CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

FACULTY OF ENVIRONMENTAL SCIENCES

DEPARTMENT OF APPLIED GEOINFORMATICS AND SPATIAL PLANNING

CLASSIFICATION ACCURACY OF LAND COVER AND ITS IMPLICATIONS FOR ECOLOGICAL MODELLING

DOCTORAL THESIS

Author: Jan Komárek

Supervisor: doc. Ing. Petra Šímová, Ph.D.

Consultant: Ing. Vítězslav Moudrý, Ph.D.

08/2018

FOR MY WIFE MICHAELA

Declaration

I have written the thesis by myself, and have not used sources or means without their declaration in the text. Any thoughts by others or literal quotations are clearly referenced. The thesis was not published elsewhere.

Acknowledgement

I would like to acknowledge everyone who contributed towards this thesis, all my colleagues at the department and all my co-authors. I would like to thank my supervisor Petra and my consultant Vítek. He together with my officemate Katka took care of me throughout the entire period of my studies. My great thanks go to my parents and of course to my loving wife. My thanks go also to all my friends and to Jarek for his correction of my English.

In addition, many thanks go to the Czech University of Life Sciences in Prague and CULS Internal Agency (CIGA Nos. 20154209, 20174208 and 20184206), Internal Grant Agency of FES (IGA No. 20154254) and the Technology Agency of the Czech Republic (TJ01000428) for providing financial support.

Water
imagery
case
classification
plant
using
data
datasets
cover
UAV
results
land
use
many
time
spatial
resolution
NDVI

Foreword

Land Use and Land Cover (LULC) is a cornerstone of a wide range of applications in the fields of landscape ecology, agriculture, forestry, etc. My Master's degree comes from the field of landscape planning and, therefore, the issues of LULC are close to my background. Besides, LULC data are often acquired through Remote Sensing (RS) methods, the study of which started once I enrolled in my Ph.D. studies. Over time, I have progressed from satellites to unmanned aerial vehicles and gradually begun to understand the various aspects of the use of those technologies, which was one of the reasons I opted for this topic of my doctoral thesis. Novel technologies, techniques and data always face limitations and uncertainties and it was my goal to examine their potential for the use in (especially) environmental science. Although RS is a broad field encompassing many different techniques and means, I devoted my attention particularly to imaging data from passive (mostly multispectral) sensors mounted on satellite or UAV platforms. Therefore, whenever I speak of RS in this thesis, this is the relatively narrow part of the field I have in mind.

To me, the study of LULC can be in a simplified way represented by three principal aspects – data classification, detection of changes in the classes and the utilization of LULC data for modelling. And it is exactly those three aspects that are being the focus of presented studies. This thesis comes as a set of three published/accepted studies, compiling my recent and current research interests interconnecting RS, GIS and (landscape) ecology. The thesis has four parts, beginning with the common general introduction and theoretical background, followed by a brief study concept of each of the presented studies. In the third part, the actual results of the three individual studies are presented in the form of a title and abstract (full texts are attached in the Supplements). The final chapter represents a discussion both related to the individual studies and to the general issues of LULC and RS, followed by conclusions and information about further ongoing/planned research.

As I deal with the LULC topic, one never-ending issue I would like to describe in the beginning. Over the years, two similar basic terms have been established – land use and land cover. The difference between these terms is quite clear. Land use stands for characterization of how people utilize the land or the land management while land cover means a real surface cover, meaning the actual vegetation or material on the surface. Despite this, as the meanings are interconnected, those terms are often mistaken for each other. A good explanation gives Fisher et al. (2005).

Finally, I would like to mention one thing – I like a brevity. That is why I wrote this thesis quite brief, but responsible. I tried to avoid repetition and hope I wrote my thoughts aptly and understandable. Thank you all those, who will read and comment the thesis.

The speed at which any given scientific discipline advances will depend on how well its researchers collaborate with one another, and with technologists, in areas of eScience such as databases, workflow management, visualization, and cloud computing technologies.

The Fourth Paradigm book.

Table of contents

1. Aims of the thesis

The main objective is to assess the classification accuracy of land use/land cover data and evaluate its aspect and potential for environmental studies and ecological modelling. The aim of this thesis is to contribute to a more understanding of the relation between input data, expected results, and possible uncertainties within a study. The thesis focuses on utilization different platforms of remote sensing technologies and discusses the potential and drawbacks of used platform/sensor/approach/data in the field of (landscape) ecology. Particularly the thesis focuses on the primary classification of land cover using unmanned aerial systems, detection of land cover change using satellite imagery and application of land cover datasets for ecological modelling.

2. Introduction & theoretical background

The land use and land cover (LULC) play an important role in the ecosystem of the Earth. The information about land cover is considered to be a factor of utmost importance for understanding the system and modelling its dynamics as well as for maintaining sustainable development or utilization of natural resources. Understanding the significance of the land cover depends on the availability of accurate and up-to-date information, which makes land mapping a research topic of utmost importance. Many national as well as several international programmes for land use/land cover classification schemes have been initialized. The land cover change can affect both the local and global ecosystems. Many programs for mapping changes in the land use and land cover categories across the space and time were created as a response to those classifications needs. No ultimate solution was however found and it is likely that such a universal solution will not be found even in the foreseeable future so the issue of the detection of changes in land use/land cover is still a prominent research topic, aiming at a production of accurate land cover maps and keeping them up-to-date.

LULC & Remote sensing

Remote sensing (RS) is a unique approach focused on data acquisition remotely, without a direct contact with the measured phenomenon for both small and large extents. An approach using RS techniques for acquiring data has been used with advantage for many years. Remote sensing represents a very useful technology for obtaining land cover data as it allows acquisition of continuous spatial information across any extent of the surface (Pfeifer et al., 2012). RS, or, more specifically, Earth observation, via tens of man-made satellites, provides nowadays uninterrupted recording of the Earth surface on a global scale. More and more satellites manufactured with various purposes in mind equipped with ever better technologies are being launched all the time.

Remote sensing has already become a traditional technique for deriving (among other things) the land use/land cover information. Satellites may be beneficial at any scale, especially for large spatial extents or worldwide applications. Besides the conventional optical platforms that nowadays offer spatial resolutions up to ten meters, commercial platforms with resolutions of mere tens of centimetres exist. For local scales, airborne platforms or unmanned aerial vehicles (UAVs) are also frequently used. These techniques are law- and weather dependent, they however generally provide better spatial and temporal resolutions. On the other hand, their operation is often on-demand only and the costs, especially those of airborne imaging, are high, which usually leads to acquiring of datasets solely for the purposes of individual studies. Unmanned aerial systems are nevertheless widely used for specific research activities, for example agricultural applications (Gómez-Candón et al., 2014; Zhang and Kovacs, 2012); forestry (Brovkina et al., 2018), specifically for detection of pest infestation (Näsi et al., 2015; Stoyanova et al., 2018); plant diseases and water stress detection (Nishar et al., 2016; Zarco-Tejada et al., 2012). UAVs are nowadays used also for land cover classification (Ahmed et al., 2017) or classification of vegetation (Gini et al., 2014; Husson et al., 2017; Michez et al., 2016; Weil et al., 2017). See Pajares (2015) for a review of UAV-based applications, however, it is clear that over the recent years, the use of small aerial vehicles has grown to supplement the satellite approach and UAVs have become progressive scientific tools.

The most common representation of the land classification is a thematic map (Foody, 2004, 2002). Remote sensing techniques constitute the most important source of data for thematic maps. As the land cover products are usually an outcome of remote sensing approaches, raster data definitions have to be described. The basic unit of a raster is a pixel; with coarser data resolution, it is growing more likely that it will be a pixel containing several LULC types, therefore a so-called mixed pixel or mixel. Also, the term “data resolution” is sometimes misinterpreted. One of the basic data descriptors is the scale, which for the purpose of RS combines both resolution and spatial extent, and it is perceived in the sense of cartographic scale. As can be seen from Figure 1.1, a finer resolution of vector datasets in general increases the number of polygons and the boundaries become more accurate. In the case of the raster, a coarse resolution allows only the most prominent features (e.g. largest water bodies) or objects of very basic shapes to be captured while relatively small features are ignored in the global land cover datasets. Thus, the potential use of the global datasets is often limited by a lack of detail (Congalton et al., 2014). The relation between the area and perimeter of the body shape is an important issue - while the area is more or less similar across the resolutions, perimeter varies a lot.

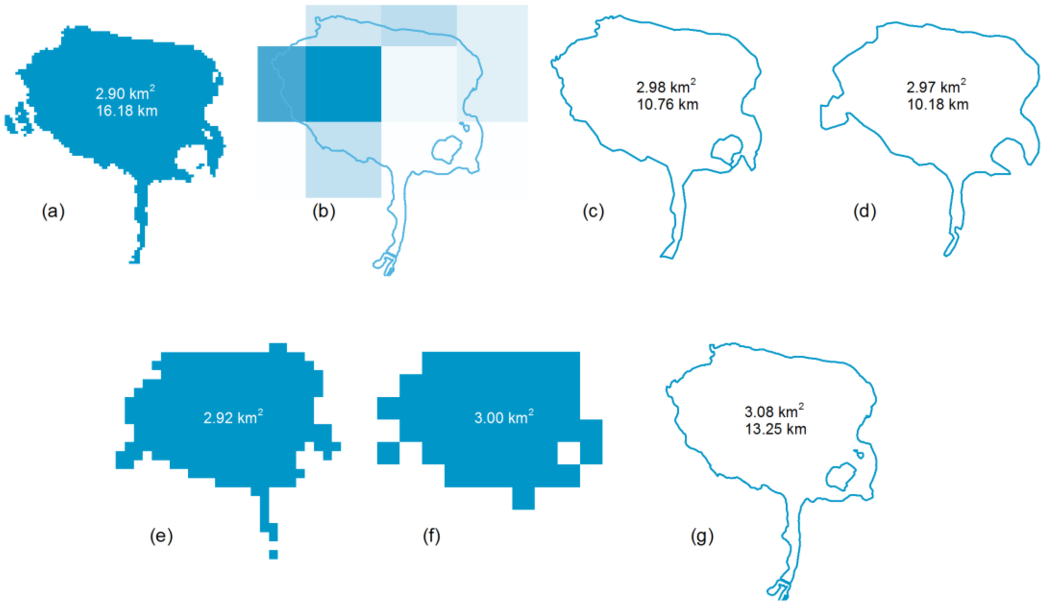

Fig. 1.1 Spatial data resolution on an example of a water body. Area and perimeter differences – datasets detail: (a) GIW, (b) GCL, (c) OSM, (d) CLC, (e) CLC_100, (f) CLC_250, (g) DIB. Dataset details stated in Table 3.3.2. Source: Author.

Data classification and quality assessment

For easier interpretation, land use and land cover need to be categorized and thus simplified. Classification of the land cover is in a long-standing research focus. Classifying satellite imagery to acquire information of land use/land cover is a traditional part of geo-science (Kuria et al., 2014; Szostak et al., 2014; Teo and Huang, 2016; Zhou and Qiu, 2015), even using unmanned aerial vehicles (Ahmed et al., 2017). Detailed species classification, from which many other applications may benefit, however, is still a challenging task (Ahmed et al., 2017) despite extremely high spatial resolution and variable spectral resolution of current sensors. Therefore, a fusion approach combining the spectral information with the elevation information is usually used (Husson et al., 2017). Specifically, combinations of multispectral (Bork and Su, 2007; Holmgren et al., 2008) or hyperspectral (Alonzo et al., 2014; Sankey et al., 2017) data with the LiDAR or image-matching based height data are quite common. However, inexperienced users often neglect the height information during the classification process (Feng et al., 2015), even though the height of objects can be in the case of UAV-borne data easily derived during the image-matching workflow. Besides the type of the data, the classification approach and classifier may affect the results. Generally, pixel-based (Myint et al., 2011; Yu et al., 2006) and object-based (Blaschke, 2010; Liu et al., 2015) approaches can be distinguished. Selection of different classifiers can yield completely different results as shown in several studies (Huang et al., 2002; Pal and Mather, 2003) or reviews (e.g. Lu and Weng, 2007).

One of the most classified land cover class is a surface water (Feng et al., 2016; Klein et al., 2017). Inland waters have been shown, for example, to be an important variable for modelling species distribution, one of the reasons being that they are not associated with the climate (Thuiller et al., 2004). However, disagreements for classes representing wetlands are common between land cover datasets (Arsanjani et al., 2015; Giri et al., 2005). For example, recently announced global land-cover product for biodiversity and ecosystem modelling (Tuanmu and Jetz, 2014) performed reasonably well in modelling bird species distribution, except for wetland species. Water has a relatively specific spectral trace, hence it is relatively easily identifiable from the spectral images. If we are however unable to distinguish the heterogeneity of the land cover inside an individual pixel, it can be easily misclassified, thus incorrectly increasing the representation of a majority class while neglecting minority classes. The best-known satellite family, Landsat, is a typical example of successful classification of water bodies in both the local (Frazier et al., 2000; Toomey and Vierling, 2005) and global scale (Chen et al., 2015; Feng et al., 2016). Images from Landsat satellites also served as source data for the Landsat GeoCover dataset, which can be successfully used for water body classification (Verpoorter et al., 2012). For improving the classification of the water bodies, other supportive data such as terrain elevation models (digital surface/terrain models) can be used. The global representatives of those are e.g. Shuttle Radar Topography Mission (Rabus et al., 2003) or the Advanced Spaceborne Thermal Emission and Reflection Radiometer model (Tachikawa et al., 2011) that cover the entire Earth surface and are freely available. It can be generally stated that the use of combined spectral and topographic data can allow an automated detection of water bodies. The key to the correct classification is to find an algorithm capable of detecting a water body with a good local accuracy while at the same time providing good global consistency despite locally specific conditions (Tuanmu and Jetz, 2014).

As the classification is a simplification of the reality, it therefore naturally contains mistakes, and the classification quality has to be assessed. However, an evaluation of the quality of the LULC classification is quite difficult. So far, it is not possible to verify every single area worldwide; on the other hand, assessment of the accuracy of the land classification in a small spatial extent is possible. Local-scale products obviously tend to be more accurate in the land classification for that area than global products due to the spatial extent and data resolution. However, for hard decision-making, accurate information on a global scale in the best possible spatiotemporal resolution is often necessary (see Fig. 1.2, bottom right corner). Such necessity is one of the reasons why the product quality must be correctly evaluated and interpreted so that the data can be used for particular purposes (Foody, 2002).

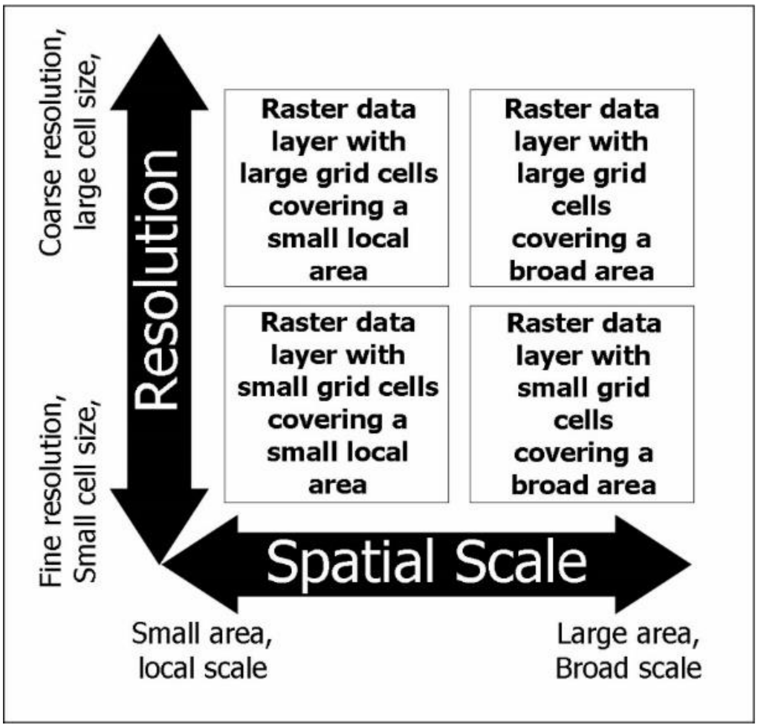

Fig. 1.2 Raster data resolution and spatial scale relation. Source: GISinEcology.com.

Land cover datasets face limits due to data uncertainties or inconsistency (Verburg et al., 2011). Differences in aggregations of source/resolution/classification data may result in bias, therefore, detail product metadata must be recorded and available (Congalton et al., 2014). Products fusion, which shall bypass the aggregation limitations, have appeared recently (e.g. Tuanmu and Jetz, 2014). In addition, the classification schemes differ across land cover datasets. Therefore, the scheme should be properly chosen a described in detail in order to allow combining and updating of the individual products (Congalton et al., 2014). Another possible source of uncertainty may lie in ignoring minority land cover classes within a spatial scale. The land cover information is usually provided only in a categorical format, i.e., the land cover class is assigned to each pixel and thus the “within pixel heterogeneity” is usually not taken into account (Fig. 1.3), which results in the image quality worsening. If multiple classes are present in the pixel, classifications typically use the most represented class within the pixel, which is usually the most common class. Cells of coarse (or any) spatial resolution often include multiple land cover types leading to mixed pixels (Foody, 2004; Mittal and Kaur, 2003). This leads to overestimation of common land cover classes at the expense of underestimation of minor classes (e.g. Blanco et al., 2013) and may result in different outcomes for the same area when using different datasets or algorithms (Fritz and See, 2008) and thus any modelling may suffer from classification errors. Although the spectral unmixing techniques (Keshava and Mustard, 2002), which can decompose the material composition mixture, are known in remote sensing community, it is not used widely.

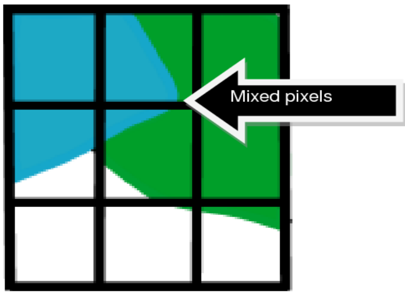

Figure 1.3 Pixel mixing, more than one category within each cell.
Source: Mittal and Kaur (2003).

<u>Detection of changes in LULC</u>

As the information about the land use/land cover is fundamental and plays a key role in many (not only) environmental applications, it is necessary to keep this information up to date. Detection of such changes is one of the basic tasks of RS techniques. Classification schemes may be different for each product, which makes LULC change detection more complicated. For LULC, any of RS technologies can be used for mapping the current state or for detection of its changes. Land cover change detection (CD) is as old as the land cover mapping itself. One may detect the change in the sense of a physical change of the cover type using a bi-temporal analysis or time-series or be interested in the change of condition of the objects (e.g. health of vegetation or stages of phenology). The change detection efforts are growing in importance with the landscape modification trends (e.g. afforestation/deforestation, intensification, urbanization), as well as with intensive international requirements and needs to categorize and monitor LULC. The most common way of LULC change detection using RS is an analysis of multispectral imagery based on changes in the spectral characteristics (Hussain et al., 2013). Numerous possible sources of multispectral imagery are available nowadays, it is, however, crucial to use only appropriate data (Lu et al., 2014) and pre-processing steps suitable for the data in question (Song et al., 2001) along with the proper change detection variables (Lu et al., 2014). Many studies focused on analysing specific change of the land cover, for example in the forest ecosystems (Lu et al., 2008; Szostak et al., 2018) or urban areas (Liu and Zhou, 2004); nevertheless, only few studies exist in the field of agriculture (Tarantino et al., 2016).

Change detection of land use/land cover is not as simple as it might seem and there are many studies dealing with this issue, using different approaches (Hussain et al., 2013; Lu et al., 2004; Radke et al., 2005). The land cover change is associated, besides the changes of bio-physical cover, also with the climate and its changes. That is another reason why the detection of changes is still a hot research topic (Gandhi et al., 2015; Tarantino et al., 2016). The expected result of change detection is a thematic map showing areas that have and have not undergone change over a certain period. Besides the indicated changes, understanding of the result and its right interpretation is a key to success (Coppin et al., 2004). There are many types of LULC changes. The cover can change completely (e.g. arable land to grassland), be only modified (different phenological stages of agricultural crops) or just vary in the geometry. For satisfactory results, it is necessary to take into account many aspects related to natural processes and different environments as well as spatial, temporal, and spectral resolutions of different platforms. Chosen techniques and technologies have to fit the aims of a study and such selection is one of the most difficult tasks of change detection (Coppin et al., 2004; Lu et al., 2004; Singh, 1989).

In case of remote sensing techniques, a detectable change in spectral characteristics between the original and new observed objects is a necessary condition for change detection. However, this change may be also caused by using a different sensor and it is, therefore, important to distinguish such true changes from methodological artefacts arising during the analysis (Singh, 1989). The conventional satellites (family of Landsats, SPOT or Sentinel newcomers) have been successfully used for these analyses for years (Hansen and Loveland, 2012; Lu et al., 2008). For global detection, platforms with a coarse spatial resolution (e.g. TERRA) are often used (Coppin et al., 2004); on the other hand, satellites of very high spatial resolution (like QuickBird or WorldView) can be used for detailed analyses (Blaschke, 2010). In addition, several different approaches are available. A bi-temporal analysis uses only two images from different dates for identification of the change between two time points (e.g. Singh and Singh, 2018). Alternatively, images taken throughout a period can be used for a time-series analysis (e.g. Lhermitte et al., 2011). Using time-series, the characteristics of an observed object are known throughout the observed period, which may be beneficial for many applications; however, the computational demands for such approach are obviously much higher.

LULC data application

One of the typical examples of LULC data application is an ecological modelling, e.g. species habitat/distribution models are strongly related to land cover. Ecology is increasingly changing into a data-intensive science (Michener and Jones, 2012) and the advancement of ecological studies on species-environment relationship is based on the availability of environmental data. Exploring relationships between species and their environment is a current issue in the ecological literature (Guisan et al., 2013) attracting increasing attention both due to methodological advances in the physical geography that nowadays allow creating robust digital models of both the terrestrial surface and sea bottom (Elith and Leathwick, 2009) and due to novel statistical methods and GIS instruments (Guisan and Zimmermann, 2000). Species distribution models (SDMs) have become popular and frequently used tools to assess species-environment relationships, for example to investigate drivers of invasions (Bellard et al., 2016), to support conservation decision making (Guisan et al., 2013), to predict wildlife space use (McCue et al., 2014), or to assess potential impacts of climate change on species distribution (Randin et al., 2009).

Only one land cover product is typically used within a model of species distribution and, consequently, differences in classification of land cover products may lead to biased conclusions. Land cover data are among the essential data for a wide range of environmental studies (see e.g. Grekousis et al., 2015). Explanatory variables derived from land use/land cover data have been proven to be important components of SDMs (e.g. Stanton et al., 2012). The selection of environmental variables has been recently identified as one of the caveats in SDM (Jarnevich et al., 2015). Although it is often acknowledged (e.g. Austin, 2002, 2007), many studies use readily available variables without a proper consideration of ecological theory. Besides ecologically inappropriate or missing variables, the among-data inconsistency is another source of problems. The existing datasets are based on various data acquisition methods (e.g. remote sensing, field measurements, manual digitization over orthophoto images) and often differently represented in GIS (e.g. data models: vector/raster). The spatial and temporal scales of both the occurrence and environmental data also play a significant role. Environmental data have to match the data of species occurrence to gain sufficient modelling accuracy (Gottschalk et al., 2011; Guisan et al., 2007; Lechner et al., 2012a, 2012b).

Existing studies that examined the influence of the resolution of environmental variables (i.e. observational scale sensu (Lecours et al., 2015)) on modelling species distribution concentrated mostly on raster data (e.g. Seoane et al., 2004; Venier et al., 2004). Although raster data representation (e.g. of temperature, precipitation, land cover, terrain attributes, etc.) is probably used in the studies dealing with SDMs more frequently, vector data representations are also common, for example to calculate distances from linear features such as rivers and roads. While the resolution of raster data is explicitly defined by the size of the cells and the performance of data of various resolutions has been assessed many times by the SDM community (Lassueur et al., 2006; Pradervand et al., 2014), defining resolution for vector data is problematic and vector data are often mistakenly considered as having infinitely fine resolution (see Goodchild, 2011). Besides, only the most important features (e.g. largest water bodies) of the phenomenon are often captured, while relatively small features are ignored in global land cover datasets.

The quality of input data for SDM is of greater importance than the quantity. There is a multitude of factors potentially deteriorating the data quality (Gottschalk et al., 2011; Rocchini et al., 2011) – to name but a few of the most important ones, we should mention that inaccurate recording of the position of a species (incorrect field measurement, instrumental errors, incorrect georeferencing) is still of concern, although it has improved over the years; the size of the observed sample (a greater amount of occurrence data requires more predictors); the scale of input data (non-uniform scales of the explanatory and dependent variables); incorrect selection of predictors (including irrelevant environmental variables), etc. The data quality, or, to be more precise, their accuracy or resolution, are a primary requirement for improving the predictive properties of the model. Spatial resolution plays a great role, especially where qualitative predictors are concerned, such as, for land cover (Pradervand et al., 2014).

LULC datasets & contribution of volunteers

As was mentioned above, the land cover plays a key role in ecosystems and the knowledge of it is essential for many ecological applications including understanding the dynamics of surface processes and land cover change. Therefore, many land cover datasets have been produced (see for example Grekousis et al. (2015) for a review of the datasets). The first RS-based global land cover datasets were prepared as long ago as 1980s (Bartholomé and Belward, 2005; Loveland et al., 2000) and the availability of global land cover maps has greatly improved over the last two decades. Many land cover products based on remote sensing techniques with different scales have been derived. Available land cover datasets are based on information from different sensors, for example (a) Meris (e.g. Defourny et al., 2007), (b) Modis (e.g. Broxton et al., 2014); (c) Landsat (Enhanced) Thematic Mapper (e.g. Büttner et al., 2004), or (d) their combinations (e.g. Tuanmu and Jetz, 2014). Global land cover monitoring at 30 m has become possible due to the free availability of Landsat data. Only recently, a new generation of regional and global land cover datasets with very high spatial resolution became available (e.g. Chen et al., 2015; Feng et al., 2016). However, land cover datasets significantly differ in their spatial, thematic, and temporal resolution (Giri et al., 2013; Grekousis et al., 2015). Several datasets are available at coarse spatial resolutions ranging from 300 m to 1 km (Bontemps et al., 2011; Channan et al., 2014; Tuanmu and Jetz, 2014). Although these datasets have been widely used, comparative studies highlighted a low level of agreement among these datasets (McCallum et al., 2006; Vintrou et al., 2012), which may complicates utilization or further analyses. A possible solution to overcoming data inconsistencies lies in combining several datasets (Tuanmu and Jetz, 2014). Fonte et al. (2017) performed a fusion of a global product with crowd-sourced data, which allowed improving the accuracy of the data and helped keeping them up-to-date. That is also a way to overcome data seasonality.

For land cover mapping and its change detection, volunteer projects and citizen science approach – crowdsourcing – can be also utilized with considerable advantage (Goodchild, 2007; Silvertown, 2009). With the availability of geoinformation technologies and mobile internet, this trend of volunteered geographic information became a topic of many studies, for example projects on monitoring of invasive species (Delaney et al., 2007), of water or air quality, population ecology, zoology (Wiersma, 2010), even astronomy (Raddick et al., 2010). Citizen science has become over the last decade a subject of many studies (Elwood, 2008; Flanagin and Metzger, 2008; Goodchild, 2007; Source et al., 2008). In ornithology, for example, citizen science is irreplaceable for a long time already (Greenwood, 2007), it can be used, among other things, for solving complicated problems in the field of biochemistry (Kawrykow et al., 2012). What is important for the thesis is volunteers contribution in creating and evaluating land cover data (Foody and Boyd, 2013; Fritz et al., 2012; Fritz and See, 2008; Perger et al., 2012) or collection of data about species occurrence for distribution modelling (Hochachka et al., 2012; Hurlbert and Liang, 2012; Snäll et al., 2011; Sullivan et al., 2009). The collection of data by volunteers is an interesting way to obtain low-cost up-to-date data, it is, however, necessary to understand its potential and limitations (Coleman and Eng, 2010).

Citizen science has a potential to replace (or, at least, keep up-to-date and supplement) some databases of national or private agencies for data collection (Coleman and Eng, 2010; Goodchild, 2007). A typical project collecting and validating LULC data is the Geo Wiki project (Fritz et al., 2012). The application works in the web browser on the Google Earth platform, allowing the validation of global land cover datasets through generating differences between datasets and offering the users to validate the data on the basis of Google Earth or geo-tagged photographs (e.g. Panoramio). The Degree Confluence project (Foody and Boyd, 2012) provides spatially extensive information as photographs of the intersections of meridians and parallels worldwide. The project thus can be helpful in the interpretation of aerial photos, evaluation of the landscape condition, land cover classification, and many other environmental applications. Thanks to a systematic design of the project that was instrumental in creating extensive data, those have a potential to be subsequently utilized for evaluation of the quality of other datasets and maps (Foody et al., 2013). Of course, there are limitations associated with the quality, credibility and spatial heterogeneity of the collected data. Nevertheless, if a suitable design of data collection is chosen, we can indeed acquire current data with a minimum effort.

3. Overview of the studies

The thesis consists of a set of three studies with a commentary. The topic covers the issues of land use/land cover and assessment of its usability and application in various areas of (landscape) ecology. In this chapter, only brief methodology and conclusions of each study are described.

3.1 Detail classification of plant species

The study concept

The aim was to explore the potential of UAV-borne data for classification of land cover, particularly of individual plant species. The study interest was to verify if data from RGB, multispectral and thermal imagery can classify individual plant species with a sufficient accuracy. We also looked for answers to questions if it is possible to substitute additional spectral bands of a multispectral sensor by a better spatial resolution of RGB sensor and if the addition of thermal data can improve the classification accuracy.

Brief methods

The object of the study was an arboretum within the university campus. The area takes approx. 2.5 ha and contains hundreds of different plant species. Throughout the site, Ground Control Points were placed and surveyed for further data processing. Low altitude aerial survey was performed using a light fixed-wing UAV mounted with (a) low-cost RGB camera, (b) 4-chanell multispectral sensor, (c) thermal sensor. The sensors differed in their spectral as well as spatial resolution (see Table below). The data were acquired during the full vegetation period, processed using image-matching Structure from Motion photogrammetric approach using the Pix4DMapper software. Besides three orthomosaics, normalized digital surface model (nDSM) was built in order to obtain the height of the vegetation.

Table 3.1.2. Characteristics of used sensors.

Sensor (abbreviation)	Image resolution	GSD* at 100 m (cm/px)	FWHM** (nm)	Band Peak (nm)	Weight (g)
DSC-WX220 (RGB)	17.98 MPx (4896 x 3672)	2,75	-	B: 460 G: 530 R: 660	113
Multispec4C (MSC)	4x 1.23 MPx (1280 x 960)	10	G: 530 - 570 R: 640 - 680 RE: 730 - 740 NIR: 770 - 810	G: 550 R: 660 RE: 735 NIR: 790	160
ThermoMAP (TMP)	0.33 MPx (640 x 512)	18,5	LWIR: 7,500 - 13,500	-	134

*GSD (Ground Sampling Distance)

**Full width at half maximum

Field survey was conducted using a Collector for ArcGIS application to gain ground truth data about the vegetation. Collected data was divided into 24 categories within a 3-level legend. For each category, five items were randomly selected for training data and five items for validation data. Eight combinations (a) RGB or MSC mosaic, (b) each mosaic + thermal, (c) each mosaic + nDSM, (d) each mosaic + nDSM + thermal were classified using object-based segmentation and non-parametric Support Vector Machine classifier (Blaschke, 2010; Blaschke et al., 2014) in ENVI image analysis software. For validation assessment, confusion matrices were built (Foody, 2013; Olofsson et al., 2014; Stehman, 2013).

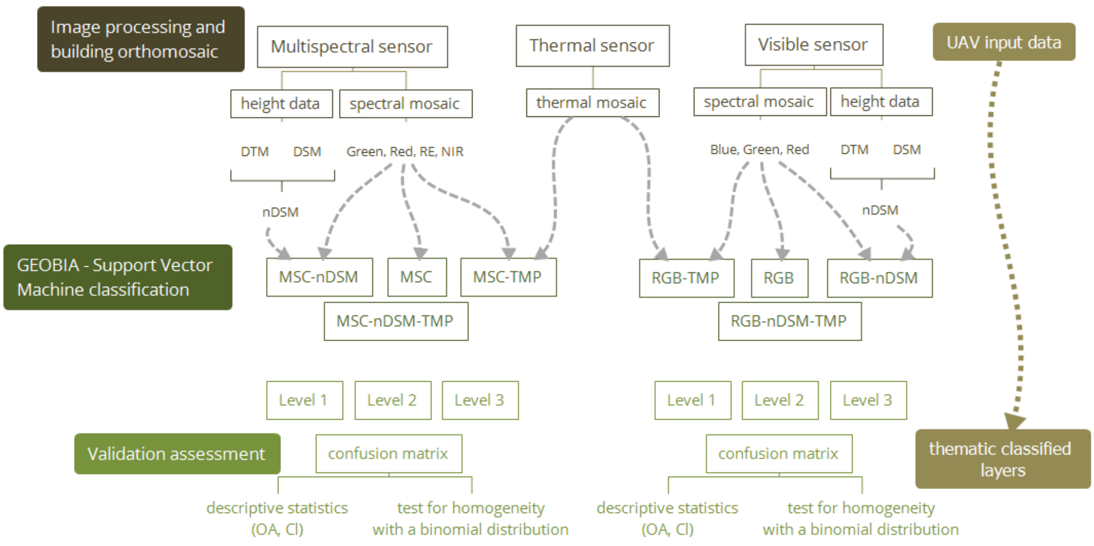

Figure 3.1.2a. Study processing workflow.

Results & Conclusion

The fusion of different types of UAV-borne imagery and its application in the environmentally specific area was performed. In general, RGB and multispectral sensors offered similar results, and their supplementing with any additional information further increased the classification accuracy. A multispectral sensor performs better, which is why it is not possible to substitute the spectral resolution with a higher spatial resolution. The data on the vegetation height increase the accuracy and, therefore, we strongly recommend to use it as an additional classification input. The thermal data is also an important source of information; however, we cannot confirm if the contribution of the thermal data is higher than that of the height data. In all, we can say that the UAV-borne imagery is a powerful source of information for plant species classification, even for species which are difficult to distinguish.

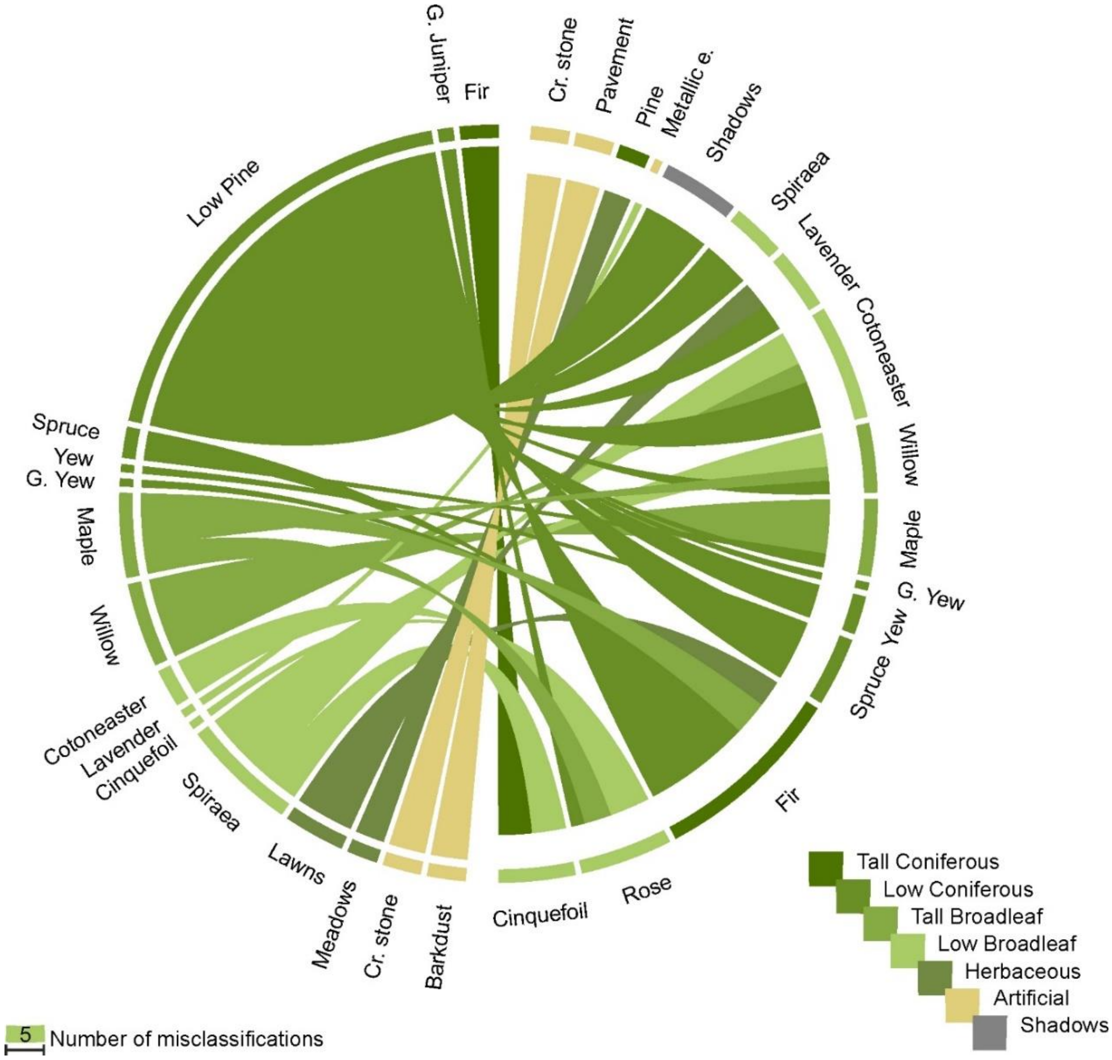

Figure 3.1.2b. Confusion matrix visualization using a circular plot. It represents the best model at the most detailed classification level and its misclassifications (lines connect misclassified categories, hence the larger section, the more incorrectly classified polygons in the category).

3.2 Land Use Land Cover Change Detection

The study concept

Despite the long-lasting interest in this issue, the detection of land cover change is still a much discussed research topic. The aim of this study was to assemble convenient variables for detecting change in a specific land cover type. Landsat 8 imagery was used for detecting change in land cover types from grassland to cropland. A specific objective was to verify the potential of selected variables for application in that particular change detection. We also assumed that the use of additional variables can provide a better accuracy and that spectral variables perform better than the textural ones.

Brief methods & methodology

The study site covers a western part of the Czech Republic (approximately half of the country), making the area topographically heterogeneous indeed. Landsat 8 OLI Level 1 satellite images from two different years (three years apart) in the late summer seasons due to the suitability of the time period were selected. For classification, we used the Land Parcel Identification System – a government vector reference database. From that database, change and no-change plots were identified. The total number of 59 variables were created for change detection and mean values were calculated for each LPIS plot using the ENVI image analysis software and GIS.

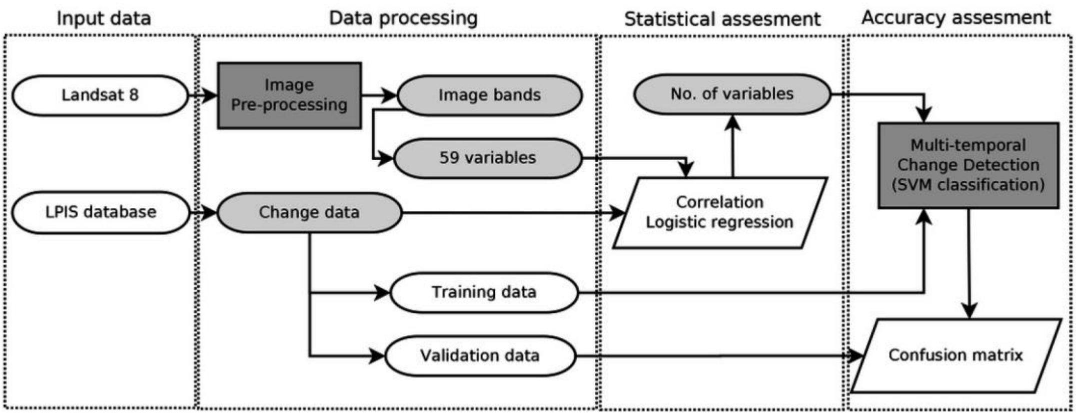

Figure 3.2.2a. Study workflow. For validation of models, multi-temporal change detection was used.

First, highly inter-correlated (r>0.9) variables were excluded; only variables often used in change detection were subsequently included into the analysis. Therefore, the number of variables decreased to 18 items of vegetation indices, texture, tasselled cap and principal component analysis. Akaike Information Criterion (AIC) obtained from the individual generalized linear models was used to specify the best sets of variables. For the object-based classification, 300 plots with change and 1200 plots without change were stratified randomly selected (Congalton and Green, 2009); Support Vector Machine classifier was selected due to the non-normal distribution of the input data. The accuracy assessment used 200 validation samples for the change plots and 800 for plots without change (Olofsson et al., 2014; Zhen et al., 2013).

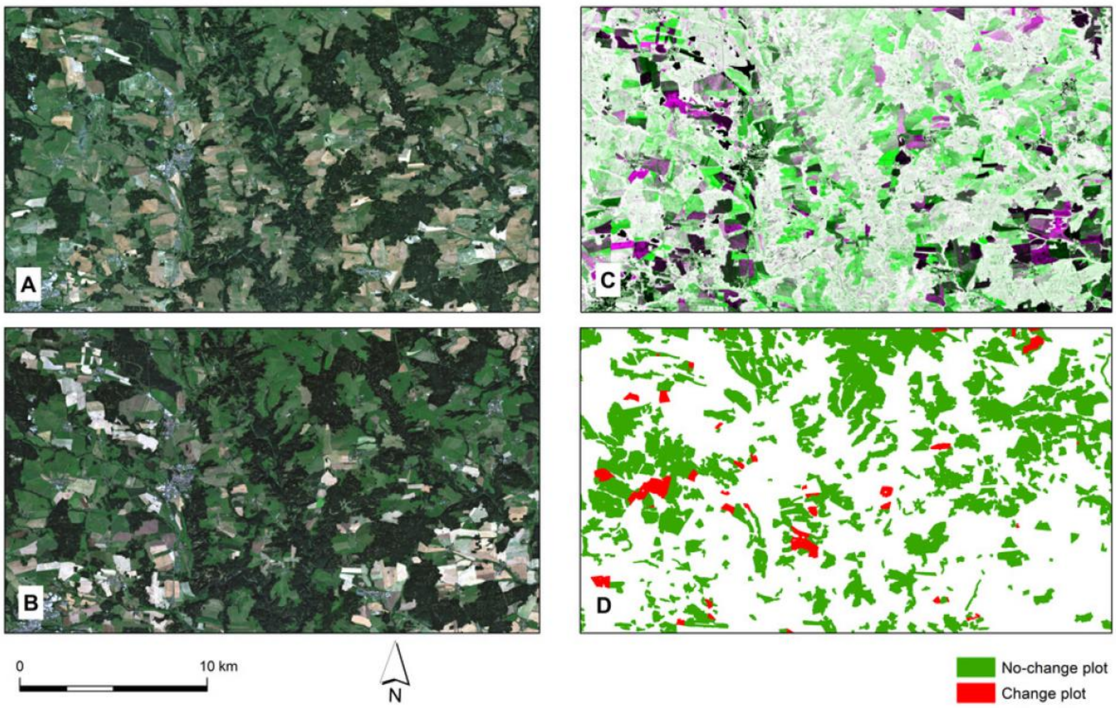

Figure 3.2.2b. An example of the study site. (A) Landsat 8 image from 2013. (B) Landsat 8 image from 2016. (C) NDVI RGB composite (R = NDVI 2013, G = NDVI 2016, B = NDVI 2013). (D) (No-)change grassland to cropland plots as acquired from the LPIS database.

Results & Conclusion

Multiple sets of variables were tested in order to find the best one for grassland to cropland change detection. In that way, models containing one, three, five, seven, and fourteen variables were built. A simple Landsat image was also tested for the same reason. Generally, increasing the number of variables in the model improved the model accuracy. However, the effect of additional variables was not so great when comparing it with results from a model with only one variable, namely the Normalized Difference Vegetation Index (NDVI). Most surprisingly however, in the conditions of the central Europe, a simple Landsat image surprisingly achieved the best results.

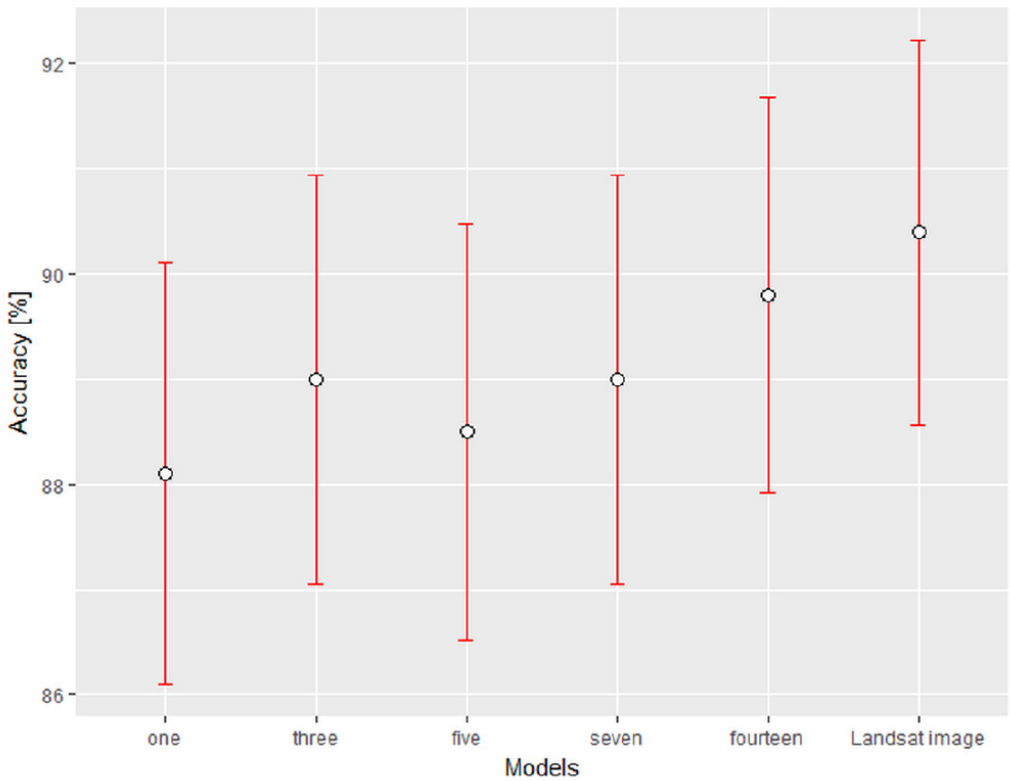

Figure 3.2.2c. Overall accuracy (%) of calculated models with 95% confidence intervals.

3.4 Water birds distribution modelling

The study concept

The aim of our study was to verify the capability of environmental datasets of various origins and scales to predict the occurrence of nesting birds dependent on water body environment. The primary research aims were to investigate the effect of the used datasets on the prediction accuracy and to find out how a selection of different explanatory variables affects the predictive model performance. We also assumed that (a) the perimeter of the water bodies would explain the species distribution better than the other explanatory variables; (b) the scale of Corine Land Cover should show the best fit with the species data from the species distribution atlas (c) the spatial scale of the consensus data would not correspond with atlas scale, i.e., the results would be poor.

Brief methods & methodology

The area of interest covers 67,742 km^2 of the Czech Republic, approx. 2% of which are water bodies. It was divided into mapping squares by meridians and parallels (by 10'E × 6' N; approx. 12 × 11.1 km). The data on species occurrence was obtained from the Third Atlas of Nesting Birds (Šťastný et al., 2006), representing a traditional source of information about the presence and absence of bird species in the Czech Republic. The occurrence data within mapping squares are divided into three categories (confirmed, probable, possible). In this thesis, only the "confirmed" category was considered as presences, remaining categories as absences of the species. The following species were selected: *Tachybaptus ruficollis* (Pallas, 1764), *Podiceps cristatus* (Linnaeus, 1758), *Podiceps nigricollis* (Brehm, 1831), *Anas strepera* (Linnaeus, 1758), *Anas crecca* (Linnaeus, 1758), *Aythya ferina* (Linnaeus, 1758), *Aythya fuligula* (Linnaeus, 1758).

As a source of explanatory variables, the study used global and regional land cover datasets created through remote sensing methods, namely (a) Global 1-km Consensus Land Cover, (b) Corine Land Cover, (c) Global Inland Water, (d) OpenStreetMap, (e) Dibavod. The selection of the environmental variables respected the ecological requirements of the species (Guisan et Zimmermann, 2000).

The used explanatory variables were (1) water body area, (2) water body perimeter, (3) number of water bodies. All predictors were related to a single mapping square.

Table 3.3.2. Description of tested water datasets.

	Global Inland Water	**Global 1-km Consensus Land Cover**	**OpenStreetMap**	**Corine Land Cover**	**Dibavod**
Abbreviation	GIW	GCL	OSM	CLC	DIB
Type / representation	raster / discrete	raster / continuous	vector	vector raster / discrete	vector
Extent	global	global	global	regional (EU)	local (CZ)
Resolution, scale	30 m	1 km	approx. 1:10000	1:100000 100 m, 250 m	1:10000
Sensor	Landsat 7 ETM+			Landsat 7 ETM+	
Coordinates	WGS 1984 UTM	WGS 1984	WGS 1984	ETRS 1989 LAEA	S-JTSK Krovak
Data classification	Water	Open water	Water	Water bodies, Water courses	Water bodies, Water courses
Reference	Feng et al., 2016	Tuanmu et Jetz, 2014	Haklay et Weber, 2008	Büttner et al. 2002	T. G. M. Water Research Institute

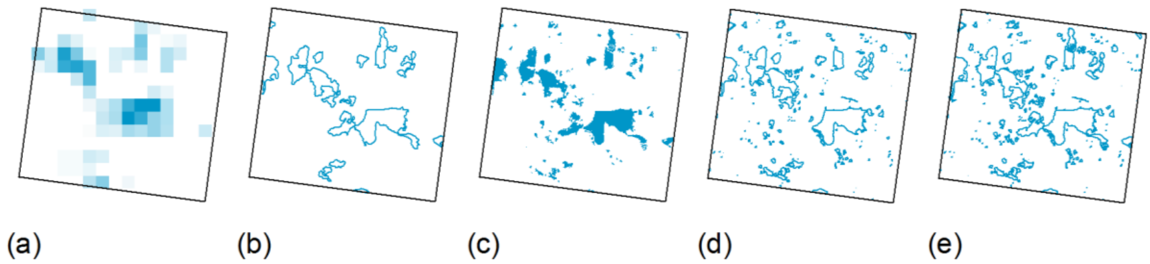

Figure 3.3.2. A detail of a mapping square for (a) GCL, (b) CLC, (c) GIW, (d) OSM, (e) DIB; GCL dataset is represented by a pixel sized 1km, darker colour means a greater representation of water within the pixel.

The relationship of the explanatory variables and dependent variable was investigated using both Generalized Linear Model and Generalized Additive Model (Guisan et al., 2002; McCullagh and Nelder, 1989) in the R environment. Models were performed individually for each variable, i.e., a single predictor approach was used for modelling (Guisan and Hofer, 2003). A binomial distribution and logistic function, i.e., logistic regression, were used. In total, 91 models (13 predictors, 7 species) were performed. K-distribution cross-validation was used for the model evaluation (k=5). For comparison of the predictive capabilities of the individual models, area under curve (AUC) of the receiver operating characteristic plot (Brown and Davis, 2006; Fawcett, 2006) and true skill statistics (TSS) (Allouche et al., 2006) were used.

Results & Conclusions

Species distributions of selected water birds were tested on different water datasets. Generally, models based on datasets with a higher spatial resolution performed better despite the coarse grain of the species data. Corine and GLC datasets performed worse than others with a better spatial resolution (GIW, OSM, DIB). The data with the best resolution generally give the best results, it may be however available only for limited extents; therefore, using a crowdsource dataset (OSM) is a suitable compromise and may be recommended. Also, the area and perimeter predictors of water bodies provided better occurrence prediction than the number of water bodies. The results indicate that even data with a high spatial resolution may not substitute a proper selection of explanatory variables.

4. Results of the thesis

The thesis presents three aspects of the issue of land use/land cover. It consists of three studies dealing with a primary classification of land cover (Study 1), detection of specific LULC change (Study 2), and distinctive application of different land cover datasets for ecological modelling (Study 3). The potential contribution of this thesis lies in the description and comparison of different remote sensing platforms and remotely sensed data for various environmental applications. In this chapter, brief descriptions and abstracts are provided, full texts are attached as a supplementary material. Commentary and discussion are mentioned in the following caption.

- **Komárek J**, Klouček T, Prošek J, **2018**. The potential of Unmanned Aerial Systems: A tool towards precision classification of hard-to-distinguish vegetation types?

  International Journal of Applied Earth Observation and Geoinf., 71: 9 – 19.
  IF_{2017} 4.003, Q1

- Klouček T, Moravec D, **Komárek J**, Lagner O, Štych P. Selecting appropriate variables for detecting grassland to cropland changes using high resolution satellite data.

  PeerJ – accepted
  IF_{2017} 2.118, Q2

- Šímová P, Moudrý V, **Komárek J**, Hrach K, Fortin MJ. Fine scale waterbody data improve prediction of waterbirds occurrence despite coarse species data.

  Ecography – accepted
  IF_{2017} 4.520, Q1

The first study is focused on evaluating various UAV-mounted sensors for distinguishing plant species. The contribution of this study is (a) an assessment of the potential of UAVs for land cover classification in very detail scale and (b) usability for various ecology analysis in the environmentally specific areas. The second study deals with the land cover change detection. The study contributes with the determination of appropriate variables for change detectability of specific LULC types with spectral similarity. The third study covers the topic of ecological modelling using different land cover datasets. The main contribution of the study is an evaluation of different data type/source/spatial scale effect for modelling of species distribution.

4.1 The potential of Unmanned Aerial Systems: A tool towards precision classification of hard-to-distinguish vegetation types?

Abstract

Detail species classification using very high spatial resolution data is a challenging task. Exploring the potential of imagery acquired by Unmanned Aerial Vehicle (UAV) to identify individual species of vegetation and assessing values of additional inputs such as height and thermal information into classification process are hot research topics. Our study uses a fusion of visible, multispectral and thermal imagery acquired through low altitude aerial survey for a detail classification of land cover. The study area is located in the central part of the Czech Republic and situated in an environmentally very specific area – an arboretum of 2.45 hectares. Visible (i.e. RGB), multispectral, and thermal sensors were mounted on a flying fixed-wing Unmanned Aerial System. Imagery was acquired at a very detailed scale with Ground Sampling Distance of 3 – 18 cm. Besides three mosaics (one from each sensor), normalized Digital Surface Models were built from visible and multispectral sensors. Eight classification models were created – each mosaic (visible/multispectral) was enriched with height data, thermal data, and combined height and thermal information. A classification into a three level system was performed through Geographic Object-based Image Analysis using Support Vector Machine algorithm. In general, Overall Accuracy grew with the amount of information entering the classification process. Accuracy reached 77 – 91 % depending on the level of generalization for the best model based on multispectral data and 67 – 80 % for data from visible sensor. Both thermal data and height information improved the accuracy; however, the statistical evaluation did not reveal any significant difference between contribution of height and thermal data. Results also indicate that increasing spectral resolution leads to a significantly better performance of the models than higher spatial resolution. Finally, UAVs equipped with a proper sensor provide a convenient technology for detail land cover classification even in areas with many similar vegetation types.

4.2 Selecting appropriate variables for detecting grassland to cropland changes using high resolution satellite data

Abstract

Grassland is one of the most represented, while at the same time, ecologically endangered land cover categories in the European Union. In view of the global climate change, detecting its change is growing in importance from both an environmental and a socio-economic point of view. A well-recognised tool for Land Use and Land Cover (LULC) Change Detection (CD), including grassland changes, is Remote Sensing (RS). An important aspect affecting the accuracy of change detection is finding the optimal indicators of LULC changes (i.e. variables). Inappropriately selected variables can produce inaccurate results burdened with a number of uncertainties. The aim of our study is to find the most suitable variables for the detection of grassland to cropland change, based on a pair of high resolution images acquired by the Landsat 8 satellite and from the vector database Land Parcel Identification System (LPIS). In total, 59 variables were used to create models using Generalised Linear Models (GLM), the quality of which was verified through multi-temporal object-based change detection. Satisfactory accuracy for the detection of grassland to cropland change was achieved using all of the statistically identified models. However, a three-variable model can be recommended for practical use, namely by combining the Normalised Difference Vegetation Index (NDVI), Wetness and Fifth components of Tasselled Cap. Increasing number of variables did not significantly improve the accuracy of detection, but rather complicated the interpretation of the results and was less accurate than detection based on the original Landsat 8 images. The results obtained using these three variables are applicable in landscape management, agriculture, subsidy policy, or in updating existing LULC databases. Further research implementing these variables in combination with spatial data obtained by other RS techniques is needed.

4.3 Fine scale waterbody data improve prediction of waterbirds occurrence despite coarse species data

Abstract

While modelling habitat suitability and species distribution, ecologists must deal with issues related to the spatial resolution of species occurrence and environmental data. Indeed, given that the spatial resolution of species and environmental of datasets range from centimeters to hundreds of kilometers, it underlines the importance of choosing the optimal combination of resolutions to achieve the highest possible modelling prediction accuracy. We evaluated how the spatial resolution of land cover/waterbody datasets (meters to 1 km) affect waterbird habitat suitability models based on atlas data (grid cell of 12 × 11 km). We hypothesized that area, perimeter and number of waterbodies computed from high resolution datasets would explain distributions of waterbirds better because coarse resolution datasets omit small waterbodies affecting species occurrence. Specifically, we investigated which spatial resolution of waterbodies had better explain the distribution of seven waterbirds nesting on ponds/lakes of area 0.1 ha to hundreds of hectares. Our results show that the area and perimeter of waterbodies derived from high resolution datasets (raster data with 30 m resolution, vector data corresponding with map scale 1:10,000) explain the distribution of the waterbirds better than those calculated using less accurate datasets despite the coarse grain of the species data. Taking into account the spatial extent (global vs regional) of the datasets, we found the Global inland waterbody dataset to be the most suitable for modelling distribution of waterbirds. In general, we recommend using land cover data of a sufficient resolution to be able to capture the smallest patches of the habitat suitable for given species presence for both fine and coarse grain habitat suitability and distribution modelling.

5. Annotation & comments

From a general point of view, remote sensing means acquiring, processing, and analysing satellite, airborne or UAV imagery (or any flying thing). Increasing amount of remotely sensed data makes the land cover monitoring more easily accessible. On the other hand, selection of the most suitable map/data for a requested application is challenging due to limitations associated with the product inconsistency, data format, different data acquisition, or classification disagreements. The conclusions of my studies confirm the necessity of selecting appropriate input data/variables in order to gain accurate and meaningful results. Many recently published studies also confirm that this research direction is topical in the world of science.

<u>Detail land cover classification</u>

Although unmanned aerial systems and their utilization in land cover classification is nowadays a common task, their applicability for classification of plant species with similar spectral characteristics is still not easy. Differentiation of hard-to-distinguish plant types was tested using various vendor-provided sensors. We assessed the contribution of visible and multispectral sensors as well as that of additional inputs (normalized height and thermal information) into the classification process. An accuracy of almost 81 % was achieved for individual plant species using a multispectral sensor supplemented with the plant height and thermal information. Nevertheless, for some plant categories, the accuracy is not consistent. This inconsistency may originate from an absence of blue spectral channel in the multispectral sensor as some plant categories were better distinguished using the visible sensor, especially for coniferous plants. Not surprisingly, results indicated that the sensors are interchangeable for distinguishing low and tall vegetation. For problematic categories (e.g. shadows), where sensors themselves did not provide good enough results, additional inputs in a form of height or thermal information were needed or use of special workflows was necessary (Milas et al., 2017). The overall results correspond to other recently published studies (Ahmed et al., 2017; Husson et al., 2017; Sankey et al., 2017; Weil et al., 2017), however, to the best of our knowledge, no study assessed the utilization of thermal data for a detailed plant species classification. There were several possible uncertainties affecting not only our results but also applicable to results of any study dealing with the land cover and plant species classification. The chosen classification approach (pixel vs object base) and classifier substantially influence the resulting accuracy (Blaschke, 2010; Liu et al., 2015; Yu et al., 2006). In addition, in case of UAV-borne imagery, the chosen image matching as well as image analysis software may affect the results. Besides other issues, we can affect (possibly increase) the accuracy of the analysis by using different sensors, though our study was limited by vendor's mercy. Professional solutions are available on the market; however, the price is far from favourable. Moreover, these devices tend to require more experienced users for both operating and data processing, which makes them more suitable for research than for industry use.

Detection of LULC change

As the knowledge of land cover is essential for many ecological applications, land cover change knowledge is a key for understanding the dynamics of surface processes. Therefore, the knowledge of land use land cover changes is as important as that of the land cover itself, because the (bio)physical surface cover is changing constantly. While humans are responsible for many of those changes, others are results of natural processes (seasonality or continuous climate change). The change plays a key role not only for environmental scientists and landscape protection but also for economists and decision makers. As LULC maps are usually produced through classification, maps originating from different time points can be compared, which is the principle of CD. Remote sensing makes the land cover mapping efficient; however, spatial resolutions provided by satellite imagery may be insufficient for many applications because land cover changes often occur at a much finer resolution.

NDVI vegetation ratio index is widely applied as the explanatory variable due to its correlation with a plenty of phenomena. It may be also used for change detection (Gandhi et al., 2015; Lunetta et al., 2006; Mallick et al., 2012; Pu et al., 2008; Wardlow et al., 2007); however, result interpretation can be difficult. The NDVI recognizes only the change in spectral characteristics and, therefore, phenological stages have to be taken into consideration. In our case, NDVI provided a poor accuracy in the case of grassland to cropland change detection due to the topographical heterogeneity across the study area (some fields may have still been covered with green crops while others were already harvested). In this case, additional information must be introduced into a classification process (e.g. Tasselled Cap components). Of course, choosing the right time for image acquisition is crucial for several reasons

(Müllerová et al., 2017). It is especially necessary to compare data taken approximately at the same time point within a periodical repetition (e.g. every late spring) to make sure that the same basic conditions apply. Another issue that has to be considered during the study planning is the selection of a suitable phenological stage allowing the best differentiation between (among) classes. It is also necessary to bear in mind that the phenological stages of an identical plant species will differ across longitudes, latitudes or altitudes (Coppin et al., 2004; Tarantino et al., 2016). Besides, the use of additional explanatory variables may not lead to better results (Lu and Weng, 2007). In our case, raw bands of Landsat image provide the best resulting accuracy, which is an important outcome because it leads to the possibility of leaving out all the calculations variables/indices and thus to simplify the entire analysis. In general, results of any change detection analysis may be influenced by several uncertainties associated especially with the raw image pre-processing, classification analysis, and errors in a reference database.

LULC data utilization

One of the common utilizations of remotely sensed land cover datasets in ecology is their use as an explanatory variable for statistical modelling, which is also the case with species distribution/habitat models. One of the big tasks in this field is dealing with the use of appropriate scales. Therefore, we assessed the effect of water-related land cover datasets varying in spatial scales on a prediction of bird species distribution. A finer thematic resolution (i.e., finer grain size) results in general in a better habitat classification (i.e. better model performance). Prediction of species having a close relationship to their preferred habitats are more sensitive to grain size and a model performance for those species is then strongly affected by grain size coarsening (Gottschalk et al., 2011). Goodchild (2011) acknowledged that the results could be confusing when some details (e.g. habitats) are smaller than the spatial resolution of the used dataset. It is necessary to know which resolution is sufficient for the analysis, i.e., how much information can be lost with coarser resolution. A better spatial resolution generally increases the number of water bodies and makes its perimeters more precise when comparing calculations from individual datasets. For example, see Fig. 1.3 in the Introduction where the difference in the area parameter was only 0.18 sq. km while it was 6 km in the perimeter on the example of one water body).

LULC characteristics are quite easily measurable, unlike other species-distribution dependent factors such as inter-species relationships (Rüdisser et al., 2015). Generally, the mutual correlation of similar-scale datasets (DIB and OSM) was high. In our case, across all predictors, OSM a DIB provided very similar results, which were at the same time also the best results of all datasets, despite the fact that species data are in a much coarser scale. The area and perimeter parameters are the best predictors of waterbird distribution, especially if using data with the highest spatial resolution. Nevertheless, data with highest spatial resolution are typically only available for small extents, which underlines the potential of crowdsourced datasets due to their global character despite the possible uncertainties. Our study also showed that a higher spatial resolution of used datasets, although important, cannot rectify problems caused by selecting improper explanatory variables.

Classification of inland water

As the modelling of distribution of waterbirds is related the occurrence of water bodies, let me introduce issue of classification of this specific land cover type. As the knowledge of land-use land-cover is an essential for understanding the planetary ecosystem, the knowledge of the occurrence and size of water bodies is crucial for prediction of floods, modelling catchment areas or a simple evaluation of water supply. Water is however, a highly changeable element of the landscape, which is the principal cause for traditional terrestrial data collection methods being difficult to apply. Water area can also vary seasonally and its classification is particularly challenging, as it is difficult to detect water under a vegetation canopy, especially with increasing data resolution. With the increasing level of technology and data availability, remote sensing can deal with those challenges due to the fact that water has a specific spectral change. It absorbs energy the best in the mid-IR band (approx. 1,300 – 2,500 nm) and partially in the near IR band (750 – 1,300 nm) of the spectrum, which is the reason why these spectral characteristics and relative indices from these parts of spectrum are the most frequently utilized for water detection (Gao, 1996; McFeeters, 1996; Xu, 2006). Besides several remotely sensed global land cover datasets, there are also some detailed land cover products with a nationwide range. A major problem is that some products were made for political reasons and in effect, they may not be shared openly or they may have ceased being updated. The advantage lies however in the fact that the nation-wide products tend to be more detailed and accurate, usually covering smaller extents or focusing on particular parts of land cover. This is also a case of Dibavod, one of the used datasets, which only covers the area of the Czech Republic while specifically focused on water-related phenomena at a level of detail that global products are unable to capture.

The Globeland30, the world's first global land cover dataset at a 30m resolution, was created in 2014 by China's donation and belongs to Chen et al. (2015). The dataset comes from extraction of more than 20k satellite images and provides a worldwide land cover map at a very detailed scale. However, due to the inconsistencies and uncertainties were mentioned above, it is also an example of a partially incorrect result of water related land cover classification (Fonte et al., 2017). When using satellite imagery, one of the problematic categories is the category of clouds or, more specifically, shadows. It is quite common that shadows are incorrectly classified during the classification process (Fig. 5a). Globeland30 is distributed in overlapping tiles, which are classified probably using different images. That is why one may finds disagreements (Fig. 5b) in classification of the same phenomenon at neighbouring tiles as well as disagreement in pixel positioning in the same area. We performed an unpublished study, in which we assessed the accuracy of the water classification in the Globeland30 Global Inland Water dataset (mentioned in caption 3.3; Feng et al. (2016)) and a widely known Corine Land Cover datasets in comparison with the above-mentioned Czech Dibavod database. While the broadly used Corine data yielded the lowest accuracy, the other two global products did relatively well (Producer's accuracy of approx. 70 % and User's accuracy of almost 90 %). Despite numerous misclassifications and spatial disagreements, Globeland30 offers a detailed land cover classification with sufficient accuracy, which implies a wide usability of global products not only for environmental applications but also for economical and other applications, especially in the areas of the world where detailed national products are not available (Jokar Arsanjani et al., 2016).

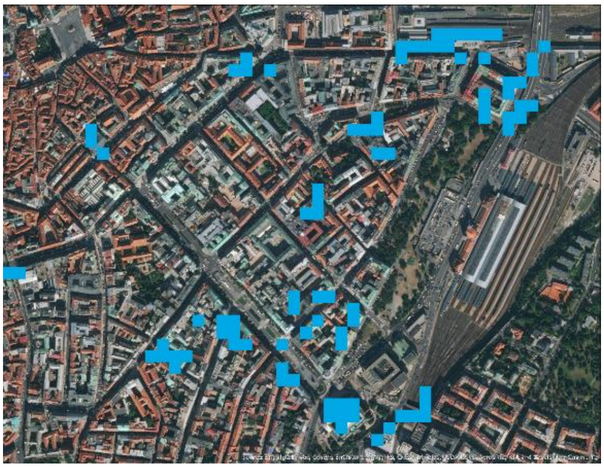

Figure 5a. Clouds incorrectly classified as water in a highly urbanised area, surrounding Prague main railway station. Globeland30. Source: Author.

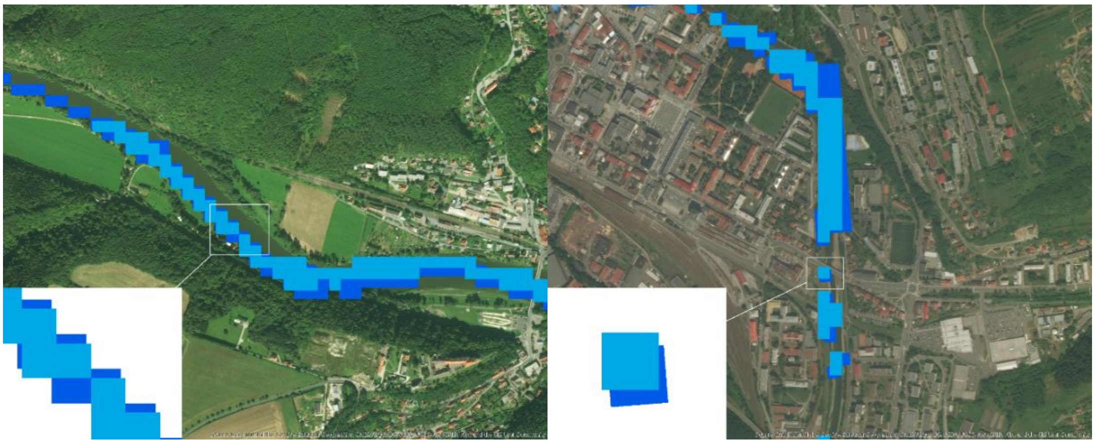

Figure 5b. Pixel positioning disagreement of GL30 neighbouring overlapping tiles: on the left, two tiles in the same coordinate projection; on the right, overlapping tiles in a different projection. Source: Author.

Promising platforms of remote sensing

Unmanned Aerial Systems are widely used for various research tasks (see a review by Pajares 2015); however, it is still quite a novel technique and the current use is limited by country-specific regulations. These systems are quite susceptible to failures (Freeman and Balas, 2014; Zuiev et al., 2015) compared to traditional remote sensing techniques so there are still numerous challenges to be overcome. However, their broad utilization introduces a photogrammetric approach in a greater detail also to interested public. As the photogrammetric solutions offer a low-cost alternative to expensive high-tech solutions (i.e., LiDAR), the use of UAVs is on the rise for many different applications (Fonstad et al., 2013). The mentioned photogrammetric approach or, better, image-matching algorithm (widely known as the Structure from Motion) performs an alignment of UAV-borne imagery and generates point clouds. During the first step, an algorithm tries to refine both interior (properties of lens) and exterior (position and orientation of cameras) parameters, the second step generates point clouds. Interior parameters are crucial and imply the estimation of the distortion parameters (Fig 5c); exterior parameters are acquired from onboard GNSS and IMU units. As the interiors are adjusted automatically during the image aligning process, many authors neglect the precise computation of the parameters, which requires a little more effort. It is however, worth the effort as neglecting a correct geometry reconstruction using accurately measured ground control points may lead to errors. The resulting generated point clouds can be classified and transformed into digital elevation models. As the digital surface model is a necessary output, subtracting a classified terrain model from it results in creation of a model with normalized heights (known also as normalized digital surface model or canopy height model). As mentioned above, classification results may benefit from supplementing with such height models.

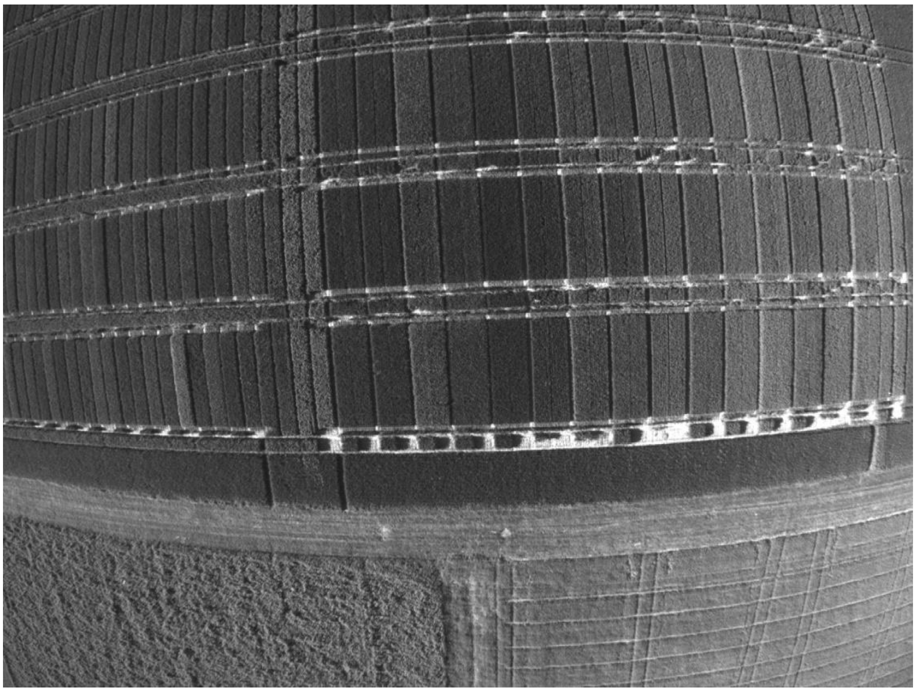

Figure 5c. Obvious radial distortions in a single non-calibrated image. Source: Author.

Across the remote sensing platforms, unmanned aerial systems are becoming the most popular ones over the last years. There are many pros and cons to favour each of the platforms. However, in many cases, users prefer or are forced to use the newest technologies and most recently available satellites, which goes sometimes against rational decision and the cost effectiveness is often neglected or forgotten. A selection of a correct platform is strongly associated with the intended utilization and aims or requirements of the use. All platforms are specific in some way and their comparison is often rather difficult than obvious. Many factors can affect the decision with spatial resolution being just one of them. It is also necessary to take into account for example processing time, flexibility, reliability, dependency, endurance, and last but not least – costs and expenses associated with the particular data. Even if equipment costs are disregarded, there may be still expenses for licencing and for an operator or a pilot, which can be quite high sums nowadays. Nevertheless, if the researcher wants to acquire imagery as a service, the most explicit variable is a unit price. The cost-effectiveness of the use of satellite, air-borne and UAV-borne data also depends on the spatial extent of the data. With increasing extent, the price of UAV imagery grows exorbitantly (Matese et al., 2015). As the Fig. 5 shows, the use of UAV is more cost-effective for small extents when compared with airborne or satellite data while from an extent of approx. 20 ha (Matese et al. (2015) found even lower threshold value), acquiring satellite data makes much more sense from the financial point of view. This is of course logical – while for a small extent, UAV imagery can be acquired and processed simply, doing the same with a large area would require immense amount of both time in the field and processing time. Another issue is of course the spatial resolution, which is very fine when using UAVs. The spatial resolution also affects the price of satellite imagery. Images with pixel size of 30 m (Landsat) or even 10 m (Sentinel) are available free of charge within a few hours after imaging. However, even the price of higher spatial resolution images is affordable, it is a few USD per sq. km or few tens USD for a sub-meter pixel size. It is likely that these prices will drop further in the future. Nevertheless, expenses for imagery processing can be significantly higher if one is not able to do the analysis by himself. Satellite imagery fits a large scale of applications but there are still fields where its spatial resolution is not sufficient (e.g. surveying or civil engineering).

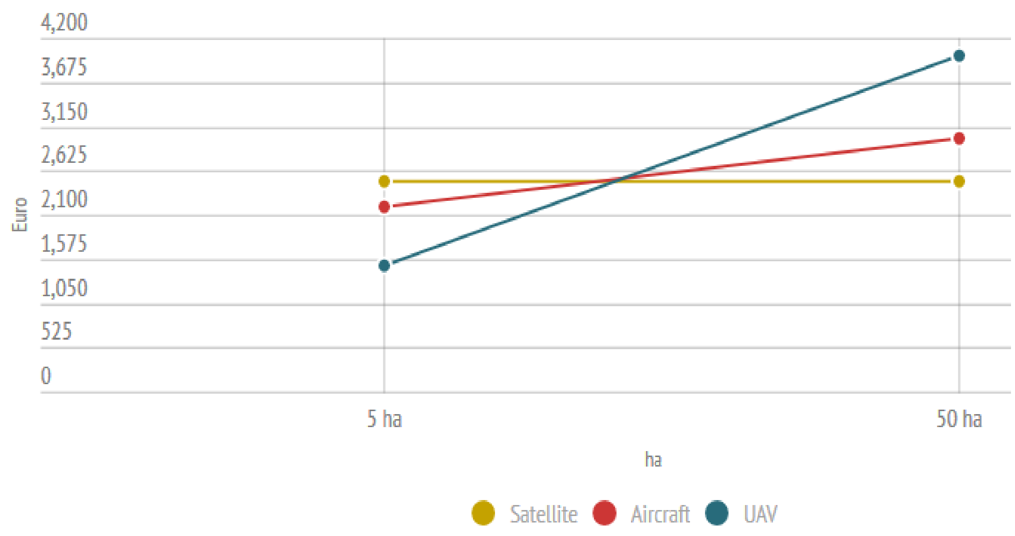

Figure 5d. Unit costs. Source: https://droneapps.co.

Besides price, other factors are also important, such as flexibility. On-demand solutions are growing more and more popular. While freely available imagery is orbit-driven and offers periodical imaging of the same area every few days, the use of commercial platforms allows to select the date of imaging to project needs. Both air-borne and UAV-borne imagery can be acquired, due to their rapid deployment, approximately at a chosen date and time. UAVs in particular can deal with a challenge of timing necessary to capture some research phenomenon (Müllerová et al., 2017). However, these technologies are strongly weather dependent, especially the unmanned ones. On the other hand, an UAV or an aircraft may be deployed under a cloud cover when satellite imagery may not be useful. Processing precision grows with the above ground altitude disproportionately; on the other hand, the processing time rises with the ground sampling distance. That is why the real potential of unmanned aerial systems does not lie in the cost savings but rather in the emerging flexibility for smaller extents. A rapid reaction in the matter of hours can outweigh the acquisition costs due to the possible economic benefits of quick information.

Traditional (satellite-based) remote sensing faces its limits in terms of the spatial resolution while terrestrial measurements are quite labour intensive and time consuming. Therefore, unmanned aerial systems offer the potential to fill the gap between satellites and fieldwork. Various unmanned aerial platforms are available on the market and their price keeps dropping, while their popularity and use in many research fields as well as in industry and agriculture increase. The suitability of UAVs for particular tasks varies, just as the possibility of equipping the platform with various sensors. In general, the customer is able to choose between a full generic vendor-provided solution and between using platforms that are more customizable and finding the solution by himself. Although vendor solutions come typically ready for deployment and their promotion is sometimes stunning, they can have very user-friendly environment and be easy to operate, home-assembled solutions may offer an even higher quality at lower expenses (Moudrý et al., n.d.).

6. Conclusions

Land-use land-cover is an important variable that can be of interest to researchers in many fields. It is therefore likely that more datasets will be created and that the information in both the new and old ones will be kept updated in the general interest. Datasets can be created using various sensors, classification algorithms, for different purposes, in various spatial extents and scales, and the dataset creators can affect the results through their individual more or less qualified decisions. There is no one universal dataset that would perfectly suit any purpose. However, to aid the reproducibility of the experiments, global and (if possible) open datasets should be used for studies in lower scales (large extents). On the other hand, accurate detailed data should be used for local studies regarding desired detail. For any study, a potential of volunteered data should be considered. In many cases, volunteered based data may at least keep up-to-date and supplement the other data source.

Many remote sensing platforms exist. As satellites have a fixed-timing acquisition, aircraft as well as UAV timing of acquisition is much more flexible. When UAV is situated for small extents in detail scale, aircrafts and mainly satellites are able to cover large areas. There are many other issues to be compared, for example questions about payload, endurance, weather dependency, reliability, but also organization efforts etc. That is why the chosen platform has to match a study aim and awaited results. An important aspect of proper platform/organization selection should be also the thinking about a financial point of the thing. Therefore, a cost analysis of planned study/survey should be included in the process of making a decision.

In the current digital age, many data sources exist and a user with limited experience gives in to temptation of using the newest, the most detailed, the easiest to access datasets, or to use as many as possible regardless of the rationality. This data availability is in a way quite dangerous and seems like a trap for the users. For many applications, a multitude of variables may be created, although the reasonability of these variables is sometimes lacking. Moreover, many of them are strongly intercorrelated. In remote sensing, variables are often derived from raw emitted data and, typically, ratio indices are calculated. The real contribution of such approach is however questionable, because raw data may often reflect the reality or explain the issue much better than derived variables. Hence, a rational approach to the selection of variables prior to initializing computations is crucial for improving the effectiveness of researcher's work.

Let me just mention one of many examples. Perhaps everyone who ever worked with multispectral data knows the NDVI vegetation index. Over the last few decades, it became a universal tool utilized in various environmental analyses. NDVI (Rouse et al., 1973; Tucker, 1977) was created when Landsat satellite data became available and was developed as a tool for qualitative evaluation of the presence or state of vegetation. Since then, the index became very popular due to its simplicity and was used in a number of diverse research applications. At present, it is computed in addition to satellite data also from UAV data. Unfortunately, its interpretation is much more difficult than the users realise. NDVI values change with seasons but it can undergo a much faster change within a few days or even within one day (e.g. depending on the time of day or on the weather). An NDVI map measured at a single time point therefore often leads to imprecise decisions, typically in (precision) agriculture. Uncertainties can also be borne by the use of various sensors (spatial or spectral resolution) or the calculations and calibrations. NDVI is undoubtedly an effective and very easily attainable RS data indicator (typically used for the assessment of the vegetation health or state). On the other hand, its overuse is associated with limited possibilities of results interpretation and its utilization should always be based on rational consideration rather than on the popularity of the index; alternatively, the acquired results should be at least complemented or confronted with other RS indicators to make sure that no misinterpretation occurred.

Afterword

The formulated aims were reached. I believe that and the presented studies appropriately demonstrate the principal issues of the LULC/RS combination and that their results contribute towards better understanding of those issues and of the environmental science in general. It is however necessary to mention that those approaches are not by far the only possible approaches, regardless whether we discuss land cover classification, change detection or the application of data for ecological modelling. In fact, not even the best model can completely encompass the reality and we can be sure that it will always represent a better or worse simplification and generalization of that reality. I can, as we can all, only strive for providing models, which are the best possible approximation of that reality.

7. Further research

As the thesis was dealing with the issues of land cover classification and land cover change detection, I would like to focus my further research on the same field, especially with the utilization of unmanned aerial systems. The plan is to assess its still largely unknown potential and the frontiers of its possible utilization as UAVs are indeed still actually quite a new technology still under development. One of the possible applications of the change detection is to detect the within-season spectral changes. As the pest's outbreaks become a serious environmental threat, and, therefore, a hot research topics (Abdullah et al., 2018; Fassnacht et al., 2014; Latifi et al., 2014; Seidl et al., 2017; Stoyanova et al., 2018), there is another ongoing project focused on detection of bark beetle infestation. One of the aims is early detection, for which it is necessary to find a detectable spectral difference between healthy and early infected trees in the shortest time possible. Besides early detection, spatiotemporal dynamics connected with topography and climatic conditions will be studied. The second near-future research topic is to assess the possibilities of temperature calculations. As the UAV-mounted thermal sensors are readily available on the market, almost nobody performs the transformation of brightness temperature into the real surface temperature anymore. One of the objectives is to revise employed techniques in the satellite remote sensing in order to modify and update these techniques for use in the close-range.

8. References

Abdullah, H., Darvishzadeh, R., Skidmore, A.K., Groen, T.A., Heurich, M., 2018. European spruce bark beetle (Ips typographus, L.) green attack affects foliar reflectance and biochemical properties. Int. J. Appl. Earth Obs. Geoinf. 64, 199–209. https://doi.org/10.1016/j.jag.2017.09.009

Ahmed, O.S., Shemrock, A., Chabot, D., Dillon, C., Williams, G., Wasson, R., Franklin, S.E., 2017. Hierarchical land cover and vegetation classification using multispectral data acquired from an unmanned aerial vehicle. Int. J. Remote Sens. 38, 2037–2052. https://doi.org/10.1080/01431161.2017.1294781

Allouche, O., Tsoar, A., Kadmon, R., 2006. Assessing the accuracy of species distribution models: Prevalence, kappa and the true skill statistic (TSS). J. Appl. Ecol. 43, 1223–1232. https://doi.org/10.1111/j.1365-2664.2006.01214.x

Alonzo, M., Bookhagen, B., Roberts, D.A., 2014. Urban tree species mapping using hyperspectral and lidar data fusion. Remote Sens. Environ. 148, 70–83. https://doi.org/10.1016/j.rse.2014.03.018

Arsanjani, J.J., Mooney, P., Zipf, A., 2015. Quality Assessment of the Contributed Land Use Information from OpenStreetMap Versus Authoritative Datasets. OpenStreetMap in GIScience 37–58. https://doi.org/10.1007/978-3-319-14280-7

Austin, M.. M., 2002. Spatial prediction of species distributiion: an interface between ecological theory and statistical modelling. Ecol. Modell. 157, 101–118. https://doi.org/10.1016/S0304-3800(02)00205-3

Austin, M., 2007. Species distribution models and ecological theory: A critical assessment and some possible new approaches, Ecological Modelling. Elsevier. https://doi.org/10.1016/j.ecolmodel.2006.07.005

Bartholomé, E., Belward, A.S., 2005. GLC2000: a new approach to global land cover mapping from Earth observation data. Int. J. Remote Sens. 26, 1959–1977. https://doi.org/10.1080/01431160412331291297

Bellard, C., Leroy, B., Thuiller, W., Rysman, J.-F.F., Courchamp, F., 2016. Major drivers of invasion risks throughout the world. Ecosphere 7, e01241. https://doi.org/10.1002/ecs2.1241

Blanco, P.D., Colditz, R.R., López Saldaña, G., Hardtke, L.A., Llamas, R.M., Mari, N.A., Fischer, A., Caride, C., Aceñolaza, P.G., del Valle, H.F., Lillo-Saavedra, M., Coronato, F., Opazo, S.A., Morelli, F., Anaya, J.A., Sione, W.F., Zamboni, P., Arroyo, V.B., 2013. A land cover map of Latin America and the Caribbean in the framework of the SERENA project. Remote Sens. Environ. 132, 13–31. https://doi.org/10.1016/J.RSE.2012.12.025

Blaschke, T., 2010. Object based image analysis for remote sensing. ISPRS J. Photogramm. Remote Sens. 65, 2–16. https://doi.org/10.1016/j.isprsjprs.2009.06.004

Blaschke, T., Hay, G.J., Kelly, M., Lang, S., Hofmann, P., Addink, E., Queiroz Feitosa, R., van der Meer, F., van der Werff, H., van Coillie, F., Tiede, D., 2014. Geographic Object-Based Image Analysis - Towards a new paradigm. ISPRS J. Photogramm. Remote Sens. 87, 180–191. https://doi.org/10.1016/j.isprsjprs.2013.09.014

Bontemps, S., Defourny, P., Bogaert, E., Arino, O., Kalogirou, V., Perez, J., 2011. {GLOBCOVER 2009 - Products description and validation report}.

Bork, E.W., Su, J.G., 2007. Integrating LIDAR data and multispectral imagery for enhanced classification of rangeland vegetation: A meta analysis. Remote Sens. Environ. 111, 11–24. https://doi.org/10.1016/j.rse.2007.03.011

Brovkina, O., Cienciala, E., Surový, P., Janata, P., 2018. Unmanned aerial vehicles (UAV) for assessment of qualitative classification of Norway spruce in temperate forest stands. Geo-Spatial Inf. Sci. 21, 12–20. https://doi.org/10.1080/10095020.2017.1416994

Brown, C.D., Davis, H.T., 2006. Receiver operating characteristics curves and related decision measures: A tutorial. Chemom. Intell. Lab. Syst. 80, 24–38. https://doi.org/10.1016/j.chemolab.2005.05.004

Broxton, P.D., Zeng, X., Sulla-Menashe, D., Troch, P.A., 2014. A Global Land Cover Climatology Using MODIS Data. J. Appl. Meteorol. Climatol. 53, 1593–1605. https://doi.org/10.1175/JAMC-D-13-0270.1

Büttner, G., Feranec, J., Jaffrain, G., Mari, L., Maucha, G., Soukup, T., George ButtnerJan Feranec...., 2004. the Corine Land Cover 2000 Project. Corine L. Cover 2000 Proj. 3, 331–346.

Channan, S., Collins, K., Emanuel, W.R., 2014. Global mosaics of the standard MODIS land cover type data. Maryland, USA.

Chen, J., Chen, J., Liao, A., Cao, X., Chen, L., Chen, X., He, C., Han, G., Peng, S., Lu, M., Zhang, W., Tong, X., Mills, J., 2015. Global land cover mapping at 30 m resolution: A POK-based operational approach. ISPRS J. Photogramm. Remote Sens. 103, 7–27. https://doi.org/10.1016/J.ISPRSJPRS.2014.09.002

Coleman, D.J., Eng, P., 2010. Volunteered Geographic Information in Spatial Data Infrastructure : An Early Look At Opportnities And Constraints. GSDI 12 World Conf. 1–18.

Congalton, R.G., Green, K., 2009. Assessing the accuracy of remotely sensed data : principles and practices. CRC Press/Taylor & Francis.

Congalton, R.G., Gu, J., Yadav, K., Thenkabail, P., Ozdogan, M., 2014. Global land cover mapping: A review and uncertainty analysis. Remote Sens. https://doi.org/10.3390/rs61212070

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., Lambin, E., 2004. Review ArticleDigital change detection methods in ecosystem monitoring: a review. Int. J. Remote Sens. 25, 1565–1596. https://doi.org/10.1080/0143116031000101675

Defourny, P., Vancutsem, C., Bicheron, C., Brockmann, C., Nino, F., Schouten, L., Leroy, M., 2007. GlobCover: A 300M Global Land Cover Product for 2005 Using ENVISAT MERIS Time Series. Proc. ISPRS Comm. VII Mid-Term Symp. 8–11.

Delaney, D.G., Sperling, C.D., Adams, C.S., Leung, B., 2007. Marine invasive species: validation of citizen science and implications for national monitoring networks. Biol. Invasions 10, 117–128. https://doi.org/10.1007/s10530-007-9114-0

Elith, J., Leathwick, J.R., 2009. Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. Annu. Rev. Ecol. Evol. Syst. 40, 677–697. https://doi.org/10.1146/annurev.ecolsys.110308.120159

Elwood, S., 2008. Volunteered geographic information: future research directions motivated by critical, participatory, and feminist GIS. GeoJournal 72, 173–183. https://doi.org/10.1007/s10708-008-9186-0

Fassnacht, F.E., Latifi, H., Ghosh, A., Joshi, P.K., Koch, B., 2014. Assessing the potential of hyperspectral imagery to map bark beetle-induced tree mortality. Remote Sens. Environ. 140, 533–548. https://doi.org/10.1016/J.RSE.2013.09.014

Fawcett, T., 2006. An introduction to ROC analysis. Pattern Recognit. Lett. 27, 861–874. https://doi.org/10.1016/j.patrec.2005.10.010

Feng, M., Sexton, J.O., Channan, S., Townshend, J.R., 2016. A global, high-resolution (30-m) inland water body dataset for 2000: first results of a topographic–spectral classification algorithm. Int. J. Digit. Earth 9, 113–133. https://doi.org/10.1080/17538947.2015.1026420

Feng, Q., Liu, J., Gong, J., 2015. UAV Remote sensing for urban vegetation mapping using random forest and texture analysis. Remote Sens. 7, 1074–1094. https://doi.org/10.3390/rs70101074

Fisher, P.F., Comber, A.J., Wadsworth, R., 2005. Land use and Land cover: Contradiction or Complement. Re-presenting GIS 85–98.

Flanagin, A.J., Metzger, M.J., 2008. The credibility of volunteered geographic information. GeoJournal 72, 137–148. https://doi.org/10.1007/s10708-008-9188-y

Fonstad, M.A., Dietrich, J.T., Courville, B.C., Jensen, J.L., Carbonneau, P.E., 2013. Topographic structure from motion: a new development in photogrammetric measurement. Earth Surf. Process. Landforms 38, 421–430. https://doi.org/10.1002/esp.3366

Fonte, C., Minghini, M., Patriarca, J., Antoniou, V., See, L., Skopeliti, A., 2017. Generating Up-to-Date and Detailed Land Use and Land Cover Maps Using OpenStreetMap and GlobeLand30. ISPRS Int. J. Geo-Information 6, 125. https://doi.org/10.3390/ijgi6040125

Foody, G.M., 2013. Ground reference data error and the mis-estimation of the Area of land cover change as a function of its abundance. Remote Sens. Lett. 4, 783–792. https://doi.org/10.1080/2150704X.2013.798708

Foody, G.M., 2004. Thematic Map Comparison. Photogramm. Eng. Remote Sens. 70, 627–633. https://doi.org/10.14358/PERS.70.5.627

Foody, G.M., 2002. Status of land cover classification accuracy assessment. Remote Sens. Environ. 80, 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4

Foody, G.M., Boyd, D.S., 2013. Using volunteered data in land cover map validation: Mapping west African forests. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 6, 1305–1312. https://doi.org/10.1109/JSTARS.2013.2250257

Foody, G.M., Boyd, D.S., 2012. Exploring the potential role of volunteer citizen sensors in land cover map accuracy assessment. 10th Int. Symp. Spat. Accuracy Assess. Nat. Resour. Environ. Sci. 203–208.

Foody, G.M., See, L., Fritz, S., Van der Velde, M., Perger, C., Schill, C., Boyd, D.S., 2013. Assessing the Accuracy of Volunteered Geographic Information arising from Multiple Contributors to an Internet Based Collaborative Project. Trans. GIS 17, 847–860. https://doi.org/10.1111/tgis.12033

Frazier, P.S., Frazier, P.S., Page, K.J., Page, K.J., 2000. Water Body Detection and Delineation with Landsat TM Data. Photogramm. Eng. Remote Sens. 66, 1461–1467. https://doi.org/0099-1112I0OI6612-1461$3.00/0

Freeman, P., Balas, G.J., 2014. Actuation failure modes and effects analysis for a small UAV, in: 2014 American Control Conference. IEEE, pp. 1292–1297. https://doi.org/10.1109/ACC.2014.6859482

Fritz, S., McCallum, I., Schill, C., Perger, C., See, L., Schepaschenko, D., van der Velde, M., Kraxner, F., Obersteiner, M., 2012. Geo-Wiki: An online platform for improving global land cover. Environ. Model. Softw. 31, 110–123. https://doi.org/10.1016/j.envsoft.2011.11.015

Fritz, S., See, L., 2008. Identifying and quantifying uncertainty and spatial disagreement in the comparison of Global Land Cover for different applications. Glob. Chang. Biol. 14, 1057–1075. https://doi.org/10.1111/j.1365-2486.2007.01519.x

Gandhi, G.M., Parthiban, S., Thummalu, N., Christy, A., 2015. Ndvi: Vegetation Change Detection Using Remote Sensing and Gis – A Case Study of Vellore District. Procedia Comput. Sci. 57, 1199–1210. https://doi.org/10.1016/J.PROCS.2015.07.415

Gao, B., 1996. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sens. Environ. 58, 257–266. https://doi.org/10.1016/S0034-4257(96)00067-3

Gini, R., Passoni, D., Pinto, L., Sona, G., 2014. Use of unmanned aerial systems for multispectral survey and tree classification: A test in a park area of northern Italy. Eur. J. Remote Sens. 47, 251–269. https://doi.org/10.5721/EuJRS20144716

Giri, C., Pengra, B., Long, J., Loveland, T.R., 2013. Next generation of global land cover characterization, mapping, and monitoring. Int. J. Appl. Earth Obs. Geoinf. 25, 30–37. https://doi.org/10.1016/J.JAG.2013.03.005

Giri, C., Zhu, Z., Reed, B., 2005. A comparative analysis of the Global Land Cover 2000 and MODIS land cover data sets. Remote Sens. Environ. 94, 123–132. https://doi.org/10.1016/j.rse.2004.09.005

Gómez-Candón, D., De Castro, A.I., López-Granados, F., 2014. Assessing the accuracy of mosaics from unmanned aerial vehicle (UAV) imagery for precision agriculture purposes in wheat. Precis. Agric. 15, 44–56. https://doi.org/10.1007/s11119-013-9335-4

Goodchild, M.F., 2011. Scale in GIS: An overview. Geomorphology 130, 5–9. https://doi.org/10.1016/j.geomorph.2010.10.004

Goodchild, M.F., 2007. Citizens as sensors: The world of volunteered geography. GeoJournal. https://doi.org/10.1007/s10708-007-9111-y

Gottschalk, T.K., Aue, B., Hotes, S., Ekschmitt, K., 2011. Influence of grain size on species–habitat models. Ecol. Modell. 222, 3403–3412. https://doi.org/10.1016/J.ECOLMODEL.2011.07.008

Greenwood, J.J.D., 2007. Citizens, science and bird conservation. J. Ornithol. 148, 77–124. https://doi.org/10.1007/s10336-007-0239-9

Grekousis, G., Mountrakis, G., Kavouras, M., 2015. An overview of 21 global and 43 regional land-cover mapping products. Int. J. Remote Sens. 1161, 1–27. https://doi.org/10.1080/01431161.2015.1093195

Guisan, A., Edwards, T.C., Hastie, T., 2002. Generalized linear and generalized additive models in studies of species distributions: Setting the scene. Ecol. Modell. 157, 89–100. https://doi.org/10.1016/S0304-3800(02)00204-1

Guisan, A., Hofer, U., 2003. Predicting reptile distributions at the mesoscale: Relation to climate and topography. J. Biogeogr. 30, 1233–1243. https://doi.org/10.1046/j.1365-2699.2003.00914.x

Guisan, A., Tingley, R., Baumgartner, J.B., Naujokaitis-Lewis, I., Sutcliffe, P.R., Tulloch, A.I.T., Regan, T.J., Brotons, L., Mcdonald-Madden, E., Mantyka-Pringle, C., Martin, T.G., Rhodes, J.R., Maggini, R., Setterfield, S.A., Elith, J., Schwartz, M.W., Wintle, B.A., Broennimann, O., Austin, M., Ferrier, S., Kearney, M.R., Possingham, H.P., Buckley, Y.M., 2013. Predicting species distributions for conservation decisions. Ecol. Lett. 16, 1424–1435. https://doi.org/10.1111/ele.12189

Guisan, A., Zimmermann, N.E., 2000. Predictive habitat distribution models in ecology. Ecol. Modell. 135, 147–186. https://doi.org/10.1016/S0304-3800(00)00354-9

Guisan, A., Zimmermann, N.E., Elith, J., Graham, C.H., Phillips, S., Peterson, A.T., 2007. What matters for predicting the occurrences of trees: Techniques, data, or species' characteristics? Ecol. Monogr. 77, 615–630. https://doi.org/10.1890/06-1060.1

Hansen, M.C., Loveland, T.R., 2012. A review of large area monitoring of land cover change using Landsat data. Remote Sens. Environ. 122, 66–74. https://doi.org/10.1016/J.RSE.2011.08.024

Hochachka, W.M., Fink, D., Hutchinson, R. a, Sheldon, D., Wong, W.-K., Kelling, S., 2012. Data-intensive science applied to broad-scale citizen science. Trends Ecol. Evol. 27, 130–7. https://doi.org/10.1016/j.tree.2011.11.006

Holmgren, J., Persson, Å., Söderman, U., 2008. Species identification of individual trees by combining high resolution LiDAR data with multi-spectral images. Int. J. Remote Sens. 29, 1537–1552. https://doi.org/10.1080/01431160701736471

Huang, C., Davis, L.S., Townshend, J.R.G., 2002. An assessment of support vector machines for land cover classification. Int. J. Remote Sens. 23, 725–749. https://doi.org/10.1080/01431160110040323

Hurlbert, A.H., Liang, Z., 2012. Spatiotemporal variation in avian migration phenology: citizen science reveals effects of climate change. PLoS One 7, e31662. https://doi.org/10.1371/journal.pone.0031662

Hussain, M., Chen, D., Cheng, A., Wei, H., Stanley, D., 2013. Change detection from remotely sensed images: From pixel-based to object-based approaches. ISPRS J. Photogramm. Remote Sens. 80, 91–106. https://doi.org/10.1016/J.ISPRSJPRS.2013.03.006

Husson, E., Reese, H., Ecke, F., 2017. Combining spectral data and a DSM from UAS-images for improved classification of non-submerged aquatic vegetation. Remote Sens. 9, 1–15. https://doi.org/10.3390/rs9030247

Jarnevich, C.S., Stohlgren, T.J., Kumar, S., Morisette, J.T., Holcombe, T.R., 2015. Caveats for correlative species distribution modeling. Ecol. Inform. 29, 6–15. https://doi.org/10.1016/j.ecoinf.2015.06.007

Jokar Arsanjani, J., Tayyebi, A., Vaz, E., 2016. GlobeLand30 as an alternative fine-scale global land cover map: Challenges, possibilities, and implications for developing countries. Habitat Int. 55, 25–31. https://doi.org/10.1016/j.habitatint.2016.02.003

Kawrykow, A., Roumanis, G., Kam, A., Kwak, D., Leung, C., Wu, C., Zarour, E., Sarmenta, L., Blanchette, M., Waldispühl, J., Waldispühl, J., 2012. Phylo: A Citizen Science Approach for Improving Multiple Sequence Alignment. PLoS One 7, e31362. https://doi.org/10.1371/journal.pone.0031362

Keshava, N., Mustard, J.F., 2002. Spectral unmixing. IEEE Signal Process. Mag. 19, 44–57. https://doi.org/10.1109/79.974727

Klein, I., Gessner, U., Dietz, A.J., Kuenzer, C., 2017. Global WaterPack – A 250 m resolution dataset revealing the daily dynamics of global inland water bodies. Remote Sens. Environ. 198, 345–362. https://doi.org/10.1016/j.rse.2017.06.045

Kuria, D.N., Menz, G., Misana, S., Mwita, E., Thamm, H.-P., Alvarez, M., Mogha, N., Becker, M., Oyieke, H., 2014. Seasonal Vegetation Changes in the Malinda Wetland Using Bi-Temporal , Multi-Sensor , Very High Resolution Remote Sensing Data Sets. Adv. Remote Sens. 3, 33–48. https://doi.org/10.4236/ars.2014.31004

Lassueur, T., Joost, S., Randin, C.F., 2006. Very high resolution digital elevation models: Do they improve models of plant species distribution? Ecol. Modell. 198, 139–153. https://doi.org/10.1016/j.ecolmodel.2006.04.004

Latifi, H., Schumann, B., Kautz, M., Dech, S., 2014. Spatial characterization of bark beetle infestations by a multidate synergy of SPOT and Landsat imagery. Environ. Monit. Assess. 186, 441–456. https://doi.org/10.1007/s10661-013-3389-7

Lechner, A.M., Langford, W.T., Bekessy, S.A., Jones, S.D., 2012a. Are landscape ecologists addressing uncertainty in their remote sensing data? Landsc. Ecol. 27, 1249–1261. https://doi.org/10.1007/s10980-012-9791-7

Lechner, A.M., Langford, W.T., Jones, S.D., Bekessy, S.A., Gordon, A., 2012b. Investigating species-environment relationships at multiple scales: Differentiating between intrinsic scale and the modifiable areal unit problem. Ecol. Complex. 11, 91–102. https://doi.org/10.1016/j.ecocom.2012.04.002

Lecours, V., Devillers, R., Schneider, D., Lucieer, V., Brown, C., Edinger, E., 2015. Spatial scale and geographic context in benthic habitat mapping: review and future directions. Mar. Ecol. Prog. Ser. 535, 259–284. https://doi.org/10.3354/meps11378

Lhermitte, S., Verbesselt, J., Verstraeten, W.W., Coppin, P., 2011. A comparison of time series similarity measures for classification and change detection of ecosystem dynamics. Remote Sens. Environ. 115, 3129–3152. https://doi.org/10.1016/J.RSE.2011.06.020

Liu, H., Zhou, Q., 2004. Accuracy analysis of remote sensing change detection by rule-based rationality evaluation with post-classification comparison. Int. J. Remote Sens. 25, 1037–1050. https://doi.org/10.1080/0143116031000150004

Liu, J., Li, P., Wang, X., 2015. A new segmentation method for very high resolution imagery using spectral and morphological information. ISPRS J. Photogramm. Remote Sens. 101, 145–162.

Loveland, T.R., Reed, B.C., Brown, J.F., Ohlen, D.O., Zhu, Z., Yang, L., Merchant, J.W., 2000. Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. Int. J. Remote Sens. 21, 1303–1330. https://doi.org/10.1080/014311600210191

Lu, D., Batistella, M., Moran, E., 2008. Integration of Landsat TM and SPOT HRG Images for Vegetation Change Detection in the Brazilian Amazon. Photogramm. Eng. Remote Sensing 74, 421–430.

Lu, D., Li, G., Moran, E., 2014. Current situation and needs of change detection techniques, International Journal of Image and Data Fusion. Taylor & Francis. https://doi.org/10.1080/19479832.2013.868372

Lu, D., Mausel, P., Brondízio, E., Moran, E., 2004. Change detection techniques. Int. J. Remote Sens. 25, 2365–2401. https://doi.org/10.1080/0143116031000139863

Lu, D., Weng, Q., 2007. A survey of image classification methods and techniques for improving classification performance, International Journal of Remote Sensing. Taylor & Francis . https://doi.org/10.1080/01431160600746456

Lunetta, R.S., Knight, J.F., Ediriwickrema, J., Lyon, J.G., Worthy, L.D., 2006. Land-cover change detection using multi-temporal MODIS NDVI data. Remote Sens. Environ. 105, 142–154. https://doi.org/10.1016/j.rse.2006.06.018

Mallick, J., Singh, C.K., Shashtri, S., Rahman, A., Mukherjee, S., 2012. Land surface emissivity retrieval based on moisture index from LANDSAT TM satellite data over heterogeneous surfaces of Delhi city. Int. J. Appl. Earth Obs. Geoinf. 19, 348–358. https://doi.org/10.1016/J.JAG.2012.06.002

Matese, A., Toscano, P., Di Gennaro, S., Genesio, L., Vaccari, F., Primicerio, J., Belli, C., Zaldei, A., Bianconi, R., Gioli, B., 2015. Intercomparison of UAV, Aircraft and Satellite Remote Sensing Platforms for Precision Viticulture. Remote Sens. 7, 2971–2990. https://doi.org/10.3390/rs70302971

McCallum, I., Obersteiner, M., Nilsson, S., Shvidenko, A., 2006. A spatial comparison of four satellite derived 1km global land cover datasets. Int. J. Appl. Earth Obs. Geoinf. 8, 246–255. https://doi.org/10.1016/j.jag.2005.12.002

McCue, A.J., McGrath, M.J., Wiersma, Y.F., 2014. Benefits and drawbacks of two modelling approaches for a generalist carnivore: can models predict where Wile E. Coyote will turn up next? Int. J. Geogr. Inf. Sci. 28, 1590–1609. https://doi.org/10.1080/13658816.2013.847444

McCullagh, P. (Peter), Nelder, J.A., 1989. Generalized Linear Models, 2nd ed. Chapman & Hall, London.

McFeeters, S.K., 1996. The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. Int. J. Remote Sens. 17, 1425–1432. https://doi.org/10.1080/01431169608948714

Michener, W.K., Jones, M.B., 2012. Ecoinformatics: supporting ecology as a data-intensive science. Trends Ecol. Evol. 27, 85–93. https://doi.org/10.1016/j.tree.2011.11.016

Michez, A., Piégay, H., Lisein, J., Claessens, H., Lejeune, P., 2016. Classification of riparian forest species and health condition using multi-temporal and hyperspatial imagery from unmanned aerial system. Environ. Monit. Assess. 188, 1–19. https://doi.org/10.1007/s10661-015-4996-2

Milas, A.S., Arend, K., Mayer, C., Simonson, M.A., Mackey, S., 2017. Different colours of shadows: classification of UAV images. Int. J. Remote Sens. 38, 3084–3100. https://doi.org/10.1080/01431161.2016.1274449

Mittal, M., Kaur, G., 2003. Mixels Resolution by hybridization approach (BBO & GA) - Semantic Scholar. Int. J. Innov. Res. Sci. Eng. Technol. 2.

Moudrý, V., Urban, R., Štroner, M., Komárek, J., Brouček, J., Prošek, J., n.d. Comparison of a commercial and home-assembled fixed-wing UAV for terrain mapping of a post-mining site under leaf-off conditions. Int. J. Remote Sens.

Müllerová, J., Brůna, J., Bartaloš, T., Dvořák, P., Vítková, M., Pyšek, P., 2017. Timing Is Important: Unmanned Aircraft vs. Satellite Imagery in Plant Invasion Monitoring. Front. Plant Sci. 8, 1–13. https://doi.org/10.3389/fpls.2017.00887

Myint, S.W., Gober, P., Brazel, A., Grossman-Clarke, S., Weng, Q., 2011. Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. Remote Sens. Environ. 115, 1145–1161. https://doi.org/10.1016/J.RSE.2010.12.017

Näsi, R., Honkavaara, E., Lyytikäinen-Saarenmaa, P., Blomqvist, M., Litkey, P., Hakala, T., Viljanen, N., Kantola, T., Tanhuanpää, T., Holopainen, M., 2015. Using UAV-based photogrammetry and hyperspectral imaging for mapping bark beetle damage at tree-level. Remote Sens. 7, 15467–15493. https://doi.org/10.3390/rs71115467

Nishar, A., Richards, S., Breen, D., Robertson, J., Breen, B., 2016. Thermal infrared imaging of geothermal environments and by an unmanned aerial vehicle (UAV): A case study of the Wairakei – Tauhara geothermal field, Taupo, New Zealand. Renew. Energy 86, 1256–1264. https://doi.org/10.1016/J.RENENE.2015.09.042

Olofsson, P., Foody, G.M., Herold, M., Stehman, S. V., Woodcock, C.E., Wulder, M.A., 2014. Good practices for estimating area and assessing accuracy of land change. Remote Sens. Environ. 148, 42–57. https://doi.org/10.1016/j.rse.2014.02.015

Pajares, G., 2015. Overview and Current Status of Remote Sensing Applications Based on Unmanned Aerial Vehicles (UAVs). Photogramm. Eng. Remote Sens. 81, 281–330. https://doi.org/10.14358/PERS.81.4.281

Pal, M., Mather, P.M., 2003. An assessment of the effectiveness of decision tree methods for land cover classification. Remote Sens. Environ. 86, 554–565. https://doi.org/10.1016/S0034-4257(03)00132-9

Perger, C., Fritz, S., See, L., Schill, C., Van Der Velde, M., Mccallum, I., Obersteiner, M., 2012. A Campaign to Collect Volunteered Geographic Information on Land Cover and Human Impact. GI Forum 2012 Geovizualisation, Soc. Learn. 83–91.

Pfeifer, M., Disney, M., Quaife, T., Marchant, R., 2012. Terrestrial ecosystems from space: A review of earth observation products for macroecology applications. Glob. Ecol. Biogeogr. https://doi.org/10.1111/j.1466-8238.2011.00712.x

Pradervand, J.-N., Dubuis, A., Pellissier, L., Guisan, A., Randin, C., 2014. Very high resolution environmental predictors in species distribution models. Prog. Phys. Geogr. 38, 79–96. https://doi.org/10.1177/0309133313512667

Pu, R., Gong, P., Tian, Y., Miao, X., Carruthers, R., Anderson, G., 2008. Using Classification and NDVI Differencing Methods for Monitoring Sparse Vegetation Coverage: A Case Study of Saltcedar in Nevada, USA. Int. J. Remote Sens. https://doi.org/http://dx.doi.org/10.1080/01431160801908095

Rabus, B., Eineder, M., Roth, A., Bamler, R., 2003. The shuttle radar topography mission—a new class of digital elevation models acquired by spaceborne radar. ISPRS J. Photogramm. Remote Sens. 57, 241–262. https://doi.org/10.1016/S0924-2716(02)00124-7

Raddick, M.J., Gay, P.L., Lintott, C.J., Haven, N., Szalay, A.S., 2010. Galaxy Zoo : Exploring the Motivations of Citizen Science Volunteers.

Radke, R.J., Andra, S., Al-Kofahi, O., Roysam, B., 2005. Image change detection algorithms: a systematic survey. IEEE Trans. Image Process. 14, 294–307. https://doi.org/10.1109/TIP.2004.838698

Randin, C.F., Engler, R., Normand, S., ZAPPA, M., Zimmermann, N.E., Pearman, P.B., VITTOZ, P., Thuiller, W., Guisan, A., 2009. Climate change and plant distribution: local models predict high-elevation persistence. Glob. Chang. Biol. 15, 1557–1569. https://doi.org/DOI 10.1111/j.1365-2486.2008.01766.x

Rocchini, D., Hortal, J., Lengyel, S., Lobo, J.M., Jiménez-Valverde, A., Ricotta, C., Bacaro, G., Chiarucci, A., 2011. Accounting for uncertainty when mapping species distributions: The need for maps of ignorance. Prog. Phys. Geogr. 35, 211–226. https://doi.org/10.1177/0309133311399491

Rouse, J.W., Hass, R.H., Schell, J.A., Deering, D.W., 1973. Monitoring vegetation systems in the great plains with ERTS. Third Earth Resour. Technol. Satell. Symp. 1, 309–317. https://doi.org/citeulike-article-id:12009708

Rüdisser, J., Walde, J., Tasser, E., Frühauf, J., Teufelbauer, N., Tappeiner, U., 2015. Biodiversity in cultural landscapes: influence of land use intensity on bird assemblages. Landsc. Ecol. 30, 1851–1863. https://doi.org/10.1007/s10980-015-0215-3

Sankey, T., Donager, J., McVay, J., Sankey, J.B., 2017. UAV lidar and hyperspectral fusion for forest monitoring in the southwestern USA. Remote Sens. Environ. 195, 30–43. https://doi.org/10.1016/j.rse.2017.04.007

Seidl, R., Thom, D., Kautz, M., Martin-Benito, D., Peltoniemi, M., Vacchiano, G., Wild, J., Ascoli, D., Petr, M., Honkaniemi, J., Lexer, M.J., Trotsiuk, V., Mairota, P., Svoboda, M., Fabrika, M., Nagel, T.A., Reyer, C.P.O., 2017. Forest disturbances under climate change. Nat. Clim. Chang. 7, 395–402. https://doi.org/10.1038/nclimate3303

Seoane, J., Bustamante, J., Dı´az-Delgado, R., Díaz-Delgado, R., 2004. Are existing vegetation maps adequate to predict bird distributions? Ecol. Modell. 175, 137–149.

Silvertown, J., 2009. A new dawn for citizen science. Trends Ecol. Evol. 24, 467–471. https://doi.org/10.1016/j.tree.2009.03.017

Singh, A., 1989. Review Articlel: Digital change detection techniques using remotely-sensed data. Int. J. Remote Sens. 10, 989–1003. https://doi.org/10.1080/01431168908903939

Singh, A., Singh, K.K., 2018. Unsupervised change detection in remote sensing images using fusion of spectral and statistical indices. Egypt. J. Remote Sens. Sp. Sci. https://doi.org/10.1016/J.EJRS.2018.01.006

Snäll, T., Kindvall, O., Nilsson, J., Pärt, T., 2011. Evaluating citizen-based presence data for bird monitoring. Biol. Conserv. 144, 804–810. https://doi.org/10.1016/j.biocon.2010.11.010

Song, C., Woodcock, C.E., Seto, K.C., Lenney, M.P., Macomber, S.A., 2001. Classification and Change Detection Using Landsat TM Data: When and How to Correct Atmospheric Effects? Remote Sens. Environ. 75, 230–244. https://doi.org/10.1016/S0034-4257(00)00169-3

Source, J.P.C., By, P., Sciences, B., 2008. Citizen Science : Can Volunteers Do Real Research ? 58, 192–197.

Stanton, J.C., Pearson, R.G., Horning, N., Ersts, P., Reşit Akçakaya, H., Re??it Ak??akaya, H., 2012. Combining static and dynamic variables in species distribution models under climate change. Methods Ecol. Evol. 3, 349–357. https://doi.org/10.1111/j.2041-210X.2011.00157.x

Šťastný, K., Bejček, V., Hudec, K., 2006. Atlas of breeding bird distribution in the Czech Republic 2001-2003. Aventinum, Praha.

Stehman, S. V., 2013. Estimating area from an accuracy assessment error matrix. Remote Sens. Environ. 132, 202–211. https://doi.org/10.1016/j.rse.2013.01.016

Stoyanova, M., Kandilarov, A., Koutev, V., Nitcheva, O., Dobreva, P., 2018. Potential of multispectral imaging technology for assessment coniferous forests bitten by a bark beetle in Central Bulgaria. MATEC Web Conf. 01005, 01005. https://doi.org/10.1051/matecconf/201814501005

Sullivan, B.L., Wood, C.L., Iliff, M.J., Bonney, R.E., Fink, D., Kelling, S., 2009. eBird: A citizen-based bird observation network in the biological sciences. Biol. Conserv. 142, 2282–2292. https://doi.org/10.1016/j.biocon.2009.05.006

Szostak, M., Hawryło, P., Piela, D., 2018. Using of Sentinel-2 images for automation of the forest succession detection. Eur. J. Remote Sens. 51, 142–149. https://doi.org/10.1080/22797254.2017.1412272

Szostak, M., Wezyk, P., Tompalski, P., 2014. Aerial Orthophoto and Airborne Laser Scanning as Monitoring Tools for Land Cover Dynamics: A Case Study from the Milicz Forest District (Poland). Pure Appl. Geophys. 171, 857–866. https://doi.org/10.1007/s00024-013-0668-8

Tachikawa, T., Hato, M., Kaku, M., Iwasaki, A., 2011. Characteristics of ASTER GDEM version 2, in: 2011 IEEE International Geoscience and Remote Sensing Symposium. IEEE, pp. 3657–3660. https://doi.org/10.1109/IGARSS.2011.6050017

Tarantino, C., Adamo, M., Lucas, R., Blonda, P., 2016. Detection of changes in semi-natural grasslands by cross correlation analysis with WorldView-2 images and new Landsat 8 data. Remote Sens. Environ. 175, 65–72.

Teo, T.-A., Huang, C.-H., 2016. Object-Based Land Cover Classification Using Airborne Lidar and Different Spectral Images. Terr. Atmos. Ocean. Sci. 27, 491. https://doi.org/10.3319/TAO.2016.01.29.01(ISRS)

Thuiller, W., Brotons, L., Araújo, M.B., Lavorel, S., 2004. Effects of restricting environmental range of data to project current and future species distributions. Ecography (Cop.). 27, 165–172. https://doi.org/10.1111/j.0906-7590.2004.03673.x

Toomey, M., Vierling, L.A., 2005. Multispectral remote sensing of landscape level foliar moisture: techniques and applications for forest ecosystem monitoring. Can. J. For. Res. 35, 1087–1097. https://doi.org/10.1139/x05-043

Tuanmu, M., Jetz, W., 2014. A global 1km consensus land cover product for biodiversity and ecosystem modeling. Glob. Ecol. Biogeogr.

Tucker, C.J., 1977. Asymptotic nature of grass canopy spectral reflectance. Appl. Opt. 16, 1151. https://doi.org/10.1364/AO.16.001151

Venier, L.A., Pearce, J., Mckee, J.E., McKenney, D.W., Niemi, G.J., 2004. Climate and satellite-derived land cover for predicting breeding bird distribution in the Great Lakes basin. J. Biogeogr. 31, 315–331. https://doi.org/10.1046/j.0305-0270.2003.01014.x

Verburg, P.H., Ellis, E.C., Letourneau, A., 2011. A global assessment of market accessibility and market influence for global environmental change studies. Environ. Res. Lett. 6, 034019. https://doi.org/10.1088/1748-9326/6/3/034019

Verpoorter, C., Kutser, T., Tranvik, L., 2012. Automated mapping of water bodies using Landsat multispectral data. Limnol. Oceanogr. Methods 10, 1037–1050. https://doi.org/10.4319/lom.2012.10.1037

Vintrou, E., Desbrosse, A., Bégué, A., Traoré, S., Baron, C., Lo Seen, D., 2012. Crop area mapping in West Africa using landscape stratification of MODIS time series and comparison with existing global land products. Int. J. Appl. Earth Obs. Geoinf. 14, 83–93. https://doi.org/10.1016/J.JAG.2011.06.010

Wardlow, B.D., Egbert, S.L., Kastens, J.H., Wardlow, B.D.;, 2007. Analysis of Time-Series MODIS 250 m Vegetation Index Data for Crop Classification in the U.S. Central Great Plains "Analysis of Time-Series MODIS 250 m Vegetation Index Data for Crop Classification in the.

Weil, G., Lensky, I., Resheff, Y., Levin, N., 2017. Optimizing the Timing of Unmanned Aerial Vehicle Image Acquisition for Applied Mapping of Woody Vegetation Species Using Feature Selection. Remote Sens. 9, 1130. https://doi.org/10.3390/rs9111130

Wiersma, Y.., 2010. Birding 2 . 0 : Citizen Science and Effective Monitoring in the Web 2 . 0 World. Avian Conserv. Ecol. 5, 13. https://doi.org/10.5751/ACE-00427-050213

Xu, H., 2006. Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. Int. J. Remote Sens. 27, 3025–3033. https://doi.org/10.1080/01431160600589179

Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M., Schirokauer, D., 2006. Object-based Detailed Vegetation Classification with Airborne High Spatial Resolution Remote Sensing Imagery. Photogramm. Eng. Remote Sens. 72, 799–811. https://doi.org/10.14358/PERS.72.7.799

Zarco-Tejada, P.J., González-Dugo, V., Berni, J.A.J., 2012. Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera. Remote Sens. Environ. 117, 322–337. https://doi.org/10.1016/J.RSE.2011.10.007

Zhang, C., Kovacs, J.M., 2012. The application of small unmanned aerial systems for precision agriculture: a review. Precis. Agric. 13, 693–712. https://doi.org/10.1007/s11119-012-9274-5

Zhen, Z., Quackenbush, L.J., Stehman, S. V., Zhang, L., 2013. Impact of training and validation sample selection on classification accuracy and accuracy assessment when using reference polygons in object-based classification. Int. J. Remote Sens. 34, 6914–6930. https://doi.org/10.1080/01431161.2013.810822

Zhou, Y., Qiu, F., 2015. Fusion of high spatial resolution WorldView-2 imagery and LiDAR pseudo-waveform for object-based image analysis. ISPRS J. Photogramm. Remote Sens. 101, 221–232. https://doi.org/10.1016/j.isprsjprs.2014.12.013

Zuiev, O.V., Demydko, V.G., Musyenko, A.O., Gerasymenko, T.S., 2015. Analysis of control processes influence on UAV equipment classification veracity, in: 2015 IEEE International Conference Actual Problems of Unmanned Aerial Vehicles Developments (APUAVD). IEEE, pp. 102–105. https://doi.org/10.1109/APUAVD.2015.7346572

9. Supplements

A – Biography & Publications

CURRICULUM VITAE

PERSONAL

Jan Komárek, born in 1990, Czech nationality, married

BELONGING

Department of Applied Geoinformatics and Spatial Planning, since 2014
Centre for Precision Farming, since 2017
Spatial Science in Environment and Ecology Research Group, since 2017

JOB POSITIONS

Since 2016/11
Assistant for UAVs at the Department of Applied Geoinformatics and Spatial Planning

2014/10 - 2016/10
Technician at the Department of Applied Geoinformatics and Spatial Planning

EDUCATION

Czech University of Life Sciences Prague, Faculty of Environmental Sciences, Territorial Technical and Administrative Services
(2009 – 2012; 2012 bachelor's degree)
Bachelor thesis topic: GNSS reliability testing in urban environment

Czech University of Life Sciences Prague, Faculty of Environmental Sciences, Landscape and Land Improvement
(2012 – 2014; 2014 master's degree)
Master thesis topic: The assessment of topographical data for the purpose of precision farming system in the Czech Republic conditions

Czech University of Life Sciences Prague, Faculty of Environmental Sciences, Applied and Landscape Ecology
(2014 – until now; PhD candidate)
PhD thesis topic: Land-cover datasets accuracy assessing and its implication for ecological modelling

Czech University of Life Sciences Prague, Institute of Education and Communication,
Complementary pedagogical studies for teachers
(2015 – 2018; certificate for teaching at technical high schools)
Final thesis topic: Design of open source GIS utilization for the teaching of technical subjects

TRAININGS

2018/06 GeoSpatial Summer School G3S Open, Olomouc, CZ
2017/06 Trans-Atlantic Training, Pécs, HU
2017/04 Fundamentals of GNSS, Warsaw, PL
2016/06 Split Summer School on Remote Sensing, Chania, GR

ACADEMIC VISITS

2018/03 Universidad Politécnica de Madrid, Spain (5 weeks)
2017/05 Universita degli Studi Roma Tre, Italy (1 week)
2017/05 Universidad Politécnica de Madrid, Spain (2 weeks)

OTHER DEGREES

2018/06 Complementary pedagogical studies for teachers
2018/02 Authorized operator of rotary-wing UAV (MTOW 1.5 kg)
2017/11 Restricted certificate for radio operator for an aeronautical mobile service
2015/06 Authorized operator of rotary-wing UAV (MTOW 10 kg)

TEACHING EXPERIENCES

Since 2014 Seminars of GIS, Remote Sensing, Remote Sensing using UAVs
Since 2016 Supervision of Bachelor and Master Thesis (applications of UAVs)
2017 High School Teaching Practise (3 weeks)

RESEARCH PROJECTS

2018 – 2019 Detection of infection forest bark beetle (Ips typographus) in advance using unmanned air vehicles. Technology Agency of the Czech Republic. *Co-leader.*

2018 – 2019 Remote sensing: an effective tool for the study of spatial dynamics of bark beetles at Krkonoše National Park. Czech University of Life Sciences Prague. *Co-investigator.*

2017 – 2019 Fusion of LiDAR and UAV borne multispectral data to assess physiographic diversity of post-mining sites. Czech Science Foundation. *UAV operator.*

2017 – 2018 Influence of Remote Sensing Data Resolution in Evaluating Ecological Measures. Czech University of Life Sciences Prague. *Co-investigator*

2016 – 2017 Development and implementation of technologies for digital soil mapping. Czech University of Life Sciences Prague. *GIS support.*

CONFERENCES & WORKSHOPS SPEAKER

2018/07 The IX Conference of the Italian Society of Remote Sensing
Firenze, Italy, *presentation of research topic, in English*

2018/06 Field days out of the air Workshop
Crop Research Institute, Prague, *invited speaker, in Czech*

2018/06 Fifth International Split Remote Sensing Professional Summer School
Prague*, workshop of UAV-borne data processing, in English*

2018/04 Workshop for start-ups, Close-range remote sensing
ESA Business Incubation Centre, Prague, *invited speaker, in Czech*

2017/06 Field days out of the air Workshop
Crop Research Institute, Prague, *invited speaker, in Czech*

2016/09 The second conference of the Alliance for Unmanned Aviation Industry
Alliance for Unmanned Aviation Industry, Prague, *invited speaker, in Czech*

RESEARCH PUBLICATIONS

Komárek J, Klouček T, Prošek J, 2018. The potential of Unmanned Aerial Systems: A tool towards precision classification of hard-to-distinguish vegetation types?
International Journal of Applied Earth Observation and Geoinformation, 71: 9 – 19.

Moravec D, Komárek J, Kumhálová J, Kroulík M, Prošek J, Klápště P, 2017. Digital elevation models as predictors of yield: Comparison of an UAV and other elevation data sources.
Agronomy Research, 15: 249 – 255.

Komárek J, Kumhálová J, Kroulík M, 2016. Surface modelling based on unmanned aerial vehicle photogrammetry and its accuracy assessment.
Engineering for Rural Development 2016, pp 888 – 892, Jelgava, Latvia.

Moudrý V, Komárek J, Šímová P, 2016. Which breeding bird categories should we use in models of species distribution?
Ecological Indicators, 74: 526 – 529.

In press:

Klouček T, Moravec D, Komárek J, Lagner O, Štych P. Selecting appropriate variables for detecting grassland to cropland changes using high resolution satellite data.
(*accepted, PeerJ*)

Moudrý V, Urban R, Štroner, Komárek J, Brouček, Prošek J, 2018. Comparison of a commercial and home-assembled fixed-wing UAV for terrain mapping of a post-mining site under leaf-off conditions.
(accepted, International Journal of Remote Sensing)

Šímová P, Moudrý V, Komárek J, Hrach K, Fortin MJ. Fine scale waterbody data improve prediction of waterbirds occurrence despite coarse species data.
(*accepted, Ecography*)

B – Full text of manuscripts

Int J Appl Earth Obs Geoinformation 71 (2018) 9–19

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

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

The potential of Unmanned Aerial Systems: A tool towards precision classification of hard-to-distinguish vegetation types?

Jan Komárek*, Tomáš Klouček, Jiří Prošek

Department of Applied Geoinformatics and Spatial Planning, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Kamýcká 129, Praha – Suchdol, 165 00, Czech Republic

A R T I C L E I N F O

Keywords:
Low altitude aerial survey
Classification accuracy
Fine spatial resolution
Normalized digital surface model (nDSM)
Geographic object-based image analysis (GEOBIA)
Multispectral and thermal imagery fusion
Image processing
Structure from motion (SfM)

A B S T R A C T

Detail plant species classification using very high spatial resolution data is a challenging task. Exploring the potential of imagery acquired by Unmanned Aerial Vehicle (UAV) to identify individual species of plants and assessing values of additional inputs such as height and thermal information into classification process are hot research topics. Our study uses a fusion of visible, multispectral and thermal imagery acquired through the low altitude aerial survey for detail classification of land cover and vegetation types. The study area is located in the central part of the Czech Republic and situated in an environmentally specific area – an arboretum of 2.45 ha. Visible (i.e. RGB), multispectral, and thermal sensors were mounted on a flying fixed-wing Unmanned Aerial System. The imagery was acquired at a very detailed scale with Ground Sampling Distance of 3–18 cm. Besides three mosaics (one from each sensor), normalized Digital Surface Models were built from visible and multispectral sensors. Eight classification models were created – each mosaic (visible/multispectral) was enriched with height data, thermal data, and combined height and thermal information. A classification into a three level system was performed through Geographic Object-based Image Analysis using Support Vector Machine algorithm. In general, Overall Accuracy grew with the amount of information entering the classification process. Accuracy reached 77 – 91 % depending on the level of generalization for the best model based on multispectral data and 67 – 80 % for data from the visible sensor. Both thermal data and height information improved the accuracy; however, the statistical evaluation did not reveal any significant difference between the contribution of height and thermal data. Results also indicate that increasing spectral resolution leads to a significantly better performance of the models than higher spatial resolution. UAVs equipped with a proper sensor provide a convenient technology for detail land cover classification even in areas with many similar plant species.

1. Introduction

Nowadays, it is relatively easy to acquire one´s own image data with a detailed spatial, sufficient spectral and variable temporal resolution. Unmanned Aerial Vehicles (UAVs) and their use are among the most dynamically developing fields of remote sensing (RS), being a suitable source of data for environmental analyses focused e.g. on classification of vegetation (Gini et al., 2014; Husson et al., 2017; Laliberte et al., 2011; Lisein et al., 2015; Michez et al., 2016; Weil et al., 2017), invasive plant detection (Müllerová et al., 2017), pests (Näsi et al., 2015), plant diseases and water stress detection (Baluja et al., 2012; Berni et al., 2009; Calderón et al., 2013; Nishar et al., 2016; Zarco-Tejada et al., 2012), modelling of individual treetops (Díaz-Varela et al., 2015), in agriculture (Moravec et al., 2017; Pérez-Ortiz et al., 2015), or for monitoring animal species (Chrétien et al., 2016).

One of the major UAV challenges lies in a detail classification of the land cover (Ahmed et al., 2017), which may support decision-making mechanisms and operations. Besides low altitude UAV surveys, other technologies are used for precision classification, e.g., for species classification of trees (Ali et al., 2004; Holmgren et al., 2008), of vegetation specific for various environment types (Alonzo et al., 2014; Bork and Su, 2007; Feng et al., 2015; Hartfield et al., 2011; Husson et al., 2017; Rampi et al., 2014; Reese et al., 2015; Sankey et al., 2017), or a complex land cover classification (Kuria et al., 2014; Szostak et al., 2014; Teo and Huang, 2016; Zhou and Qiu, 2015).

Classification accuracy can be affected by the properties and quality of both the spectral information and height data from (a) digital terrain models (DTMs); (b) digital surface models (DSMs) or (c) normalized digital surface models (nDSM). For land cover classification, a fusion approach combines multi(hyper)-spectral satellite data (Reese et al., 2015; Zhou and Qiu, 2015), airborne (Alonzo et al., 2014; Bork and Su, 2007; Teo and Huang, 2016) and UAV-borne (Sankey et al., 2017) with

* Corresponding author.
E-mail address: komarekjan@fzp.czu.cz (J. Komárek).

https://doi.org/10.1016/j.jag.2018.05.003
Received 5 February 2018; Received in revised form 2 May 2018; Accepted 9 May 2018
0303-2434/ © 2018 Elsevier B.V. All rights reserved.

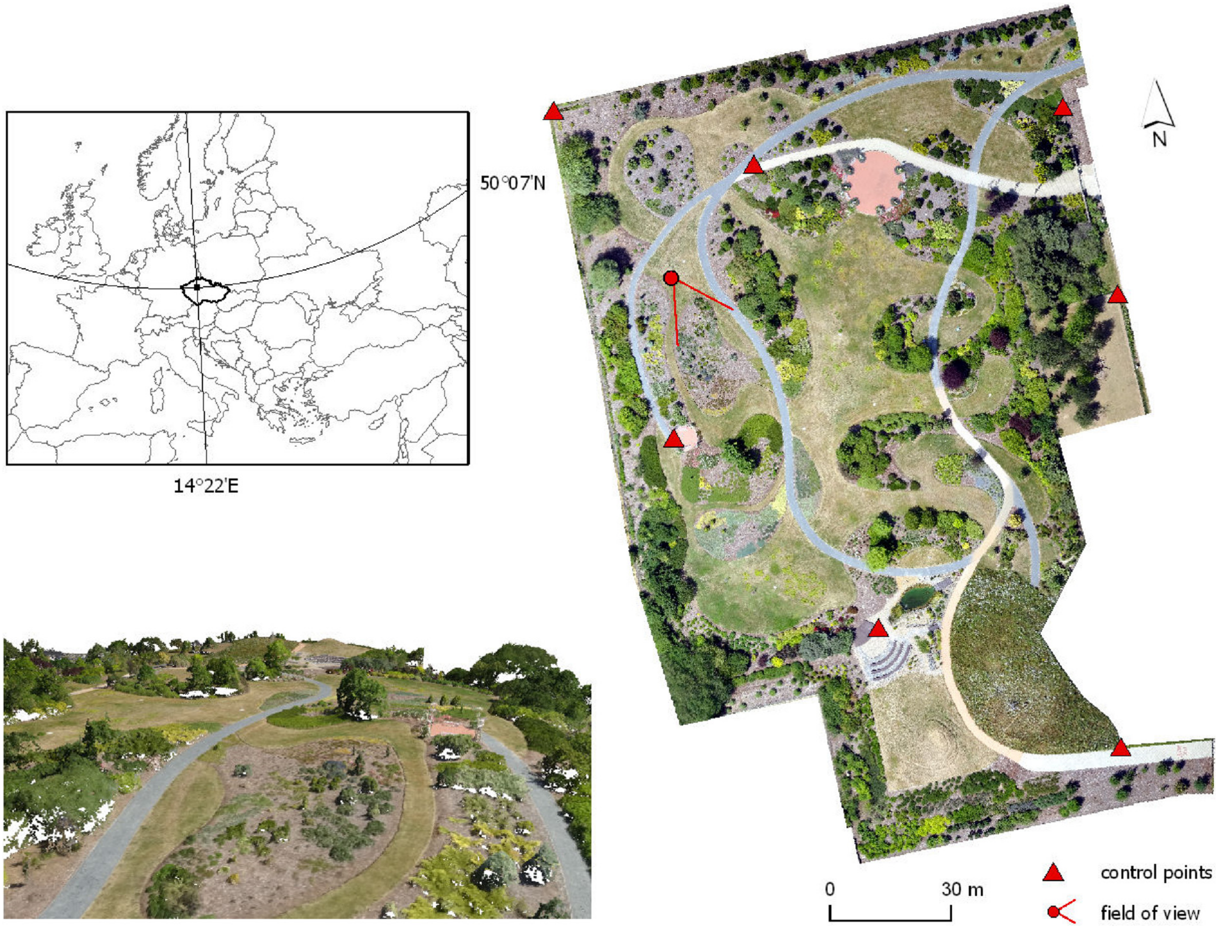

Fig. 1. (Above left) Location of the study area. (Right) The study area, a part of the Libosad arboretum (2.45 ha). Seven ground control points were used to facilitate further data processing. (Bottom left) Oblique view of the coloured densified Point Cloud from the point indicated on the orthophotomap. The map corresponds to ETRS 1898 LAEA projection (EPSG 3035).

Airborne Laser Scanning (Alonzo et al., 2014; Bork and Su, 2007; Holmgren et al., 2008; Zhou and Qiu, 2015) or with airborne images processed through photogrammetric image matching (Reese et al., 2015). The height data (point clouds) can be also derived from UAV-borne imagery by a photogrammetric Structure from Motion (SfM) method. However, the height data are frequently inappropriately neglected during classification utilizing UAV imagery (Feng et al., 2015) despite the fact that they can be instrumental in achieving better results (Husson et al., 2017).

The accuracy of resulting classification is also affected by the classification approach. If processing very high resolution data (e.g. UAV-borne data), classifications based on Geographic Object-based Image Analysis approach (GEOBIA; Blaschke, 2010; Liu et al., 2015) tend to provide better results than the traditional pixel-based approach (Yu et al., 2006). The benefit of GEOBIA has been repeatedly shown in multiple studies utilizing predominantly satellite or airborne high spatial resolution data (Addink et al., 2007; Alonzo et al., 2014; An et al., 2007; Diaz-Varela et al., 2014; Hartfield et al., 2011; Peña et al., 2013).

UAV sensors are typically RGB cameras recording images in visible (Feng et al., 2015; Gini et al., 2014; Husson et al., 2017; Müllerová et al., 2017) or in near infrared spectrum (Ahmed et al., 2017; Weil et al., 2017). RGB cameras are used on a mass scale due to their availability, their classification accuracy is however substantially lower (Ahmed et al., 2017). On the other hand, the higher spatial resolution may act as a substitution for additional spectral bands in specific RS studies. Other sensors, e.g. hyper-spectral cameras or UAV LiDAR (Sankey et al., 2017) are also available, however, their costs are high.

Due to current restrictions and regulations, use of UAV is limited by country-specific legislation. Applicability is also limited by a higher price of miniaturized sensors or a relatively high UAV susceptibility to failures (Freeman and Balas, 2014; Zuiev et al., 2015). UAV is still a novel technology, therefore use is still facing challenges and problems that need to be identified and overcome than the traditional remote sensing methods (Ahmed et al., 2017). The analysis of imagery obtained through other (non-UAV) methods have led to the development of many more or less standardized approaches over the years. It is likely, although not properly verified yet, that for various environment-related analyses, these approaches will be also applicable very high resolution data (magnitude of a few cm). Recent general reviews of UAV applications have been published (Marris, 2013; Pajares, 2015), more studies using different types of UAV imaging sensors are however needed to increase the potential of the utilization of such new platforms in vegetation inventorying and other environmental applications. Despite the fact that UAVs have been a hot research topic in the recent years, only a few studies focused on their usability for precise classification using a set of sensors have been published.

The aim of our study is to evaluate the potential of UAV acquired data (namely of images acquired using visible, multispectral and thermal sensors, and height models – nDSMs – derived from such data) for classification of land cover, particularly on the level of individual plant species. Following research questions are presented: (i) Is it possible to classify individual plant species with a sufficient accuracy based on UAV imagery? (ii) Is it possible to substitute additional spectral data by an RGB sensor with a higher spatial resolution for classification of plant species? (iii) Do the height data contribute to improving the classification more than thermal data? (iv) Do the thermal data constitute an important source of information for detailed land cover classification?

2. Materials and methods

2.1. Study area

The area of interest is an arboretum (called Libosad) on site of the campus of the Czech University of Life Sciences in Prague, Czech Republic (Fig. 1). The arboretum, founded in 2007, takes up 2.67 ha and includes approximately 900 plant species, divided into 22 thematic units. The relief of the area of interest is topographically homogeneous (elevation ranges 280–289 amsl).

2.2. Image data collection

UAV imagery was acquired during the full vegetation period between 20th and 22nd June 2017, always between 12:00 - 13:00 (proper sun angle, minimizing the effect of shadows). The eBee aerial platform (senseFly, Switzerland), a miniature fixed-wing vehicle with a maximum take-off weight approximately 0.8 kg and the wingspan of 0.96 m, was used for image acquisition. The following cameras were used for individual flights: (a) DSC-WX220 (Sony, Japan, Fig. 2A) – a consumer grade digital compact camera; (b) MultiSPEC 4 C (Airinov, France, Fig. 2B) – a 4-channel multispectral camera and (c) ThermoMAP (senseFly, Switzerland, Fig. 2C) – an eBee-ready thermal camera based on FLIR Tau sensor. Detail characteristics of the cameras are available from the manufacturer's websites, parameters important for the study are collected in Tables 1 and 2.

Flight missions were performed using eMotion 2 ground station software. The flight plan was conducted using perpendicular flight lines with 80% overlaps and sidelaps to acquire high quality data. Conditions for UAV flight mission were convenient, ceiling and visibility were fine, the weather was sunny without clouds, the temperature of 30–31 °C, and a light breeze of 2–5 m.s^{-1}. Only vendor-provided sensors, one at a time, can be mounted on the eBee platform. Therefore, three separate specific flights with the UAV equipped with (a) visible (i.e. camera records in a visible part of the spectrum) camera; (b) multispectral camera and (c) thermal camera were conducted; flight details are shown in Table 2 below. A grayscale calibration target with known reflectance values was captured for further image calibration. For data post-processing, a total number of seven Ground Control Points (GCP), designed as 0.5 m white numbered boards with a centre hole for survey rod, was surveyed using GPS Leica 1200 (Leica, Germany) through real-time kinematic connected to the CZEPOS network of permanent GNSS stations.

2.3. Image processing and orthomosaic building

All acquired imagery was processed using a photogrammetric software Pix4Dmapper 3.1.2 (Pix4D S.A., Switzerland). Firstly, point clouds (densified) were created for all data types using stereo-photogrammetry based photo-reconstruction method (Structure from Motion). Orthomosaics were built and accurately georeferenced using Ground Control Points, the Root Mean Square Error (RMSE; mean of X, Y, and Z) was 0.038 m for RGB mosaic and 0.054 m for MSC mosaic. RMSE, which indicates how was the model fitted to the GCPs, was lower than a double value of Ground Sampling Distance (GSD). As the last step, the Surface Reflectance values were calculated from the multispectral mosaic using values from onboard irradiance sensor (Sun irradiance and Sun angle) and the calibration target. The values were subsequently verified in the terrain using the GreenSeeker (Trimble, US) crop sensing system. Similarly, thermal sensor values were corrected using object emissivity values estimated from NDVI vegetation index.

2.4. Creating normalized digital surface models

Digital surface models were created through the Inverse Distance Weighing and using an algorithm implemented in Pix4Dmapper, the digital terrain model with a resolution of 5 x GSD was derived (software limitation due to robustness, see Pix4D User Manual). A normalized

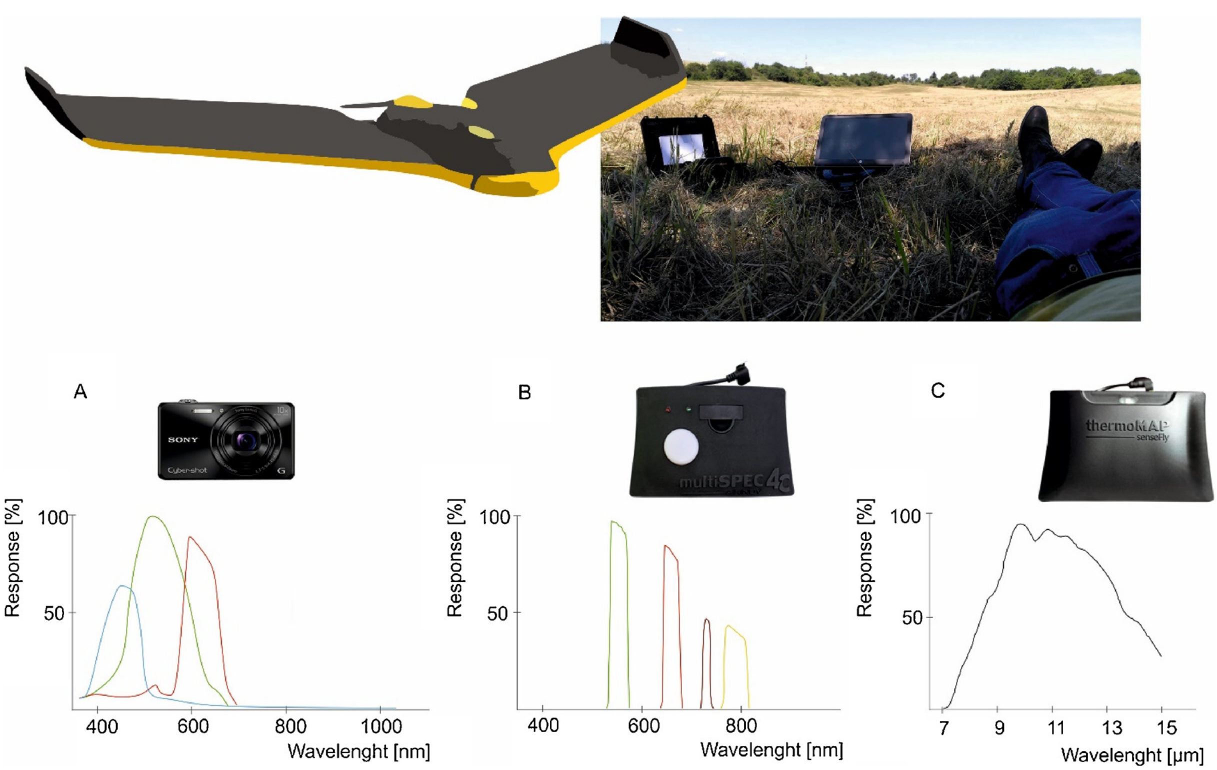

Fig. 2. Used devices: Unmanned Aerial Vehicle eBee was equipped with a visible (A), multispectral (B), and thermal camera (C).

Table 1
Selected characteristics of utilized UAV sensors; abbreviations: B (Blue), G (Green), R (Red), RE (Red Edge), NIR (Near Infrared), LWIR (Long Wavelength Infrared), GSD (Ground Sampling Distance), FWHM (Full Width at Half Maximum).

Sensor (abbreviation)	Image resolution	GSD at 100 m (cm/px)	FWHM (nm)	Band Peak (nm)	Weight (g)
DSC-WX220 (RGB)	17.98 MPx (4896 × 3672)	2.75	B: 410 - 490 G: 460 - 600 R: 580 - 660	B: 460 G: 530 R: 660	113
MultiSPEC 4C (MSC)	4 × 1.23 MPx (1280 × 960)	10	G: 530 - 570 R: 640 - 680 RE: 730 - 740 NIR: 770 - 810	G: 550 R: 660 RE: 735 NIR: 790	160
ThermoMAP (TMP)	0.33 MPx (640 × 512)	18.5	LWIR: 7,500 - 13,500	LWIR 10,000	134

Table 2
Basic parameters of the flight missions and data processing parameters. Flight height, a high number of gained images and points density for ThermoMAP is a subject of technical specification of the sensor; AGL (Above Ground Level).

Sensor	Date of Acquisition	Fly Area (ha)/Fly Time (min)	Fly Height AGL (m)	No. of gained images	No. of aligned images	Avg. points density per m^3
DSC-WX220	June 22	15.0/21	70	218	217	274.5
MultiSPEC 4C	June 20	13.8/27	60	428	408	18.8
ThermoMAP	June 20	10.1/27	100	4794	386	1.6

digital surface model was subsequently created in ArcGIS for Desktop 10.4 (ESRI, US) by subtracting DTM raster from DSM raster for both RGB and MSC mosaics, resulting in two distinct models, namely (a) $nDSM_{RGB}$ and (b) $nDSM_{MSC}$.

2.5. Classification models

Image to image registration was conducted due to different spatial resolutions of built mosaics and models (Table 3). Thermal mosaic and nDSM data were resampled (Nearest Neighbour) to the same pixel size as RGB and MSC mosaics. Input datasets were cropped to fit the study area using ArcGIS and classification models were subsequently created in ENVI 5.4 (Exelis VIS, US). Selected combinations of obtained image mosaics and nDSMs were layered into a single image using the Layer Stacking tool. In total, eight classification models were created from various combinations of input data, see Table 4.

2.6. Delineation of land cover and vegetation types

The land cover structure was created using pre-existing inventory records and maps from 2015, accurately describing the occurrence of plant species in the area of interest. Species represented by less than 10 individuals were not included. This step was necessary for the study as the area of interest was an arboretum containing a high number of species and cultivars with a small number of individuals, which could have possibly complicated the interpretation of the results. The structure contained 24 classes, consisting of 17 elements of living and 7 of inanimate nature on the most detailed level (see Table 5).

Table 4
Classification models. An overview of the eight classification models derived from combinations of selected input datasets.

Classification model	Input dataset
MSC	MSC mosaic
MSC-TMP	MSC mosaic, TMP mosaic
MSC-nDSM	MSC mosaic, $nDSM_{MSC}$
MSC-nDSM-TMP	MSC mosaic, $nDSM_{MSC}$, TMP mosaic
RGB	RGB mosaic
RGB-TMP	RGB mosaic, TMP mosaic
RGB-nDSM	RGB mosaic, $nDSM_{RGB}$
RGB-nDSM-TMP	RGB mosaic, $nDSM_{RGB}$, TMP mosaic

2.7. Ground data collection

The field survey was performed at the same time as the UAV flights by recording exact positions of objects into a detail orthomosaic built within pre-analysis. The data collection process was conducted using a Collector for ArcGIS (ESRI, US) application to verify the inventory records. In total, 436 reference polygons (each containing a single taxonomic individual) covering approx. 7 % of the area of interest were classified into 24 land cover types. For each class, 10 polygons were randomly selected for analysis and each of those sets was, again randomly, divided into training data (5 polygons) and validation data (remaining 5).

2.8. Classification process

Verification of suitability of UAV input data acquired using various sensors for classification was performed through object classification (Blaschke, 2010; Blaschke et al., 2014) using Feature Extraction method

Table 3
Input datasets. Description of the created mosaics (RGB, MSC and TMP) and normalized digital surface models (nDSM).

Input dataset	Bands	Ground Sampling Distance (cm/px)	Description
RGB mosaic	Blue, Green, Red	2.2	Image mosaic built from imagery taken by DSC-WX220 sensor.
MSC mosaic	Green, Red, RE, NIR	5.7	Image mosaic built from imagery taken by MultiSPEC 4 C sensor.
TMP mosaic	LWIR	20.1	Image mosaic built from imagery taken by ThermoMAP sensor.
$nDSM_{RGB}$	Normalized height	10.8	Normalized height created by subtraction of DTM_{RGB} from DSM_{RGB}.
$nDSM_{MSC}$	Normalized height	28.4	Normalized height of objects created subtraction DTM_{MSC} from DSM_{MSC}.

Table 5
A class structure used in the study, consisting of 24 classes divided into a 3-level system.

Level 1	Level 2	Level 3
Coniferous plants	Tall	Fir (*Abies*), Pine (*Pinus*)
	Low (under 3 m)	Juniper (*Juniperus*), Golden Juniper (*Juniperus*), Pine (*Pinus*), Spruce (*Picea*), Yew (*Taxus*), Golden Yew (*Taxus*)
Broadleaf plants	Tall	Maple (*Acer*), Willow (*Salix*)
	Low (under 3 m)	Cotoneaster (*Cotoneaster*), Lavender (*Lavandula*), Cinquefoil (*Potentilla*), Rose (*Rosa*), Spiraea (*Spiraea*)
Herbaceous (Grasses)	Lawns	Lawns
	Meadows	Meadows
Non-vegetation	Artificial surfaces	Pavement, gravel, crushed stones, barkdust, wooden elements, metallic elements
	Shadows	

in ENVI, see Fig. 4 for classification workflow. Individual classification models and training data were used as input data (Table 4). In all, therefore, eight individual classifications using identical training data and classification parameters were performed (see Fig. 3).

Image segmentation was performed using the following parameters: (a) Scale level: 30, Scale Algorithm: Edge, and Segment bands: MSC/RGB bands only; (b) Merge level: 98, Merge Algorithm: Full Lambda Schedule and Merge Bands: MSC/RGB bands only, and (c) Texture Kernel Size: 9. As the software manufacturer recommendation is not to use data with variable value range as Segment bands data, neither nDSM nor thermal data were used for segmentation (ENVI Help). The optimum setting of segmentation parameters was found experimentally using ENVI Preview. In the second step, the classification itself, we used the Support Vector Machine (SVM) classifier in default settings (Radial Basis kernel type) with selected classification attributes (chosen by logic/experimental) as follows: (a) Spectral (Mean, Standard Deviation), (b) Texture (Range, Mean, Variance, Entropy), (c) Spatial (Compactness, Elongation, Hole Area/Solid Area).

2.9. Validation assessment

The accuracy of individual models was assessed through comparison with validation samples. Stratified random sampling design utilizing supervised object-based classification suggested by Zhen et al. (2013) was used. The number of validation samples was set to 600 (Cochran, 1977). In each of the validation polygons of each class, five simple random samples were created. The relative accuracy of the classifications acquired through comparison with validation samples via Confusion Matrix (Foody, 2013; Olofsson et al., 2014; Stehman, 2013), together with 95% Confidence Interval for accuracies in order to cover classification errors. The differences among individual models were tested through a test for homogeneity with a binomial distribution using Holm's p-value adjustment method to compensate for multiple comparisons (used for example by Klouček et al., 2015), see Fig. 5. All statistical analyses were done at three hierarchical levels: (a) Level 1 (4 classes); (b) Level 2 (8 classes); (c) Level 3 (24 classes).

3. Results and discussion

The Overall Accuracy of models in general increases with the amount of information entering the classification process and with decreasing level of detail. The results imply that models based on multispectral data are of significantly better quality than those based solely on data from the visible sensor. The highest Overall Accuracy on the individual levels (Level 1, 2 or 3) was acquired through models combining all input data both for multispectral data (model MSC-nDSM-TMP 77.33 – 90.50 %) and for visible data (model RGB-nDSM-TMP 66.83 – 79.33 %). Conversely, one-input models were the least accurate on any given levels (model MSC 64.00 – 85.00 % and RGB 59.00 – 71.17 %). Addition of a second input did yield a significant improvement of the relative accuracies besides one-input models (MSC-nDSM 73.00 – 86.50 %; MSC-TMP 70.67 – 90.00 %; or RGB-nDSM 64.33 – 75.83 %: RGB-TMP 63.17 – 77.50 %); however no significant differences between the two-input models of both individual sensors were detected with respect to the Overall Accuracy, see Table 6.

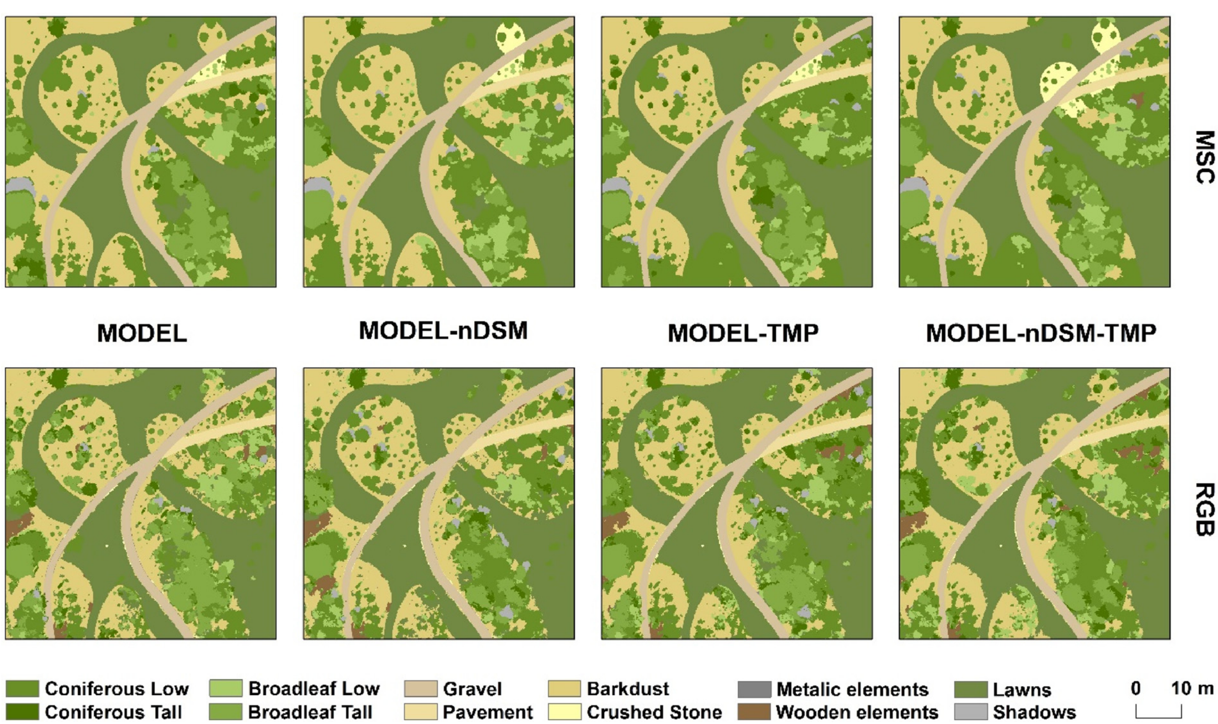

Fig. 3. An example of all created classification models. For clarity, data on artificial surfaces are presented at Level 3 while vegetation classes depicted at Level 2.

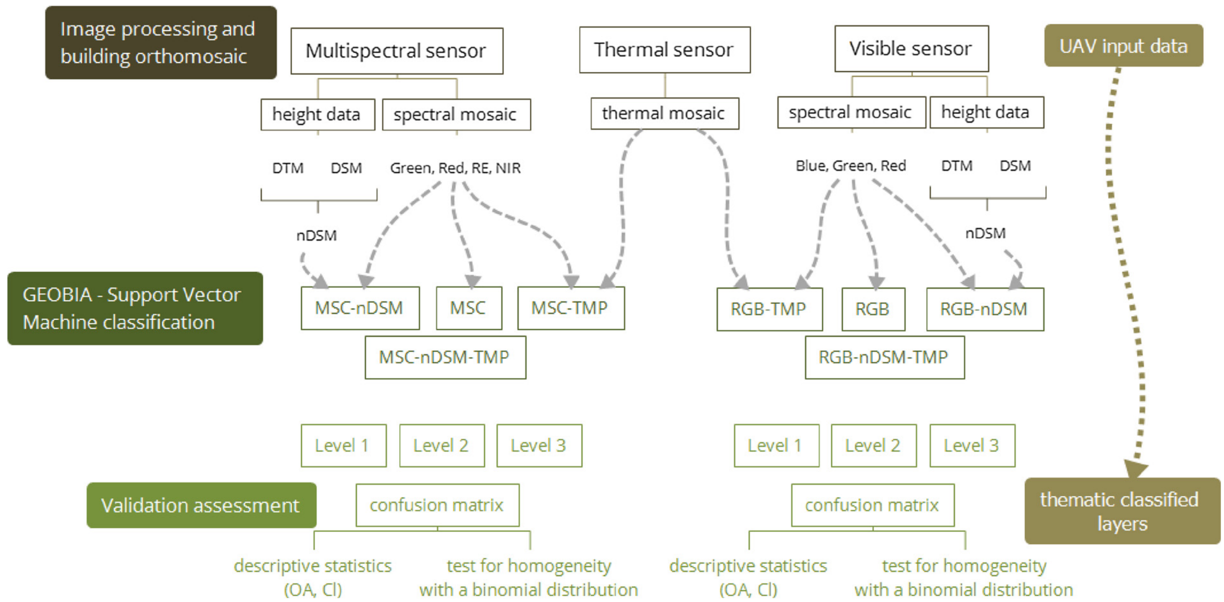

Fig. 4. A scheme depicting the principles of the methodology used in the study.

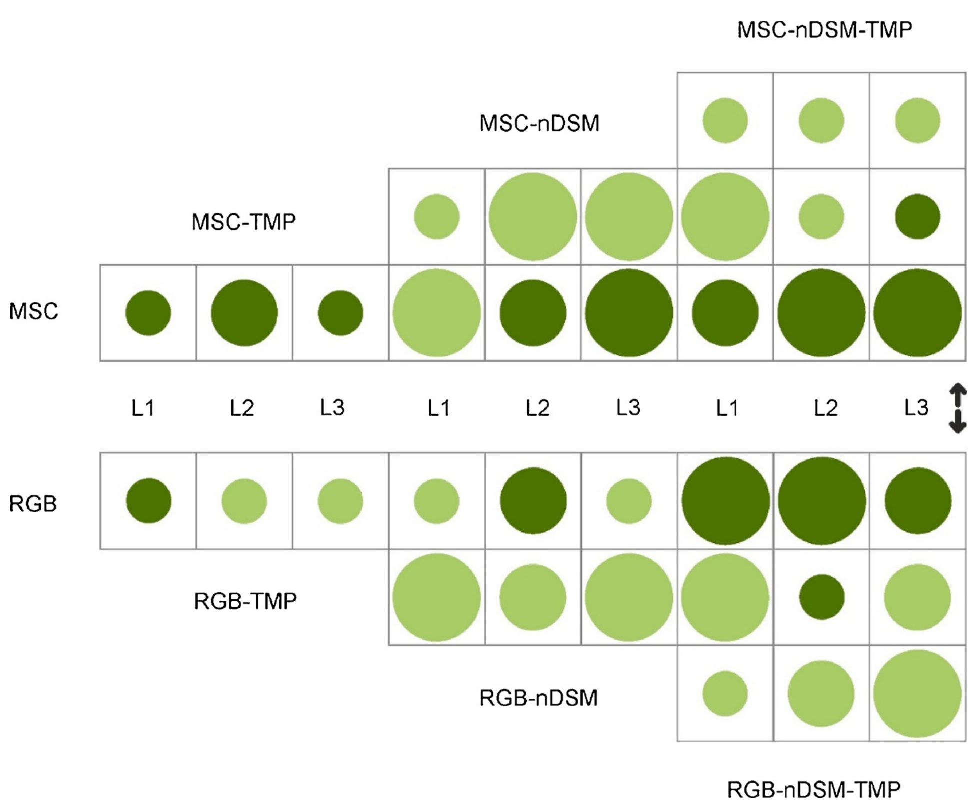

Fig. 5. Test for homogeneity with a binomial distribution of models generated from visible and multispectral sensors. The figure illustrates (dis)similarity of individual models at all levels. Dark represents the statistically significant difference between models (95% level of significance); light represents models that cannot be distinguished at the particular level. The size of the circle illustrates the strength of the relationship (high, moderate, or low).

3.1. *Assessment in individual classes*

3.1.1. *Plant species at level 3*

The overall classification accuracy of individual plant species at the most detailed level grew in the case of MSC based models with the increasing number of input data (51.47 – 69.33 %). For species recognition, the role of height data (63.20 %) appears to be greater than that of the thermal data (57.33 %). However, both inputs have a significant positive impact on the quality of models (see Table 7). MSC-only model was more accurate for recognition of a single species class (e.g. Fir). On the other hand, a two-input model combining the spectral model with thermal data provided significantly better results in four classes, with nDSM data in five classes and models using all inputs were better in eight out of fifteen classes. Regardless of the number of inputs, the worst distinguishable classes were Fir and Cotoneaster. The use of multiple inputs did not yield any significant improvement from using a single MSC input for classes Juniper, Yew, Golden Yew, Willow, Cinquefoil and Rose. The accuracy of recognition of remaining classes was however improved by additional inputs. In all MSC-based models, some classes were significantly overestimated (e.g. Low Pines) while other underestimated (e.g. Cotoneaster), see Fig. 6 for illustration. The misclassification occurred most often between these extremes and the under- and overestimation was decreasing with increasing number of inputs, see Appendix A for details.

Table 6
A comparison of the accuracies of models derived from the multispectral and visible sensors using Support Vector Machine algorithm within object classification; OA = Overall Accuracy (%); 95% CI = 95% Confidence Interval.

Classification model	OA Level 1	95% CI	OA Level 2	95% CI	OA Level 3	95% CI
MSC	85.00	82.14 – 87.86	75.33	71.88 – 78.78	64.00	60.16 – 67.84
MSC-TMP	90.00	87.60 – 92.40	82.17	79.10 – 85.23	70.67	67.02 – 74.31
MSC-nDSM	86.50	83.77 – 89.23	82.00	78.93 – 85.07	73.00	69.45 – 76.55
MSC-nDSM-TMP	90.50	88.15 – 92.85	85.83	83.04 – 88.62	77.33	73.98 – 80.68
RGB	71.17	67.54 – 74.79	64.33	60.50 – 68.17	59.00	55.06 – 62.94
RGB-TMP	77.50	74.16 – 80.84	69.00	65.30 – 72.70	63.17	59.31 – 67.03
RGB-nDSM	75.83	72.41 – 79.26	72.17	68.58 – 75.75	64.33	60.50 – 68.17
RGB-nDSM-TMP	79.33	76.09 – 82.57	75.17	71.71 – 78.62	66.83	63.07 – 70.60

Table 7
A comparison of overall percentage accuracies of models derived from the multispectral and visible sensors for individual models. Level 1a represents the accuracy of analysis focused on differentiation of Coniferous vs Broadleaf plants; Level 1b on Tall vs Low vegetation; Level 2 differentiation between Tall Coniferous, Low Coniferous, Tall Broadleaf, and Low Broadleaf plants; Level 3 presents accuracy of detail plant species classification. Values of Overall Accuracy are derived from the confusion matrix in Appendix A.

Classification model	Level 1a	Level 1b	Level 2	Level 3
MSC	81.07	78.67	65.60	51.47
MSC-TMP	86.93	82.13	74.40	57.33
MSC-nDSM	83.47	89.07	76.27	63.20
MSC-nDSM-TMP	87.73	86.93	80.27	69.33
RGB	60.53	65.87	49.60	42.67
RGB-TMP	71.47	71.73	57.87	50.13
RGB-nDSM	65.07	78.67	59.20	48.27
RGB-nDSM-TMP	74.13	86.13	67.47	55.73

RGB-based models reveal a similar pattern as the MSC-based ones. The contribution of additional inputs, however, unlike for MSC-based models, differed for individual classes and, in most cases, was lower than for corresponding MSC-derived models. The overall classification accuracy of plant species acquired through RGB-based models was in all instances lower than that of MSC-based models. The least accurate model was RGB only (42.67 %) while the most accurate model is RGB-nDSM-TMP (55.73 %). Slightly higher Overall Accuracy was achieved using thermal (50.13 %) than height data (48.27 %), see Table 7. The over- and underestimation of classified individual classes is smaller than in the case of MSC models, see Figs. 6 and 7 for comparison. Conversely, when compared to the one-input RGB model, including TMP into the model provided a significant improvement of accuracy of five classes, including nDSM of six classes and a model containing all input data led to improvement in eight classes. RGB data appear to be ineffectual (throughout all models) for distinguishing classes low Pine, low Spruce and Cinquefoil. Using additional inputs has no effect on the accuracy of classes Golden Juniper and Golden Yew. Conversely, enhancing the models by at least one input leads to a significant improvement of the accuracy of remaining classes, see Appendix A.

3.1.2. Plant species at level 2

At Level 2, MSC-based models show a better Overall Accuracy than RGB-derived models in distinguishing Tall Coniferous, Low Coniferous, Tall Broadleaf, and Low Broadleaf plants (65.60 – 80.27 % for MSC and 49.60 – 67.47 % for RGB) and the accuracy for both grew with the number of inputs, see Table 7. The only class classified more accurately through RGB-based models is Tall Coniferous plants. Conversely, the best accuracy was achieved in both instances for Low Coniferous plants, see results of Level 2 in Appendix A.

3.1.3. Plant species at level 1

Distinguishing Broadleaf and Coniferous plants were also better when using MSC-based models (Overall Accuracy of 81.07 – 87.73 % for MSC vs 60.53 – 74.14 % for RGB; depends on model, Table 7). The difference from the previous levels lies in a significantly higher accuracy of thermal-based two-input models than the height. For both sensors, the classification of Coniferous plants was more accurate than that of the Broadleaf plants (with the exception of the RGB-only model). When enhancing the models with additional inputs, however, the accuracy of the classification of Broadleaf plants grew, significantly more so for MSC-based models (65.14 – 81.14 %) than for RGB-derived models (61.71 – 65.14 %), see Level 1 accuracies in Appendix A. Conversely, when detecting differences in the vegetation height, both RGB and MSC models achieved very high accuracy (78.67 – 89.07 % for MSC vs 65.87 – 86.13 % for RGB), see Table 7. MSC-based models were more accurate where low vegetation was concerned, while RGB-based models provided very similar results for both Low and Tall vegetation.

The accuracy of the MSC and RGB models inside individual classes was increasing with decreasing level of detail, i.e. the incorrect classification occurred more frequently at more detailed levels. Results from all levels and both data types indicate that during classification, the misclassification of Coniferous and Broadleaf plants for Artificial surfaces or Herbaceous plants is negligible while the misclassification for Shadows occurs substantially more often.

3.1.4. Non-vegetation and Herbaceous classes at all levels

The accuracy of models derived from both sensors for Artificial surfaces is high. Additional inputs improve the MSC models' classification (89.33 – 96.00 %) while they do not elicit any significant improvement in RGB model (92.00 – 95.33 %) at Level 3. One of the lowest accuracies were recorded in one-input MSC model in the classification of Gravel, Crushed stone and Metallic elements, which were misclassified for Barkdust. Increasing land cover generalization corresponds with classification accuracy for all sensors and models. At Levels 1 and 2; the accuracy for both MSC and RGB-based models is very high and comparable, see Appendix A.

A similar pattern can be observed in the Herbaceous class where both MSC- and RGB-based models reveal almost similar, highly accurate, results. The Overall Accuracy for Herbaceous is 94.00 – 100 % for MSC and 92.00 – 98.00 % for RGB. Classification of Lawns was performed with lower accuracy than that of Meadows. For example, one-input RBG model lies in negligible misclassification (overestimation) of meadows for classes of low broadleaf plants. The accuracy of Lawns classification is increasing in both sensors with the addition of thermal data while the addition of height information surprisingly does not improve accuracy. Conversely, meadows achieve the same accuracy independently of sensors/models, see Appendix A.

The least accurate results were recorded for the class of Shadows, which was frequently mistaken for Coniferous plants classes (Figs. 6 and 7) and where the Overall Accuracy for either of the sensors did not exceed 60 %. Even here, however, the observation that additional inputs increase the performance was confirmed.

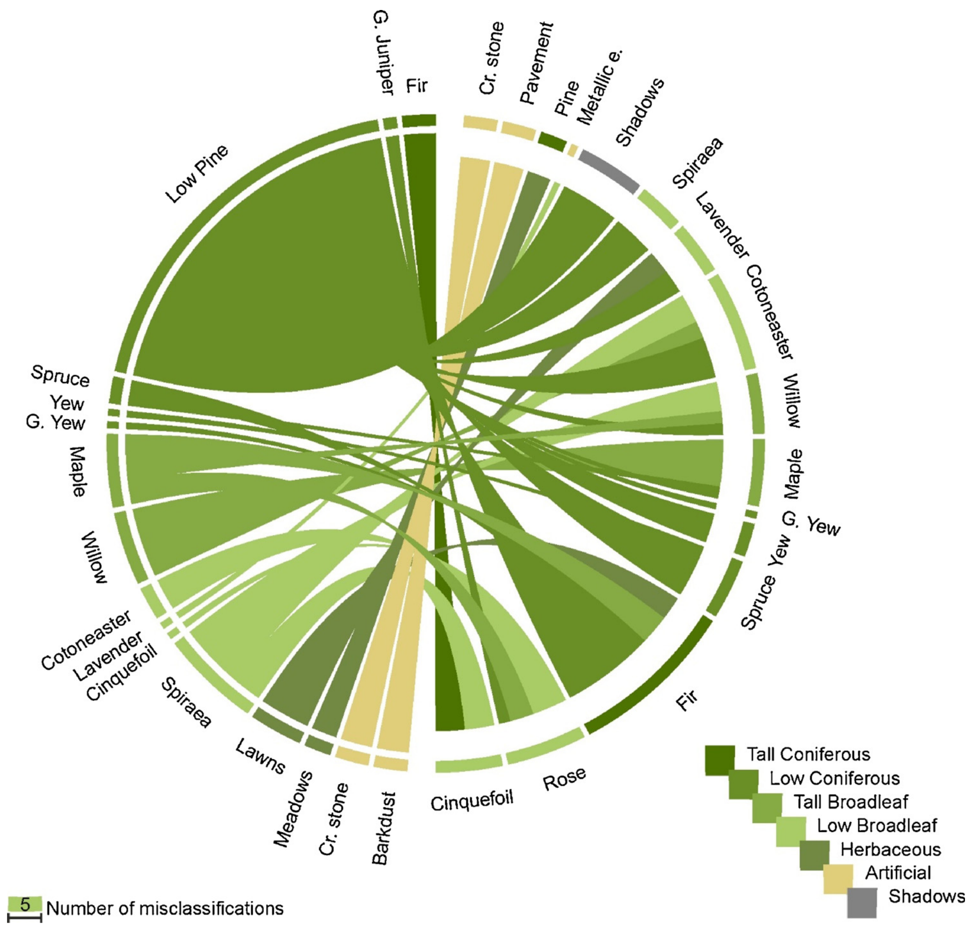

Fig. 6. Visualization of the confusion matrix. The circular plot of the MSC-nDSM-TMP model at Level 3 represents the misclassifications (lines connect misclassified classes, hence the larger section, the more incorrectly classified polygons in the class).

3.2. Overall accuracy assessment

The study results are in the general sense similar for both multispectral and visible sensors. It is obvious that multiple-input based information increases the accuracy of the classification and, therefore, models based on more information provide better results. Besides, models based on multispectral sensor perform better than RGB-derived models. To achieve a detailed classification of the vegetation types, it is therefore not feasible to substitute higher spectral resolution (multispectral sensors) with higher spatial resolution (visible sensor, see RQ ii). In both sensors, it is necessary to use both height and thermal data to achieve the best results at a detailed scale. This requirement, however, increases both the economic and temporal demands on the analysis as well as demands on the personnel performing the analysis and computational capacity. Based on the resulting accuracies, we therefore recommend using a combination of data acquired through a multispectral sensor with nDSM. However, for some classes (e.g. Lawns) or lower detail levels, thermal data are a more significant predictor than nDSM and enhancing the models with thermal data is, therefore, a welcome contribution. Our results also indicate that the land cover and vegetation types can be classified with a sufficient accuracy (almost 81 %) using UAV at the level of individual plant species (RQ i) even in an environmentally very specific area. When analyzing the usability of individual models, it is necessary to take into account, besides Overall Accuracy, their potential for individual classes of the vegetation types as well. For some classes, the accuracy may be inconsistent with the Overall Accuracy due to a lower or, contrary, higher accuracy of other classes.

3.3. Class-specific assessment

Based on the results of the individual plant species (Level 3), multispectral data are necessary for achieving a sufficient accuracy. The RGB spectral resolution is insufficient for distinguishing between these classes as their reflectance values in this bandwidth are very similar and even the addition of height or thermal data cannot make up for this lack of spectral information. The accuracy of most classes is in accordance with the trend of the Overall Accuracy and the assumption that including more inputs into the analysis improves the plant species classification accuracy was confirmed for both thermal and nDSM data.

The Fir class was frequently misclassified for low Pine and Spruce in MSC-based models. A possible explanation for this fact lies in the absence of the blue band in the multispectral data, which may be significant for distinguishing a large number of garden varieties of coniferous plants. The situation was altogether different for Pines that were classified with a sufficient accuracy; pines are present in the non-intervention zone of the arboretum and only one cultivar was present. This simple comparison can lead us to an assumption that in natural or near-natural areas, the classification can be more accurate than in an artificial landscape such as arboretum. The assumption of the blue band significance is further backed by results at Level 1 where RGB models detected Coniferous plants with a greater accuracy than MSC models. To achieve the best Overall Accuracy of classification of both Coniferous and Broadleaf plants (Level 1–3), however, it is necessary to use MSC based models. For classification of Herbaceous and Artificial surfaces, RGB and MSC data are interchangeable and thermal data do not play any significant role as the addition of nDSM data into the model is sufficient to improve the model accuracy. Conversely,

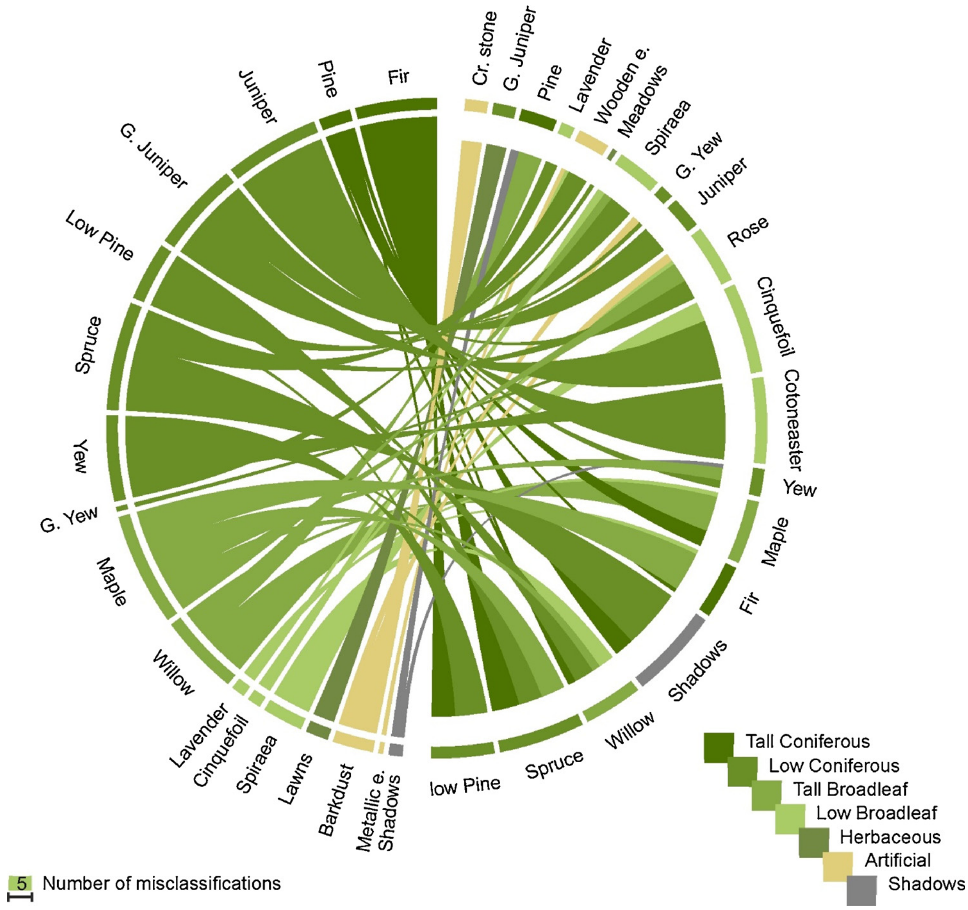

Fig. 7. Visualization of the confusion matrix. The circular plot of the RGB-nDSM-TMP model at Level 3 represents the misclassifications (lines connect misclassified classes, hence the larger section, the more incorrectly classified polygons in the class).

additional data are needed for the class of Shadows as neither MSC, not RGB sensors provide good enough results and their supplementing by nDSM (for RGB sensor) and/or TMP (MSC sensor) improves the results. The need for different additional data is caused by the different spectral characteristics acquired by the different sensors.

3.4. Uncertainties assessment

The accuracy of the performed classifications may be affected, besides the input data, by (a) the selection of the classification system (pixel-based or object-based) and, subsequently, classifier. It is customary in the remote sensing community to use object classification for high resolution data as that type of classification brings multiple benefits. In this case, an SVM non-parametric classifier was selected due to its robustness as it was shown that SVM can be used without compromising accuracy even if the reference polygons are not ideally distributed (Lu and Weng, 2007); (b) the used classification and processing software. The most commonly used classification software in the literature for GEOBIA is the eCognition Developer (Trimble, US) (Husson et al., 2017; Müllerová et al., 2017; Weil et al., 2017) or ENVI software (Ahmed et al., 2017). No study focused on the global comparison of these programs is however available and, therefore, it is hard to make a clear decision on the suitability of one or the other for a particular application. Where photogrammetry is concerned, either Pix4Dmapper or Agisoft PhotoScan (Agisoft LLC, Russia) are the most commonly used. The limitation of Pix4Dmapper is its inability to build a DTM with better spatial resolution than 5 x GSD; (c) the time of UAV image acquisition. Choosing the right season for image acquisition greatly affects the resulting accuracy (Müllerová et al., 2017; Weil et al., 2017). Zhen et al. (2013) and Husson et al. (2017) acquired images in August, Ahmed et al. (2017) in July. Late spring to early summer appeared to be the most suitable month for image acquisition under the conditions of Czech Republic (tempered zone, Northern hemisphere). Images used in our study were acquired in accordance with the literature in full vegetation (Sankey et al., 2017; Weil et al., 2017); (d) used accuracy assessment, based on randomly selected spatially independent validation data (different from the training data) (Zhen et al., 2013). The stratified random sampling design was used for the reference polygons to make sure land cover classes with low spatial extent were not omitted. The accuracy assessment was performed in accordance with the good practice as summarized e.g. by Olofsson et al. (2014). Accuracy assessment using reference polygons may lead to its overestimation by up to 10 %, as reported by Zhen et al. (2013), we minimized that effect by maintaining the percentage representation of individual classes of land cover in the reference polygons (training and validation data) proportional to reality. As accuracy assessment by Confusion Matrix is highly dependent on the area of interest (Olofsson et al., 2014), we have added 95% Confidence Intervals allowing a more general application of results. Another approach used in some studies lies in multiple selections of validation and training data (Weil et al., 2017).

3.5. Comparison with other UAV studies

Our results are in accordance with findings from previous studies, however, to our best knowledge no study published so far took thermal data in detail scale into consideration, much the less combining it with visible, multispectral or height data. Ahmed et al. (2017) achieved 79% accuracy of hierarchical classification of the land cover on a detailed scale (10 categories) when using the visible camera and 82% when using multispectral imagery; height data (DSM, it was not stated if the model was normalized) was used. When taking into account Level 2 in our study with a similar number of categories (8), 72 % accuracy was achieved for RGB and 82 % for MSC when including height data (nDSM); further enhancement of the model with thermal data led to an increase of accuracy to 75 % and 86 %, respectively. Weil et al. (2017) reported an average accuracy of their classification of nine categories to be 85 % (predominantly forest and herbaceous vegetation in the East Mediterranean). A combination of SVM and object classification was used by Müllerová et al. (2017) who achieved 65 – 86 % accuracy of their binary detection of invasive plant species in the Czech Republic by the visible camera. One of the few studies systematically utilizing nDSM for UAV-based vegetation classification is the study by Husson et al. (2017) using object based classification and Random Forest classifier. The accuracy of recognition of individual water plant species in their study ranged from 52 to 75 %. In our study, the accuracy on a similar detail based on visible data was 60 – 68 %, increasing to 63 – 71 % when including thermal data into the model and even to 74 – 81 % where visible data were replaced with multispectral. Their results are in agreement with ours also in the conclusion that the accuracy decreases with the increasing complexity of the vegetation/land cover. The contribution of the height data for classification of (semi)arid species was also confirmed by Sankey et al. (2017) who combined data from UAV-mounted hyper-spectral sensor and LiDAR for six categories (one of which were shadows as well) to achieve an 84 – 89 % Overall Accuracy and 72 – 76 % accuracy where only hyper-spectral data were involved. Similarly to our study, Shadows belonged to the most problematic categories in their study, particularly so when using hyperspectral data only.

The study results do not confirm the usability of visible sensor for a detailed classification of land cover at the level of species, which is in accordance with the findings of the above mentioned studies related to aquatic plants (Husson et al., 2017), park greenery (Gini et al., 2014) or detection of invasive plant species (Müllerová et al., 2017). It is obvious that not even higher spatial resolution can for this purpose act as a surrogate for the missing spectral channels, not even in models utilizing nDSM data where the more detailed height information could have increased the RGB model performance. The visible sensor can be however successfully used for detailed classification of Artificial surfaces and for basic classification of Herbaceous plants. Thanks to the presence of the blue channel, RGB can be used for satisfactory species classification of Coniferous plants. However, the multispectral sensor provides general better results despite the missing blue band.

We could possibly increase the accuracy by substituting the multispectral sensor with hyperspectral (Sankey et al., 2017). The question of the degree of improvement when using such an expensive high-grade technology, however, remains unanswered. We can also assume that using multispectral cameras with a higher spectral resolution, such as Micasense Rededge (Weil et al., 2017), Parrot Sequoia (Ahmed et al., 2017) or Tetracam Multi-Camera Array (Laliberte et al., 2011) could further improve the accuracy of the classification and increase the difference between the performance of the multispectral and visible sensors, a comparison is however also missing at present. On the other hand, the accuracy of SfM-derived point clouds is comparable to that of LiDAR-derived point clouds (Koska et al., 2017) and, therefore, if the vertical structure of the vegetation at each point is not of concern and only the information about the vegetation surface is sufficient, investment into this expensive sensor is not necessary for classification of vegetation.

3.6. General assessment

For a general purpose in any classification analysis based on UAV-borne data, we recommend the combination of a multispectral sensor and nDSM as the most efficient method requiring only a single flight (as the height information can be easily extracted during UAV imagery processing). A statistical evaluation has not revealed if nDSM or TMP data are more valuable for the classification (RQ iii); however, adding any one of these two into the MSC-based model significantly improved the accuracy (RQ iv). When searching for the best compromise between the number of sensors used (costs) and a sufficient classification accuracy, the answer can differ with the level of detail. As it is not possible to generalize the results, a test for homogeneity with binomial distribution was performed for every pair of models. Results indicate that models based on multiple inputs can be utilized for classification of individual plant species; however, distinguishing among individual multi-input models is more difficult (Fig. 5). Our study area contains multiple cultivars with not entirely natural height, which potentially affect the result of classification. It can be therefore assumed that in a more natural environment with a smaller number of species, it is possible to achieve even better results and accuracies. We also assume that in such environments, even various models based on two inputs could give results that will be distinguishable both mutually and from all-input models. However, further studies are needed to verify these hypotheses.

4. Conclusion

The study proves the contribution of UAV-borne thermal and height data for classification of land cover and vegetation types. Thermal data and normalized height (nDSM) inputs increase classification accuracy when compared to spectral data only, even in a very specific environment of an arboretum. The best Overall Accuracy was achieved by combining all acquired input datasets on the multispectral sensor. The results confirmed our hypotheses that (RQ i) it is possible to classify individual plant species with a sufficient accuracy using UAV-borne data; (RQ ii) RGB sensor with a better spatial resolution cannot fully substitute additional spectral information acquired using MSC sensors; and that (RQ iv) thermal data are an important source of information distinguishing some classes. On the other hand, the hypothesis (RQ iii) that the height data contribute to the accuracy more than thermal data was not confirmed. Nevertheless, it is clear that UAV technology is, providing suitable parameters and input data, a powerful tool for a detailed and accurate classification of the land cover and recognition of plant species.

Funding

This study was supported by the Czech University of Life Sciences Prague, project No. CIGA 20184206.

Acknowledgements

We acknowledge the anonymous referees for their constructive comments. Also, many thanks for the helpful comments to our colleagues from the Department of Applied Geoinformatics and Spatial Planning at the Czech University of Life Sciences Prague (CULS). We would also like to thank Michal Fogl and Magda Ejemová for help with ground data collection, Ondřej Lagner for help with the acquisition of UAV imagery and Vojtěch Barták for help with R.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jag.2018.05.003.

References

Addink, E.A., deJong, S.M., Pebesma, E.J., 2007. The importance of scale in object oriented mapping of vegetation mparameters with hyperspectral imagery. Photogramm. Eng. Remote Sens. 73, 905–912.

Ahmed, O.S., Shemrock, A., Chabot, D., Dillon, C., Williams, G., Wasson, R., Franklin, S.E., 2017. Hierarchical land cover and vegetation classification using multispectral data acquired from an unmanned aerial vehicle. Int. J. Remote Sens. 38, 2037–2052. http://dx.doi.org/10.1080/01431161.2017.1294781.
Ali, S.S., Dare, P., Jones, S.D., 2004. Fusion of remotely sensed multispectral imagery and lidar data for Forest structure assessment at the tree level. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. XXXVII, 1089–1094.
Alonzo, M., Bookhagen, B., Roberts, D.A., 2014. Urban tree species mapping using hyperspectral and lidar data fusion. Remote Sens. Environ. 148, 70–83. http://dx.doi.org/10.1016/j.rse.2014.03.018.
An, K., Zhang, J., Xiao, Y., 2007. Object-oriented urban dynamic monitoring — a case study of Haidian District of Beijing. Chin. Geogr. Sci. 17, 236–242. http://dx.doi.org/10.1007/s11769-007-0236-1.
Baluja, J., Diago, M.P., Balda, P., Zorer, R., Meggio, F., Morales, F., Tardaguila, J., 2012. Assessment of vineyard water status variability by thermal and multispectral imagery using an unmanned aerial vehicle (UAV). Irrig. Sci. 30, 511–522. http://dx.doi.org/10.1007/s00271-012-0382-9.
Berni, J.A.J., Zarco-Tejada, P.J., Suárez, L., González-Dugo, V., Fereres, E., 2009. Remote sensing of vegetation from UAV platforms using lightweight multispectral and thermal imaging sensors. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 38.
Blaschke, T., 2010. Object based image analysis for remote sensing. ISPRS J. Photogramm. Remote Sens. 65, 2–16. http://dx.doi.org/10.1016/j.isprsjprs.2009.06.004.
Blaschke, T., Hay, G.J., Kelly, M., Lang, S., Hofmann, P., Addink, E., Queiroz Feitosa, R., van der Meer, F., van der Werff, H., van Coillie, F., Tiede, D., 2014. Geographic object-based image analysis - towards a new paradigm. ISPRS J. Photogramm. Remote Sens. 87, 180–191. http://dx.doi.org/10.1016/j.isprsjprs.2013.09.014.
Bork, E.W., Su, J.G., 2007. Integrating LIDAR data and multispectral imagery for enhanced classification of rangeland vegetation: a meta analysis. Remote Sens. Environ. 111, 11–24. http://dx.doi.org/10.1016/j.rse.2007.03.011.
Calderón, R., Navas-Cortés, J.A., Lucena, C., Zarco-Tejada, P.J., 2013. High-resolution airborne hyperspectral and thermal imagery for early detection of verticillium wilt of olive using fluorescence, temperature and narrow-band spectral indices. Remote Sens. Environ. 139, 231–245. http://dx.doi.org/10.1016/J.RSE.2013.07.031.
Cochran, G.W., 1977. Sampling Techniques. Wiley.
Díaz-Varela, R.A., de la Rosa, R., León, L., Zarco-Tejada, P.J., 2015. High-resolution airborne UAV imagery to assess olive tree crown parameters using 3D photo reconstruction: application in breeding trials. Remote Sens. 7, 4213–4232. http://dx.doi.org/10.3390/rs70404213.
Diaz-Varela, R.A., Zarco-Tejada, P.J., Angileri, V., Loudjani, P., 2014. Automatic identification of agricultural terraces through object- oriented analysis of very high resolution DSMs and multispectral imagery obtained from an unmanned aerial vehicle. J. Environ. Manage. 134, 117–126. http://dx.doi.org/10.1016/j.jenvman.2014.01.006.
Feng, Q., Liu, J., Gong, J., 2015. UAV remote sensing for urban vegetation mapping using random forest and texture analysis. Remote Sens. 7, 1074–1094. http://dx.doi.org/10.3390/rs70101074.
Foody, G.M., 2013. Ground reference data error and the mis-estimation of the Area of land cover change as a function of its abundance. Remote Sens. Lett. 4, 783–792. http://dx.doi.org/10.1080/2150704X.2013.798708.
Freeman, P., Balas, G.J., 2014. Actuation failure modes and effects analysis for a small UAV. 2014 American Control Conference. IEEE 1292–1297. http://dx.doi.org/10.1109/ACC.2014.6859482.
Gini, R., Passoni, D., Pinto, L., Sona, G., 2014. Use of unmanned aerial systems for multispectral survey and tree classification: a test in a park area of northern Italy. Eur. J. Remote Sens. 47, 251–269. http://dx.doi.org/10.5721/EuJRS20144716.
Hartfield, K.A., Landau, K.I., van Leeuwen, W.J.D., 2011. Fusion of high resolution aerial multispectral and lidar data: Land cover in the context of urban mosquito habitat. Remote Sens. 3, 2364–2383. http://dx.doi.org/10.3390/rs3112364.
Holmgren, J., Persson, Å., Söderman, U., Persson, A., Söderman, U., 2008. Species identification of individual trees by combining high resolution LiDAR data with multi-spectral images. Int. J. Remote Sens. 29, 1537–1552. http://dx.doi.org/10.1080/01431160701736471.
Husson, E., Reese, H., Ecke, F., 2017. Combining spectral data and a DSM from UAS-images for improved classification of non-submerged aquatic vegetation. Remote Sens. 9, 1–15. http://dx.doi.org/10.3390/rs9030247.
Chrétien, L.-P., Théau, J., Ménard, P., 2016. Visible and thermal infrared remote sensing for the detection of white-tailed deer using an unmanned aerial system. Wildl. Soc. Bull. 40, 181–191. http://dx.doi.org/10.1002/wsb.629.
Klouček, T., Lagner, O., Šímová, P., 2015. How does data accuracy influence the reliability of digital viewshed models? A case study with wind turbines. Appl. Geogr. 64, 46–54. http://dx.doi.org/10.1016/J.APGEOG.2015.09.005.
Koska, B., Jirka, V., Urban, R., Křemen, T., Hesslerová, P., Jon, J., Pospíšil, J., Fogl, M., 2017. Suitability, characteristics, and comparison of an airship UAV with lidar for middle size area mapping. Int. J. Remote Sens. 38, 2973–2990. http://dx.doi.org/10.1080/01431161.2017.1285086.
Kuria, D.N., Menz, G., Misana, S., Mwita, E., Thamm, H., Alvarez, M., Mogha, N., Becker, M., Oyieke, H., 2014. Seasonal vegetation changes in the Malinda wetland using Bi-temporal, multi-sensor, very high resolution remote sensing data sets. Adv. Remote Sens. 3, 33–48. http://dx.doi.org/10.4236/ars.2014.31004.
Laliberte, A.S., Goforth, M.A., Steele, C.M., Rango, A., 2011. Multispectral remote sensing from unmanned aircraft: image processing workflows and applications for rangeland environments. Remote Sens. 3, 2529–2551. http://dx.doi.org/10.3390/rs3112529.
Lisein, J., Michez, A., Claessens, H., Lejeune, P., 2015. Discrimination of deciduous tree species from time series of unmanned aerial system imagery. PLoS One 10, 1–20. http://dx.doi.org/10.1371/journal.pone.0141006.
Liu, J., Li, P., Wang, X., 2015. A new segmentation method for very high resolution imagery using spectral and morphological information. ISPRS J. Photogramm. Remote Sens. 101, 145–162. http://dx.doi.org/10.1016/j.isprsjprs.2014.11.009.
Lu, D., Weng, Q., 2007. A survey of image classification methods and techniques for improving classification performance. Int. J. Remote Sens. http://dx.doi.org/10.1080/01431160600746456.
Marris, E., 2013. Drones in science: fly, and bring me data. Nature 498, 156–158. http://dx.doi.org/10.1038/498156a.
Michez, A., Piégay, H., Lisein, J., Claessens, H., Lejeune, P., 2016. Classification of riparian forest species and health condition using multi-temporal and hyperspatial imagery from unmanned aerial system. Environ. Monit. Assess. 188, 1–19. http://dx.doi.org/10.1007/s10661-015-4996-2.
Moravec, D., Komárek, J., Kumhálová, J., Kroulík, M., Prošek, J., Klápště, P., 2017. Digital elevation models as predictors of yield: comparison of an UAV and other elevation data sources. Agron. Res. 15, 249–255.
Müllerová, J., Brůna, J., Bartaloš, T., Dvořák, P., Vítková, M., Pyšek, P., 2017. Timing Is important: unmanned aircraft vs. Satellite imagery in plant invasion monitoring. Front. Plant Sci. 8, 1–13. http://dx.doi.org/10.3389/fpls.2017.00887.
Näsi, R., Honkavaara, E., Lyytikäinen-Saarenmaa, P., Blomqvist, M., Litkey, P., Hakala, T., Viljanen, N., Kantola, T., Tanhuanpää, T., Holopainen, M., 2015. Using uav-based photogrammetry and hyperspectral imaging for mapping bark beetle damage at tree-level. Remote Sens. 7, 15467–15493. http://dx.doi.org/10.3390/rs71115467.
Nishar, A., Richards, S., Breen, D., Robertson, J., Breen, B., 2016. Thermal infrared imaging of geothermal environments and by an unmanned aerial vehicle (UAV): a case study of the Wairakei – Tauhara geothermal field, Taupo, New Zealand. Renew. Energy 86, 1256–1264. http://dx.doi.org/10.1016/J.RENENE.2015.09.042.
Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., Wulder, M.A., 2014. Good practices for estimating area and assessing accuracy of land change. Remote Sens. Environ. 148, 42–57. http://dx.doi.org/10.1016/j.rse.2014.02.015.
Pajares, G., 2015. Overview and current Status of remote sensing applications based on unmanned aerial vehicles (UAVs). Photogramm. Eng. Remote Sens. 81, 281–329. http://dx.doi.org/10.14358/PERS.81.4.281.
Peña, J.M., Torres-Sánchez, J., Isabel De Castro, A., Kelly, M., López-Granados, F., 2013. Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) images. PLoS One 8. http://dx.doi.org/10.1371/journal.pone.0077151.
Pérez-Ortiz, M., Peña, J.M., Gutiérrez, P.A., Torres-Sánchez, J., Hervás-Martínez, C., López-Granados, F., 2015. A semi-supervised system for weed mapping in sunflower crops using unmanned aerial vehicles and a crop row detection method. Appl. Soft. Comput. 37, 533–544. http://dx.doi.org/10.1016/J.ASOC.2015.08.027.
Rampi, L.P., Knight, J.F., Pelletier, K.C., 2014. Wetland mapping in the Upper Midwest United States. Photogramm. Eng. Remote Sens. 80, 439–448. http://dx.doi.org/10.14358/PERS.80.5.439.
Reese, H., Nordkvist, K., Nyström, M., Bohlin, J., Olsson, H., 2015. Combining point clouds from image matching with SPOT 5 multispectral data for mountain vegetation classification. Int. J. Remote Sens. 36, 403–416. http://dx.doi.org/10.1080/2150704X.2014.999382.
Sankey, T., Donager, J., McVay, J., Sankey, J.B., 2017. UAV lidar and hyperspectral fusion for forest monitoring in the southwestern USA. Remote Sens. Environ. 195, 30–43. http://dx.doi.org/10.1016/j.rse.2017.04.007.
Stehman, S.V., 2013. Estimating area from an accuracy assessment error matrix. Remote Sens. Environ. 132, 202–211. http://dx.doi.org/10.1016/j.rse.2013.01.016.
Szostak, M., Wezyk, P., Tompalski, P., 2014. Aerial orthophoto and airborne laser scanning as monitoring tools for Land cover dynamics: a case study from the Milicz Forest District (Poland). Pure Appl. Geophys. 171, 857–866. http://dx.doi.org/10.1007/s00024-013-0668-8.
Teo, T.-A., Huang, C.-H., 2016. Object-Based Land cover classification using airborne lidar and different spectral images. Terr. Atmos. Ocean. Sci. 27, 491. http://dx.doi.org/10.3319/TAO.2016.01.29.01(ISRS).
Weil, G., Lensky, I., Resheff, Y., Levin, N., 2017. Optimizing the timing of unmanned aerial vehicle image acquisition for applied mapping of woody vegetation species using feature selection. Remote Sens. 9, 1130. http://dx.doi.org/10.3390/rs9111130.
Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M., Schirokauer, D., 2006. Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery. Photogramm. Eng. Remote Sens. 72, 799–811. http://dx.doi.org/10.14358/PERS.72.7.799.
Zarco-Tejada, P.J., González-Dugo, V., Berni, J.A.J., 2012. Fluorescence, temperature and narrow-band indices acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera. Remote Sens. Environ. 117, 322–337. http://dx.doi.org/10.1016/J.RSE.2011.10.007.
Zhen, Z., Quackenbush, L.J., Stehman, S.V., Zhang, L., 2013. Impact of training and validation sample selection on classification accuracy and accuracy assessment when using reference polygons in object-based classification. Int. J. Remote Sens. 34, 6914–6930. http://dx.doi.org/10.1080/01431161.2013.810822.
Zhou, Y., Qiu, F., 2015. Fusion of high spatial resolution WorldView-2 imagery and LiDAR pseudo-waveform for object-based image analysis. ISPRS J. Photogramm. Remote Sens. 101, 221–232. http://dx.doi.org/10.1016/j.isprsjprs.2014.12.013.
Zuiev, O.V., Demydko, V.G., Musyenko, A.O., Gerasymenko, T.S., 2015. Analysis of control processes influence on UAV equipment classification veracity. 2015 IEEE International Conference Actual Problems of Unmanned Aerial Vehicles Developments (APUAVD). IEEE 102–105. http://dx.doi.org/10.1109/APUAVD.2015.7346572.

Q1

Please only ANNOTATE the proof. Do not edit the PDF. If multiple authors will review this PDF, please return one file containing all corrections.

Selecting appropriate variables for detecting grassland to cropland changes using high resolution satellite data

Tomáš Klouček[1], David Moravec[1], Jan Komárek[1], Ondřej Lagner[1] and Přemysl Štych[2]

[1] Department of Applied Geoinformatics and Spatial Planning, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Czech University of Life Sciences Prague, Prague, Czech Republic

[2] Department of Applied Geoinformatics and Cartography, Faculty of Science, Charles University in Prague, Charles University in Prague, Prague, Czech Republic

Submitted 27 February 2018
Accepted 30 July 2018
Published 23 August 2018

Corresponding author
Tomáš Klouček, tkloucek@fzp.czu.cz

Academic editor
Le Yu

Additional Information and Declarations can be found on page 15

DOI 10.7717/peerj.5487

Copyright
2018 Klouček et al.

Distributed under
Creative Commons CC-BY 4.0

OPEN ACCESS

ABSTRACT

Grassland is one of the most represented, while at the same time, ecologically endangered land cover categories in the European Union. In view of the global climate change, detecting its change is growing in importance from both an environmental and a socio-economic point of view. A well-recognised tool for Land Use and Land Cover (LULC) Change Detection (CD), including grassland changes, is Remote Sensing (RS). An important aspect affecting the accuracy of change detection is the finding the optimal indicators of LULC changes (i.e., variables). Inappropriately selected variables can produce inaccurate results burdened with a number of uncertainties. The aim of our study is to find the most suitable variables for the detection of grassland to cropland change, based on a pair of high resolution images acquired by the Landsat 8 satellite and from the vector database Land Parcel Identification System (LPIS). In total, 59 variables were used to create models using Generalised Linear Models (GLM), the quality of which was verified through multi-temporal object-based change detection. Satisfactory accuracy for the detection of grassland to cropland change was achieved using all of the statistically identified models. However, a three-variable model can be recommended for practical use, namely by combining the Normalised Difference Vegetation Index (NDVI), Wetness and Fifth components of Tasselled Cap. Increasing number of variables did not significantly improve the accuracy of detection, but rather complicated the interpretation of the results and was less accurate than detection based on the original Landsat 8 images. The results obtained using these three variables are applicable in landscape management, agriculture, subsidy policy, or in updating existing LULC databases. Further research implementing these variables in combination with spatial data obtained by other RS techniques is needed.

Subjects Natural Resource Management, Spatial and Geographic Information Science
Keywords Change detection (CD), Grassland, Tasseled Cap (TC), Cropland, Normalized Difference Vegetation Index (NDVI), Variables

INTRODUCTION

Land Use and Land Cover (LULC) techniques form an integral part of many studies (*Kindu et al., 2013*; *Gupta & Shukla, 2016*; *Chaudhuri & Mishra, 2016*) overlapping with other research fields (*Cardinale et al., 2012*). LULC is considered an important factor influencing the environment and its changes have a demonstrable impact on climate change (Tasser, Leitinger & Tappeiner, 2017). Among the land cover types in the European Union (EU), grassland and cropland are the most prominent, accounting for 44% of the total area (Eurostat, 2017). Since the 1990s, the main LULC change trends in most post-communist Central European countries are afforestation, grassing over, intensification, and urbanisation. Even though the change of grassland to cropland is not as frequent a transition as it was during the communist era (Kupková & Bičík, 2016), it still elicits a significant impact on the ecosystem. Grassland plays an irreplaceable role as a natural habitat of many organisms, helps with the accumulation of greenhouse gases, prevents erosion, keeps water in the landscape and reduces pollution (European Union, 2016). However, these benefits are easily disrupted by ploughing the grassland, thus turning it into cropland. It is, therefore, important to detect such changes, quantify them and continuously monitor the developments. The occurrence of new cropland at the expense of grassland is especially prominent in post-communist states that have recently joined the EU and started to receive agricultural subsidies (Pazúr et al., 2014). This process is also affected by a number of national and European agricultural policies and initiatives (Sklenicka et al., 2014), such as the Good Agricultural and Environmental Conditions (GAEC) (Sklenicka et al., 2015). Change data acquired from remote sensing based models can, therefore, serve both as a basis for decision-making in the landscape management and have a socio-economic application in agriculture and its subsidy policy (Esch et al., 2014).

The primary data source for LULC Change Detection (CD) is Remote Sensing (RS). Multi-spectral satellite images are one of the most commonly used types of RS data, among which Landsat satellites images stand out due to long-term imaging, a suitable compromise between spectral, spatial and temporal resolution and free availability (Wulder et al., 2008; Xian, Homer & Fry, 2009; Chen et al., 2012; Roy, Ghosh & Ghosh, 2014). LULC change detection using RS data is based on the theoretical assumption that each LULC type has its own typical spectral signatures. If an LULC type changes, so will change its spectral signatures (Hussain et al., 2013). In practice, it is often difficult to distinguish the signal of true changes from the false signals arising from external factors (different atmospheric conditions, soil moisture, or the phenological stage Jensen, 1996), the selection of RS data (Lu, Li & Moran, 2014), pre-processing (Dai, 1998) and atmospheric corrections (Song et al., 2001), the choice of the change detection method, the selection of the variables or the inexperience of the analyst (Lu et al., 2003). The significance of these uncertainties is even greater in LULC objects with very similar spectral signatures, which is exactly the case of croplands with a high degree of heterogeneity and significant effects of different phenological phases of individual crops and plants (Lu et al., 2003).

Some studies dealing with the classification and change detection of grassland and cropland have been published (Chen & Rao, 2008; Esch et al., 2014). These categories are often a part of a comprehensive change detection study (Mas, 1999; Bergen et al., 2005; Wondrade, Dick & Tveite, 2014; Vorovencii, 2014). We can also find studies aimed at a more detailed classification on the level of individual croplands (Wardlow, Egbert & Kastens, 2007; Turker & Ozdarici, 2011) or on grassland change detection (Weeks et al., 2013). Studies focusing specifically on grassland to cropland change are, however, still exceedingly rare (*Tarantino et al., 2016*). Among the studies closest to the topic of our study, the papers by *Tarantino et al. (2016)*, who achieved 86.91% accuracy in the detection of semi-natural grassland to cropland changes in Italy using a cross-correlation analysis of Landsat 8 OLI images, and by *Weeks et al. (2013)*, who used NDVI differencing for the change of "indigenous" grasslands in New Zealand and achieved 56% accuracy, can be mentioned.

Many papers have been published that reviewed the methods and techniques used for the detection of LULC changes (*Singh, 1989*; *Lyon et al., 1998*; *Lu et al., 2003*; *Coppin et al., 2004*; *Berberoglu & Akin, 2009*; *Bhandari, Kumar & Singh, 2012*; *Hussain et al., 2013*; *Lu, Li & Moran, 2014*; *Tewkesbury et al., 2015*), in forest ecosystems (*Coppin & Bauer, 1996*; *Woodcock et al., 2001*; *Lu, Batistella & Moran, 2008*), urban areas for building detection (*Liu & Zhou, 2004*; *Sohn & Dowman, 2007*; *Aleksandrowicz et al., 2014*) or for the detection of imperious surfaces (*Xian, Homer & Fry, 2009*). Other studies focus on the problem of mapping the general land use change (*Yin et al., 2014*) or on agricultural land specifically (*Weeks et al., 2013*; *Müller et al., 2015*; *Tarantino et al., 2016*). The application of RS in agriculture is summarised, for example, in a review by *Atzberger (2013)*. The current trend uses a time series for agricultural change detection (for example, all the available Landsat imagery), which provides additional phenological information (*Müller et al., 2015*). In many cases, an insufficient number of satellite images is available due to cloud cover and, therefore, bi-temporal change detection is still needed. The alternative approach uses imagery from two dates, for which the time of the acquisition and the variable selection are crucial. The potential usefulness of various CD variables and their impact on LULC CDs has not been sufficiently studied either.

Variables used for CD may be divided into three categories. One category consists of spectral variables that include spectral bands and derived vegetation indices, transformed images, segments, sub-pixel features, and classification results. The second category includes spatial variables such as textures, different scales, the complexity of the landscape or topography. The temporal variables comprise the third category (*Lu, Li & Moran, 2014*). With more than 40 modifications, vegetation indices form the most numerous group of variables (*Bannari et al., 1995*). Significant variability and the amount of RS data, as well as the choice of variables, are very likely to affect the LULC CD, as was shown in other spatial analyses (*Barry & Elith, 2006*; *Moudrý & Šímová, 2012*; *Klouček, Lagner & Šímová, 2015*). Using a large number of variables can potentially improve the accuracy of the CD. On the other hand, such an approach can introduce a number of uncertainties into the detection and make the interpretation of obtained results difficult (*Lu & Weng, 2007*).

Despite the fact that LULC change detection has been one of the most discussed RS topics for decades, to the best of our knowledge, only few studies have focused their attention on selection of appropriate variables for detection of changes in croplands. The aim of our study is to find the optimal variable(s) for grassland to cropland detection based on the Landsat 8 OLI high resolution data and the vector database, called the Land Parcel Identification System (LPIS), and to test the results for the 2013-2016 period on the selected territory. We hypothesised that (1) it is possible to find a suitable variable or group of variables capturing the change of the grassland to cropland due to different spectral

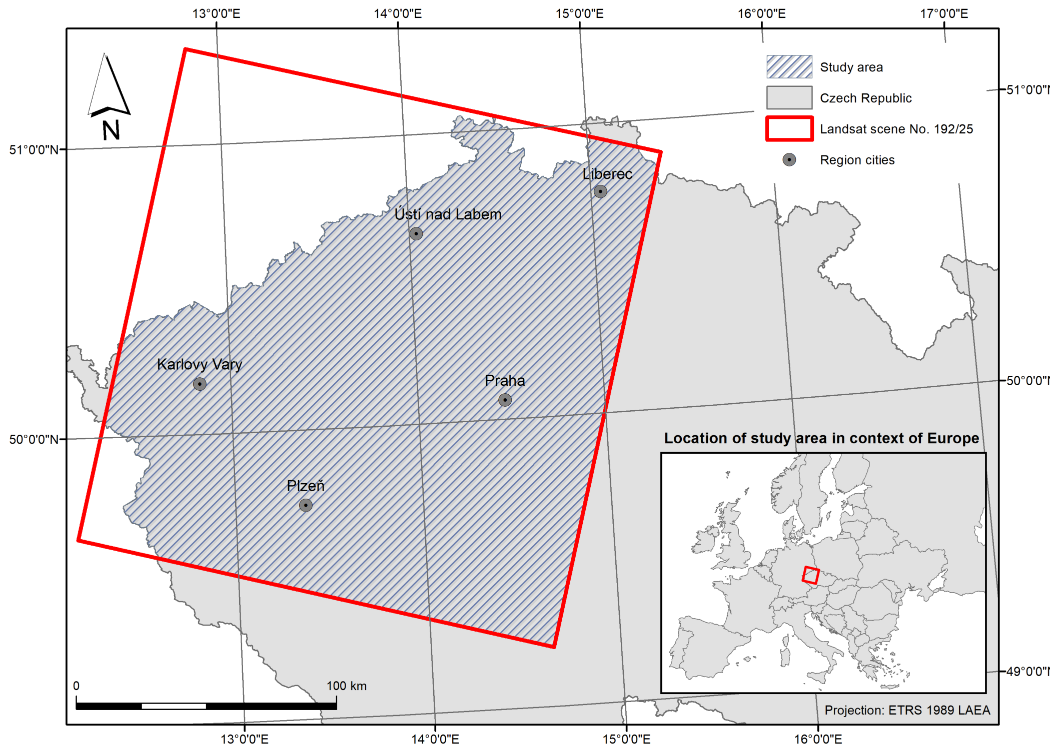

Figure 1 The study area is (located in the Czech Republic, specifically) comprising a part of Landsat 8 scene Path 192 Row 25.

Full-size DOI: 10.7717/peerj.5487/fig-1

profiles; (2) the greater the amount of the incorporated variables, the more accurate the CD would be; (3) spectral variables would be more significant than textural ones; (4) an important aspect of the grassland to cropland change detection would be the time of the acquisition input satellite data.

MATERIALS AND METHODS

Study area

The study area is located in Central Europe, namely in the western part of the Czech Republic intersecting with Landsat 8 scene No. 192/25 with centre point coordinates approximately 50°22′N, 13°41′E, see Fig. 1. The study area is on a regional scale (approx. 36,260 km^2) and is characterised by notable variability (topographical, landscape ecology as well as vegetational variability). This scale and localisation therefore warrants the occurrence of a sufficient number of both grassland to cropland changes and of no-change areas. The expected occurrence of changes was manually verified prior to the analysis using freely available CORINE Land Cover data (http://land.copernicus.eu/pan-european/corine-land-cover/).

Input data

The main data source was a pair of high resolution images taken by the Landsat 8 OLI on August 3rd, 2013 and August 27th, 2016. The images downloaded from the US Geological

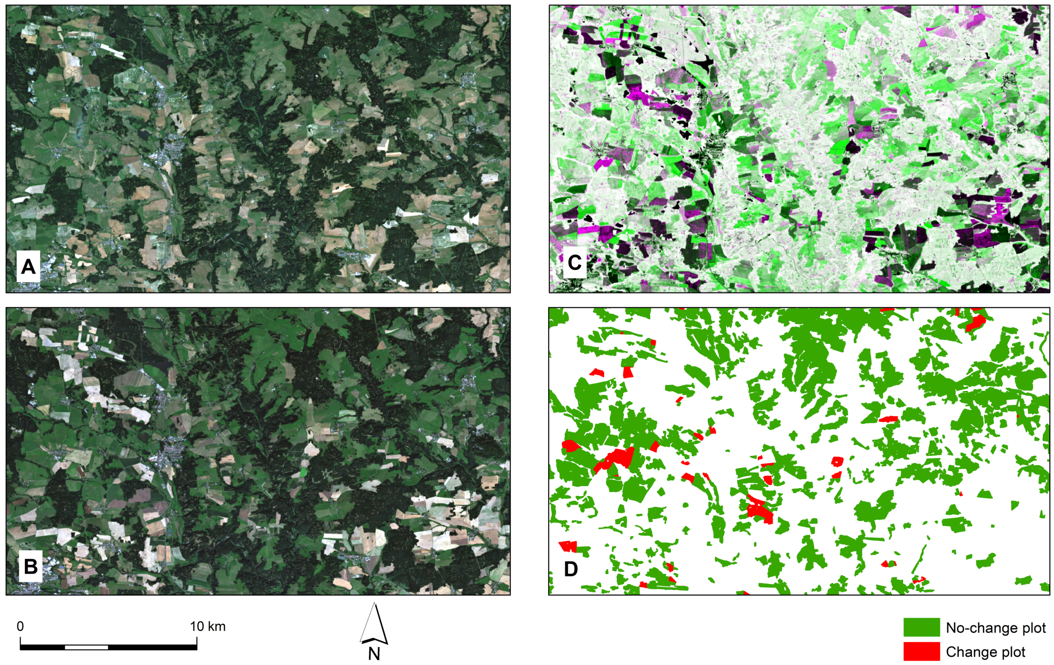

Figure 2 An example of used datasets. Landsat 8 images, NDVI vegetation index, and (no-)change grassland to cropland plots (LPIS database) from 2013 and 2016. (A) Landsat 8 image from 2013. (B) Landsat 8 image from 2016. (C) NDVI RGB composite (R = NDVI 2013, G = NDVI 2016, B = NDVI 2013). (D) (No-)change grassland to cropland plots from LPIS database.

Full-size DOI: 10.7717/peerj.5487/fig-2

Survey (http://earthexplorer.usgs.gov/) contain 9 spectral bands with a resolution of 30 m (multi-spectral) and 15 m (panchromatic), respectively. Detailed specifications of the OLI sensor can be found in *Roy et al. (2014)*. At the time of the image selection, the chosen images were the only one's available for a pair of scenes that, besides being almost cloudless, also met the other criteria including the suitable extent, the sufficient temporal distance between the imaging data, and acquisition at the suitable phenological stage. The most suitable period for the grassland to cropland change detection is the period shortly after harvest (late summer, early autumn) (*Esch et al., 2014*).

As a source of reference data on the use of the agricultural land, we used the Land Parcel Identification System and its vector database containing the land use data for the entire territory of the Czech Republic from 2004. The basic unit of LPIS is a group of adjacent plots representing a continuous area farmed by a single farmer with a single crop plant. The database classifies the agricultural land into 11 land use categories. Data from years corresponding with the Landsat images, i.e., 2013 and 2016, was used, see Fig. 2. In accordance with LPIS classification, cropland is defined as a "farmed land producing crop plants requiring annual replanting, which is not grassland" in this study. Grassland, on the other hand, is defined as a "farmed land under permanent pasture or, where appropriate, contiguous vegetation dominated by grass, used predominantly for feeding or technical purposes" (*The Ministry of Agriculture of the Czech Republic, 2016*).

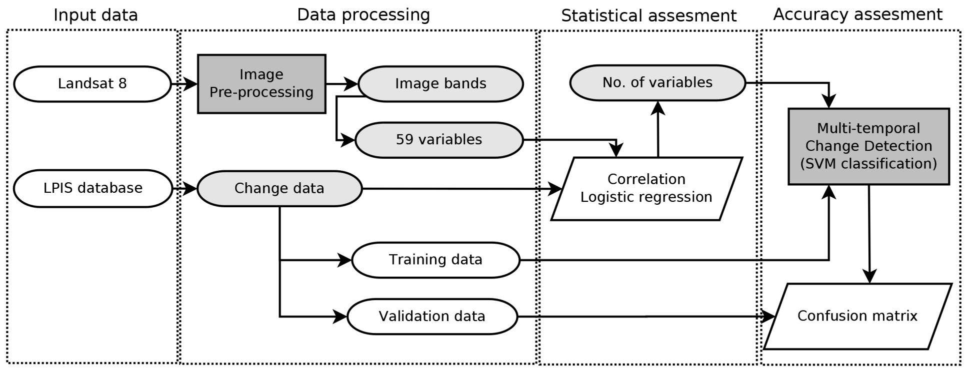

Figure 3 A scheme of the study methods describing data processing workflow. For validation of models was used multi-temporal change detection based on object-based classification using Support Vector Machine algorithm.

Full-size DOI: 10.7717/peerj.5487/fig-3

Images and data pre-processing

Landsat 8 OLI images were obtained at a Level-1T processing level, which includes standard radiometric, geometric and terrain correction using Ground Control Points and the Digital Elevation Model. The results of this step were visually inspected for accuracy with regard to the geometric overlay of the images and the LPIS database. No additional image to image registration was needed. The raw Digital Number data was converted to surface reflectance (*Song et al., 2001*) using FLAASH (Fast Line-of-sight Atmospheric Analysis of Hypercubes) in ENVI software (version 5.4), and any areas obscured by clouds were manually removed from the image.

From the LPIS database, both plots with grassland to cropland change and those on which the grassland remained were extracted. Plots detected as croplands in both time points (information acquired from LPIS also) were removed from the calculation. In the area of interest, 570 changed LPIS plots and 33,196 no-change LPIS plots were identified. To minimise the mixed pixel effect, only plots larger than 1 hectare with a non-elongated shape were selected. A non-elongated shape was defined as the proportion between the shape area (ha) and the shape length (m), which had to be greater than 0.045. This threshold value was expertly set based on the visual inspection and knowledge of the LPIS database. On the acquired sample, a visual check that focused on the homogeneity of the selected plots was carried out based on the freely available orthophotos of the Czech Republic. See Fig. 3 for data processing workflow.

Selection and calculation of the variables

For each scene, 59 LULC change detection variables were calculated. Specifically, the calculated variables included 36 vegetation indices, 10 textural characteristics, 7 components of Principal Component Analysis, and 6 Tasselled Cap components (Table 1). The numbers of variables represent, in our opinion, potentially used spectral and spatial indicators for change detection in the ENVI software by a common user. The calculation of the variables was performed by algorithms implemented in ENVI. Spectral-based variables were calculated from pre-processed spectral bands, while textural variables were calculated

Table 1 59 change detection variables used in the study for detection of (no-)change from grassland to cropland. Specifically, 36 vegetation indices, 10 texture characteristics, 7 components of Principal Component Analysis and 6 components of Tasseled Cap were used. Numbers represent almost all available variables in ENVI software. For details see external links.

Group	Change detection variables
Vegetation Indices	Atmospherically Resistant Vegetation Index, Burn Area Index, Clay Minerals, Difference Vegetation Index, Enhanced Vegetation Index, Ferrous Minerals, Global Environmental Monitoring Index, Green Atmospherically Resistant Index, Green Difference Vegetation Index, Green Normalized Difference Vegetation Index, Green Ratio Vegetation Index, Green Vegetation Index, Infrared Percentage Vegetation Index, Iron Oxide, Leaf Area Index, Modified Non Linear Index, Modified Normalized Difference Water Index, Modified Simple Ratio, Modified Triangular Vegetation Index, Modified Triangular Vegetation Index, Improved Non-Linear Index, Normalized Burn Ratio, Normalized Difference Built Up Index, Normalized Difference Snow Index, Normalized Difference Vegetation Index, Optimized Soil Adjusted Vegetation Index, Red Green Ratio Index, Renormalized Difference Vegetation Index, Simple Ratio, Soil Adjusted Vegetation Index, Structure Insensitive Pigment Index, Sum Green Index, Transformed Difference Vegetation Index, Visible Atmospherically Resistant Index, WorldView Improved Vegetative Index, WorldView Water Index
Texture	Contrast, Correlation, Data Range, Dissimilarity, Entropy, Homogeneity, Mean, Skewness, Second Moment, Variance
Principal Component Analysis	PCA 1, PCA 2, PCA 3, PCA 4, PCA 5, PCA 6, PCA 7
Tasseled Cap	Brightness, Greenness, Wetness, Fourth, Fifth, Sixth

Notes.
For more information about the variables visit http://www.harrisgeospatial.com/docs/alphabeticallistspectralindices.html or http://www.harrisgeospatial.com/docs/backgroundtexturemetrics.html.

from the panchromatic band (see ENVI help in Table 1). For each variable, the mean value for every plot of the LPIS-acquired database was obtained using the ArcGIS (version 10.4) Zonal Statistics tool for both 2013 and 2016.

Statistical assessment

To determine the optimal set of variables for grassland to cropland change detection, we first excluded the highly correlated ones ($r > 0.9$) from the full correlation matrix (see Supplemental Information 1). Where correlations were detected, only the variable most frequently used in the available literature was included into the subsequent analysis. From the original set of 59 variables, 41 were eliminated in preselection due to high correlation and the uncorrelated variables are presented in Table 2.

The best set of variables was found using logistic regression specifically based on the lowest AIC (Akaike Information Criterion) (*deLeeuw, 1992*) using Generalised Linear Models (GLM) with a defined binominal distribution of errors (more about GLM can be found, e.g., in *Dobson & Barnett, 2008*). Models, from one to seven members, were found by permutation of all the combinations of variables with the 'glmulti' package in R (version

Table 2 Non-correlated variables used for detecting grassland to cropland (no-)changes.

Group	Not correlated variables
Vegetation indices	Normalized Difference Vegetation Index, Simple Ratio, Sum Green Index
Texture	Contrast, Data Range, Entropy, Homogenity, Mean, Second Moment, Skewness
Principal component analysis	PCA 1, PCA 2, PCA 3, PCA 4, PCA 7
Tasseled cap	Brightness, Wetness, Fifth

3.3.2). Models with a higher number of variables than seven were best found by AIC in a Stepwise Algorithm in R because of the time-consuming nature of the previous method. The calculated AIC values for the models based on two - fourteen variables were very similar (only one-variable model using AIC values was significantly different), so only the models, where the AIC values are at least slightly changed (one, three, five, seven, fourteen), were chosen for the accuracy assessment.

Classification and accuracy assessment

A practical accuracy assessment of the created models and the Landsat 8 images only (Table 3) was undertaken using the object-based multi-temporal change detection. The variables of the models from both years were merged, based on statistic calculation, into a single image (Layer stacking tool). The training data for classification was selected from all of the 33,766 plots from pre-prepared LPIS database ('Images and data pre-processing'). Based on stratified random sample design, 300 plots with change and 1200 without change were chosen (*Congalton & Green, 2009*). Borders of selected plots from LPIS database were used as the segments of the object-based classification. Using slides consisting of variables and training data, change maps were created in ENVI software. Due to non-normal distribution of the input data, the non-parametric Support Vector Machine (SVM) classifier (*Lu & Weng, 2007*) was used for classification. The settings of the SVM algorithm was set as the default. The Kernel type: Radial Basic Function; Gamma in Kernel Function: the inverse of the number of bands in the input image; The Penalty Parameter: 100; The Pyramid Levels: 0; and the Classification Probability Threshold: 0. The same methodology was used for the change detection based only on the Landsat 8 images (the amount of training and validation samples, classification algorithm, etc.).

Finally, the accuracy of the change maps was calculated by comparison with stratified random validation (testing) samples extracted from the pre-prepared LPIS database (excluding the training data) using an confusion matrix. The sampling design was inspired by *Zhen et al. (2013)* and *Olofsson et al. (2014)*. The assessment was based on evaluating the number of correctly classified 200 change and 800 no-change plots into change maps with validation plots from the LPIS database. A 95% confidence interval was calculated from the overall accuracy of the models. The models accuracy has been tested with a homogeneity test of binominal distribution. The models have been tested against each other using Holm's p-value adjustment for multiple comparisons.

Table 3 Summary of the validated models for the grassland to cropland change detection based on different set of variables. The value of AIC specifies the information potential of models.

No. of variables	Change detection model	AIC[a]
One	Normalized Difference Vegetation Index	**5,633.39**
Three	Normalized Difference Vegetation Index, Wetness, Fifth	**4,592.41**
Five	Normalized Difference Vegetation Index, Wetness, Fifth, Brightness, Sum Green Index	**4,263.74**
Seven	Normalized Difference Vegetation Index, Wetness, Fifth, Brightness, Sum Green Index, Second Moment, PCA 2	**4,060.35**
Fourteen	Normalized Difference Vegetation Index, Wetness, Fifth, Brightness, Sum Green Index, Second Moment, PCA 2, PCA 1, PCA 3, PCA 4, PCA 7, Data Range, Contrast, Skewness	**3,950.90**

Notes.
[a]AIC (Akaike Information Criterion).

Table 4 The accuracy of models (%) calculated based on different sets of variables by non-parametric classifiers Support Vector Machine (SVM).

No. of variables/model	Change PA	No-change PA	Change UA	No-change UA	OA	95% CI
One	46.00	98.63	89.32	87.96	**88.10**	86.09–90.11
Three	49.50	98.88	91.67	88.68	**89.00**	87.07–90.94
Five	46.50	99.00	92.08	88.10	**88.50**	86.52–90.48
Seven	52.00	98.25	88.14	89.12	**89.00**	87.06–90.94
Fourteen	55.50	98.38	89.52	89.84	**89.80**	87.93–91.68
Landsat image	59.00	98.25	89.39	90.55	**90.40**	88.57–92.23

RESULTS

Models for change detection

The lowest AIC was obtained from the model with fourteen variables (3950.90), the highest from the model using a single variable (5633.39). The single most significant variable was the NDVI (Normalised Difference Vegetation Index), which was represented in all the models. In the models with a lower number of variables, variables based on spectral information were predominantly used. The separability of the model with one variable (NDVI) is demonstrated by Fig. 4. With additional variables, textural variables began to play a greater role, see Table 3. The summary of calculated models can be found in Supplemental Information 2.

Change maps evaluation

The overall accuracy of the change maps generally increases with the increasing number of variables in the models. The best change map was created from the highest number of variables (89.80% accuracy, Kappa 0.63), however classification based on a single variable provided only slightly inferior results (88.10% accuracy, Kappa 0.55) as illustrated in Table 4. These findings were statistically confirmed by the homogeneity test for binominal

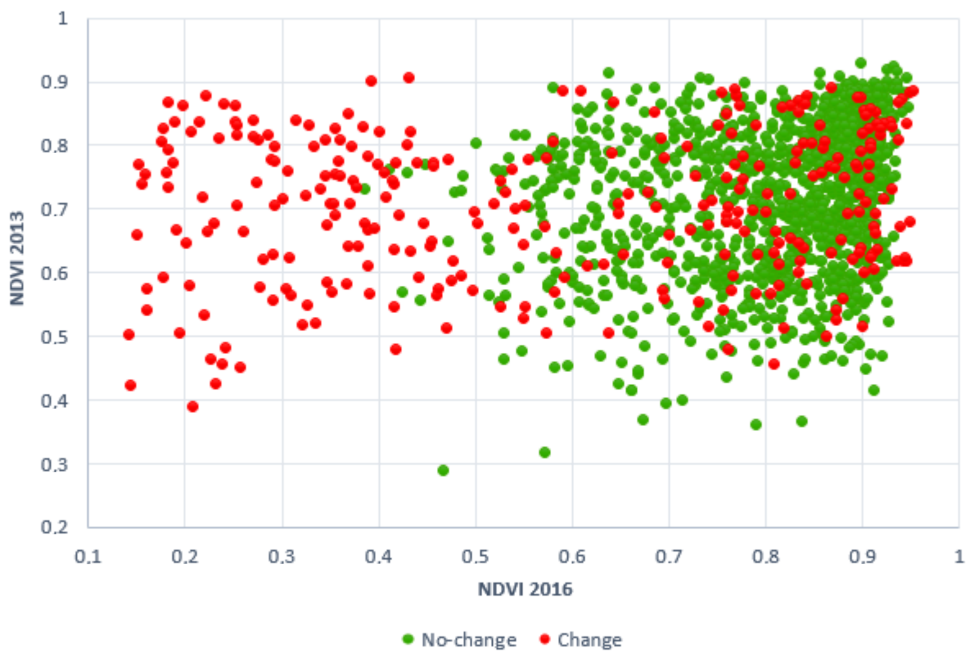

Figure 4 2D scatter plot created from NDVI average values of change and no-change plots. Points represent training data (300 change, 1,200 no-change plots). *X*-axis belongs to NDVI 2016 and *Y*-axis belongs to NDVI 2013 (one-variable model).

Full-size DOI: 10.7717/peerj.5487/fig-4

distribution. So, we cannot conclude (on a 95% confidence level), that one of the models is more accurate, see Fig. 5.

Looking more closely, the improvement in accuracy with an increasing number of variables is associated only with the increasing Producer's Accuracy (PA) of the change class (one-variable model 46.00% and fourteen-variable model 55.50%). As shown in Table 4, there is an improvement in the change class PA quality of the model between the models using one and three variables. The rest of the confusion matrix parameters (User's Accuracy, Commission and Omission) were very similar in all the cases. Contrary, the no-change detection did not show any notable improvement with an increasing number of variables (PA 98.25–99.00%). All change maps, however, underestimated the number of change plots and overestimated the number of grassland to cropland no-change plots (Fig. 6). The results indicate that classification of the change and no-change plots has achieved sufficient accuracy. If we compare the accuracy of the change maps based on a statistically selected set of variables with change maps created from the Landsat images (OA 90.40%, Kappa 0.66), there is not any significant difference. The detailed confusion matrices are available in Supplemental Information 3.

DISCUSSION

In accordance with the results, it is possible to use statistically selected variables for detection of grassland to cropland land cover changes. At first sight, it could be apparent that it is sufficient to only use the NDVI vegetation index for this type of analysis. However, based

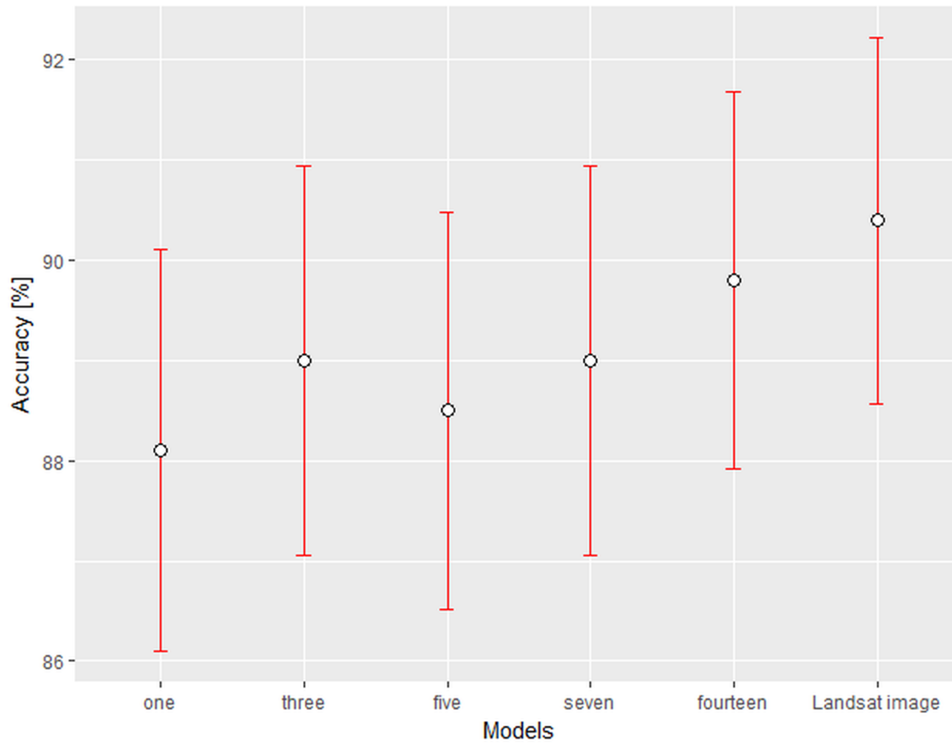

Figure 5 **Overall accuracy (%) of calculated models with 95% confidence intervals.**
Full-size DOI: 10.7717/peerj.5487/fig-5

on the visual inspection of the misclassification in all the change maps and the confusion matrix (Supplemental Information 3), it is clear that the largest change detection inaccuracy is in a case when differentiating grassland and cropland plots with green plants. The largest number of these plots were poorly classified in the case of using only a one-variable model based on NDVI (the lowest Producer's Accuracy). This result is not surprising because the surface reflectance of both categories is, in the spectral range of the Landsat 8 bands, almost identical and the NDVI index even uses two spectral bands (Red and Near Infrared). Only the NDVI variable can be used in the situation, when almost all plots are in the same phenological phase. However, this is not the case of our study and it is not common in the most of analyses, where some parts of the area (mountains vs. lowlands) are in different phenological phases. Therefore, the addition of some variables based on another spectral band is needed.

In our study, almost all vegetation indices were significantly correlated. The NDVI variable was chosen as the most appropriate because of its frequency of use in research. The statistical evaluation, however, indicates that very similar results would be achieved with any of the other vegetation indices closely correlated with the NDVI one, see the correlation matrices in Supplemental Information 1.

A good compromise among improving the accuracy of detection, the demands for computational time and complications of the interpretation of the obtained results, seems to be supplied by NDVI with the Wetness and Fifth components of Tasselled

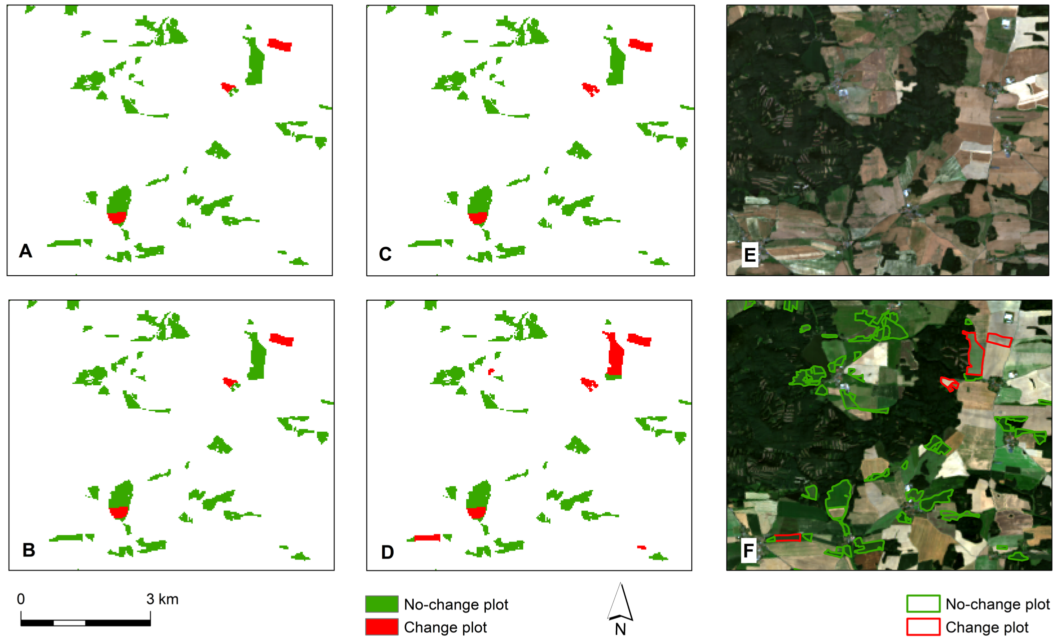

Figure 6 Comparison of created change maps with Landsat 8 images and LPIS database. (A) One-variable model. (B) Three-variable model. (C) Fourteen-variable model. (D) Landsat 8 images only model. (E) Landsat 8 image from 2013. (F) Landsat 8 image from 2018 with (no-)change plots from LPIS database.

Full-size DOI: 10.7717/peerj.5487/fig-6

Cap (three-variable model in the study). These variables are more sensitive to different conditions of the grassland plots and cropland plots with the green plants. The advantage of the three-variable model is also the relatively small number of variables, allowing the utilisation of methods based on the determination of an optimal change detection threshold (*Chen & Rao, 2008*; *Otukei & Blaschke, 2010*). These findings related to crop phenology, besides other conclusions, point an importance of appropriate time acquisition of satellite images. It also confirms the hypothesis about an importance of this aspect for the grassland to cropland change detection.

The suitability of NDVI for the classification and change detection has been demonstrated in several studies (*Lunetta et al., 2006*; *Wardlow, Egbert & Kastens, 2007*; *Pu et al., 2008*; *Bhandari, Kumar & Singh, 2012*; *Esch et al., 2014*; *Aleksandrowicz et al., 2014*; *Gandhi et al., 2015*; *Nagendra et al., 2015*) as well as in those studies successfully combining NDVI with Tasselled Cap (e.g., *Chen & Rao, 2008*).

Introducing too many variables into a model does not necessarily lead to achieving better results (*Lu & Weng, 2007*), which underlines the importance of selecting the most appropriate variables for change detection. In this case, the best accuracy was achieved by using directly bands of Landsat image instead of calculated models due to almost all variables (outside the spatial variables) were based on similar spectral bands.

The study results could have been, theoretically, influenced by a number of uncertainties that we, however, strived to eliminate, e.g., through the pre-processing of the satellite images (atmospheric correction, registration of images and its visual verification). No object is shifted by more than 1/2 a pixel between two frames (Dai, 1998). The selection of the Landsat 8 OLI pairs was predominantly limited by the launch of the satellite mission (2013) and by the cloud cover. Still, a suitable pair of pictures in a suitable phenological phase according to the recommendations (Coppin et al., 2004; Hájková et al., 2012; Esch et al., 2014; Tarantino et al., 2016) was found. The selection of the suitable acquisition period depends on the geographical conditions (especially longitude, latitude or altitude) of the observed area. From this point of view, the presented methods and results are relevant for similar environmental conditions in central Europe. Another uncertainty is a possible error in the LPIS reference database as the land use data is entered directly by the farmers themselves. Also, the information in the LPIS differs slightly from the date of acquisition of the satellite imagery, as it refers to the end of the particular year. No better reference database covering the entire territory of the Czech Republic on such a detailed scale is available however. Moreover, using such a high number of individual plots combined with suitable statistical methods ensured that even if the information was inaccurate by a small fraction, it should not have any significant impact on the results of our study. The accuracy of the resulting change maps could have been affected by selection of the change detection method also. An object-based classification was used in the multi-temporal change detection as it is, according to literature, a more suitable approach for high resolution data, when the pixels are significantly smaller than the object. In this case, grouping pixels into segments is needed (Blaschke, 2010). The ratio of change to no-change units in our study is approximately 1:50 and, therefore, the stratified random sampling design with a proportion of 1:4 (change vs. no-change) for the training and validation data was used.

LULC change detection most commonly employs Post-Classification Comparison (PCC) (Otukei & Blaschke, 2010), it is, therefore, rather a classification than a pure change detection task. For many applications, it is important to describe the trajectory of the change. On the other hand, the knowledge about the occurrence of (no-)change (so-called pre-classification, or bi-temporal change detection Coppin et al., 2004) is sufficient for many other tasks. If this is the case, the choice of suitable variables is the key to acquiring quality results, and this is where the contribution of our study can be deemed significant. The methods used here can be applied to CDs of other LULC categories as well. It is a well-known fact that finding suitable variables streamlines analyses, while at the same time improves the results (Lu, Li & Moran, 2014).

Our results indicate that we are nearing a maximum accuracy of the grassland to cropland change detection achievable from a pair of high resolution multi-spectral images. Possible improvements could be brought about by implementing new data into the models. Examples of such supplementary data could include a time series of high resolution images, e.g., Landsat or Sentinel-2 (Esch et al., 2014), very high resolution data (Tarantino et al., 2016), data with a different resolution (Lu, Batistella & Moran, 2008; Turker & Ozdarici, 2011), data captured by other RS methods (Smith & Buckley, 2011), for example radar (Sentinel-1) and thermal data (Landsat 8 TIRS) or the incorporation of an existing GIS database (Hussain et al., 2013). Hussain et al. (2013) and Lu et al. (2003) both state that hybrid methods of change detection combining multiple approaches can increase the accuracy of change detection.

The variables selected in this study can be used with sufficient precision as a source of data for updating existing LULC databases or as a tool for setting agricultural subsidy policies and their implementation. As the reference dataset used in the presented study was quite large, it is relatively safe to assume the applicability of using the results for other studies addressing this change detection problem in the whole of Central Europe. The results are relevant for areas with similar geographical conditions, especially regarding the latitude. However, the selected statistical methods and classification algorithms should be robust due to the used images (full scene of Landsat 8) covered a large area with topographical variable conditions (lowlands, highlands, mountains).

CONCLUSIONS

This study provides an analysis of the utilisation of selected remote sensing variables (vegetation indices, textures, Principal Component Analysis, and Tasselled Cap analysis) for grassland to cropland change detection based on a pair of Landsat 8 OLI images and the Land Parcel Identification System (LPIS) vector database. The results confirm the principal hypotheses that (1) there are suitable variables usable for grassland to cropland change detection; (2) increasing the number of variables used in a model leads to increased accuracy of the change detection, but to achieve the highest accuracy, it is necessary to use original Landsat 8 bands; (3) spectral variables play a more important role than textural variables in the change detection; (4) the appropriate time of the acquisition satellite images is important for grassland to cropland change detection. In view of the accuracy of the created change maps, which was verified using the reference database, we consider a model utilising three variables (namely NDVI, Wetness and Fifth components) the most suitable. Incorporation of additional variables into the model does not significantly improve the accuracy of the change map. By analogy, the methods used in this study can be applied for the CD of other LULC categories than solely those based on grassland to cropland change. The models prepared in this way can serve as data sources for updating the current LULC databases or as a tool for creating agricultural subsidy policies. As the selection of variables was based on a large dataset of reference data on grassland to cropland change detection, the applicability for other studies can be safely assumed. Our conclusions are valid for analyses on a regional scale in Central Europe using high resolution data. To further improve the grassland to cropland change detection using RS, research combining our variables with spatial data acquired using other RS techniques is needed.

ACKNOWLEDGEMENTS

In advance, we acknowledge the anonymous referees for their constructive comments. Thanks to our colleagues from the Department of Applied Geoinformatics and Spatial Planning at the Czech University of Life Sciences Prague (CULS) for their helpful advice.

ADDITIONAL INFORMATION AND DECLARATIONS

Funding

This work was supported by the Czech University of Life Sciences Prague (CULS) under grant no. 20174208 and by Internal Grant Agency of the Faculty of Environmental Sciences, Czech University of Life Sciences Prague under grant no. 423001312423155. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Grant Disclosures

The following grant information was disclosed by the authors:
Czech University of Life Sciences Prague (CULS): 20174208.
Internal Grant Agency of the Faculty of Environmental Sciences.
Czech University of Life Sciences Prague: 423001312423155.

Competing Interests

The authors declare there are no competing interests.

Author Contributions

- Tomáš Klouček conceived and designed the experiments, performed the experiments, analyzed the data, contributed reagents/materials/analysis tools, prepared figures and/or tables, authored or reviewed drafts of the paper, approved the final draft.
- David Moravec performed the experiments, analyzed the data, contributed reagents/materials/analysis tools, prepared figures and/or tables, authored or reviewed drafts of the paper, approved the final draft.
- Jan Komárek analyzed the data, contributed reagents/materials/analysis tools, prepared figures and/or tables, authored or reviewed drafts of the paper, approved the final draft.
- Ondřej Lagner analyzed the data, contributed reagents/materials/analysis tools.
- Přemysl Štych conceived and designed the experiments, performed the experiments, authored or reviewed drafts of the paper, approved the final draft.

All supplemental information will be made available for download exactly as they were supplied. This link to the SI will only work when the article is published.

Q2

Data Availability

The following information was supplied regarding data availability:

Figshare: https://figshare.com/s/2b6a020a8fbb63f3ea95
https://figshare.com/s/944bb02f5442f5d86323
https://figshare.com/s/a2ee610f7974ea9fc438.

Supplemental Information

Supplemental information for this article can be found online at http://dx.doi.org/10.7717/peerj.5487#supplemental-information.

REFERENCES

Aleksandrowicz S, Turlej K, Lewiński S, Bochenek Z. 2014. Change detection algorithm for the production of land cover change maps over the European union countries. *Remote Sensing* **6**:5976–5994 DOI 10.3390/rs6075976.

Atzberger C. 2013. Advances in remote sensing of agriculture: context description, existing operational monitoring systems and major information needs. *Remote Sensing* **5**:949–981 DOI 10.3390/rs5020949.

Bannari A, Morin D, Bonn F, Huete AR. 1995. A review of vegetation indices. *Remote Sensing Reviews* **13**:95–120 DOI 10.1080/02757259509532298.

Barry S, Elith J. 2006. Error and uncertainty in habitat models. *Journal of Applied Ecology* **43**:413–423 DOI 10.1111/j.1365-2664.2006.01136x.

Berberoglu S, Akin A. 2009. Assessing different remote sensing techniques to detect land use/cover changes in the eastern Mediterranean. *International Journal of Applied Earth Observation and Geoinformation* **11**:46–53 DOI 10.1016/j.jag.2008.06.002.

Bergen KM, Brown DG, Rutherford JF, Gustafson EJ. 2005. Change detection with heterogeneous data using ecoregional stratification. *statistical summaries and a land allocation algorithm. Remote Sensing of Environment* **97**:434–446 DOI 10.1016/j.rse.2005.03.016.

Blaschke T. 2010. Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing* **65**:2–16 DOI 10.1016/j.isprsjprs.2009.06.004.

Cardinale BJ, Duffy JE, Gonzalez A, Hooper DU, Perrings C, Venail P, Narwani A, Mace GM, Tilman D, Wardle DA, Kinzig AP, Daily GC, Loreau M, Grace JB, Larigauderie A, Srivastava DS, Naeem S. 2012. Biodiversity loss and its impact on humanity. *Nature* **489**:326–326 DOI 10.1038/nature11373.

Chaudhuri G, Mishra NB. 2016. Spatio-temporal dynamics of land cover and land surface temperature in Ganges-Brahmaputra delta: a comparative analysis between India and Bangladesh. *Applied Geography* **68**:68–83 DOI 10.1016/j.apgeog.2016.01.002.

Chen G, Hay GJ, Carvalho LMT, Wulder MA. 2012. Object-based change detection. *International Journal of Remote Sensing* **33**:4434–4457 DOI 10.1080/01431161.2011.648285.

Chen S, Rao. 2008. Land degradation monitoring using multi-temporal Landsat TM/ETM data in a transition zone between grassland and cropland of northeast China. *International Journal of Remote Sensing* **29**:2055–2073 DOI 10.1109/ICISE.2009.878.

Q3 **Congalton RG, Green K. 2009.** *Assessing the accuracy of remotely sensed data*.

Coppin P, Bauer M. 1996. Digital change detection in forest ecosystems with remote sensing imagery. *Remote Sensing Reviews* **13**:207–234 DOI 10.1080/02757259609532305.

Coppin P, Jonckheere I, Nackaerts K, Muys B, Lambin E. 2004. Digital change detection methods in ecosystem monitoring: a review. *International Journal of Remote Sensing* **25**:1565–1596 DOI 10.1080/0143116031000101675.

Dai X. 1998. The effects of image misregistration on the accuracy of remotely sensed change detection. *IEEE Transactions on Geoscience and Remote Sensing* **36**:1566–1577 DOI 10.1109/36.718860.

deLeeuw J. 1992. Introduction to Akaike (1973) information theory and an extension of the maximum likelihood principle. In: Kotz S, Johnson NL, eds. *Breakthroughs*

Q4

Q5

Q6

in statistics: foundations and basic theory. New York: Springer New York, 599–609 DOI 10.1007/978-1-4612-0919-5_37.

Dobson AJ, Barnett A. 2008. *An introduction to generalized linear models* DOI 10.1002/pst.486.

Esch T, Metz A, Marconcini M, Keil M. 2014. Combined use of multi-seasonal high and medium resolution satellite imagery for parcel-related mapping of cropland and grassland. *International Journal of Applied Earth Observation and Geoinformation* **28**:230–237 DOI 10.1016/j.jag.2013.12.007.

European Union. 2016. *Eurostat regional yearbook—2016 edition*. 274 DOI 10.2785/29084.

Eurostat. 2017. Land cover statistics—statistics explained. *Available at http://ec.europa.eu/eurostat/statistics-explained/index.php/Land_cover_statistics#Land_cover_in_the_EU* (accessed on 8 August 2017).

Exelis Visual Information Solutions. 2015. ENVI Help.

Gandhi GM, Parthiban S, Thummalu N, Christy A. 2015. Ndvi: vegetation change detection using remote sensing and gis—a case study of vellore district. In: *Procedia computer science*. Elsevier Masson SAS, 1199–1210 DOI 10.1016/j.procs.2015.07.415..

Gupta SK, Shukla DP. 2016. Assessment of land use/land cover dynamics of Tso Moriri Lake, a Ramsar site in India. *Environmental Monitoring and Assessment* **188** DOI 10.1007/s10661-016-5707-3.

Hájková L, Voženílek V, Tolasz R, Kohut M, Možný M, Nekovář J, Novák M, Richterová D, Stříž M, Vávra A, Vondráková A. 2012. *Atlas fenologických poměrů Česka*. Olomouc: Univerzita Palackého v Olomouci.

Hussain M, Chen D, Cheng A, Wei H, Stanley D. 2013. Change detection from remotely sensed images: from pixel-based to object-based approaches. *ISPRS Journal of Photogrammetry and Remote Sensing* **80**:91–106 DOI 10.1016/j.isprsjprs.2013.03.006.

Jensen JR. 1996. *Introductory digital image processing: a remote sensing perspective*. Second edition. Toronto: Prentice Hall DOI 10.2113/gseegeosci.13.1.89.

Bhandari AK, Kumar A, Singh GK. 2012. Feature extraction using normalized difference vegetation index (NDVI): a case study of jabalpur city. *Procedia Technology* **6**:612–621 DOI 10.1016/j.protcy.2012.10.074.

Kindu M, Schneider T, Teketay D, Knoke T. 2013. Land use/land cover change analysis using object-based classification approach in Munessa-Shashemene landscape of the ethiopian highlands. *Remote Sensing* **5**:2411–2435 DOI 10.3390/rs5052411.

Klouček T. 2016. *Detection of land cover change focusing on agricultural land*. Charles University in Prague.

Klouček T, Lagner O, Šímová P. 2015. How does data accuracy influence the reliability of digital viewshed models? A case study with wind turbines. *Applied Geography* **64**:46–54 DOI 10.1016/j.apgeog.2015.09.005.

Kupková L, Bičík I. 2016. Landscape transition after the collapse of communism in Czechia. *Journal of Maps* **5647**:1–6 DOI 10.1080/17445647.2016.1195301.

Liu H, Zhou Q. 2004. Accuracy analysis of remote sensing change detection by rule-based rationality evaluation with post-classification comparison. *International Journal of Remote Sensing* **25**:1037–1050 DOI 10.1080/0143116031000150004.

Lu D, Batistella M, Moran E. 2008. Integration of Landsat TM and SPOT HRG images for vegetation change detection in the Brazilian Amazon. *Photogrammetric Engineering & Remote Sensing* **74**:421–430 DOI 10.14358/PERS.74.4.421.

Lu D, Li G, Moran E. 2014. Current situation and needs of change detection techniques. *International Journal of Image and Data Fusion* **5**:13–38 DOI 10.1080/19479832.2013.868372.

Lu D, Mausel P, Brondízios E, Moran E. 2003. Change detection techniques. *International Journal of Remote Sensing* **25**:2365–2407 DOI 10.1080/0143116031000139863.

Lu D, Weng Q. 2007. A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing* **28**:823–870 DOI 10.1080/01431160600746456.

Lunetta RS, Knight JF, Ediriwickrema J, Lyon JG, Worthy LD. 2006. Land-cover change detection using multi-temporal MODIS NDVI data. *Remote Sensing of Environment* **105**:142–154 DOI 10.1016/j.rse.2006.06.018.

Lyon JG, Yuan D, Lunetta RS, Elvidge CD. 1998. A change detection experiment using vegetation indices. *Photogrammetric Engineering and Remote Sensing* **64**:143–150.

Mas J-F. 1999. Monitoring land-cover changes: a comparison of change detection techniques. *International Journal of Remote Sensing* **20**:139–152 DOI 10.1080/014311699213659.

Moudrý V, Šímová P. 2012. Influence of positional accuracy, sample size and scale on modelling species distributions: a review. *International Journal of Geographical Information Science* **8816**:1–13 DOI 10.1080/13658816.2012.721553.

Müller H, Rufin P, Griffiths P, Barros Siqueira AJ, Hostert P. 2015. Mining dense Landsat time series for separating cropland and pasture in a heterogeneous Brazilian savanna landscape. *Remote Sensing of Environment* **156**:490–499 DOI 10.1016/j.rse.2014.10.014.

Nagendra H, Mairota P, Marangi C, Lucas R, Dimopoulos P, Honrado JP, Niphadkar M, Mücherg CA, Tomaselli V, Panitsa M, Tarantino C, Manakos I, Blonda. 2015. Satellite Earth observation data to identify anthropogenic pressures inselected protected areas. *International Journal of Applied Earth Observation and Geoinformation* **37**:124–132 DOI 10.1016/j.jag.2014.10.010.

Olofsson P, Foody GM, Herold M, Stehman SV, Woodcock CE, Wulder MA. 2014. Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment* **148**:42–57 DOI 10.1016/j.rse.2014.02.015.

Otukei JR, Blaschke T. 2010. Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. *International Journal of Applied Earth Observation and Geoinformation* **12** DOI 10.1016/j.jag.2009.11.002.

Pazúr R, Lieskovský J, Feranec J, Oahel'J. 2014. Spatial determinants of abandonment of large-scale arable lands and managed grasslands in Slovakia during the periods of post-socialist transition and European Union accession. *Applied Geography* **54**:118–128 DOI 10.1016/j.apgeog.2014.07.014.

Pu R, Gong P, Tian Y, Miao X, Carruthers RI, Anderson GL. 2008. Using classification and NDVI differencing methods for monitoring sparse vegetation coverage: a case study of saltcedar in Nevada. *USA. International Journal of Remote Sensing* **29**:3987–4011 DOI 10.1080/01431160801908095.

Roy M, Ghosh S, Ghosh A. 2014. A novel approach for change detection of remotely sensed images using semi-supervised multiple classifier system. *Information Sciences* **269**:35–47 DOI 10.1016/j.ins.2014.01.037.

Roy DP, Wulder MA, Loveland TR, CE W, Allen RG, Anderson MC, Helder D, Irons JR, Johnson DM, Kennedy R, Scambos TA, Schaaf CB, Schott JR, Sheng Y, Vermote EF, Belward AS, Bindschadler R, Cohen WB, Gao F, Hipple JD, Hostert P, Huntington J, Justice CO, Kilic A, Kovalskyy V, Lee ZP, Lymburner L, Masek JG, McCorkel J, Shuai Y, Trezza R, Vogelmann J, Wynne RH, Zhu Z. 2014. Landsat-8: Science and product vision for terrestrial global change research. *Remote Sensing of Environment* **145**:154–172 DOI 10.1016/j.rse.2014.02.001.

Singh A. 1989. Digital change detection techniques using remotely sensed data. *International Journal of Remote Sensing* **10**:989–1003 DOI 10.1080/01431168908903939.

Sklenicka P, Molnarova KJ, Salek M, Simova P, Vlasak J, Sekac P, Janovska V. 2015. Owner or tenant: who adopts better soil conservation practices? *Land Use Policy* **47**:253–261.

Sklenicka P, Šímová P, Hrdinová K, Salek M. 2014. Changing rural landscapes along the border of Austria and the Czech Republic between 1952 and 2009: roles of political, socioeconomic and environmental factors. *Applied Geography* **47**:89–98 DOI 10.1016/j.apgeog.2013.12.006.

Smith AM, Buckley JR. 2011. Investigating RADARSAT-2 as a tool for monitoring grassland in western Canada. *Canadian Journal of Remote Sensing* **37**:93–102 DOI 10.5589/m11-027.

Sohn G, Dowman I. 2007. Data fusion of high-resolution satellite imagery and LiDAR data for automatic building extraction. *ISPRS Journal of Photogrammetry and Remote Sensing* **62**:43–63 DOI 10.1016/j.isprsjprs.2007.01.001.

Song C, Woodcock CE, Seto KC, Lenney MP, Macomber SA. 2001. Classification and change detection using Landsat TM data: when and how to correct atmospheric effects? *Remote Sensing of Environment* **75**:230–244 DOI 10.1016/S0034-4257(00)00169-3.

Tarantino C, Adamo M, Lucas R, Blonda P. 2016. Detection of changes in semi-natural grasslands by cross correlation analysis with WorldView-2 images and new Landsat 8 data. *Remote Sensing of Environment* **175**:65–72 DOI 10.1016/j.rse.2015.12.031.

Tasser E, Leitinger G, Tappeiner U. 2017. Climate change versus land-use change—what affects the mountain landscapes more? *Land Use Policy* **60**:60–72 DOI 10.1016/j.landusepol.2016.10.019.

Tewkesbury AP, Comber AJ, Tate NJ, Lamb A, Fisher PF. 2015. A critical synthesis of remotely sensed optical image change detection techniques. *Remote Sensing of Environment* **160**:1–14 DOI 10.1016/j.rse.2015.01.006.

The Ministry of Agriculture of the Czech Republic. 2016. LPIS—modul iLPIS. *Available at http://eagri.cz/public/web/file/2127/LPIS_modul_iLPIS_prirucka_20140831.pdf* (accessed on 21 March 2017).

Turker M, Ozdarici A. 2011. Field-based crop classification using SPOT4, SPOT5, IKONOS and QuickBird imagery for agricultural areas: a comparison study. *International Journal of Remote Sensing* **32**:9735–9768 DOI 10.1080/01431161.2011.576710.

Vorovencii I. 2014. Assessment of some remote sensing techniques used to detect land use/land cover changes in South-East Transilvania, Romania. *Environmental Monitoring and Assessment* **186**:2685–2699 DOI 10.1007/s10661-013-3571-7.

Wardlow BD, Egbert SL, Kastens JH. 2007. Analysis of time-series MODIS 250 m vegetation index data for crop classification in the U.S Central Great Plains. *Remote Sensing of Environment* **108**:290–310 DOI 10.1016/j.rse.2006.11.021.

Weeks ES, Ausseil AGE, Shepherd JD, Dymond JR. 2013. Remote sensing methods to detect land-use/cover changes in New Zealand's indigenous grasslands. *New Zealand Geographer* **69**:1–13 DOI Doi 10.1111/Nzg.12000.

Wondrade N, Dick ØB, Tveite H. 2014. GIS based mapping of land cover changes utilizing multi-temporal remotely sensed image data in Lake Hawassa Watershed, Ethiopia. *Environmental Monitoring and Assessment* **186**:1765–1780 DOI 10.1007/s10661-013-3491.

Woodcock CE, Macomber SA, Pax-Lenney M, Cohen WB. 2001. Monitoring large areas for forest change using Landsat: generalization across space, time and Landsat sensors. *Remote Sensing of Environment* **78**:194–203 DOI 10.1016/S0034-4257(01)00259-0.

Wulder MA, White JC, Goward SN, Masek JG, Irons JR, Herold M, Cohen WB, Loveland TR, Woodcock CE. 2008. Landsat continuity: issues and opportunities for land cover monitoring. *Remote Sensing of Environment* **112**:955–969 DOI 10.1016/j.rse.2007.07.004.

Xian G, Homer C, Fry J. 2009. Updating the 2001 National Land Cover Database land cover classification to 2006 by using Landsat imagery change detection methods. *Remote Sensing of Environment* **113**:1133–1147 DOI 10.1016/j.rse.2009.02.004.

Yin H, Pflugmacher D, Kennedy RE, Sulla-Menashe D, Hostert. 2014. Mapping annual land use and land cover changes using MODIS time series. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* **7**:3421–3427 DOI 10.1109/JSTARS.2014.2348411.

Zhen Z, Quackenbush LJ, Stehman SV, Zhang L. 2013. Impact of training and validation sample selection on classification accuracy and accuracy assessment when using reference polygons in object-based classification. *International Journal of Remote Sensing* **34**:6914–6930 DOI 10.1080/01431161.2013.810822.

ECOGRAPHY

Fine scale waterbody data improve prediction of waterbirds occurrence despite coarse species data

Journal:	*Ecography*
Manuscript ID	ECOG-03724.R1
Wiley - Manuscript type:	Research
Keywords:	spatial resolution, atlas data, wetlands

Abstract:	While modelling habitat suitability and species distribution, ecologists must deal with issues related to the spatial resolution of species occurrence and environmental data. Indeed, given that the spatial resolution of species and environmental of datasets range from centimeters to hundreds of kilometers, it underlines the importance of choosing the optimal combination of resolutions to achieve the highest possible modelling prediction accuracy. We evaluated how the spatial resolution of land cover/waterbody datasets (meters to 1 km) affect waterbird habitat suitability models based on atlas data (grid cell of 12 × 11 km). We hypothesized that area, perimeter and number of waterbodies computed from high resolution datasets would explain distributions of waterbirds better because coarse resolution datasets omit small waterbodies affecting species occurrence. Specifically, we investigated which spatial resolution of waterbodies better explain the distribution of seven waterbirds nesting on ponds/lakes of area 0.1 ha to hundreds of hectares. Our results show that the area and perimeter of waterbodies derived from high resolution datasets (raster data with 30 m resolution, vector data corresponding with map scale 1:10,000) explain the distribution of the waterbirds better than those calculated using less accurate datasets despite the coarse grain of the species data. Taking into account the spatial extent (global vs regional) of the datasets, we found the Global inland waterbody dataset to be the most suitable for modelling distribution of waterbirds. In general, we recommend using land cover data of a sufficient resolution to be able to capture the smallest patches of the habitat suitable for given species presence for both fine and coarse grain habitat suitability and distribution modelling.

SCHOLARONE™
Manuscripts

Title:

Fine scale waterbody data improve prediction of waterbirds occurrence despite coarse species data

Petra Šímová[1], Vítězslav Moudrý[1], Jan Komárek[1], Karel Hrach[1], Marie-Josée Fortin[2]

[1] *Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Kamýcká 129, Praha – Suchdol, 165 00, Czech Republic*

[2] *Department of Ecology and Evolutionary Biology, University of Toronto, 25 Willcocks, Toronto (Ontario) M5S 3B2 Canada*

Corresponding author: Petra Šímová

ORCID 0000-0003-2480-1171

simova@fzp.czu.cz

phone: +420 22438 2142

fax: +420224382658

Vítězslav Moudrý

moudry@fzp.czu.cz

ORCID 0000-0002-3194-451X

Jan Komárek

komarekjan@fzp.czu.cz

ORCID 0000-0002-3505-6755

Karel Hrach

hrach@fzp.czu.cz

Marie-Josée Fortin

mariejosee.fortin@utoronto.ca

ORCID 0000-0002-9935-1366

For Review Only

Abstract

While modelling habitat suitability and species distribution, ecologists must deal with issues related to the spatial resolution of species occurrence and environmental data. Indeed, given that the spatial resolution of species and environmental of datasets range from centimeters to hundreds of kilometers, it underlines the importance of choosing the optimal combination of resolutions to achieve the highest possible modelling prediction accuracy. We evaluated how the spatial resolution of land cover/waterbody datasets (meters to 1 km) affect waterbird habitat suitability models based on atlas data (grid cell of 12 × 11 km). We hypothesized that area, perimeter and number of waterbodies computed from high resolution datasets would explain distributions of waterbirds better because coarse resolution datasets omit small waterbodies affecting species occurrence. Specifically, we investigated which spatial resolution of waterbodies better explain the distribution of seven waterbirds nesting on ponds/lakes of area 0.1 ha to hundreds of hectares. Our results show that the area and perimeter of waterbodies derived from high resolution datasets (raster data with 30 m resolution, vector data corresponding with map scale 1:10,000) explain the distribution of the waterbirds better than those calculated using less accurate datasets despite the coarse grain of the species data. Taking into account the spatial extent (global vs regional) of the datasets, we found the Global inland waterbody dataset to be the most suitable for modelling distribution of waterbirds. In general, we recommend using land cover data of a sufficient resolution to be able to capture the smallest patches of the habitat suitable for given species presence for both fine and coarse grain habitat suitability and distribution modelling.

For Review Only

Keywords

spatial resolution; wetlands; atlas data, species distribution models

Introduction

Habitat suitability models (HSMs), also known as species distribution models (SDMs) or ecological niche models, are used to model the relationship between geographical occurrences of species with environmental variables (Guisan et al. 2013, 2017). While modelling habitat suitability and species distribution, ecologists must deal with the problem of spatial resolutions, both resolution of data on species occurrence entering the models as a dependent variable (species data) and resolution of environmental predictors (McPherson et al. 2006, Guisan et al. 2007, 2017, Gottschalk et al. 2011, Rocchini et al. 2011, Moudrý and Šímová 2012, Pradervand et al. 2013, Lecours et al. 2015). Spatial resolution of species data can vary from centimeters to tens or hundreds kilometers depending on a wide range of underlying factors such as data collecting method, time (e.g. recent data collected using modern technologies versus historical records), species characteristics (e.g. mobile versus sedentary species) among others (Elith et al. 2006, Guisan et al. 2007, Osborne and Leitão 2009, Reside et al. 2011, Moudrý and Šímová 2012). Similarly, spatial resolution of environmental predictors can range from centimeters to hundreds of kilometers, depending on the method of data acquisition (e.g. satellite remote sensing versus imaging with unmanned aerial vehicles or detailed ground mapping) and of data processing (e.g. classification of multispectral imagery into land cover classes with or without aggregating classified pixels into greater patches). The aggregation can be based for instance on minimal mapping unit (MMU) defining the smallest patch in the landscape that is captured in a land cover layer. MMU is usually much larger than the pixel size (for example MMU of 25 ha applied on 30 m Landsat image pixel in CORINE land cover (Büttner et al. 2004)) and size is often set arbitrary (Saura 2002, Lechner et al. 2012a). Given such wide range of spatial datasets and resolution (Figures 1 and 2, Table 1), it is important to find the optimal spatial resolution of environmental predictors to match the species data available in order to achieve the highest possible HSM prediction accuracy (Guisan et al. 2007, Gottschalk et al. 2011, Lechner et al. 2012a,b, Cord et al. 2014, Mertes and Jetz 2018).

Although several studies have examined the effect of changing grain on prediction accuracy of HSMs, no definite guidelines can be drawn on the basis of their results. For example, Guisan et al. (2007) tested the effects of a 10-fold coarsening of grain size, namely from 100 m to 1 km and 1 km to 10 km. They concluded that changing grain size did not consistently affect models' accuracy across regions, modelling techniques, and species types. Gottschalk et al. (2011) started at 1 m pixel size and coarsened it to 1 km in seven increments, where they found that model performance for the most of 13 bird species under study

For Review Only

degraded continuously with coarsening resolution but two species were best modelled at 3 m and one species at 32 m grain size. Moreover, it is important to add that these studies were not specifically focused on the effect of environmental predictors pixel size (and thus on changing the predictors' pixel size while keeping grain of species data constant) but, at the same time, the grain of analysis was also coarsened (Figure 1). In such multi-scale (sensu McGarigal et al., 2016) approach, the effect of the quality of the environmental datasets on HSMs prediction accuracy cannot be separated from the other scaling aspects such as modifiable areal unit problem (Jelinski and Wu 1996, Lechner et al. 2012b) and from a possible finding of a spatial scale matching the strongest species' response to the environment (Jackson and Fahrig 2015, McGarigal et al. 2016, Lipsey et al. 2017). Here, we investigate the effect of the environmental predictors resolution separately, using a priori single scale study (as defined McGarigal et al., 2016).

It is essential to know if a given spatial resolution can describe details of the environmental phenomena important for distribution of a given species. For instance, low resolution land cover data may poorly describe a potentially suitable habitat, simply due to omitting the minor landscape features (Gottschalk et al. 2011). It is possible, for example, that small patches (e.g. hectares or smaller) of waterbodies are sufficient for the presence of a waterbird species, and thus environmental predictors such as area or perimeter of waterbodies derived from datasets with a MMU of tens of hectares or a pixel size of square kilometer(s) would explain the species distribution less than predictors based upon high resolution datasets, such as land cover layers based on aerial photographs, very high resolution satellite data (e.g. IKONOS, QuickBird, WorldView) or detailed field mapping.

Such high resolution datasets pre-processed to a form suitable for HSMs, however, might not be readily available for the study area, could be prohibitively expensive (especially for studies conducted in a large extent) and their use for modelling could be inadequately demanding on data processing time. Hence, researchers are faced with a decision of a trade-off between potential pros and cons of using high resolution environmental datasets describing habitats probably better than the coarser ones. A logical solution could be to use high resolution predictors only for fine grain analyses, together with high resolution species data, such as birds' presence/absence sampled using point or transect methods. Similarly, we can assume that low resolution environmental predictors could be sufficient for coarse grain modelling, and therefore, that continental or global habitat data such as CORINE Land cover (Büttner et al. 2004) or Global Consensus Land cover (Tuanmu and Jetz 2014) are sufficient

For Review Only

for the use in combination with species data with positional uncertainties in the order of kilometers. However, if small but potentially sufficient patches of suitable habitats are missing in a coarse resolution land cover dataset, the use of a high resolution one could be beneficial even for the studies based on coarse grain species data such as atlases' data.

One of the likely reasons why especially models combining high resolution environmental data with coarse grain species data have not been sufficiently investigated so far is because environmental data with declared high resolution are usually not readily available or are prohibitively expensive for extents of states or continents (extent of species atlases). As inland waterbodies are undoubtedly an important predictor of waterbird presence and a high resolution layer of waterbodies for the Czech Republic is freely available, we compared the effect of spatial resolution of five land cover/waterbody datasets on accuracy of HSMs based on atlas data. We hypothesized that (i) high resolution waterbodies datasets would explain distribution of waterbird species better than those calculated using coarser datasets because the presence of relatively small water bodies in the atlas mapping grid cell can be sufficient for species presence (and higher resolution datasets thus describe ecological requirements of the species more accurately), and (ii) area and perimeter of waterbodies predict the presence of the species requiring open water surface and/or water edge habitats better than the simple number of waterbodies. We predicted that higher resolution datasets representing inland waterbodies would lead to more accurate HSMs. We tested this hypothesis using seven waterbird species that utilize waterbodies of area varying from approximately 0.1 ha to several square kilometers (Šťastný et al. 2006) in the Czech Republic and land cover/waterbody datasets varying in spatial resolution (from the high resolution layer corresponding with a map scale 1:10,000 and MMU in the order of several square meters to low resolution data of pixel size 1 × 1 km). The species data originated from the Atlas of Breeding Birds in the Czech Republic (Šťastný et al. 2006) with grain (grid cell of species presence mapping) of approximately 11 × 12 km. The explanatory variables were based on a fine scale water body layer from the Czech spatial database DIBAVOD and continent-wide and world-wide land cover datasets CORINE Land Cover (CLC), Global Inland Water (GIW), Global Consensus Land Cover (GCL), and Open Street Map (OSM). As crowd-sourced datasets (OSM) could be on the one hand a valuable source of environmental predictors for HSM but, on the other hand, their spatial resolution is uncertain, an additional data-oriented objective was to evaluate the suitability OSM for modelling waterbirds' distribution in the study area.

For Review Only

Materials and Methods

Study area and species data

The study area (approx. 68.000 km^2) covers the entire Czech Republic. We used species data from the Atlas of Breeding Birds in the Czech Republic 2001–2003 (Šťastný et al. 2006) with grid cell of species presence mapping of 10' east longitude and 6' north latitude (approximately 12 × 11 km) with 679 grid cells covering the entire country. As the species data in grid cells intersecting country's border can be inconsistent, we used only 507 grid cells belonging completely to the Czech Republic (Figure 3).

Birds' presence was mapped by hundreds of ornithologists over three years specifically for the purpose of the atlas. Bird mapping in every grid cell was undertaken by at least one person, most cells were however mapped by several people. The ornithologists systematically and repeatedly (usually several times a year over the period of 2-3 years) searched for evidence of breeding occurrence of each species in all habitats present in the particular grid cell. In accordance with standards used in Europe (Hagemeijer and Blair 1997), the occurrences were recorded in three categories defining probability of breeding as possible breeding, probable breeding, and confirmed breeding while the highest category found for a given grid cell is recorded in the atlas. As the detection probability of the waterbird species (ducks and grebes, see below) used in this study is very high, we used all three breeding categories (possible, probable and confirmed breeding) as presences while remaining squares were considered as absences in habitat suitability modelling (but see Moudrý et al. 2017 for possible effect of the breeding category selection on prediction accuracy).

We selected waterbird species on the basis of habitat preferences and spatial pattern of species' breeding occurrence in the study area. We focused on the species utilizing open water surface for feeding and water edges (and their close proximity) for hiding and nesting, the occurrence of which within the study area is at the same time not restricted to a narrow range of elevation only. Rare species (breeding in less than 20 % of atlas grid cells), species with only local, strongly clustered occurrence, and species breeding in an overwhelming majority of cells (more than 75 %) were excluded because their distribution is obviously strongly affected by more factors than just the presence of waterbodies in the grid cell (for example, the breeding occurrence for some species is obviously strongly linked with large fishpond systems covering several contiguous squares with low elevation). As a result, we selected seven waterbird species: three grebes – the little grebe *(Tachybaptus ruficollis)*, great crested grebe *(Podiceps cristatus)* and black-necked grebe *(Podiceps nigricollis)*; two swimming ducks – the gadwall *(Anas strepera)* and common teal *(Anas crecca);* and two diving ducks –

For Review Only

the common pochard *(Aythya ferina)* and tufted duck *(Aythya fuligula).* From the habitat characteristics and feeding strategies view point, species preferring both shallow and deeper waterbodies with various amounts of littoral or floating vegetation, species preferring various ranges of elevation, as well as predominantly herbivorous, carnivorous and omnivorous species foraging both on the water surface and by diving are included. An important factor for our analysis is the size of preferred waterbodies. Most of these species (in the Czech Republic) nest at ponds/lakes of various sizes ranging from approx. 0.1 ha up to several square kilometers, without a particular preference for small or larger ones. The only exceptions are *Anas crecca* preferring smaller ponds and *Podiceps cristatus* preferring larger (2 ha and above) ponds/lakes (Šťastný et al. 2006).

Environmental predictors

We derived *area*, *perimeter* and *number* of water bodies from five datasets with varying resolution, differing in methods of acquisition of the information about the water surface presence, and with extent ranging from regional (covering the Czech Republic only) to world-wide (see Table 1 for overview). (1) As a reference (most accurate) dataset, the vector layer of water bodies covering the entire Czech Republic was used; it is a part of a hydrological database DIBAVOD (www.dibavod.cz) administered by the T. G. Masaryk Water Research Institute. Data detail in DIBAVOD is in accordance with a cartographical ratio of 1:10,000, the smallest polygons are in the order of several square meters and data are based on field mapping and aerial orthophotos. (2) Second dataset, also focused primarily on water surfaces, was a global (world-wide extent), 30 m resolution inland waterbody dataset (GIW) derived from Landsat satellite data by Feng et al. (2016). Other three datasets were land cover layers from which only water bodies were extracted. We used (3) a European database CORINE Land Cover (CLC), that is based on Landsat satellite data with 30 m resolution just as GIW, however, its MMU is 25 ha (Büttner et al. 2004), which obviously leads to a substantial generalization of water bodies in comparison with GIW. (4) The Global Consensus Land Cover (GCL) database created by (Tuanmu and Jetz 2014) for biodiversity and ecosystem modelling uses an even lower spatial resolution (1 km). GCL integrates four global land cover datasets to maximize accuracy and reduce errors of omissions (Tuanmu and Jetz 2014). (5) The last dataset was the Open Street Map (http://www.openstreetmap.org), a free crowd-sourced spatial database.

For Review Only

Based on the methods of creating the datasets and a simple comparison using GIS overlay analysis, we assumed the following accuracy ranking from: GCL (the most generalized) < CLC < GIW < OSM < DIB (the most accurate). Area, perimeter and number of water bodies within each mapping square were calculated using CLC, GIW, OSM and DIB layers. Calculation of perimeter and number of geographical entities from a continuous raster (GCL) is irrelevant and, therefore, only the area of waterbodies was calculated for GCL using cell values, cell size and mapping square area. We used ArcGIS 10.3 software (ESRI, USA) for all GIS analyses. See Table 1 for details of datasets, Figure 2 for an example of dataset quality and Table 2 for mean values of the variables.

Statistical analysis

We assessed effects of environmental variables using generalized linear models (GLMs) and generalized additive models (GAMs) (Guisan et al. 2002) within the free statistical software environment R 3.2.2 (R Core Development Team 2017). We adopted the univariate modelling approach to compare the predictive performance of individual variables (*number*, *perimeter* and *area* of water bodies) derived from GLC, CLC, GIW, OSM and DIB as data of different resolution (see also Guisan and Hofer 2003, Venier et al. 2004, Lassueur et al. 2006). We built 91 individual univariate models (five datasets x seven bird species for *area* and four datasets x seven species for *perimeter* and *number*). In order to evaluate the models and assess the difference in terms of predictive performance between the datasets and individual calculated variables, we used 5-fold cross validation. To compare the predictions, we used the area under the curve (AUC) of the receiver operating characteristic plot (Fielding and Bell 1997) and true skill statistics (TSS) (Allouche et al. 2006). We calculated the mean values of AUC and TSS across all 5-folds using the *PresenceAbsence* R package (Freeman and Moisen 2008). According to an arbitrary guideline presented in BIOMOD manual (Thuiller et al. 2009), fail/null model (TSS $\leq$ 0.4; 0.5 $\leq$ AUC < 0.7), fair model (0.40 < TSS < 0.6; 0.70 $\leq$ AUC < 0.8); good model (0.60 < TSS < 0.8; 0.80 $\leq$ AUC < 0.9), and excellent/high model (0.80 < TSS < 1; 0.90 $\leq$ AUC < 1) can be distinguished.

We used repeated measures ANOVA to test the effect of (1) waterbody dataset (i.e. input data resolution) and (2) used explanatory variable (total area, or total perimeter, or number of waterbodies) on values of TSS and AUC, respectively. Due to satisfactory normality of the data, it was possible to use the standard parametric version. If the ANOVA test was significant, we followed up with the paired Tuckey post-hoc tests to test the

For Review Only

significance of differences between pairs of datasets/variables. STATISTICA 12 software was used for these analyses.

Results

As GLM yielded very similar results to the GAM, we only present the latter. Mean TSS and AUC values of all univariate models varied between 0.25 - 0.59 and 0.62 - 0.84, respectively (Table 3), i.e. accuracy of individual univariate models varied between poor and fair. Accuracy of some models was good but only according to AUC. Simple color visualization of TSS and AUC values in Table 3 indicates, in general, that models based on higher resolution datasets performed better than models based on low resolution datasets and that *area* and *perimeter* of waterbodies are more appropriate predictors of occurrence of the group of waterbirds than the *number* of waterbodies.

According to ANOVA results (Figure 4, Table 4), the effect of a dataset on HSMs accuracy (measured by TSS and AUC) was significant, as well as the effect of variables (*area*, *perimeter* and *number* of water bodies). *Area* and *perimeter* showed similar trends of dependence of HSM accuracy on dataset resolution (Figure 4), given both by TSS and AUC scores. For *area* and *perimeter*, CLC-based models performed significantly (p<0.0001) worse than models based on GIW, OSM and DIB. Analysis conducted separately for *Area* with GCL showed that GCL performed significantly (p<0.001) worse than CLC. Thus, HSMs accuracy was lower for low resolution datasets (GCL, CLS) while higher for high resolution datasets (GIW, OSM and DIB). In comparison, accuracy of models based on *Number* of water bodies did not show any dependency on the dataset resolution, with GIW-based models performing significantly better than those based on OSM, DIB and CLC (TSS scores) or significantly better than OSM, DIB and similarly as CLC (AUC scores). See Table 4 for significance levels and for differences between TSS and AUC.

Discussion

Our results show that the area and perimeter of waterbodies derived from high resolution land cover datasets (raster data with 30 m resolution and vector data corresponding with cartographic ratio 1:10,000) explain the distribution of waterbirds under study better than those calculated using less accurate water datasets despite the coarse grain of the species data. In spite of the previously published findings and opinions that using detailed land cover maps

For Review Only

can only improve models based on a corresponding level of detail in the species data (Gottschalk et al. 2011), our results indicate that utilizing fine scale land cover data can be in some instances beneficial even in combination with coarse grain species data. As suggested by several studies (Šťastný et al., 2006, Sebastián-González and Green, 2014), the presence of waterbodies of only a few hectares (3 ha) or even less then 1 ha is sufficient to support occurrence of many waterbirds. However, the minimum mapping unit of CLC is 25 ha and GCL uses a percentage of land cover class in a 1 × 1 km pixel size (despite building upon data with resolution of 1 km, 500 m and 300 m) and small waterbodies are therefore not correctly recorded in these datasets or are missing altogether. As shown in Table 2, more than 45% atlas cells in the Czech Republic are completely without water surfaces according to GCL (232 cells) and CLC (230 cells). A more detailed DIB and OSM dataset, however, states that water surfaces are present in each cell, which corresponds to the reality. Thus, it is logical that the variables *area* and *perimeter* based on DIB datasets perform better. The accuracies obtained with GIW and DIB were similar for the *area* and *perimeter* variables. When compared to DIB, GIW omits the smallest waterbodies (according to GIW, waterbodies are missing in 27, i.e. in 5.4%, of atlas cells), however, its 30 × 30 m resolution allows a good capture of waterbodies from approx. 0.1 ha, i.e., the size sufficient for species preferring or capable of utilizing small waterbodies (Šťastný et al. 2006). The fact that small waterbodies (which are not captured in the coarser datasets such as GCL) are sufficient for the occurrence of numerous waterbird species may be one of the reasons why Tuanmu and Jetz (2014) found GCL performing less accurately for studied water species than for species that require other types of environment. Although CLC and GCL are utilized in habitat suitability and distribution modelling (Krojerová-Prokešová et al. 2008, Šímová et al. 2015, Valerio et al. 2016, Vallecillo et al. 2016), our results imply that using higher resolution datasets could yield higher prediction accuracy.

Unlike the *area* and *perimeter* variables, performance of the *number* of waterbodies was unpredictable. *Number* produced significantly less accurate models than those for *area* and *perimeter* when extracting it from the high resolution datasets DIB and OSM (the most accurate ones). This corresponds with the assumption that *area* and *perimeter* are better predictors of waterbird distribution than *number*. On the other hand, however, all three variables performed similarly in the case of GIW and CLC, respectively (in case of CLC, the *number* of waterbodies performed even better than their *area* and *perimeter* according to AUC). In the case of GIW, we suspect that the result is more likely an artefact of deriving a

For Review Only

number of patches from the raster data than the number of waterbodies being an equally good predictor of the occurrence of waterbirds as the *area* or *perimeter*. Although raster land cover datasets are commonly used to calculate the number of patches of a land cover class and even the software most widely used for calculations of landscape metrics (Fragstats; McGarigal, 2015), is based on raster data, determining the number of patches from a raster is problematic. While the number of entities (polygons) in a vector dataset is explicitly given, their calculation from a grid depends on the method of joining individual pixels into a patch (Figure 1. For example, each pixel in a 3×3 pixels kernel can be considered as part of the patch in some methods while in others, only pixels sharing sides are included and diagonal neighbors are omitted (McGarigal, 2015). In CLC, where small water bodies are not captured and the average performances of models are generally lower than those of more detailed datasets, values of all three variables (*area*, *perimeter*, *number*) are significantly affected (Figures 1 and 2). It is therefore tricky to consider any of the predictors better than the others and the result should be only considered as an artefact of data used to derive the explanatory variables. These findings therefore imply that the use of high resolution environmental data cannot substitute a thorough selection of predictors for habitat suitability modelling as fine scale environmental predictors can still lead to inaccurate models if the wrong environmental predictor is chosen.

As AUC was criticized by some authors (Lobo et al. 2008, Moudrý 2015), we used also TSS. According to the arbitrary scale (Thuiller et al. 2009), AUC tends to rate the results better than TSS, particularly in models based on high resolution datasets (see Table 3). As shown in Figure 4, the general trends of the response on predictor resolutions are similar for both AUC and TSS. For some individual species, however, the AUC value leads to different conclusions than that of TSS. For example, the average accuracy of models from the high resolution datasets (GIW, OSM and DIB) using *area* predictor for *Anas crecca* was the worst according to TSS while it was the second best according to AUC. On the other hand, the models of occurrence of *Aythia ferina* and *Aythia fuligula* perform better according to TSS than according to AUC when compared to the other species.

As far as the sizes of the waterbodies preferred for nesting by individual species are concerned, it would be difficult to draw any conclusions. Models for *Anas crecca*, which is the only of our model species clearly preferring small ponds, yielded the lowest TSS values of all species for *area*, using CLC as well as high resolution datasets. Contrary, the performance of models for *Podiceps cristatus*, which is the only species avoiding the small ponds (less

For Review Only

than 2 ha), is according to TSS the best of all species throughout CLC as well as high resolution datasets. The probable causes may include effects of topographical and climatic factors (Moudrý and Šímová 2013) as well as the fact that no species preferring really large waterbodies (25 ha and larger, corresponding to the MMU of CLC) nest in the study area.

In conclusion, comparing models derived from the tested datasets, the best results were acquired using *area* and *perimeter* variables, specifically those calculated from high resolution Global Inland Water, DIBAVOD and Open Street Map datasets. National datasets such as DIBAVOD could provide the best spatial information about the waterbodies, they are however only available for smaller extents and their form and availability usually depend on the policies of state institutions. The Open Street Map could be, despite the potential inconsistencies or inaccuracies caused by its crowd-sourced character (Haklay et al. 2010, Mooney et al. 2010), a high quality input for HSM; however, its accuracy and completeness can significantly vary from region to region. Hence, taking into account the spatial extent (world-wide vs regional) and the methods utilized for creating these datasets (remote sensing, field mapping, crowd sourcing), we found the Global Inland Water dataset to be the most suitable source of values on the area and perimeter of waterbodies for modelling distribution of waterbird species. In general, we recommend using land cover data of a sufficient resolution to be able to capture the smallest patches of the habitat suitable for given species presence for both fine and coarse grain habitat suitability and distribution modelling; the use of high resolution environmental data, however, cannot substitute a thorough selection of explanatory variables to be used for modelling.

For Review Only

Declarations

Acknowledgments

This study was funded by the Czech University of Life Sciences Prague, Faculty of Environmental Sciences, Grant No. 423001312423155. We would like to thank to Jaroslav Janosek for his helpful comments and the English proof-reading of the manuscript.

Author contributions

P. Šímová is author of the main idea of the research and wrote majority of the text. V. Moudrý partly improved the idea, supervised GLMs and GAMs computing and contributed to the text. J. Komarek and Karel Hrach computed statistical models and contributed to the Methods and Results parts, J. Komarek also processed GIS analysis. M-J. Fortin substantially contributed to improving the manuscript.

References

Allouche, O. et al. 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). - J. Appl. Ecol. 43: 1223–1232.

Büttner, G. et al. 2004. The Corine Land Cover 2000 Project. - EARSeL eProceedings 3: 331–346.

Cord, A. F. et al. 2014. Comparing the suitability of classified land cover data and remote sensing variables for modeling distribution patterns of plants. - Ecol. Modell. 272: 129–140.

Elith, J. et al. 2006. Novel methods improve prediction of species' distributions from occurrence data. - Ecography. 29: 129–151.

European Environment Agency 2000. Corine Land Cover 2000.

Feng, M. et al. 2016. A global, high-resolution (30-m) inland water body dataset for 2000: first results of a topographic–spectral classification algorithm. - Int. J. Digit. Earth 9: 113–133.

Fielding, A. H. and Bell, J. F. 1997. A review of methods for the assessment of prediction errors in conservation presence/ absence models. - Environ. Conserv. 24: 38–49.

Freeman, E. a and Moisen, G. 2008. PresenceAbsence: An R Package for Presence Absence Analysis. - J. Stat. Softw. 23: 1–31.

Gottschalk, T. K. et al. 2011. Influence of grain size on species-habitat models. - Ecol. Modell. 222: 3403–3412.

Guisan, A. and Hofer, U. 2003. Predicting reptile distributions at the mesoscale: Relation to climate and topography. - J. Biogeogr. 30: 1233–1243.

Guisan, A. et al. 2002. Generalized linear and generalized additive models in studies of species distributions: Setting the scene. - Ecol. Modell. 157: 89–100.

Guisan, A. et al. 2007. Sensitivity of predictive species distribution models to change in grain size. - Divers. Distrib. 13: 332–340.

Guisan, A. et al. 2013. Predicting species distributions for conservation decisions. - Ecol. Lett. 16: 1424–1435.

Guisan, A. et al. 2017. Habitat suitability and distribution models with applications in R.

Hagemeijer, E. J. M. and Blair, M. J. 1997. The EBCC atlas of European breeding birds - Their distribution and abundance. - T & A Poyser.

Haklay, M. 2010. How good is volunteered geographical information? A comparative study of OpenStreetMap and ordnance survey datasets. - Environ. Plan. B Plan. Des. 37: 682–703.

Haklay, M. (Muki) M. (Muki) et al. 2010. How many volunteers does it take to map an area well? The validity of Linus' law to volunteered geographic information. - Cartogr. J. 47: 315–322.

Jackson, H. B. and Fahrig, L. 2015. Are ecologists conducting research at the optimal scale? - Glob. Ecol. Biogeogr. 24: 52–63.

Jelinski, D. E. and Wu, J. 1996. The modifiable areal unit problem and implications for

For Review Only

landscape ecology. - Landsc. Ecol. 11: 129–140.

Krojerová-Prokešová, J. et al. 2008. Species richness of vertebrates in the Czech Republic. - Folia Zool. 57: 452–464.

Lassueur, T. et al. 2006. Very high resolution digital elevation models: Do they improve models of plant species distribution? - Ecol. Modell. 198: 139–153.

Lechner, A. M. et al. 2012a. Are landscape ecologists addressing uncertainty in their remote sensing data? - Landsc. Ecol. 27: 1249–1261.

Lechner, A. M. et al. 2012b. Investigating species-environment relationships at multiple scales: Differentiating between intrinsic scale and the modifiable areal unit problem. - Ecol. Complex. 11: 91–102.

Lecours, V. et al. 2015. Spatial scale and geographic context in benthic habitat mapping: review and future directions. - Mar. Ecol. Prog. Ser. 535: 259–284.

Lipsey, M. K. et al. 2017. Extending utility of hierarchical models to multi-scale habitat selection. - Divers. Distrib. 23: 783–793.

Lobo, J. M. et al. 2008. AUC: a misleading measure of the performance of predictive distribution models. - Glob. Ecol. Biogeogr. 17: 145–151.

McCullagh, P. and Nelder, J. A. 1989. Generalized Linear Models. - Chapman & Hall.

McGarigal, K. 2015. Fragstats.Help.4.2.: 1–182.

McGarigal, K. et al. 2016. Multi-scale habitat selection modeling: a review and outlook. - Landsc. Ecol. 31: 1161–1175.

McPherson, J. M. et al. 2006. Using coarse-grained occurrence data to predict species distributions at finer spatial resolutions—possibilities and limitations. - Ecol. Modell. 192: 499–522.

Mertes, K. and Jetz, W. 2018. Disentangling scale dependencies in species environmental niches and distributions. - Ecography. in press.

Mooney, P. et al. 2010. Towards quality metrics for OpenStreetMap. - Proc. 18th SIGSPATIAL Int. Conf. Adv. Geogr. Inf. Syst. GIS 10: 514–517.

Moudrý, V. 2015. Modelling species distributions with simulated virtual species. - J. Biogeogr. 42: 1365–1366.

Moudrý, V. and Šímová, P. 2012. Influence of positional accuracy, sample size and scale on modelling species distributions: a review. - Int. J. Geogr. Inf. Sci. 26: 2083–2095.

Moudrý, V. and Šímová, P. 2013. Relative importance of climate, topography, and habitats for breeding wetland birds with different latitudinal distributions in the Czech Republic. - Appl. Geogr. 44: 165–171.

Moudrý, V. et al. 2017. Which breeding bird categories should we use in models of species distribution? - Ecol. Indic. 74: 526–529.

Osborne, P. E. and Leitão, P. J. 2009. Effects of species and habitat positional errors on the performance and interpretation of species distribution models. - Divers. Distrib. 15: 671–681.

For Review Only

Pradervand, J.-N. et al. 2013. Very high resolution environmental predictors in species distribution models: Moving beyond topography? - Prog. Phys. Geogr. 38: 79–96.

R Core Development Team 2015. R: a language and environment for statistical computing, 3.2.1. - Doc. Free. available internet http//www. r-project. org in press.

Reside, A. E. et al. 2011. Incorporating low-resolution historic species location data decreases performance of distribution models. - Ecol. Modell. 222: 3444–3448.

Rocchini, D. et al. 2011. Accounting for uncertainty when mapping species distributions: The need for maps of ignorance. - Prog. Phys. Geogr. 35: 211–226.

Saura, S. 2002. Effects of minimum mapping unit on land cover data spatial configuration and composition. - Int. J. Remote Sens. 23: 4853–4880.

Sebastián-González, E. and Green, A. J. 2014. Habitat Use by Waterbirds in Relation to Pond Size, Water Depth, and Isolation: Lessons from a Restoration in Southern Spain. - Restor. Ecol. 22: 311–318.

Šímová, P. et al. 2015. Refugial role of urbanized areas and colonization potential for declining Crested Lark (Galerida cristata) populations in the Czech Republic, Central Europe. - J. Ornithol. 156: 915–921.

Šťastný, K. et al. 2006. Atlas of breeding bird distribution in the Czech Republic 2001-2003. - Aventinum.

Thuiller, W. et al. 2009. BIOMOD - a platform for ensemble forecasting of species distributions. - Ecography. 32: 369–373.

Tuanmu, M. N. and Jetz, W. 2014. A global 1-km consensus land-cover product for biodiversity and ecosystem modelling. - Glob. Ecol. Biogeogr. 23: 1031–1045.

Valerio, F. et al. 2016. The reliability of a composite biodiversity indicator in predicting bird species richness at different spatial scales. - Ecol. Indic. 71: 627–635.

Vallecillo, S. et al. 2016. A habitat quality indicator for common birds in Europe based on species distribution models. - Ecol. Indic. 69: 488–499.

Venier, L. a et al. 2004. Climate and satellite-derived land cover for predicting breeding bird distribution in the Great Lakes basin. - J. Biogeogr. 31: 315–331.

For Review Only

Tables

Table 1. Description of the sources of waterbody data. Waterbodies are represented for the different types of GIS representation: Continuous raster – each cell value is the percent of the cell area that is covered by water; Boolean raster – each cell value is the binomial presence or absence of waterbodies within the cell; Vector – the size and shape of each waterbody is outlined in detail corresponding with the map scale of the data.

	Global Consensus Land Cover	**CORINE Land Cover**	**Global Inland Water**	**Open Street Map**	**Dibavod**
Acronym	GCL	CLC	GIW	OSM	DIB
GIS representation	continuous raster	vector	Boolean raster	vector	vector
Extent	global	Europe	global	global	Czech
Resolution	1 km	1:100,000 (MMU 25 ha)	30 m	N/A	1:10,000 (MMU several metres)
Time relevance	1999-2006	2000	2000	2007-15	2004
Categories used	Open water	511 Water courses, 512 Waterbodies	Inland water	Water	Waterbodies
Reference	(Tuanmu and Jetz 2014)	(Büttner et al. 2004)	(Feng et al. 2016)	(Haklay 2010)	T. G. Masaryk Water Research Institute www.dibavod.cz

Table 2. Area, perimeter and number of water bodies within atlas grid cells (Mean ± Std within the entire dataset). NoWater denotes the number of grid cells with no waterbody captured within the dataset.

	AREA [km^2]	**PERIMETER [km]**	**NUMBER**	**NoWater**
GCL	0.43 ± 1.07	N/A	N/A	230
CLC	0.85 ± 1.08	7.05 ± 12.52	1.24 ± 2.04	232
GIW	0.96 ± 1.67	22.13 ± 26.08	26.43 ± 26.81	27
OSM	1.19 ± 1.72	32.37 ± 26.51	129.19 ± 82.31	0
DIB	1.35 ± 2.03	33.85 ± 29.51	124.39 ± 80.42	0

For Review Only

Table 3. Mean TSS and AUC values based on a 5-fold cross validation for each of the seven water bird species for the five waterbody predictor datasets among the three versions of the predictor (area, perimeter, or total number of water bodies) and its simple visualization. Legend Fail/null model: TSS ≤ 0.4; 0.5 ≤ AUC < 0.7; Fair model (lower half of the interval): 0.40 < TSS < 0.5; 0.70 ≤ AUC < 0.75; Fair model (upper half of the interval): 0.50 < TSS < 0.6; 0.75 ≤ AUC < 0.80; Good model 0.60 ≤ TSS; 0.8 ≤ AUC (Thuiller et al. 2009).

	AREA									
	GCL		CLC		GIW		OSM		DIB	
SPECIES	TSS	AUC	TSS	AUC	TSS	AUC	TSS	AUC	TSS	AUC
Tachybaptus ruficollis	0.253	0.672	0.331	0.683	0.445	0.734	0.490	0.756	0.473	0.749
Podiceps cristatus	0.419	0.669	0.455	0.695	0.541	0.781	0.550	0.816	0.590	0.817
Podiceps nigricollis	0.369	0.664	0.416	0.688	0.436	0.781	0.430	0.811	0.441	0.813
Anas strepera	0.322	0.683	0.387	0.710	0.493	0.812	0.517	0.841	0.516	0.837
Anas crecca	0.331	0.712	0.341	0.737	0.412	0.816	0.444	0.830	0.423	0.836
Aythya ferina	0.334	0.696	0.402	0.713	0.517	0.739	0.539	0.760	0.540	0.751
Aythya fuligula	0.353	0.624	0.406	0.666	0.548	0.759	0.590	0.780	0.592	0.769

	PERIMETER							
	CLC		GIW		OSM		DIB	
SPECIES	TSS	AUC	TSS	AUC	TSS	AUC	TSS	AUC
Tachybaptus ruficollis	0.343	0.673	0.463	0.720	0.479	0.754	0.472	0.743
Podiceps cristatus	0.459	0.697	0.507	0.776	0.474	0.817	0.497	0.818
Podiceps nigricollis	0.408	0.693	0.409	0.784	0.403	0.811	0.376	0.811
Anas strepera	0.391	0.704	0.477	0.800	0.549	0.825	0.545	0.821
Anas crecca	0.340	0.728	0.407	0.791	0.427	0.784	0.416	0.791
Aythya ferina	0.389	0.715	0.514	0.725	0.527	0.732	0.515	0.718
Aythya fuligula	0.408	0.666	0.534	0.760	0.543	0.779	0.566	0.776

	NUMBER							
	CLC		GIW		OSM		DIB	
SPECIES	TSS	AUC	TSS	AUC	TSS	AUC	TSS	AUC
Tachybaptus ruficollis	0.330	0.717	0.490	0.717	0.390	0.680	0.383	0.680
Podiceps cristatus	0.448	0.740	0.425	0.771	0.390	0.751	0.404	0.756
Podiceps nigricollis	0.415	0.728	0.369	0.763	0.268	0.738	0.277	0.737
Anas strepera	0.397	0.727	0.462	0.787	0.429	0.746	0.446	0.754
Anas crecca	0.448	0.758	0.425	0.742	0.390	0.693	0.404	0.701
Aythya ferina	0.399	0.744	0.461	0.713	0.438	0.637	0.430	0.641
Aythya fuligula	0.391	0.685	0.532	0.772	0.448	0.703	0.439	0.709

Table 4. Significance of the dataset effect on HSMs accuracy according to TSS/AUC values (Repeated measures ANOVA, Tuckey post-hoc tests). **** p<0.0001, *** p<0.001, ** p<0.01, - non-significant. Where results for TSS differed from those for AUC, the cells are highlighted in pink.

	Variable	Area					Perimeter				Number			
Statistics	**Dataset**	GCL	CLC	GIW	OSM	DIB	CLC	GIW	OSM	DIB	CLC	GIW	OSM	DIB
TSS	CLC	****		****	****	****		****	****	****		***	-	-
	GIW	****	****		-	-	****		-	-	***		***	**
	OSM	****	****	-		-	****	-		-	-	***		-
	DIB	****	****	-	-		****	-	-		-	**	-	
AUC	CLC	****		****	****	****		****	****	****		-	-	-
	GIW	****	****		**	-	****		-	-	-		****	****
	OSM	****	****	**		-	****	-		-	-	****		-
	DIB	****	****	-	-		****	-	-		-	****	-	

For Review Only

Figures

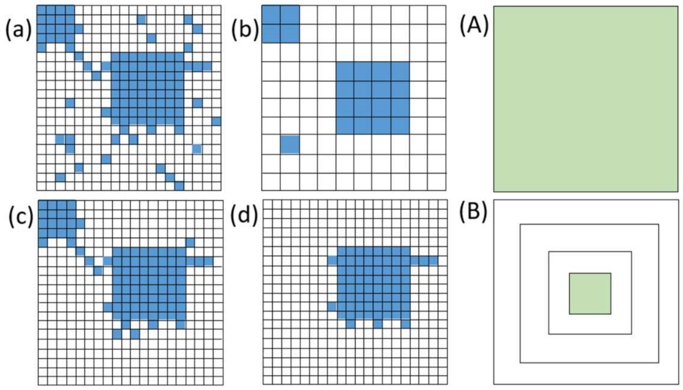

Figure 1. Examples of different resolutions of land cover data classified as preferred/non-preferred habitat (a – d; preferred habitat is in blue) and grain of species data (A, B; grain of species data is in green). For instance, patches of 1 ha are sufficient for a species presence. (a) Pixel size 100 m. (b) Coarsening pixel size to 200 m. (c, d) Minimal mapping unit 64 ha is applied while original pixel size is kept. (c) Diagonal neighbors are considered as members of the same patch. (d) Only side neighbors are considered as members of the same patch. We can see substantial changes in amount and shape of the preferred habitat. If only patches of 1 ha are present, no preferred habitat will be in b – d. (A) HSM without changing grain of species data can be conducted with a, b, c or d, or (B) HSM with a change of scalar can be applied with a, b, c, or d.

For Review Only

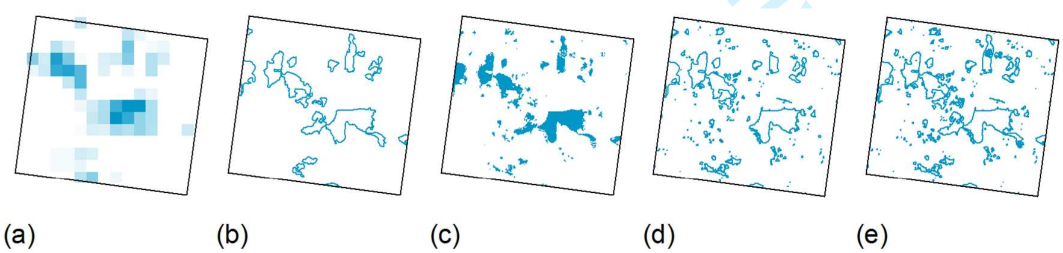

Figure 2. Example of datasets resolution and the amount of waterbodies within an atlas grid cell (12 × 11.2 km) according to individual datasets in order of increasing resolution: (a) GCL, (b) CLC, (c) GIW, (d) OSM, (e) DIB. Solid fill indicates raster datasets while vector datasets are indicated by outlines of waterbodies. GCL dataset is represented by 1 km pixels, darker pixel color means a higher proportion of inland water within the pixel.

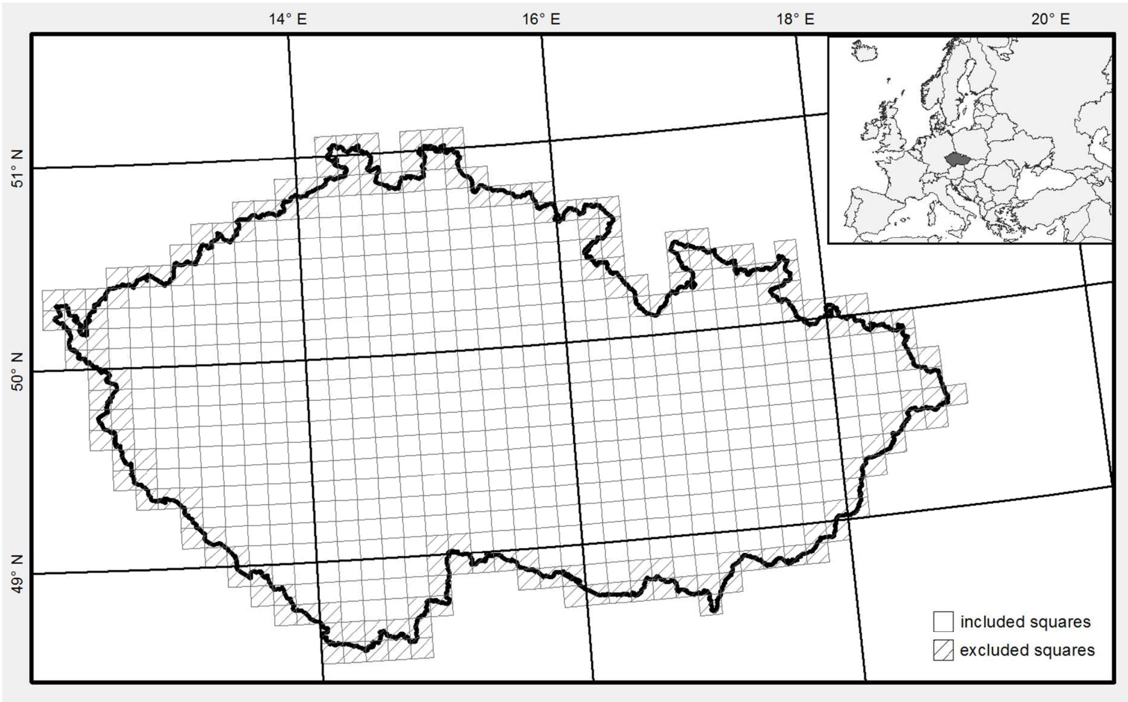

Figure 3. The Czech Republic as the study area. Grid of 10' east longitude × 6' north latitude (approximately 12 × 11.2 km) as used in the breeding birds atlases of the Czech Republic. Grid cells used for this study (*n*=507) are white, cells intersecting country border (hatched) were excluded.

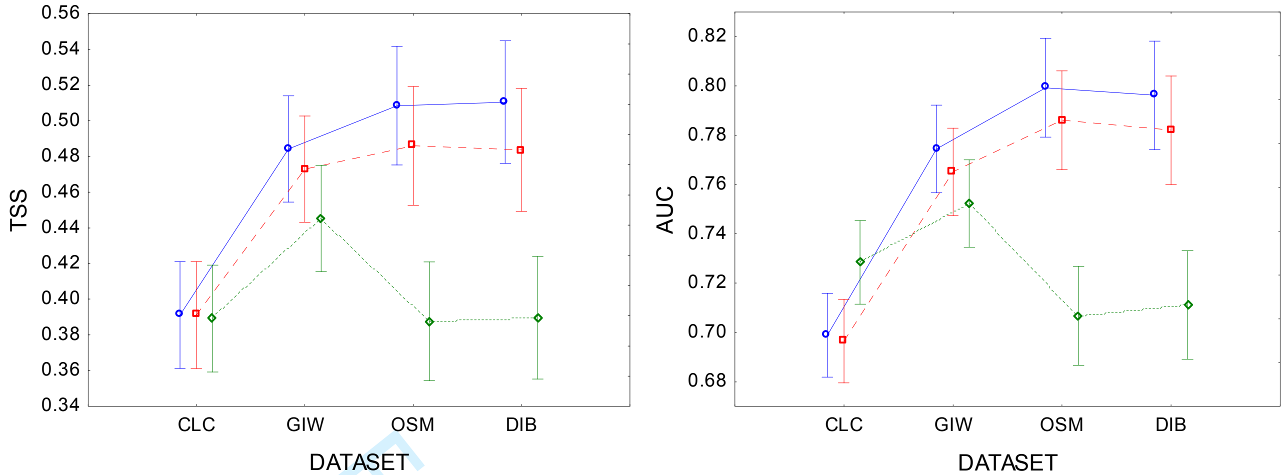

Figure 4. Comparison of mean TSS (left) and AUC (right) values among datasets (excluding GCL where only *area* could be calculated due to the continuous nature of the dataset) and variables (blue – *area*, red – *perimeter*, green – *number*). The datasets are listed on the *x*-axis in the order of increasing resolution, from coarse scale (left) to fine scale (right).

For Review Only