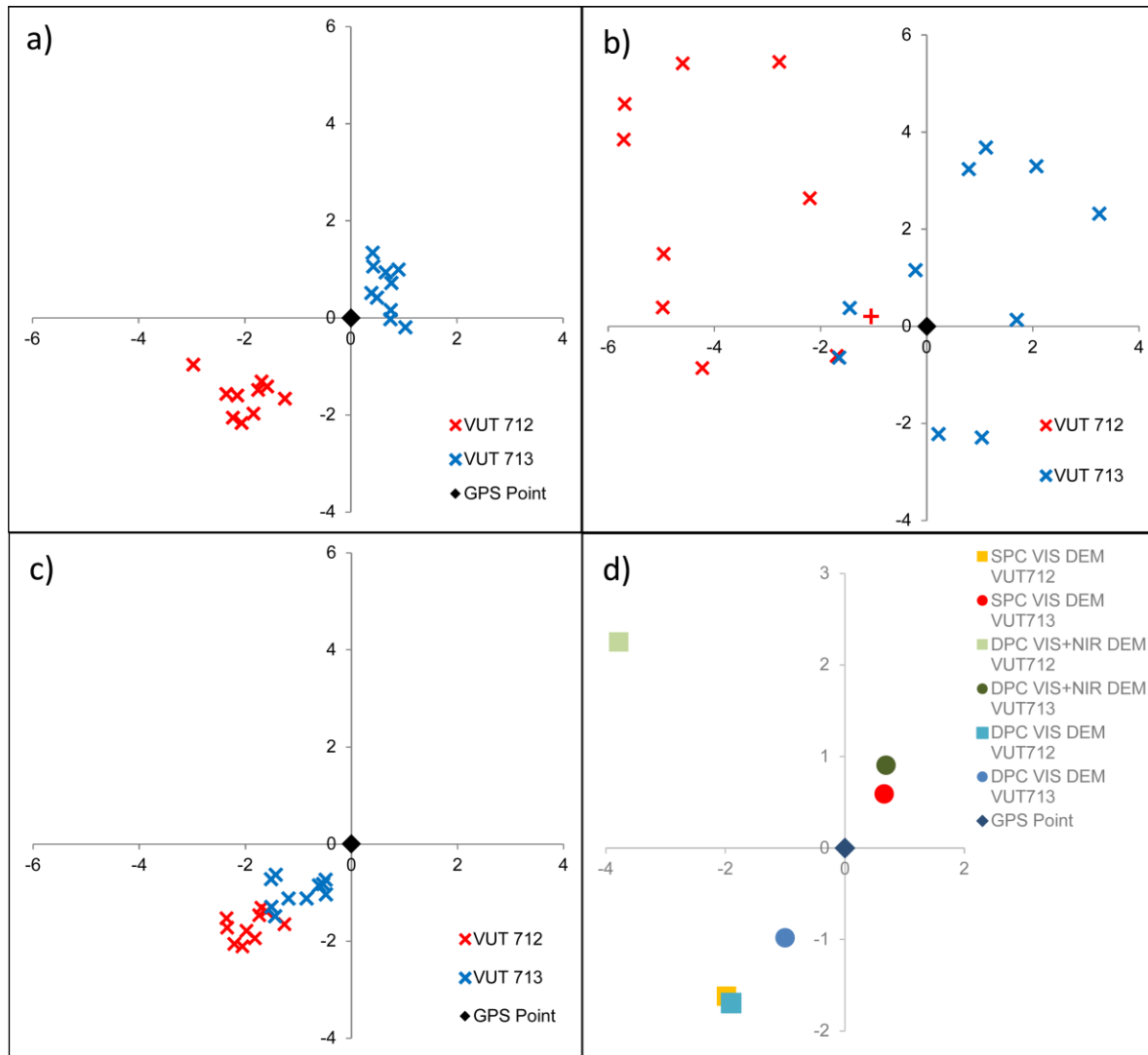


Figure 5. Errors of image projection (in meters) from two different unmanned systems (VUT 712 with Canon S100 Camera and internal GPS; and VUT 713 with Sony A5100 camera and autopilot differential GPS) compared to 10 GCP targets measured in the field with differential GPS (estimated error $<0.1\text{m}$). Orthomosaics were generated using sparse point cloud based DSM from VIS images (a); dense point cloud based DSM from VIS and NIR images (b), and from VIS images only (c). The mean error of orthomosaics for VUT 712 was $2.56\text{m} \pm 0.38$ (a), $4.82\text{m} \pm 2.07$ (b), and $2.56\text{m} \pm 0.35$ (c), whereas for VUT 713 it was $0.99\text{m} \pm 0.26$ (a), $2.60\text{m} \pm 1.03$ (b), and $1.44\text{m} \pm 0.40$ (c). X and Y shifts are summarized in (d). SPC = sparse point cloud, DPC = dense point cloud.

SfM method implemented within Agisoft PhotoScan (Agisoft 2016) for generation of RGB+NIR orthomosaic enables different parametrization to adapt the processing workflow according to the required purpose. This may lead to balanced procedure reflecting the required radiometric and geometric quality at reasonable processing time. Since two separate cameras were used continuously for RGB and NIR, separate or co-processed option for computation is an option. Separate RGB processing results in appropriate image quality (Figure 5a) with no visible artefacts in DSM (Figure 6a). However, for proper vegetation mapping and monitoring the NIR spectrum is crucial and therefore NIR band needs to be co-registered with the other bands. Several tests of co-processed RGB and NIR imagery revealed an obvious error in DSM generation causing 'islands' of unrealistic elevations and noisy point clouds (Figure 6b). Such artefacts are directly projected to orthomosaic generation causing blurred and deformed areas within the imagery with influence on classification, reduced reliability (Figure 6e) and higher spatial error (Figure 5b). Even the fastest processing option using sparse point cloud method from RGB imagery results in better spatial accuracy (Figure 5a). Dense point cloud method applied to RGB data also produces more accurate results (Figure 5b) and is still faster than RGB and NIR co-processing.

Aggressive depth filtering during the dense point cloud generation can be used to alleviate the aforementioned problems (Figure 6c). However, highly detailed DSM based on the dense point is prone to create mosaic artefacts in areas of complex patterns and steep DSM transitions. To minimize the distortions, the generated DSM can be exported with significantly lower spatial resolution (a factor of 100 seems to ensure balanced results) and re-imported for the orthomosaic creation - resulting in a smoother surface representation (Figure 6d). Alternatively, an external standard image processing software or package can be used for resampling combined with further filtering (extreme or missing values etc.). As a result, most of the artefacts are eliminated and overall image quality is enhanced (Figure 6f), and the original detailed DSM is preserved as a suitable ancillary data source for classification (e.g. vegetation height and heterogeneity).

The VUT 713 equipped with Sony A5100 camera produced the most spatially precise results independent from the orthomosaic processing settings (Figure 5d).

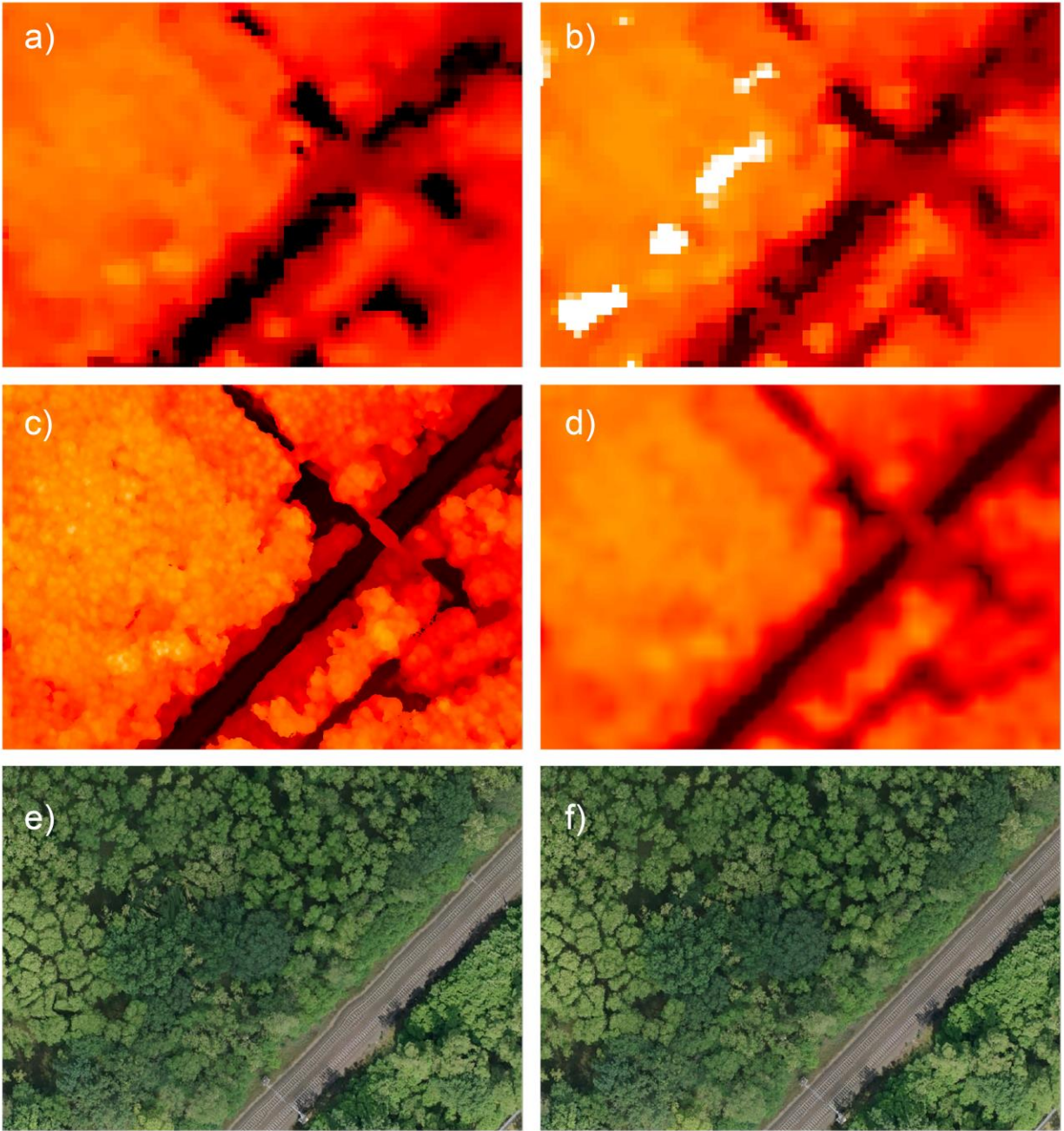


Figure 6. Digital Elevation Models resulting from different processing settings. Only RGB data processed – DSM based on sparse point cloud (a); RGB+NIR images co-processed – DSM based on sparse point cloud displaying artifacts (b); dense point cloud with aggressive depth filtering applied to RGB+NIR co-processed data (c); resampled DSM in order to provide smooth base for orthomosaic texture (d); visual artefacts resulting from distorted DSM shown in b (e); final mosaic based on resampled DSM shown in d (f).

2.3 *Field data collection*

Field data are crucial for successful training of automatic/semiautomatic algorithms and for validation purposes. Considering the resolution of the final UAV imagery, it is obvious that a classical field GPS and even a differential GPS is not precise enough. This is especially true in forested environment where the estimated precision drops to several decimetres or even meters. The differential GPS would also be costly and time consuming option for large scale field data collection.

To overcome mentioned problems, we decided to use a field computer (a tablet with Android OS to decrease the costs) with UAV imagery or other available orthomosaics as a base for manual delineation of invasive species patches in the field with a help of integrated GPS. UAV imagery proved to be the most useful source of data for this purpose, because its high resolution provided enough detail necessary for precise delineation of vegetation polygons. To choose the best application/software for field data collection, we made a short review (Table 4), and after initial testing, chose Collector for ArcGIS as the most viable alternative since it allowed us to: (i) collect the data offline (i.e. independent from the internet availability); (ii) use our own imagery as a background; (iii) attach photographs and several attributes to the collected polygons in the field; (iv) distribute data to multiple users in the field which collect data to a centralized database; (v) use other supporting data overlays; and (vi) sync the data afterwards and make them directly accessible in ArcGIS for further processing including field photographs.

Table 4. A review of available applications/software for collection of field data.

Name	Operating system	Price	Offline use	Custom maps	Multi-user environment	Easy to use	Easy to prepare	HW Price	Comments
Trimble TerraSync	Windows Mobile	Fixed	Yes	Yes	No	Yes	Yes	Medium/high	Precise measurements based on expensive GPS
Trimble TerraFlex	Multiple	Subscription based Free with			Yes			Low	Not tested in the field
Collector for ArcGIS	Multiple	ArcGIS maintenance	Yes	Yes	Yes	Yes	Yes	Low	Works well in ArcGIS workflow
NextGIS Mobile	Android	Free	Yes	No			No	Low	Limited English documentation
QField, QGIS Mobile	Android	Free				No	No	Low	Complicated
ODK Collect	Android	Free	Yes	No	Yes	Yes	Yes	Low	Simple app for citizen science

2.4 *Invasive species*

In our study we focused on black locust (BL, *Robinia pseudoacacia*). This deciduous tree has thick and deeply furrowed bark with stipular spines and alternate pinnately compound leaves. It flowers in May with distinct pendant large racemes of white flowers. In ideal conditions it can grow up to 30 m tall, however if water limited can take the shrubby dwarf appearance with unshaped crown and deformed trunk of 3 to 5 m.

It is native to the south-eastern USA, listed amongst the 40 most invasive woody angiosperms globally (Richardson and Rejmánek 2011), categorized as highly invasive in several international databases (DAISIE, CABI, NOBANIS, EPPO, ISSG) and mentioned in national Black Lists in many countries (Nehring et al. 2013; Pergl et al. 2016). It was introduced to Europe at the beginning of the 17th century as an ornamental and soon became planted mainly thanks to its quality durable timber, fast growth, honey production and ability to stabilize and restore sandy or degraded soils (Vítková et al. 2017). Its area is still increasing; currently it is planted across Europe, temperate Asia, temperate South America, northern and southern Africa, Australia and New Zealand (Cierjacks et al. 2013; Li et al. 2014). Despite of economic benefits, it represents a serious threat to nature conservation.

BL is a light-demanding pioneer species able to disperse quickly over short distances (2 m per year; Crosti et al. 2016) by numerous root suckers forming a connected system with the mother plant (Kowarik 1996; Cierjacks et al. 2013). Deliberate planting and transport of soil containing seeds and roots represent the main vectors for its long-distance dispersal (Pyšek et al. 2012). It is extremely resistant to disturbance; mechanical damage of roots or trunks causes an increase in stem density and rejuvenation (Kowarik 1996). Moreover, it colonizes a broad range of xeric to mesic habitats, including steep rocks or toxic man-made substrata (Vítková and Kolbek 2010; Vítková et al. 2015; Cierjacks et al. 2013). As a nitrogen fixing species living in symbiosis with *Rhizobium* bacteria (Batzli et al. 1992) it increases soil nitrogen (Van Miegroet and Cole 1984; Vítková et al. 2015), supporting expansion of nitrophilous plants (Vítková and Kolbek 2010). If invading grasslands, it can cause scrub encroachment and canopy closure due to its fast growth, influencing considerably the light and microclimatic conditions of invaded habitats. This is especially true for dry and semi-dry grasslands, sites of high natural value, where it can cause extinction of many endangered light-demanding plants and invertebrates (Kowarik 1996; Matus et al. 2003; Vítková and Kolbek 2010). Other threatened habitat types are open dry

forests, scrublands, alluvial habitats, agrarian landscapes, urban and industrial environments, and disturbed sites, such as post-fire sites, forest clearings and degraded forestry plantations. Removal of the species is costly and time-consuming, and requires repeated eradication measures and monitoring for at least three years due to its exceptional resprouting ability. In Central Europe, it is limited by late spring frost and short vegetation period (Vítková et al. 2017).

2.5 Study area and analysed data

Study area is located in central part of Czech Republic in typical Central European agricultural landscape of flat lowlands surrounding the river Elbe. It consists of managed mixed forests surrounded by arable fields. Forests are composed of native oak forests with variable proportion of elm, Scots pine and lime, and plantations of Scots pine and BL (both in monocultures and admixture). Two sites named Kozlovice (site 1) and Podvlčí (site 2) were covered by repeated UAV campaigns using VUT 712 and VUT 713; Figure 7). In flat terrain of the study site 1 (37 ha; BL was used for stabilization of aeolian sands and is therefore planted in monocultures altered by monocultures of Scots pine or mixed stands with old native oaks. BL plantations are regenerated by coppicing in stripes. The study site 2 (30 ha) is a reclamation dump site from a nearby power station. BL stands are located on both slope and flat parts of the spoil tip, mostly in mixed stands with admixture of Scots pine, poplar, willow and birch. BL stands are unmanaged and younger compared to the site 1.

In classification, UAV imagery from 6 June 2015 was analysed for both sites (Figure 7). As a reference WorldView-2 (WV-2) satellite multispectral data were used with nominal spatial resolution of 2 m consisting of four standard bands (red, green, blue and near-infrared), four additional bands (coastal, yellow, red edge, and near-infrared2) and panchromatic channel with 0.5 m spatial resolution. The image was acquired on 30 August 2013 and covered the site 2 (Figure 8). RPC (Rational Polynomial Coefficients) metadata provided with the imagery and detailed DSM were used for orthorectification. The quality of spatial accuracy of the orthomosaic was visually inspected by comparison to national aerial orthophoto (CUZK 2015).

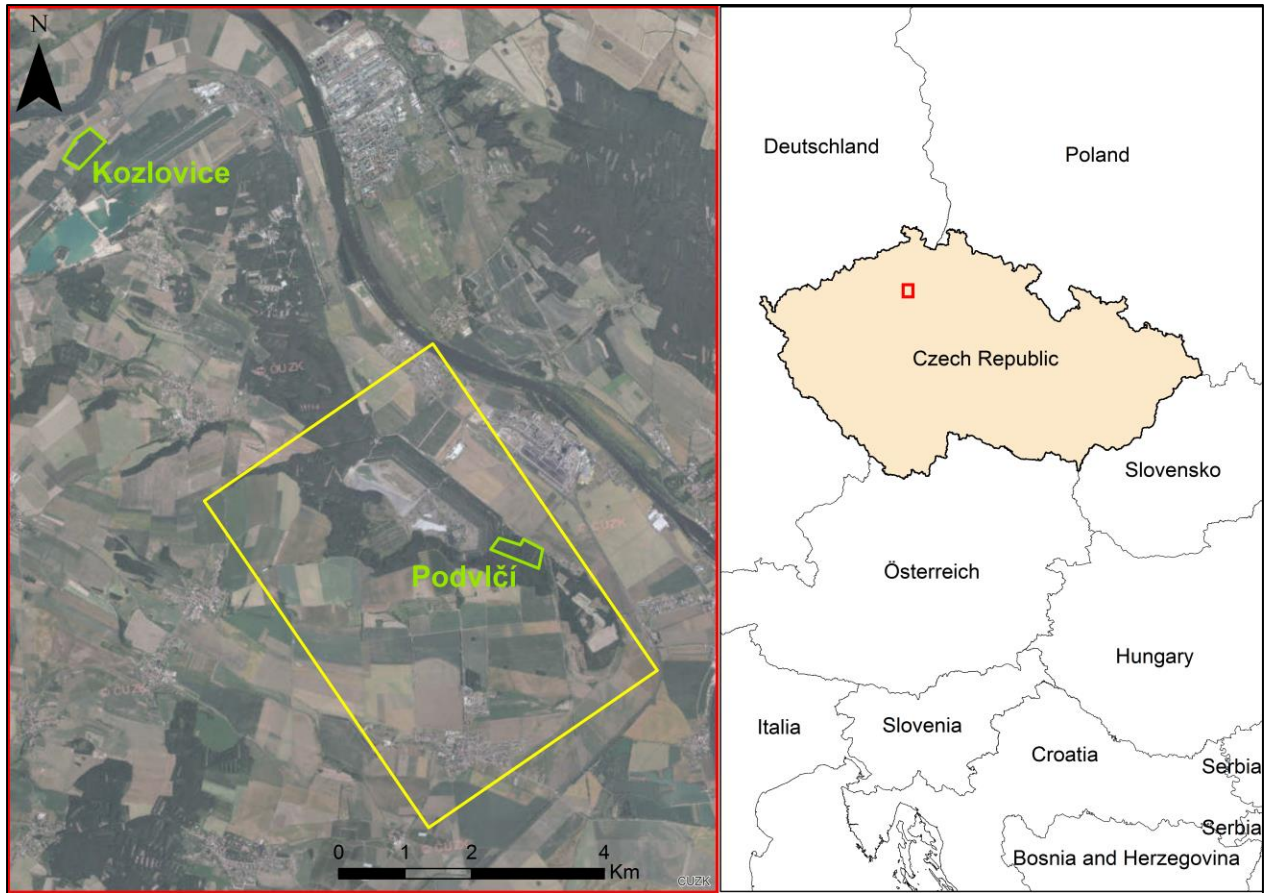


Figure 7. Study area with delineated areas of interest –Kozlovice (site 1) and Podvlčí (site 2). In green are UAV flights acquired on 6 July 2015 (both sites), in yellow is WorldView-2 imagery from 30th August 2013.

2.6 Classification and validation

Pixel-based approach was explored for classification. Supervised Maximum-Likelihood and Support Vector Machines (SVM) algorithms were tested. Reason for choosing SVM was that this algorithm is supposed to be less susceptible to the noise and unbalanced or limited number/size of training sites (see e.g., Camps-Valls and Bruzzone 2009). Training classes were selected with the main purpose to distinguish among invasive black locust and other types of vegetation. For each site and data, separate class signatures were generated, and subsequently the site 1 class signatures were applied to the UAV data from the site 2 acquired at the same day.

To include the texture (surface heterogeneity/roughness) and context of the classified pixel into the classification process, information on surface structure were derived from DSM

generated as a by-product of UAV processing. Standard deviation and range of surface elevations parameters were tested using moving window of 5×5, 10×10, 50×50 and 100×100 pixels with range of 50×50 pixel window being the most informative. This information was included in classification as an additional layer. Due to geolocation inaccuracies of DSM and unavailability of detailed digital terrain model (DTM), precise vegetation height could not be calculated.

Validation was performed using 200 randomly distributed points at each site outside the training areas, with ca half within the BL stands. User's accuracy (UA; ratio of the correctly classified and total classified, evaluating reliability of the results for the user), producer's accuracy (PA; ratio of the correctly classified and observed), and Kappa analysis (conditional Kappa index evaluating the statistical significance of the classifications, considers the actual agreement of the class in relation to the chance agreement, Congalton and Green 1999; Foody 2002) of BL detection were calculated from error matrices. Kappa statistics, despite the strong criticism due to the randomness used as a baseline (Pontius and Millones 2011), is still a widely used mean of the accuracy measure providing an opportunity to compare our results with other studies.

3. Detection results

The accuracies achieved for the invasive BL were very high, with UAV imagery providing better results (up to 92/81% and 75/92% PA/UA for site 1 and 2, respectively) compared to the satellite imagery (WV-2; up to 61/81% PA/UA). Maximum Likelihood and SVM algorithms reached similarly high accuracies in most cases (Figure 8 and 9), still SVM seem to be less prone to the distortion artefacts of orthomosaic. Including surface roughness derived from DSM of UAV origin helped in discriminating forests from arable fields since BL was sometimes misclassified as arable land; still it did not improve discrimination of BL and other tree species with similar surface heterogeneity values.

The spectral signatures derived from training classes at site 1 were applied to the classification of site 2 with moderate agreement of 73/81% PA/UA and 0.66 conditional Kappa (for Maximum Likelihood algorithm; SVM gave very poor results). Due to the differences in spectral sensitivities of sensors the signatures could not be transferred between UAV and satellite data. Also the class signatures incorporating the surface roughness did not give satisfactory results if applied from one site to the other.

The UAV flight campaign in 2015 was organized to capture BL in flower, however since the trees did not flower simultaneously even at the same site, only several trees were actually flowering on the orthomosaic (visible in white on Figure 9, uppermost part). Nevertheless this fact did not deteriorate the detection results, probably thanks to good separability from other tree species in NIR part of the spectrum based on leaf and not only flower signatures (Figure 10).

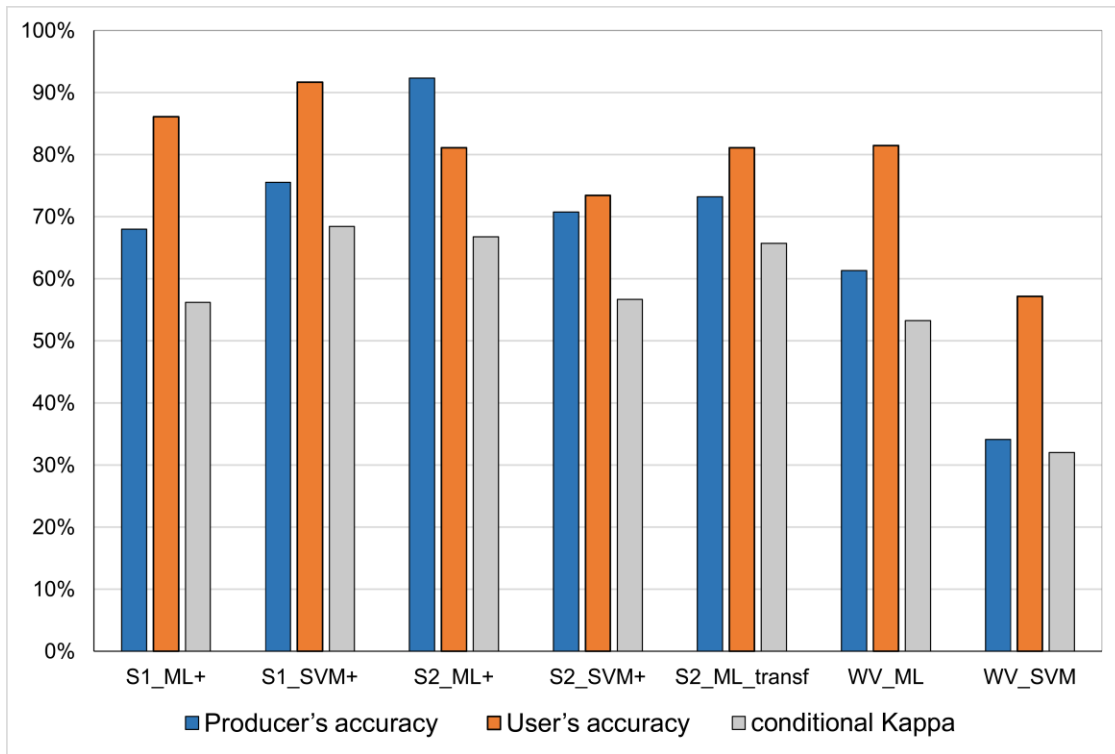


Figure 8. Classification accuracies of different data origin (UAV imagery of site 1 – S1 – and site 2 – S2, and WorldView 2 imagery – WV) and classification algorithms (‘ML’ = Maximum Likelihood, ‘SVM’ = Support Vector Machines, ‘+’ = DSM roughness included, ‘transf’ = algorithm transformed from the site 1).

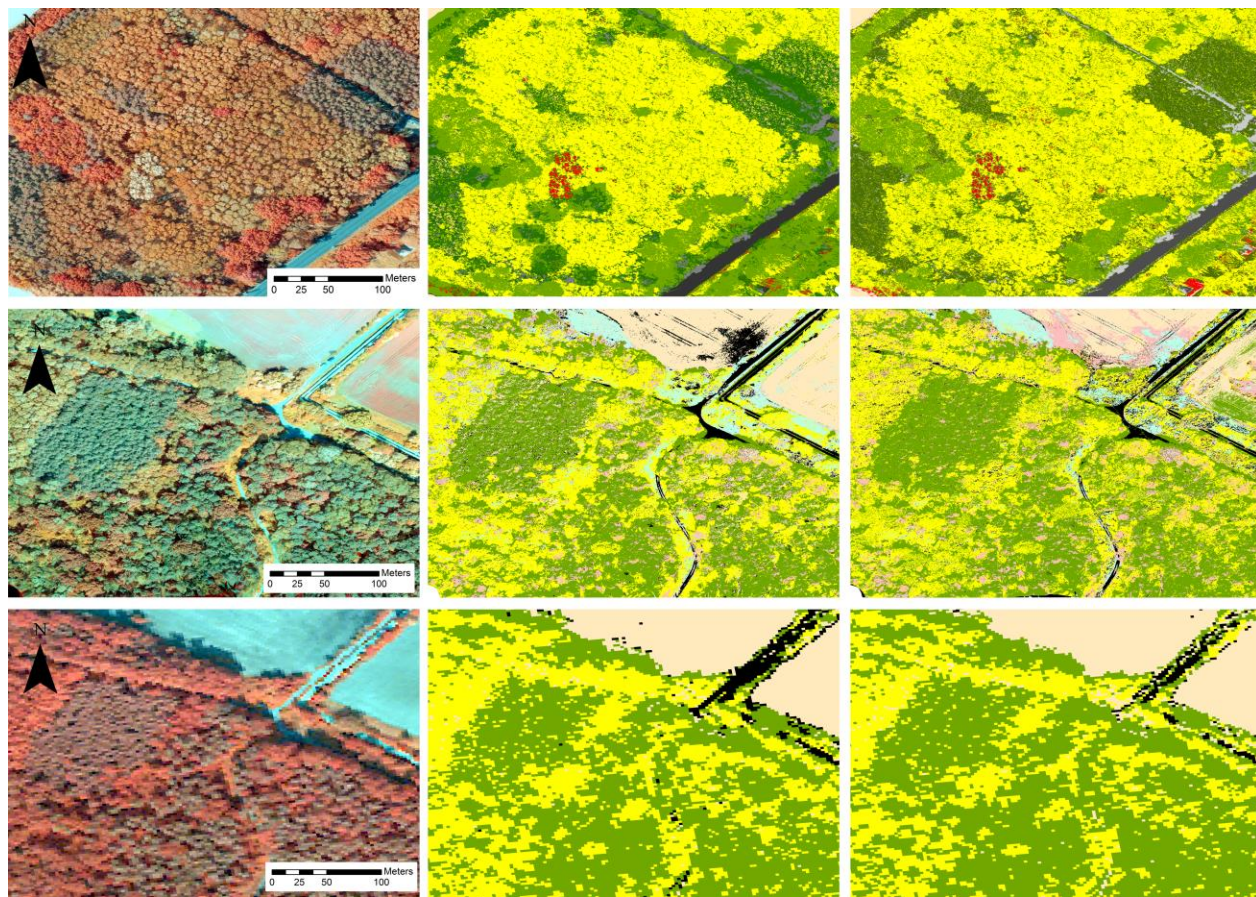


Figure 9. Classification of UAV site 1 and 2 (upper and middle rows, respectively), and WV-2 satellite imagery (lower row). False color composites of the original imagery (NIR-G-B, left column), and results of Maximum Likelihood classification (central column), and Support Vector Machines (right column) are shown. Legend - BL yellow, BL flowering red, other tree species green, non-forest light brown, shadows grey, and roads black.

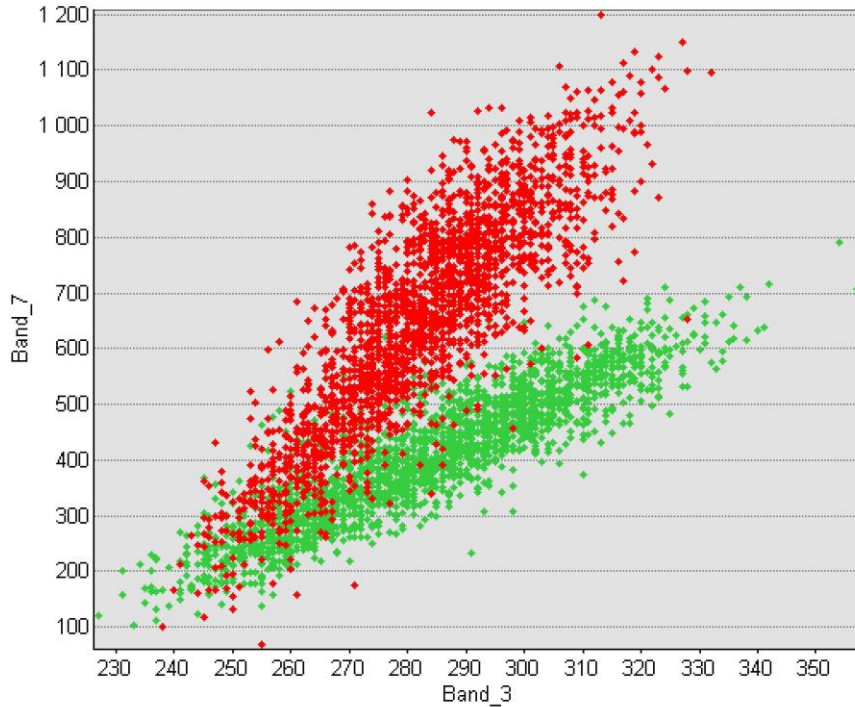


Figure 10. Separability of classes (BL – red, other tree species – green) shown on the scatterplot of Green (Band_3) and NIR 1 (Band_7) bands of WV-2 satellite.

4. Discussion

An important step in application of UAV approach in invasive monitoring seem to be generation of precise combined RGB + NIR orthomosaic from UAV images acquired during the flight campaign. This is because the NIR part of the spectrum is very important for the plant recognition as demonstrated here on case of black locust. For further processing such as classification and validation, it is important to achieve high precision in both co-registration of the channels and geolocation of the imagery. The target accuracy should therefore meet the condition of possible inter-comparison with other EO sources as satellite imagery or repeated acquisition to avoid possible mis-matches within the given target resolution for change monitoring.

In our research, we replaced an initial setup of separate RGB and NIR acquisition by continuous imaging of both spectra on the newer unmanned platform VUT 713. Since the image quality and positional accuracy were still not satisfactory, further adaptations were introduced to improve the overall quality. A DGPS module was added to the autopilot setup to increase

positional accuracy of camera stations. RAW GPS data stored in the autopilot log served as an input into the automated geotagging workflow along with CZEPOS correction data, ionosphere map and shutter lag correction. This approach belongs to the Post-Processed Kinematics (PPK) class of methods being currently employed by a growing number of commercial and academic bodies (Kais et al. 2005). Compared to the Real-Time Kinematics approach it is more robust, not relying on the datalink between rover and base stations. It also features lower cost due to less hardware required. The overall aim of the developed geotagging workflow is to eliminate laborious GCP collection and measurements for operational service. The distribution of reference GCPs may be limited by site disposition, e.g. continuous tree cover may restraint the selection excluding the central forested part of the site.

The tests of different settings of DSM generation proved the advantage of our concept of DSM resampling to eliminate various defects caused by highly detailed DSM. Such procedure expelled most of the artefacts and thus reduced subsequent classification errors. Still further evaluation of parametrization during the data processing is needed to comprehensively evaluate the influence of partial processing steps on final imagery used for classification. Co-processing of both RGB and NIR imagery results in lower spatial accuracy than RGB orthomosaic alone and extend the time needed for its processing. However as demonstrated here, the NIR data are indispensable for BL classification and proper co-registration with RGB data is more important than the temporal co-registration.

Accuracy of invasive BL detection from UAV orthomosaics was very high, although values of acceptable classification accuracy presented in the literature differ considerably, ranging from 70% (Pringle et al. 2009) to 85% for PA and UA (Foody 2002), and 0.61 for Kappa (Landis and Koch 1977). Our accuracies fell within this range, signifying good to excellent agreement. Lower accuracies for satellite WV-2 imagery were probably due to lower spatial resolution; still different timing could also play a role. This must be proved by further tests analysis UAV imagery acquired in different periods of the vegetation season.

Measures of textural and spatial context can augment results of classification in case the spectral information is not sufficient (Wang et al. 2015), such as mixing arable land and BL stands (Somodi et al. 2012). Using range of elevation values instead of vegetation height derived by subtraction DSM to existing DTM can overcome the problem of geolocation impreciseness since it only defines relative differences within the defined neighbourhood. In case of abrupt

change in surface height, such as at the border of forest/non forest, it brought noise into the classification, however since in our case non forest areas at the borders with forest were shaded (and classified as ‘shade’), it did not influence the quality of the final results.

The timing of the data acquisition can be crucial in plant detection, since plants are often best recognized during flowering time (Everitt, Escobar and Davis 2001; Müllerová et al. 2013). According to Somodi et al. (2012), BL is the best separable during flowering however this approach has following drawbacks impeding practical application: (a) BL individuals do not flower exactly at the same time even at the same site, and (b) the time window for flowering is very short (1-2 weeks) and difficult to predict (depending very much on May temperatures in particular year). In our study we found that if the data provide high spatial detail (UAV) and include NIR band, the species is separable very well even if not flowering. Importance of NIR band for discrimination of vegetation was reported from previous studies (Everitt et al. 2005; Wang et al. 2015).

In our further research we would like to explore the potential benefits of sequence of orthomosaics with different timing in discriminating tree species (such as in Hill et al. 2009). For this approach precise georeferencing is indispensable, therefore we will continue testing the methodology of data pre-processing to make the workflow as simple and automatic as possible (reducing the manual input such as GCP collection) and robust at the same time. Reduction of geometric distortions on the UAV orthomosaics will enable us to test the object-based approach accounting for the spatial structure and context information (Blaschke 2010). This approach is expected to improve the results by reducing the effects of shadows, within-class spectral variation and mis-registration (Laliberte et al. 2012; Tewkesbury et al. 2015).

5. Conclusions

The paper presents and discusses application of low cost UAV technology in environmental monitoring. Our study showed that UAV data are well suitable for detection of selected invasive species (black locust in our case), still processing of the data (mainly creation of the orthomosaic) can be problematic and must be handled with care. We provide evidence that good results can be obtained using a low cost solution of unmanned system composed from affordable off-the-shelf components such as Radio Controlled (RC) airplanes and consumer cameras modified for RGB/NIR spectrum in case the right methodology is applied to the important steps of image

acquisition, pre-processing (mosaicking and georeferencing), ground-truthing and classification. For practical application of this novel, flexible and cheap tool in plant invasion management as well as other environmental actions, well proven and tested methodology is crucial, and our study brings insights in this area.

Acknowledgements

The research was supported by TAČR TA0402045, the Praemium Academiae award to P. Pyšek from the Czech Academy of Sciences, was part of long-term research development project No. RVO 67985939 and received funding from the MEYS under the National Sustainability Programme I (Project LO1202).

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