Images from Unmanned Aircraft Systems for Surveying Aquatic and Riparian Vegetation

Eva Husson
Faculty of Natural Resources and Agricultural Science
Department of Aquatic Sciences and Assessment
Uppsala

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Cover: Aquatic and riparian vegetation in UAS-orthoimages of Lake Ostträsket (left) and Vormbäcken River (right) that were produced for this thesis
(Image editing: E. Husson)

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Abstract

Aquatic and riparian vegetation in lakes, streams, and wetlands has important ecological and regulatory functions and should be monitored to detect ecosystem changes. Field surveys are often tedious and in countries with numerous lakes and streams a nationwide assessment is difficult to achieve. Remote sensing with unmanned aircraft systems (UASs) provides aerial images with high spatial resolution and offers a potential data source for detailed vegetation surveys. The overall objective of this thesis was to evaluate the potential of sub-decimetre resolution true-colour digital images acquired with a UAS for surveying non-submerged (i.e., floating-leaved and emergent) aquatic and riparian vegetation at a high level of thematic detail.

At two streams and three lakes in northern Sweden we applied several image analysis methods: Visual interpretation, manual mapping, manual mapping in combination with GPS-based field surveys, and automated object-based image analysis and classification of both 2D images and 3D point data. The UAS-images allowed for high taxonomic resolution, mostly at the species level, with high taxa identification accuracy (>80%) also in mixed-taxa stands. UAS-images in combination with ground-based vegetation surveys allowed for the extrapolation of field sampling results, like biomass measurement, to areas larger than the sampled sites. In automatically produced vegetation maps some fine-scale information detectable with visual interpretation was lost, but time-efficiency increased which is important when larger areas need to be covered. Based on spectral and textural features and height data the automated classification accuracy of non-submerged aquatic vegetation was ~80% for all test sites at the growth-form level and for four out of five test sites at the dominant-taxon level.

The results indicate good potential of UAS-images for operative mapping and monitoring of aquatic, riparian, and wetland vegetation. More case studies are needed to fully assess the added value of UAS-technology in terms of invested labour and costs compared to other survey methods. Especially the rapid technical development of multi- and hyperspectral lightweight sensors needs to be taken into account.

Keywords: Aquatic vegetation, drone, DSM (digital surface model), OBIA (Object-based image analysis), Riparian vegetation, species identification, UAS (unmanned aircraft system), UAV (Unmanned aerial vehicle), RPAS (remotely piloted aircraft system), sub-decimetre spatial resolution, Vegetation mapping

Author's address: Eva Husson, SLU, Department of Aquatic Sciences and Assessment
P.O. Box 7050, 75007 Uppsala, Sweden
E-mail: Eva.Husson@slu.se

Även den som går sakta kommer fram. (Slow and steady wins the race.)

Swedish proverb.

Contents

List of Publications

This thesis is based on the work contained in the following papers, referred to by Roman numerals in the text:

I Husson, E., Hagner, O., & Ecke, F. (2014). Unmanned aircraft systems help to map aquatic vegetation. *Applied Vegetation Science* 17(3), 567−577.

II Husson, E., Lindgren, F., & Ecke, F. (2014). Assessing biomass and metal contents in riparian vegetation along a pollution gradient using an unmanned aircraft system. *Water, Air, & Soil Pollution* 225(6), Article number: 1957.

III Husson, E., Ecke, F., & Reese, H. (2016). Comparison of manual mapping and automated object-based image analysis of non-submerged aquatic vegetation from very-high-resolution UAS images. *Remote Sensing* 8(9), Article number: 724.

IV Husson, E., Reese, H., & Ecke, F. Combining spectral data and a DSM from UAS-images for improved classification of non-submerged aquatic vegetation. *Manuscript*.

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The contribution of Eva Husson (EH) to the papers included in this thesis was as follows (other acronyms: Frauke Ecke (FE), Olle Hagner (OH), Fredrik Lindgren (FL), and Heather Reese (HR)):

I EH conceived and designed the study together with FE; EH performed parts of the field work together with FE; EH analysed the data and produced vegetation maps; EH wrote the paper with contributions of FE and OH; and EH had the main responsibility for the publication process.

II EH conceived and designed the study together with FE; EH performed parts of the field work and mapping together with FL; EH analysed the data; EH wrote the paper with contributions of FE; and EH had the main responsibility for the publication process.

III EH conceived and designed the study together with FE and HR; EH performed the field work and analysed the image data; EH wrote the paper with contributions of FE and HR; and EH had the main responsibility for the publication process.

IV EH conceived and designed the study together with HR and FE; EH derived the digital surface models and analysed the image data; and EH wrote the paper with contributions of HR and FE.

Abbreviations

BNDVI	Blue normalized difference vegetation index
BGNIR	Blue green near infrared
CCD	Charge-coupled device
Cd	Cadmium
CIR	Colour infrared
Cu	Copper
DSM	Digital surface model
GPS	Global positioning system
GRNIR	Green red near infrared
MILC	Mirrorless interchangeable lens camera
Mpx	Megapixels
NIR	Near infrared
OBIA	Object-based image analysis
P	Phosphorous
PAMS	Personal aerial mapping system
RGB	Red green blue
RPAS	Remotely piloted aircraft system
3D	Three-dimensional
tot-N	Total nitrogen
2D	Two-dimensional
UAS	Unmanned aircraft system
UAV	Unmanned aerial vehicle
Zn	Zink

1 Introduction

1.1 Freshwater shore zones

The shore zone of aquatic freshwater systems forms a transition between two ecosystems thus providing habitats for both terrestrial and aquatic organisms. Such a “transitional habitat”, also called an ecotone, is characterized by a zonation across small gradients leading to high variation in environmental factors and high biodiversity (Wetzel, 2001, Kalff, 2002, Schmieder, 2004). Different approaches to define and classify the shore zone are currently in use. For this thesis I refer to the classification by Ostendorp et al. (2004) as reviewed by Strayer (2010; Figure 1). The shore zone reaches from the highest high water mark to the lower limit of submerged vegetation. Regularly flooded wetlands also belong to the shore zone. In shallow lakes, the whole lake can represent the shore zone if the pelagic zone is missing.

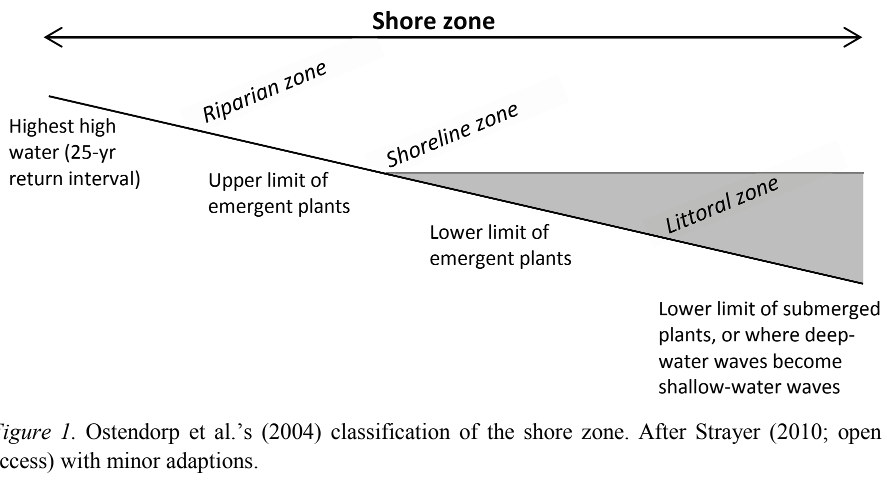

Figure 1. Ostendorp et al.’s (2004) classification of the shore zone. After Strayer (2010; open access) with minor adaptions.

1.1.1 Aquatic and riparian vegetation in freshwater shore zones

In the shore zone of natural freshwater systems, varying environmental factors like water depth, sediment type, wind and wave exposure and water level fluctuations result in a high diversity of aquatic and riparian plant species (Schmieder, 2004, Kalff, 2002). Vegetated shore zones form an interface between the surrounding land and water and have important regulatory and ecological functions (Figure 2). They intercept terrestrial nutrient run-off, retain sediments, improve water quality, and regulate water yield (Strayer, 2010, Johnston, 1991, Tabacchi et al., 2000, Salemi et al., 2012). Aquatic and riparian vegetation serves as habitat for a variety of species including, depending on geographic location, microflora, zooplankton, macro-invertebrates, and vertebrates like fish, amphibians, turtles, waterfowl, and certain mammals (Strayer, 2010). As major primary producers, aquatic plants provide organic matter and food for aquatic and riparian biota. They are important for nutrient cycling and metabolism regulation in freshwater systems (Pieczynska, 1993) and can transfer nutrients and oxygen between the sediment and the water (Smith and Adams, 1986, Møller and Sand-Jensen, 2012). In the littoral zone of lakes, aquatic vegetation absorbs the energy of waves, thereby stabilizing shore and sediments (Strayer, 2010). In streams, riparian vegetation controls channel and bank stability and has an impact on water flow (Tabacchi et al., 1998, Tabacchi et al., 2000). By trapping sediment and seeds certain aquatic plants can physically modify stream habitats thereby working as ecosystem engineers (Asaeda et al., 2010, O'Hare et al., 2011). Riparian corridors are a major vector for the transport of matter, energy, and organisms and are important for landscape connectivity (Tabacchi et al., 1998).

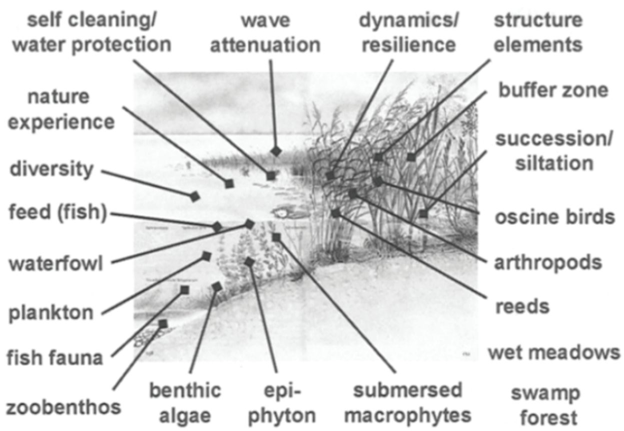

Figure 2. Ecological functions, plant and animal communities of lake shore zones. Reproduced from Schmieder (2004) with permission of the publisher.

1.1.2 The need to monitor vegetation in freshwater shore zones

Different aquatic plant species respond differently to changes in environmental conditions. Certain species have well-defined ecological optima and ranges and their presence and/or absence can be related to an environmental pressure gradient, for example, the level of eutrophication. Therefore, such indicator species with species-specific responses to environmental pressures are integrated globally in the assessment of environmental status of aquatic ecosystems (e.g., EU, 2000, EPA, 1998, Hart et al., 1993). In the European Water Framework Directive (EU, 2000) the "Composition and abundance of aquatic flora" is included as an ecological quality element for the assessment of lakes and streams. Additionally, the assessment includes the "structure of the lake shore" and the "structure and condition of the riparian zone", for lakes and streams respectively, as part of the quality element "Morphological condition". For the assessment of water quality parameters like eutrophication, indicator metrics are typically based on submerged, floating, and floating-leaved aquatic species (e.g., Penning et al., 2008, Kolada et al., 2014, Fabris et al., 2009). In Nordic countries however, helophytes (emergent aquatic plants) have been shown to increase the predicting power of indicator metrics and their inclusion in trophic indices is under debate (Kolada et al., 2014, Alahuhta et al., 2012, Alahuhta et al., 2014). In contrast to temperate regions, helophytes naturally form a significant share of the species pool in boreal lakes and wetlands (e.g., Toivonen and Huttunen, 1995) and their exclusion can drastically limit the number of species on which a bioassessment is based (Alahuhta et al., 2014). Helophytes are also effective bioindicators for hydromorphological alteration (Mjelde et al., 2013).

To increase our understanding of the complex processes in shore zones and their response to environmental pressures, it is critical to assess the occurrence and cover of plants at a high taxonomic resolution, preferably at the species level. Biomass assessment is necessary to understand the turnover of organic matter and elements like carbon, nutrients, trace elements, and pollutants.

Operational monitoring of aquatic and riparian vegetation is to a large extent based on field work. The European Committee for Standardisation recommends a transect-based method for aquatic vegetation surveys in both lakes and streams (CEN, 2007, CEN, 2014) and in most EU member states transect methods are applied (Kolada et al., 2009). In general, transects are established perpendicular to the shore line and cover the complete depth range to the maximum colonisation depth. Along these transects, the quantitative share of identified species is estimated. The time effort to sample aquatic vegetation in lakes <5 km^2 using a transect method has been estimated to up to four days (two days for two people; Naturvårdsverket, 2010). Biomass assessment is also traditionally based on field sampling usually with the help of sampling plots and thus restricted to relatively small areas (Gibson, 2002, Mueller-Dombois and Ellenberg, 2002). Individual plants growing inside the plot are harvested to determine their weight. Due to the use of small sample plots (typically ≤ 1 m^2) variance is generally high and a large number of samples is needed to adequately estimate the biomass of a site, making this method time-consuming (Global Rangelands, 2016).

Aquatic ecosystems are under increasing pressure, for example, from climate change, intensification of land use, and spread of non-indigenous and invasive species. Predicted consequences include changes in hydrological regimes, loss of biodiversity and habitats, and deterioration of water quality (Markovic et al., 2014, Davis et al., 2015, Vitousek et al., 1997, Ström, 2011, Vorosmarty et al., 2010). As a result, the need to monitor changes in aquatic ecosystems is larger than ever and field work alone might not be efficient enough to meet the increasing demand of environmental monitoring and assessment.

1.2 Remote sensing

> "Remote sensing is the science (and to some extent, art) of acquiring information about the Earth's surface without actually being in contact with it. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information " (CCMEO, 2016)

There is a wide variety of different sensors which can be mounted on different platforms, and used to record energy reflected by the surface of the earth. Platforms can range from terrestrial-based (e.g., hand-held or placed on a stative), to various airborne crafts such as balloons, blimps, helicopters or airplanes, and up to space-borne satellites. Sensors have developed over time from analogue panchromatic cameras to digital multi- and hyperspectral cameras. The difference between those cameras, besides the transition from film to digital format, is the number of spectral bands, or wavelength intervals, in which the incoming electromagnetic radiation is recorded (Liang et al., 2012). The more spectral bands there are, the higher the spectral resolution of the recorded images. The radiation from the Earth's surface can either be detected as a continuous signal with the help of a moving mirror (across-track scanners; Lillesand and Kiefer, 2000) or by arrays of charge-coupled devices (CCDs) as used in along-track scanners and digital frame cameras (Lillesand and Kiefer, 2000, Tempfli et al., 2009). For example, in true-colour small format frame cameras, three CCDs next to each other (one for each of the red, green, and blue band) form tiny squares (Tempfli et al., 2009). A matrix of such squares is exposed to the incoming radiation and each square corresponds to one pixel in the recorded image (Tempfli et al., 2009). The linear dimension that each pixel represents on the ground is therefore determined by the size of the squares and the distance to the ground (Tempfli et al., 2009). The smaller the pixels in the image are, the higher the spatial resolution, determining the size of the smallest objects that can be resolved in the image (Liang et al., 2012). Another important feature of digital images is the radiometric resolution which is defined as the sensitivity of the sensor and described by the potential range of output numbers in each band, for example, 0-255 in 8-bit data (Liang et al., 2012). The more bits, the higher the radiometric resolution; this is important because it can affect the ability to detect small differences in incoming energy. Digital cameras are so-called "passive sensors", recording energy emitted by the sun and reflected by objects or vegetation. Active sensors that emit energy are nowadays also used frequently in remote sensing, such as laser scanners and radar (CCMEO, 2016).

1.2.1 Image analysis

There is a long tradition of visually interpreting aerial photographs for land cover mapping (e.g., Colwell, 1960). This method is well established and, if performed by trained interpreters, usually very reliable and allows for a high level of thematic detail thanks to the outstanding capacities of the human eye-brain system (Tempfli et al., 2009). Elements used in the complex process of visual image interpretation include size, shape, shadow, tone and colour, texture, pattern, and location of objects and associations with the object's surrounding (Colwell, 1960, Lillesand et al., 2008, Tempfli et al., 2009). The main drawback of visual interpretation is that it is time-consuming. Valta-Hulkkonen et al. (2003) compared visual interpretation of non-submerged aquatic plants from an aerial image (colour infrared (CIR) photograph, scale 1:20,000) with automated classification using a maximum likelihood classifier. The automated approach could only discriminate between different growth forms. Visual interpretation allowed for species identification but took 3.5 times longer than automated classification (Valta-Hulkkonen et al., 2003).

With the development of more powerful computers and increased accessibility of remote sensing images, automated data processing became more and more common. There are two approaches for automated image analysis: The pixel-based approach, which has a longer tradition, and the object-based approach; due to the increased use of the object-based approach, Blaschke et al. (2014) recently declared it to be a new paradigm in image analysis. In the pixel-based approach, each pixel is assigned to one class, according to its spectral characteristics (Lillesand and Kiefer, 2000, Tempfli et al., 2009). This approach is appropriate when the spatial resolution and the size of the objects to classify are approximately in the same order of magnitude (Blaschke, 2010). In high-resolution images however, one object might consist of several pixels and the probability is high that neighbouring pixels belong to the same land cover class (Blaschke and Strobl, 2001). In a pixel-based classification this may lead to the "salt and pepper" effect, when individual pixels are classified differently from their neighbours (Pu et al., 2011). A first step in Object-based image analysis (OBIA) is therefore the segmentation of the image into areas made up of contiguous pixels that have relatively homogenous spectral values as compared to neighbouring areas; these areas are referred to as image-objects or segments (Blaschke and Strobl, 2001). In addition to spectral features of these image-objects, texture, shape, and contextual features can then be considered in the classification (Laliberte and Rango, 2009, Yu et al., 2006, Dronova, 2015).

1.2.2 Conventional remote sensing in freshwater shore zones

Satellite and aerial images from manned aircrafts have frequently been used in surveying freshwater environments. Examples for successful applications are land cover and vegetation community mapping, detection of large-scale single species stands (e.g., invasive species), wetland delineation, biomass estimation, vegetation health assessment, and change detection (Ozesmi and Bauer, 2002, Adam et al., 2010, Ashraf et al., 2010, Silva et al., 2008).

Freshwater shore zones are characterized by highly variable land cover/vegetation and thus have high spectral variability. Shore zones can have a limited width and common vegetation types include smaller plants species such as herbs and shrubs. For these reasons, the possibility to use conventional remote sensing for detailed survey has been limited. Insufficient spatial resolution has been pointed out as a major limitation for the identification and mapping of aquatic and riparian vegetation at a high taxonomic level (Muller, 1997, Goetz, 2006, Adam et al., 2010, Ashraf et al., 2010). The existing automated image analysis and classification methods, which are necessary to time-efficiently cover large spatial scales, can also be a limiting factor for taxonomic resolution compared to visual interpretation (e.g., Valta-Hulkkonen et al., 2003).

1.3 Unmanned aircraft systems (UAS)

Unmanned aircraft systems are referred to under many names like unmanned aerial vehicle (UAV), remotely piloted aircraft system (RPAS), or drones (e.g., ACUA, 2016). In Swedish flight regulation the term unmanned aircraft system (UAS) is used (Transportstyrelsen, 2009). UASs fly autonomously or are remotely controlled and come in a large variety of sizes and forms (Figure 3 and Table 1; Anderson and Gaston, 2013, Klemas, 2015, van Blyenburgh, 2016), such as planes, rotor-based "copters", balloons and blimps, or paragliders and kites. In case of remote sensing missions, they are equipped with a sensor. Lightweight UASs have been predicted to revolutionize environmental remote sensing and spatial ecology (Anderson and Gaston, 2013, Klemas, 2015, Johnson et al., 2015). The main benefits of UASs are that they allow for low-altitude flights potentially increasing the spatial resolution of collected data, thereby closing the gap between ground-based surveys and manned aircraft; flexible survey times and revisit periods can be defined by the user; and UASs can be operated at low costs (Anderson and Gaston, 2013). In remote sensing operations with high human risk, UASs can be used rather than manned aircrafts (Pajares, 2015). In the past decade, UAS platforms have undergone an intense technical development and improvement (Johnson et al., 2015, Pajares, 2015, Colomina and Molina, 2014) further increasing their potential for a variety of remote sensing applications.

1.3.1 Regulations

Flight regulations have often been pointed out as a constraint for the implementation of UAS remote sensing (e.g., Rango and Laliberte, 2010, Hardin and Jensen, 2011, Colomina and Molina, 2014, Johnson et al., 2015). The creation of an internationally harmonized regulation is, however, complicated due to the large group of contributing agents like the International Civil Aviation Organization, several European authorities and organisations, the military organisations, national civil aviation authorities, user-driven associations, and research companies (reviewed in Colomina and Molina, 2014).

In Sweden, UASs may be operated by authorized pilots at heights above 120 m without the need for individual permission for each flight when the maximum total weight does not exceed 1.5 kg and the maximum kinetic energy developed is 15 J (Transportstyrelsen, 2009). These UASs must be operated in the visual range of the pilot.

(a) Black Hornet - ProxDynamics, Norway

(b) Seeker - Fly-n-Sense, France

(c) T-15 - Arcturus, USA

(d) KUS-7 - KoreanAir, South Korea

(e) Camcopter S100 - Schiebel, Austria

(f) K2 - Unmanned Aircraft Technologies, Spain

(g) Hermes 450 - Elbit Systems, Israel

(h) Nibbio - Selex ES, Italy

(i) Aerosonde Mark 4.7 - AAI Corp., USA

(j) Mantis - BAE Systems, UK

(k) Tares (Taifun) - Cassidian Airborne Solutions, Germany

(l) Grey Eagle - General Atomics Aeronautical Systems, USA

(m) Little Bird - Boeing, USA

(n) Global Observer - AeroVironment, USA

(o) X-46 - Boeing, USA

Figure 3. Examples of UASs; one of each category after van Blyenburgh (2016). Image copyright: RPAS: The Global Perspective, Edition 2016 − © Blyenburgh, France. The images have been provided by P. van Blyenburgh, UVS International for reproduction in this thesis. Categories: Nano RPAS (a), Micro RPAS (b), Mini RPAS (c), Close range RPAS (d), Short range RPAS (e), Medium range RPAS (f), Medium range endurance RPAS (g), Low altitude deep penetration RPAS (h), Low altitude long endurance RPAS (i), Medium altitude long endurance RPAS (j), Offensive expendable RPAS (k), Missile carrying RPAS (l), Optionally piloted & Converted aircraft (m), High altitude long endurance RPAS (n), Unmanned combat aircraft (o). RPAS: Remotely piloted aircraft system.

1.3.2 Sensors

The sensors mounted on UASs can include video cameras, visible-band, near-infrared, and multispectral cameras, hyperspectral cameras, thermal infrared sensors, laser scanners, and Synthetic Aperture Radar systems (Pajares, 2015). For lightweight UASs, the limited payload often affects the choice of sensor. For this reason, off-the-shelf digital compact cameras are frequently used (Table 1). However, great advances in the miniaturisation of more advanced sensors have been achieved in recent years and will further increase the potential of UAS remote sensing in the future (Pajares, 2015, Colomina and Molina, 2014).

Table 1. *Examples of commonly used UASs. Reproduced from Colomina and Molina (2014; open access). Mpx: Megapixels, RGB: Red green blue, MILC: mirrorless interchangeable lens camera.*

Name	Manufacturer	Weight (kg)	Endurance (h)	Integrated payload (i) or Payload weight (w)
Common fixed-wing unmanned aircraft				
SwingletCAM	SenseFly	0.5	0.5	(i) 16 Mpx RGB camera
GeoScan101	GeoScan	2	1	(i) 24.3 Mpx RGB camera
UX5	Trimble	2.5	0.83	(i) 16.1 Mpx MILC RGB camera
Pteryx	FotoMapy	5	2	(w) 1 kg w/o batteries
Sirius I	MAVinci	3	0.91	(i) 16 Mpx RGB camera
Kahu	Skycam	4	2	(i) Double-head 16 Mpx MILC RGB cameras
Common rotary-wing unmanned aircraft				
Geocopter	IGI	90	2	(w) 30 kg
Scout B1-100	Aeroscout	75	1.5	(w) 30 kg
R-MAX, type II	Yamaha	100	1	(w) 28 kg
Common multi-rotor unmanned aircraft				
md4-1000	Microdrones	3	1.46	1.2 kg
HT-8-2000	Height-Tech	2.4	0.28	2 kg
Aibot x6	Aibotix	2.4	0.3	2.5 kg
Falcon 8	Ascending technologies	1.45	0.33	0.75 kg
HexaKopter	MikroKopter	1.2	0.6	1 kg

1.3.3 Image processing

In most cases the images recorded by UASs need to be processed before they can be analysed and used to create new information. A variety of software programs combining digital photogrammetry and Structure-from-Motion computer vision have evolved together with the development of UASs to accurately and automatically process UAS-images (Remondino et al., 2011, Madden et al., 2015, Colomina and Molina, 2014). Main products are orthoimages (orthorectified image-mosaics) and digital surface models (DSMs). Important moments in the processing chain are image orientation and camera calibration, image matching with the help of tie points, and surface reconstruction. In particular the introduction of Semi-Global Matching (Hirschmüller, 2005), a quick and robust pixel-by-pixel stereo matching method, leveraged the use of optical cameras as a stand-alone solution for dense 3D-point cloud and DSM production (Colomina and Molina, 2014, Haala et al., 2013).

1.3.4 UAS remote sensing in freshwater shore zones

Compared to monitoring of agricultural crops, rangeland, and forest, studies on UAS application for vegetation survey in freshwater shore zones are rare (Salami et al., 2014).

For streams, an early approach from the time before the UAS-boom, has been made by Edwards and Brown (1960) who used black-and-white photographs taken from a balloon to study the distribution of submerged aquatic vegetation in a shallow stream. More recently, Dunford et al. (2009) mapped riparian tree species in a Mediterranean forest with the help of a motorized paraglider and a true-colour camera. Also Michez et al. (2016b) focused on riparian tree species and their health condition. Using a lightweight fixed-wing UAS and two cameras in succession (RGB, and GRNIR) the authors achieved an overall classification accuracy of ~80%. The same authors also attempted to automatically detect invasive perennial herbaceous species in riparian zones in an agricultural landscape (Michez et al., 2016a). The attempt was successful for *Heracleum mantegazzianum* but needed further development for *Impatiens glandulifera* and *Fallopia sachalinensis*/*Fallopia japonica* and hybrids. Casado et al. (2015) and Tamminga et al. (2015) applied UAS-technology to survey stream hydromorphology using a lightweight quad- and octocopter, respectively, delivering true-colour images with 2.5 and 5 cm spatial resolution. Casado et al. (2015) succeeded with an automated identification of multiple structural elements including side bars, erosion, riffle, deep water, shallow water, trees, vegetated side bars, vegetated bank, submerged vegetation with floating-leaves, vegetation with floating-leaves on the water surface, grass, and shadows with an overall accuracy of 81%. The classification was particularly successful for non-submerged vegetation. Tamminga et al. (2015) used the UAS-orthoimage to map geomorphic and aquatic habitat features. In addition to the mapping, a digital elevation model derived from the UAS-images was used for hydrodynamic modelling of water depth and velocity. Kaneko and Nohara (2014) used a lightweight quadcopter equipped with a true-colour camera taking images of emergent aquatic and herbaceous riparian plant communities in a river in Japan while hovering at a height of 5 m. The achieved pixel size was ≤3 mm. Structural details of individual plants, such as the shape of leaves, could be recognized in the UAS-images allowing for visual discrimination of vegetation communities dominated by 16 different plant species along 13 transects. Visser et al. (2013) studied submerged aquatic vegetation in shallow clearwater streams. Several low-altitude remote-sensing platforms including a Helikite (a combination of helium balloon and kite) were used to collect visible and near infrared (NIR) images from different heights above the water surface (range <1.5−5.4 m). The authors found that texture and shape features were more successful than spectral features in discriminating *Ranunculus fluitans* and *Potamogeton pectinatus*. More research on submerged aquatic vegetation was performed by Flynn and Chapra (2014) who presented a method for monitoring filamentous algae (*Cladophora glomerata*) in a clear shallow stream. Their method was based on inexpensive equipment using a lightweight quadcopter and a true-colour camera, with which they achieved overall accuracies of ~90% at a resolution of 0.25 m.

Regarding lakes, van der Merwe and Price (2015) surveyed harmful algal blooms to improve effective local risk assessment. Two cameras modified to capture NIR and blue light wavelengths were mounted on a fixed-wing UAS flying at an altitude of 122 m and a multirotor UAS at an altitude of 25−50 m. Blue normalized difference vegetation index (BNDVI) values were calculated from the image data (BNDVI=(NIR−blue)/(NIR+blue)) and correlated to cyanobacteria density at the water surface. Vogt and Vogt (2016) captured NIR, red, green, and blue bands, from both nadir and oblique angles with two cameras mounted on a fixed-wing UAS to assess lake water turbidity. Turbidity estimates were correlated to traditional Secchi disc measurements and the contributions from suspended organic matter and suspended sediments could be differentiated based on the spectral UAS-data.

Regarding wetlands, Göktogan et al. (2010) employed an autonomous rotary-wing UAS with a true-colour video camera for the detection and control (integrated spraying mechanism) of two invasive aquatic plants, namely the herbaceous *Alternanthera philoxeroides* and the floating fern *Salvinia molesta*, in Australian wetlands. Species recognition was based on expert knowledge and supervised machine learning techniques. Lechner et al. (2012) mapped the vegetation extent of upland swamps surrounded by eucalypt woodland in Australia, potentially affected by subsidence caused by underground coal mining. The UAS was equipped with two cameras to record the visible and infrared spectrum with a resolution of 4 cm. A DSM derived from the infrared images was used for an initial classification which was then refined using spectral information from the UAS-images. Ishihama et al. (2012) verified that 1 cm resolution true-colour UAS-images taken by a lightweight octocopter allowed for the visual discrimination of two graminoid species, namely *Phragmites australis* and *Miscanthus sacchariflorus*, growing in mixed vegetation stands. Knoth et al. (2013) used two lightweight quadcopters, equipped with digital cameras modified to record panchromatic NIR with <1.5 cm resolution and colour infrared (BGNIR) with 3 cm resolution, respectively, for restoration monitoring in cut-over bogs. The authors achieved an overall classification accuracy of 91% for four classes: waterlogged bare peat, *Sphagnum* spp. (mosses), *Eriophorum vaginatum* (graminoid), and *Betula pubescens* (tree). Kuria et al. (2014) analysed seasonal vegetation changes in a Tanzanian wetland, based on 0.8 m resolution true-colour image data acquired with a motorized paraglider, a DSM derived from UAS-images, and commercial radar data. Thirteen land cover classes were identified, including several classes with emergent aquatic vegetation. The land cover classes were then combined to five generalized classes that had an overall accuracy of ~90% for two analysed seasons. Zweig et al. (2015) used a fixed-wing plane with a maximum take-off weight of 6.4 kg collecting true-colour images with 5 cm resolution to automatically classify wetland vegetation communities mainly on the growth-form level. Depending on the level of thematic detail the overall accuracy was 69% (nine classes) and 91% (three classes). Because their pixel-based approach resulted in a "salt and pepper" classification, the images were resampled to a resolution of 0.5 m. Boon et al. (2016) used a multi-rotor UAS and a true-colour camera for wetland delineation and wetland vegetation health assessment in South Africa. In addition to a 1.8-cm resolution orthoimage they used a DSM derived from a 3.8-cm resolution point cloud and found that the inclusion of height data significantly enhanced wetland delineation and classification.

These studies underline the potential of UAS remote sensing for detailed surveys in freshwater environments. However, to my knowledge, no attempt for the comprehensive identification and mapping of herbaceous riparian and aquatic plant taxa in shore zones has been undertaken so far. The majority of Sweden is part of the boreal region, which has the highest number of lakes in the world (Lehner and Doll, 2004). The boreal region covers 10% of the Earth's land surface (Walter and Breckle, 1991) and many areas are remote and difficult to access for field work. Freshwater systems in the boreal region are predominately humic (Likens, 2010) with low water transparency, which impedes the possibility to detect submerged vegetation by remote sensing. Concurrently, the development of submerged vegetation is hampered due to low light penetration into the water column (Sondergaard et al., 2013).

2 Objectives

The objective of this thesis is to evaluate the potential of sub-decimetre resolution true-colour digital images acquired with an unmanned aircraft system (UAS) for surveying non-submerged (i.e., floating-leaved and emergent) aquatic and riparian vegetation at a high level of thematic detail.

In particular, the following research questions have been addressed:

- Which taxonomic resolution can be achieved with the UAS-images? (Paper I, III)
- Are the UAS-images suited for vegetation mapping and assessment of cover? (Paper I, III)
- Do the UAS-images support comprehensive assessment of entire riparian zones regarding species composition, plant biomass, and accumulation of heavy metals in vegetation along a contaminated stream? (Paper II)
- To which extent can the image-analysis and classification process be automated and what are the implications of automation for time-efficiency, classification accuracy, and level of thematic detail? (Papers III and IV)

3 Methodology

3.1 Study sites

UAS remote sensing was tested at five study sites in northern Sweden (Figure 4). Four sites are located in the middle boreal subzone, and one, Rakkurijoki River, in the northern boreal subzone (Sjörs, 1999). Two sites are streams (Rakkurijoki in Paper I, and Vormbäcken in Paper II) and three sites are humic lakes (Bälingsträsket and Bruträsket in Paper I, and Ostträsket in Papers III and IV). The study sites were chosen because of their variety in species and cover of riparian and non-submerged aquatic plants. The riparian vegetation at the studied sites is dominated by herbaceous plants, mainly graminoids, and shrubs. The Vormbäcken system is affected by high concentrations of Cd, Cu, and Zn resulting from mining in the catchment. In Paper II, the accumulation of these elements in riparian vegetation along a longitudinal gradient was studied (at locations 7, 15, and 23 km downstream of the source of contamination). Rakkurijoki River and Lake Bruträsket are also impacted by mining; however, at these study sites, impact of mining was not the focus of my thesis. Lake Bälingsträsket and Lake Ostträsket are natural lakes located near the Bothnian Bay and under influence of isostatic rebound.

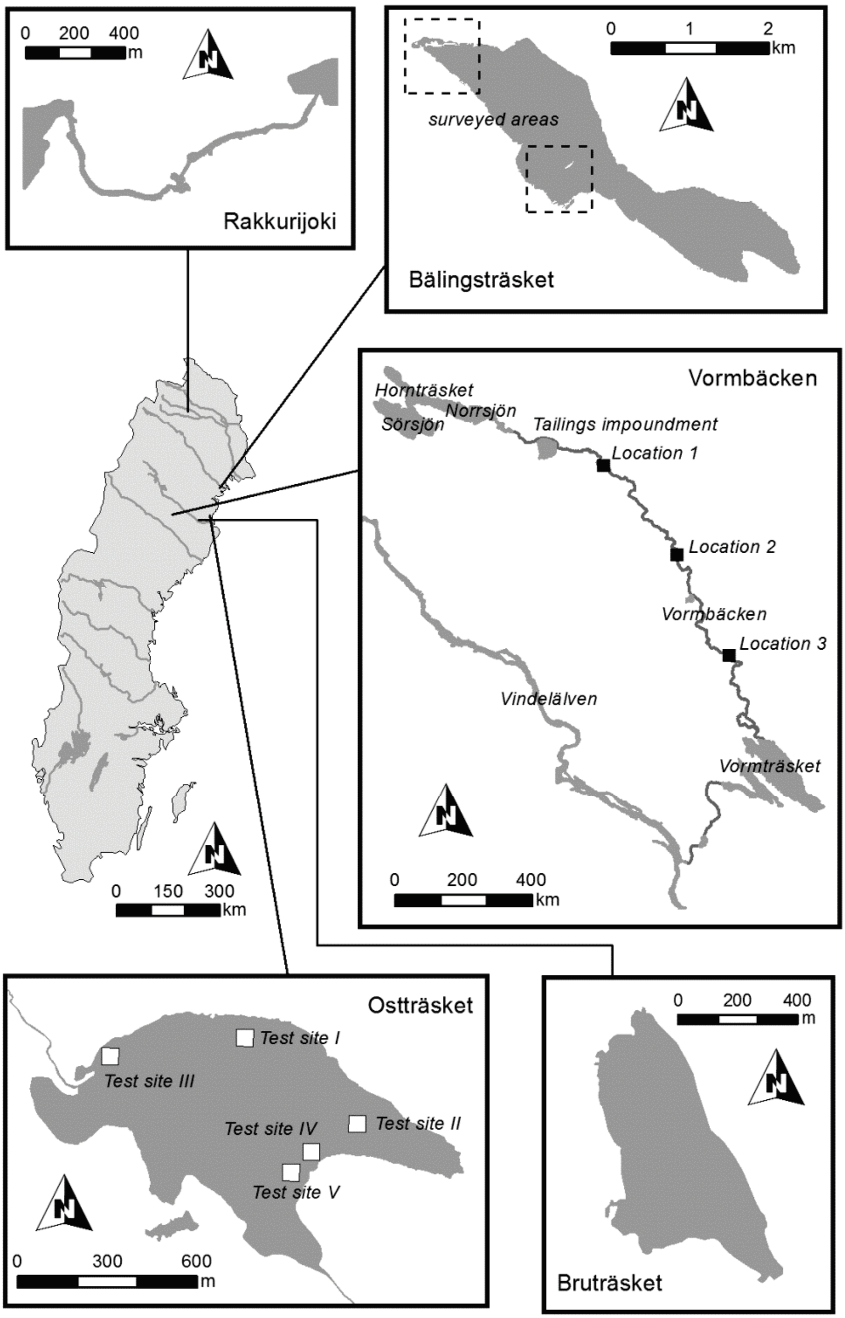

Figure 4. Geographic location of the study sites.

3.2 SmartPlanes' micro-UAS

The UAS used in this thesis was the Personal Aerial Mapping System (PAMS; Figure 5) developed by SmartPlanes Sweden AB (Skellefteå, Sweden). The lightweight micro-UAS (van Blyenburgh, 2016) consisted of the following components:

- The *SmartOne* aircraft, a hand-launched flying wing (wingspan 1.2 m) optimised for aerial mapping and surveying. The *SmartOne* was equipped with an autopilot with a LEA-4 GPS module from u-blox (Thalwil, Switzerland) and six infrared thermopiles for pitch and roll control (MLX90247 from Melexis, Iper, Belgium). From Paper II, an upgraded version with an inertial measurement unit instead of infrared horizon detection was used. The *SmartOne* has a take-off weight of 1.1−1.5 kg, including 200−600 kg of payload. The cruise speed is 13 m/s with a maximum airtime of 40−90 min. The aircraft complies with strict safety standards required by civil aviation authorities and has been approved for routine operations in unsegregated airspace (above 120 m) in Sweden since 2007.
- The ground station, consisting of a laptop computer loaded with flight planning and control software, a radio module for telemetry downlink as well as command uplink, and a remote-control transmitter for manual flight modes and emergency manual override. The equipment of the ground station was transported in a backpack.
- An off-the-shelf lightweight digital compact camera with calibrated optics. The used camera was a Canon Ixus 70® (Canon Inc., Tokyo, Japan), with a seven megapixel charge-coupled device sensor (5.715 mm × 4.293 mm), an image size of 3072 × 2304 (columns × rows), a focal length of 5.8 mm, and an F-number of 2.8. The camera recorded data in the visible spectrum (380−750 nm) using an RGB colour filter.
- The SmartPlanes AerialMapper software for automated on-site production of image mosaics for quality control.

Figure 5. UAS by SmartPlanes Sweden AB; a) *SmartOne* aircraft, b) control station, c) ready for take-off.

3.3 UAS-image acquisition and processing

The study sites were surveyed in the vegetation period (July−August) when aquatic and riparian plants were fully developed. Images were acquired in flight blocks, typically of a size that can be covered in 10−20 min of flying time. We used a flying height of ~150 m, resulting in a ground sampling distance of ~5.6 cm. The along- and across-track image overlap was 70%. Once the flight plan was uploaded to the autopilot, the system had all the information needed to complete the survey and return. A typical flight block consisted of 200−300 images and covered an area of 15−35 ha.

For image processing and production of sub-decimetre-resolution UAS-orthoimages a post-processing service was used provided by SmartPlanes Sweden AB in cooperation with GerMAP GmbH (Welzheim, Germany). Inpho® software (Trimble Navigation Limited, Westminster, USA) was used for the production of the orthoimages which had a pixel size of 5 cm.

For Paper IV, I produced dense 3D point clouds from the original overlapping UAS-images to derive height data in the form of DSMs with the software PhotoScan® (Professional edition, v. 1.2.4, Agisoft LLC, St. Petersburg, Russia).

3.4 Training, validation, and field sampling

Field work performed for this thesis fulfilled several goals:

1) Getting familiar with local plant taxa as well as vegetation types and image-interpreter training (Papers I−III)
2) Validation of vegetation identification results (Papers I−III)
3) Biomass sampling by harvesting vegetation from sample plots (Paper II)
4) Water and plant sampling for chemical analysis (Paper II)

3.5 Image analysis and classification

Several approaches for image analysis were applied in this thesis:

- Visual identification of plant taxa on paper printouts (Papers I and III)
- Visual interpretation and manual mapping of continuous shore zones (Papers I and II; for Paper II in combination with GPS-based field survey with sampling plots) and of five aquatic test sites (100 m × 100 m each) with varying vegetation complexity (Paper III)
- Automated image analysis and classification of the five aquatic test sites (the same that were mapped manually; Papers III and IV)

  Visual taxa-identification was based on paper printouts of UAS-images at a scale of 1:800 for Lake Bälingsträsket and Rakkurijoki River (Paper I) and at a scale of 1:200 for Lake Ostträsket (Paper III).

Manual mapping of shore zone vegetation was done in ArcGIS® (v. 9.3 and 10.0; ESRI Inc., Redlands, USA). To test the feasibility of mapping vegetation at a high taxonomic resolution and of mapping the percentage vegetation cover, respectively, I manually mapped the composition of taxa in the riparian zone of Rakkurijoki River and the percentage cover of *Phragmites australis* in the littoral zone of Lake Bruträsket (Paper I). The cover was mapped at a four-graded scale: ≤25%, 26–50%, 51–75%, and >75%. Along the mining-impacted Vormbäcken River, the entire riparian zone from the floating-leaved and emergent-aquatic-vegetation belt up to the forest layer was mapped manually at three locations (320-m stream stretches; Paper II). Manually produced maps of non-submerged aquatic vegetation at five test sites in Lake Ostträsket were used as reference information to evaluate the accuracy of a more automated mapping approach (Paper III and reused in Paper IV). In total six taxa were present and both dominant (i.e., the taxa with the highest cover) and non-dominant taxa contributing ≥25% to the vegetation cover in mixed vegetation stands were mapped.

For the automated image analysis and classification approach on spectral and textural features from a UAS-orthoimage (Paper III) I applied object-based image analysis in combination with two classification methods: A simple classification based on empirical thresholds and a Random Forest classification (Breiman, 2001). Segmentation (i.e., the delineation of image-objects) and vegetation classification at three levels of thematic detail (water vs. vegetation, growth form, and dominant taxon) was performed using the software eCognition Developer® (v. 9.1, Trimble Germany GmbH, Munich, Germany). As a next step, height information derived from DSMs created from dense 3D point clouds was added to the spectral and textural features for classification with the Random Forest algorithm. The benefit of adding height data in order to increase the classification accuracy at two levels of thematic detail (growth form and dominant taxon) was then evaluated (Paper IV).

3.6 Accuracy assessment

The accuracy of the results from two different image analysis approaches was assessed: a) Visual identification of taxa from paper printouts to assess the reliability of visual interpretation (Paper I) and b) automated image analysis and classification (Papers III and IV). As the spatial assessment unit for the accuracy assessment, I used polygons instead of single pixels which is the most appropriate unit of assessment when OBIA has been used (Congalton and Green, 2009). For assessment of the visual interpretation, the polygons represented vegetation stands delineated manually on paper printouts. For assessment of the automated classification, the polygons represented segments created during the segmentation step. Error matrices were produced including measures of Producer's, User's and total classification accuracy (Paper I) and Cohen's kappa coefficient (Congalton, 1991; Papers III and IV). The interpretation of these accuracy measures is summarized in Table 2. The use of Kappa in the remote sensing context has been criticised as misleading and flawed (Pontius and Millones, 2011). Therefore, I also calculated the overall quantity disagreement and the overall allocation disagreement as suggested by Pontius and Millones (2011; Papers III and IV; Table 2). Since the validation segments showed a large variation in size, I also produced area-based error matrices (related to the number of pixels inside the selected validation segments) as proposed by Radoux et al. (2011) and additionally calculated overall, Producer's and User's accuracy to evaluate the map's usability by assessing the correctly classified area (Papers III and IV).

Table 2. *Applied accuracy measures and their interpretation*

Accuracy measure	Interpretation
Overall accuracy[1]	Proportion of correctly classified validation samples.
Producer's accuracy[1]	The probability that a sampled polygon on the map is that particular class in the reference data.
User's accuracy[1]	The probability that a certain reference class has also been labelled that class in the map.
Cohen's Kappa coefficient[1]	The Kappa statistic takes into account that even assigning class labels at random results in a certain degree of accuracy and is therefore corrected for the agreement occurring by chance.
Overall quantity disagreement[2]	The difference between two data sets due to an imperfect match in proportions of the mapped classes.
Overall allocation disagreement[2]	The difference between two data sets due to an imperfect match between the spatial allocations of the mapped classes.

[1] reference: Lillesand and Kiefer (2000) [2] reference: Pontius and Millones (2011)

3.7 Analysis of field samples

The analysis of water and plant samples from the mining-impacted aquatic system of Vormbäcken River (Paper II) was done by ALS Scandinavia AB, Luleå, Sweden, which is certified for all of the performed analyses. Samples were sent by mail to the laboratory on the day of sampling and were analysed the day after. Evaluated variables include the concentrations of Cd, Cu, and Zn in both water and plants, and concentrations of tot-N and P in the water (Paper II).

3.8 Statistical analysis

To test if the concentrations of Cd, Cu, and Zn in water and plant samples showed statistically significant differences between species, vegetation belts with increasing distance to the shoreline, and locations, I used non-metric Mann-Whitney *U* tests when comparing two groups and Kruskal-Wallis tests when comparing multiple groups (Paper II; Zar, 1999). When the multiple group comparisons indicated overall significant differences, I performed multiple post hoc comparisons of the mean ranks of all pairs of groups to identify specific group differences. The analysis was done in Statistica® (v. 10, StatSoft Inc., Tulsa, USA). In Paper II, I also applied non-metric multidimensional scaling to analyse general patterns of relationships between metal concentrations in the water and different vegetation types with PAST 2.16 software (Hammer et al., 2001).

In Paper IV, I used non-metric Wilcoxon matched-pairs signed-rank tests (Zar, 1999) to test for a potential increase of classification accuracy for growth forms and dominant taxa due to incorporation of height data in addition to spectral and textural features from a UAS-orthoimage. The results with height data were compared to results from the classification in Paper III based on spectral and textural features alone. For the statistical analysis in Paper IV, Statistica® (v. 13, Dell Inc., Tulsa, USA) was used.

4 Results and Discussion

4.1 Taxonomic resolution and vegetation mapping (Papers I and III)

In total 19 non-submerged aquatic and riparian taxa could be recognized visually from the UAS-images (Table 3), mainly at the species level and also when growing in mixed vegetation stands. Difficulties occurred in the discrimination of *Nymphaea*/*Nuphar* spp., due to the similar colour and shape of their floating leaves (Papers I and III). Also *Salix* spp., *Sphagnum* spp. (Paper I) and *Sparganium* spp. with only floating leaves (Paper III) were treated at the genus level. *Sparganium* spp. with only floating leaves are recognized to be difficult to distinguish even in the field. The identification of *Sphagnum* spp. in field is also difficult since it requires a high level of taxonomic knowledge. The species identification of *Salix* spp. at Rakkurijoki River and Vormbäcken River was difficult due to hybridisation, which is common in northern Europe (Karlsson and Agestam, 2014). At Lake Bälingsträsket, *Salix* spp. could, however, be identified at the species level. The overall accuracy of taxa identification based on printouts of UAS-images (scale 1:800) was high (>80%; Paper I). Also the validation of image-interpreter skills at Lake Ostträsket, including six aquatic taxa, confirmed high accuracy of visual interpretation. Only one misclassification occurred among 25 vegetation stands, based on printouts of the UAS-orthoimage at a scale of 1:200 (Paper III).

A UAS-orthoimage allowed for the production of a continuous vegetation map along Rakkurijoki River at the same taxonomic resolution as in the taxa identification from paper printouts of UAS-images (Paper I). However, to keep the time needed for manual mapping at a reasonable level, class definitions which contained a mix of multiple taxa were necessary. Assessment of percentage vegetation cover in one large single-species stand of *P. australis* expanding over the whole littoral zone of Lake Bruträsket was possible based on a UAS-orthoimage (Paper I). The speed at which percentage vegetation cover could be mapped was twice as fast as mapping the taxa composition of riparian vegetation (0.5 and 0.25 ha/h, respectively; Paper I).

Another UAS-orthoimage was used for manual mapping of non-submerged aquatic vegetation at Lake Ostträsket (five test sites; Paper III). All taxa contributing ≥25% to the vegetation cover were mapped at a speed ranging from 0.5 to 0.2 ha/h depending on vegetation complexity. The maps produced by manual mapping could then be used as reference information for assessment of automatically produced vegetation maps in Papers III and IV.

Table 3. *List of taxa identified on UAS-images sorted in alphabetic order*

Taxa	Common name	Paper
Betula bubesens subsp. *czerepanovi*	Downy Birch[1]	I
Calla palustris	Bog Arum[1]	I
Carex acuta	Slender Tufted-sedge[1]	I
Carex canescens	White Sedge[1]	I
Carex nigra	Common Sedge[1]	I
Carex rostrata	Bottle Sedge[1]	I
Comarum palustre	Marsh Cinquefoil[1]	I
Eleocharis palustris	Common Spike-rush[1]	I
Equisetum fluviatile	Water Horsetail[1]	I and III
Hippuris vulgaris	Mare's-tail[1]	I
Menyanthes trifoliata	Bogbean[1]	I
Nymphaea/Nuphar spp.	Water-lilies[1]	I and III
Phragmites australis	Common Reed[1]	I and III
Polytrichum commune	Common Hair Cap Moss[2]	I
Potamogeton natans	Broad-leaved Pondweed[1]	I and III
Salix spp.	Willows[1]	I
Salix lapponum	Downy Willow[1]	I
Salix phylicifolia × *myrsinifolia*	Tea-leaved × Dark-leaved Willow[1]	I
Schoenoplectus lacustris	Common Club-rush[1]	I and III
Sparganium spp. (only floating leaves)	Bur-reeds[1]	III
Sparganium emersum	Unbranched Bur-reed[1]	I
Sphagnum spp.	Sphagnum Moss	I

[1] source: Naturhistoriska riksmuseet (2016) [2] source: Tree of Life (2016)

4.2 Comprehensive assessment of entire riparian zones (Paper II)

The riparian zone of three 320-m stream stretches along Vormbäcken River was successfully surveyed at a high level of thematic detail based on a 5-cm resolution true-colour UAS-orthoimage and field investigations. Vegetation stands were delineated manually on the UAS-orthoimage based on differences in visual appearance (i.e., colour, texture, and shape). The delineated stands could be related to species compositions derived from the field survey, including those taxa that were too small or too sparse to be identified from the UAS-image alone. Eighty-three vegetation classes were determined (the majority of them containing multiple species) including trees, shrubs, herbaceous, and non-submerged aquatic plants. The high spatial heterogeneity of the riparian vegetation probably would have been missed by images with lower spatial resolution. The detailed vegetation map in combination with biomass sampling and the chemical analysis of plants allowed for further calculations on the amount of vegetation-bound Cd, Cu, and Zn in the studied riparian zones. The concentrations of Cd, Cu, and Zn showed large variations among species. This emphasizes the need for species-specific assessments of freshwater shore zones to increase our knowledge of the functioning of these complex ecosystems including processes like nutrient and element uptake and cycling.

4.3 Automation of image analysis and classification (Papers III and IV)

Ecologically relevant information on non-submerged aquatic vegetation in Lake Oststräsket could be extracted in an automated way from a 5-cm resolution true-colour UAS-orthoimage, offering a time-efficient alternative to manual mapping when larger areas need to be covered, for example, entire lakes. In a classification based on spectral and textural features (Paper III), classification accuracy at the growth-form and dominant-taxon level decreased with increasing vegetation complexity. By including height data in the Random Forest classification in addition to spectral and textural features (Paper IV), classification accuracy increased significantly. The overall accuracy was at least ~80% for all five test sites for growth forms (classes: water, floating-leaved, emergent) and for four out of five test sites for dominant taxa. An overall classification accuracy of 82% was achieved at the test site with highest vegetation complexity. The dominant-taxon level included six taxa and seven vegetation classes: Dense *E. fluviatile*, sparse *E. fluviatile*, *Nymphaea*/*Nuphar* spp., *Potamogeton natans*, *Schoenoplectus lacustris*, and *Sparganium* spp.

4.4 The potential of UAS-technology for surveying non-submerged aquatic and riparian vegetation in freshwater shore zones

Our results confirm that the UAS-images used in our studies were able to capture the high spatial heterogeneity of vegetation in freshwater shore zones and allowed for surveying of non-submerged aquatic and riparian plants at a high taxonomic resolution (i.e., to a large extend at the species level). The list of species that can potentially be recognized on sub-decimetre-resolution images can probably be extended (e.g., for aquatic plants see Birk and Ecke, 2014). A determining factor for the success of remote-sensing-based taxa-identification is the taxa composition at the surveyed site. Differences in morphological traits need to be large enough to be captured in the image data and small taxa that are obscured by the canopy of larger ones cannot be seen. In two studies presented here, vegetation maps were successfully created in an automated way, which allows more efficient mapping over larger areas. However, some of the fine-scale information detectable with visual interpretation was lost in automated mapping, creating a trade-off between the degree of thematic detail and spatial coverage.

The UAS used in this thesis was easy to use and highly flexible in time and space, as it could be transported and operated by a single person and without applying for flight permissions.

For a successful classification with high taxonomic resolution, prior knowledge of species occurrence and field training was necessary. Field visits were also needed for validation. Thus, field work should remain a vital part in UAS remote sensing of freshwater shore zones. UAS-technology has, however, the potential to reduce field work in comparison to the amount that would have been necessary to assess the entire surveyed area by field work alone. Therefore, UASs are especially suited for remote areas which are difficult to access. The full potential of UASs in remote areas is, at the moment, hampered by flight regulations which restrict their use to the range of vision. Nevertheless it is easier to transport a 1.5 kg plane and a backpack with ground-control-station equipment to a remote forest lake than a boat and other equipment needed for field work applying, for example, a transect method for lakes.

The collection of image data with UASs has often been described as cost-effective (e.g., Anderson and Gaston, 2013). Many stand-alone software systems for assisted UAS-image processing can today be run on a high-end laptop, however, the processing and storing of data with high spatial accuracy challenges computational power. Finally, the image data need to be analysed to extract the desired information, either visually/manually or automated.

Automated image analysis and classification is demanding with regard to processing power. The number of man-hours in the office, computational power, and the volume of data need to be considered in planning and evaluating UAS-missions. The higher the number of UAS-flights to which an image processing and data analysis chain can be applied, the higher the efficiency of UAS remote sensing, making UASs especially suited for repeated monitoring missions and change detection.

Another point that needs to be considered during the planning process is the required spatial resolution for the surveying task. Spatial resolution can be increased by decreasing UAS operation height, potentially further increasing the possibility for species discrimination. At the same time the area covered by each image is reduced, increasing the amount of data needed to cover the survey area and therefore increasing the cost.

Information on percentage vegetation cover, growth forms, and dominant taxa, especially when extracted in an automated way, is highly applicable in lake and stream management. Examples of such applications could be aquatic plant control, evaluation of rehabilitation measures, survey of aquatic plant succession and terrestrialization, studying impact of stream regulation, and assessing habitat values. For assessment of the ecological status of lakes and streams according to the Water Framework Directive (EU, 2000), UAS-images can contribute critical information, for example, on shore zone structure (see also Casado et al., 2015). UAS-images can also provide an overview of the whole lake/stream section facilitating estimates of cover and the selection of meaningful and representative transects. Since submerged aquatic vegetation is more difficult to detect on true-colour UAS-images, especially in cases where water transparency is low, the prospects for UAS-based trophic status assessment are limited in most European countries. However, the large number of humic lakes in the vast boreal region might form an exception. For those lakes, Birk and Ecke (2014) successfully developed an ecological assessment index entirely based on non-submerged aquatic taxa that are potentially detectable on 5-cm-resolution remote-sensing images. The taxonomical resolution achieved in our automated classification corresponds to the resolution used for the suggested index.

5 Conclusions

True-colour images taken by UASs with sub-decimetre resolution will be increasingly available for ecological applications in freshwater shore zones in the future. This thesis demonstrates that the extraction of relevant information on non-submerged aquatic and riparian vegetation visible in the images is possible at a high taxonomic resolution (i.e., mainly at the species level). UAS-images can also support ground-based vegetation surveys and allow for the extrapolation of field sampling results, like biomass measurements, to areas larger than the sampled sites.

The production of vegetation maps can be automated which increases time-efficiency greatly when larger areas need to be covered. As a trade-off some fine-scale information detectable with visual interpretation might be lost in automated classification. The required level of thematic detail and accuracy for each specific surveying task needs to be considered when choosing the most suitable image analysis method.

6 Future perspectives

To further assess the potential of sub-decimetre resolution true-colour UAS-images for vegetation surveys in freshwater shore zones and wetlands, more UAS-case studies are necessary. Further research should address direct comparisons regarding invested labour and costs with

a) operational field work methods such as transect methods
b) UAS-images taken with other sensors such as multispectral or hyperspectral cameras, that are increasingly available for use with lightweight UASs (e.g., Lucieer et al., 2014). The inclusion of more wavelength bands, especially in the (near-) infrared region will probably increase the possibilities for higher taxonomic resolution in the future. Hyperspectral sensors also increase prospects for detecting submerged aquatic vegetation (Silva et al., 2008)
c) Images from other remote-sensing techniques (e.g., manned aircraft and satellites) since technical development also here have led to increased spatial resolution in recent years

The benefits of using 3D point data derived from highly overlapping UAS-images in addition to information from 2D images should also be explored further.

A challenge in OBIA and automated classification is the relative flexibility in the framework (e.g., Dronova, 2015). Segmentation parameters and the selection of discriminating object features are to a large extent based on expert knowledge and influence the classification results. More research is necessary to develop objective methods for the determination of these parameters.

The use of non-metric off-the-shelf cameras, illumination differences between individual UAS-images, and movement of the platform may be problematic for photogrammetric processing, radiometric calibration, and automated classification (Pajares, 2015, Whitehead and Hugenholtz, 2014a, Whitehead and Hugenholtz, 2014b). A systematic exploration of the types and extents of UAS-image quality problems in relation to the utility of the image data and the impact on classification results should be addressed in the future.

Finally, potential and challenges of using non-submerged aquatic vegetation in UAS-based assessment of ecological status in boreal lakes, streams, and wetlands need to be further investigated.

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