CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE
Faculty of Environmental Sciences
Department of Applied Geoinformatics and Spatial Planning

ČESKÁ ZEMĚDĚLSKÁ UNIVERZITA V PRAZE

Dissertation Thesis

Remote sensing and ground survey as tools for assessment of local changes in the environment

Ph.D. student: Ing. David Moravec
Advisor: doc. Ing. Jan Wild, Ph.D.

Prague, August 2018

Table of contents:

1. Foreword

This thesis is a compilation of several papers prepared over the course of my doctoral studies at the Department of Geoinformatics and Spatial Planning, Faculty of Environmental Sciences of the Czech University of Life Sciences. A lot has changed over the course of my studies. When I enrolled, the department focused predominantly on geoinformatic technologies and remote sensing (RS) was only a marginal scientific activity. This is the reason why the first papers created during my doctoral study were devoted especially to ground surveys.

When I entered the second third of my studies, I was presented with an opportunity to participate in the first study using RS techniques. Ever since the first moments of working with RS, I recognised its strong points and potential for monitoring of extensive areas or of utilization of freely available data collected over more than 40 years. I have begun to use RS data more and more. At the same time, RS grew in importance all over the Department and, also in our lessons. The purchase of two unmanned aerial vehicles (UAV) and procurement of commercial satellite data further supported the "boom" of RS at our department. Nowadays, RS and various forms of its utilization amount for a significant part of our Department's activities as well as of mine.

The gradual development of RS at our department allowed me to also gradually progress from basic data and RS techniques to the advanced ones. Scientific papers presented in this thesis document my development from local surveys to pure remote sensing. This experience allows me to critically evaluate the suitability of various approaches for particular applications. I believe that my future scientific career will be predominantly about remote sensing.

2. Introduction and Aims

On the turn of the millennium, Blake et al. (1999) declared that remote sensing (RS) will grow in importance in the next millennium – both as an independent scientific field and as a part of an integrated interdisciplinary approach for tracking environmental changes caused by human or natural processes. 18 years later, it is obvious that they were correct in their assumption. New technologies allowing new applications are still being introduced in the field of RS. Geoinformatics and RS became interdisciplinary sciences with a wide range of possible applications. Every phenomenon that can be observed using remote sensing is however unique and requires an individual approach. There is therefore no such thing as a "universal approach" applicable to every situation. The expertise of a specialist in geoinformatics lies in the deep knowledge of various techniques of observation and the knowledge of strong and weak points of these techniques. Thanks to such knowledge, the researcher can competently choose and apply the most suitable method of the observation.

The aims of this study is to a) introduce possibilities of different approaches to the observation of the different environment from ground sampling to the remote sensing; b) describe the advantages and disadvantages of each approach; c) to usage them in the scientific articles in different conditions (type of environment, temporal or spatial resolution).

In the first chapters of this thesis, I describe the types of the environment and changes that were subject of study in my research. The theoretical background then lays grounds for the subsequent chapters devoted to RS. Those chapters describe sources of RS data from direct ground surveying, which is surprisingly often important for acquisition of high quality RS data, through airborne platforms up to satellite systems. Then, the most frequently types of data (optical, radar and lidar) are described. The subsequent chapter deals with the issue of RS data resolution, which is crucial for the selection of the most suitable data or of the most suitable method of measurement. In the final chapters, I describe the techniques of the work with RS data, especially indices, change detection and creation of digital 3D models out of 2D data (structure from motion, SfM).

After that theoretical introduction, my published papers originating from my Ph.D. studies are inserted in the thesis. These constitute the principal part of the thesis.

In the last part, I added my comments on the published papers. As a full discussion to the individual studies is already included in the studies themselves, these comments are somewhat different, more subjective and aiming at offering the reader a different view at the problems that had to be solved over the course of the individual experiments. Finally, a brief general outlook on the future of remote sensing is included in the final chapter.

3. Changes of environment

3.1. History of changes

People influence the environment to a smaller or greater degree for the entire period of Holocene (a period from 10,000 BC till present). At the beginning of the Holocene, the climate was the dominant factor and the effect of humans on the environment was almost negligible and difficult to detect (Magny 2004). At the beginning of the Holocene, the European landscape had a character of a mosaic and provided the hunters-gatherers with various sources of food. Later, however, a gradual expansion of the forests occurred and the Mesolithic humans in Europe were forced to abandon the hunting of the herd animals and focus on individual hunting of forest animals in small open areas inside the forests (Clark and Robinson 1993). In that period, environmental changes were predominantly caused by climate changes. Those in turn were driven especially by changes in the solar activity or some sudden events, such as huge freshwater pulses into the Atlantic from melting ice or, in a short term, volcanic explosions (Treml 2009).

During the mid-Holocene (6000 – 4000 BC), the first signs of human influence on the environment can be observed (Magny 2004). At first, these were just small local changes in the vegetation cover of the central Europe, which was predominantly covered with a continuous forest at that time (Zolitschka, Behre, and Schneider 2003). Nevertheless, the human influence could have been observed as soon as the in Epiatlantic period (4000–2500 BC) in the region of the present-day Czech Republic, especially in the lowlands. There, human activities gradually turned the continuous forest into the original steps known from the beginning of the Holocene (Ložek 1973) and the humans-farmers introduced the first non-native species into the area (Treml 2009; Ložek 1973; Kalis, Merkt, and Wunderlich 2003).

From the end of the Neolithic age (8000 – 5000 BC), farming and pastures spread into the entire Central Europe (Kalis, Merkt, and Wunderlich 2003). Thanks to the pollen records in the sediments, it is obvious that the forests significantly receded. The anthropogenic influence gradually became the most important driver of the environmental changes (Zolitschka, Behre, and Schneider 2003).

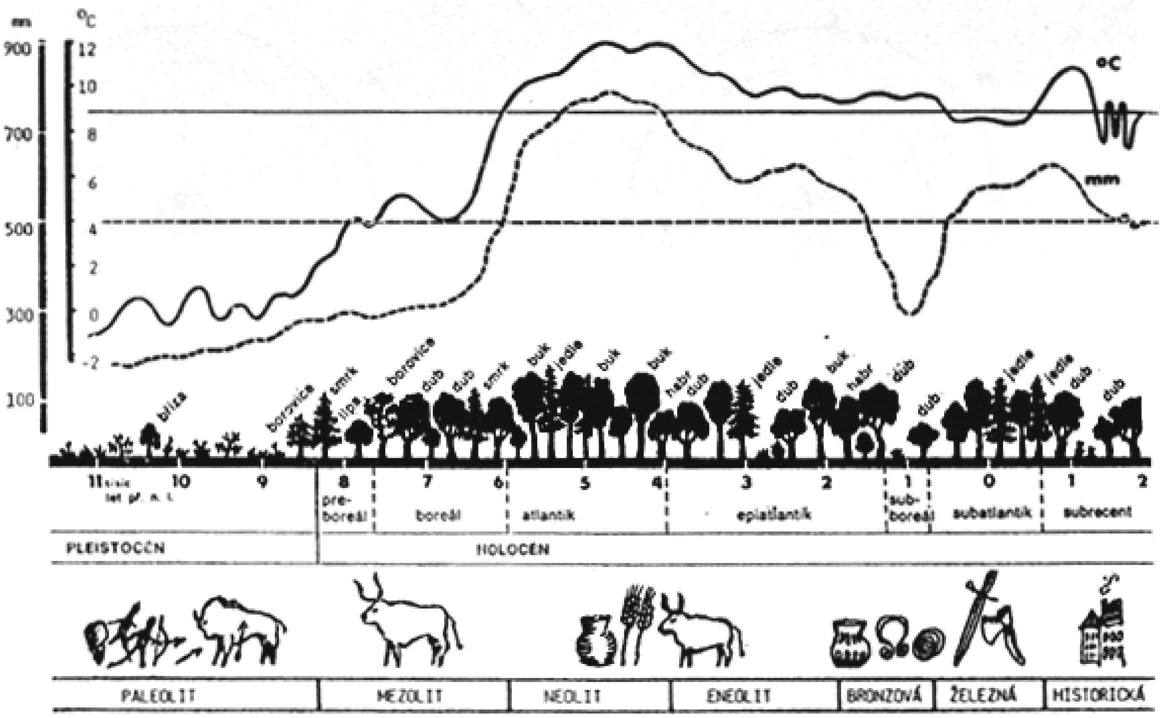


Fig. 1 Climatic fluctuations, development of vegetation, Holocene classification and main cultures in Europe over the last 11 thousand years (Krajinná ekologie – online textbook (in Czech): www.uake.cz/vyukove_materialy/frvs1269/kapitola3.html according to Kubíková from Strejček et al. 1982, amended)

3.2. Current environmental changes

At present, humans face many challenges in the field of environment. The pressure on the environment is maintained predominantly by the effort to provide food, clothing, water and shelter to more than 6 billion people on this planet (Foley et al. 2005). Such pressure, however, causes fundamental human-driven changes of the environment. Such changes include especially changes in the land use and greenhouse gasses emissions. The changes in the land use and land cover (LULC) are caused especially by the transformation of the original natural vegetation types into agricultural land or expansion of urban areas (Kalnay and Cai 2003). The emissions of greenhouse gasses are caused both by fossil fuels combustion and by land use change (IPCC 2014; Raupach et al. 2007). Although the type of land use differs across the countries or continents, the result is in most cases similar – acquisition of the natural resources to satisfy immediate human needs and subsequent degradation of the original environment (Foley et al. 2005). Such degradation mostly manifests as a reduced environmental diversity, leading to extinction of species. Although we have not discovered all species yet (it is likely that there are approx. 15% of plants out of 450,000 plant species awaiting documenting, the number being even higher in animals where approx. 1.9 million of species are documented and the estimated totals range from 4 to 13 millions), it is assumed that the current pace of extinction is approximately 1000 times higher than the natural pace (Pimm et al. 2014).

Despite the constant increase in the measures adopted by governments to fight the global environmental changes, greenhouse gasses emission are still on the rise. One of the ways of reduction of those emissions is the increase in use of renewable energy sources (IPCC 2014). Building wind farms is a good example of such technology, being the most quickly growing of all electrical energy producing technologies (Pineda and Wilkes 2015). Nevertheless, even such technologies may affect the surrounding climatic conditions, which has not been sufficiently explored yet (S. Baidya Roy, Pacala, and Walko 2004; Daniel Andrew Rajewski 2013) .

Another area of human activities significantly affecting the climate is agriculture, which is at the same time the reason of the most extensive transformations of the original ecosystems (Ramankutty and Floey 1999). In this field, the efforts to reduce the negative effects of agriculture manifest especially through ecological agriculture (Willer and Kilcher 2010). The reverse impact of ecological agriculture has however not been adequately explored so far.

The presence of humans in the landscape can have, and often has, a destructive effect on the original environment in the respective location (Foley et al. 2005). We can however occasionally also observe the reverse effects – as an example, some Mediterranean mountains can be mentioned. The mountain areas have been inhabited for centuries and people have been actively changing and maintaining the landscape (Sitzia, Semenzato, and Trentanovi 2010). Since 1950s, however, the population in these areas has been ebbing away. This results in a gradual return of forest stands, which is however at the same time associated with the reduction of the original heterogeneity and of the number of biotopes tied to the human presence (Sitzia, Semenzato, and Trentanovi 2010; Campagnaro et al. 2017).

The most transformed areas, when compared to the natural state of the landscape, are the urban areas. Urban environment is specific by the total dominance of humans. Besides the population increase, a mass migration to the cities is probably one of the most fundamental ecological changes of the last 100 years (Rees 1997). Several studies showed that health impairment or death due to long-term effect of hot weather is much more common among people living in urban areas than those living outside such developments (Kovats and Hajat 2008). It is also well known that urbanization has a severe impact on the local biodiversity (Newbold et al. 2016). Both these negative phenomena could be however minimized by increasing the amount of vegetation in the urban areas. For example, green roofs are among the most progressively developing measures. The influence of green areas on the surface temperature or water retention is also well known (Takebayashi and Moriyama 2007). Moreover, green areas can serve as local refuges for many animal species and thus reduce the impact of human activities (Morelli et al. 2017).

3.3.1 Energy and Power

Energy and Power play a crucial role in the socieconomic development and increase in the standard of living worldwide. Most of the world energy is however produced and consumed in a way that will not be sustainable in the long term if the energy demands grow further and technologies remain the same (Reviews 2008). At present, this consumption is covered predominantly by the use of fossil fuels (Panwar, Kaushik, and Kothari 2015). According to the estimates, the worldwide energy consumption will rise by approx. 60% before 2030 when compared with 2002 (Reviews 2008). The negative environmental impacts associated with the power industry based on the utilization of fossil fuels increase the interest in clean sources of energy (DeCarolis and Keith 2006). It must be however kept in mind that despite the fact that the energy from renewable sources can be distributed through high voltage power lines, the main benefits become apparent only if its use is greatly decentralized. Particularly in the poorer countries where building a power line network would be non-economical, renewable sources can play a crucial role. If such a decentralized network of renewable sources of energy exists in those countries, it could reduce their dependency on fuel import while at the same time increase the population life standard (Reviews 2008). In 2015, renewable sources (biomass, water energy, geothermal, solar and wind energy) covered approximately 14% of the worldwide energy consumption (Panwar, Kaushik, and Kothari 2015)

The most rapidly growing field of renewable energy are wind farms. On average, their global production doubles every three years. Despite economic crises, this growth continues over the last 20 years (Saidur et al. 2011). The electrical energy produced by wind farms could theoretically replace the fossil fuels and thus reduce CO_2 emissions by more than 50% (DeCarolis and Keith 2006). However, every technology of power generation has its negatives. Several research studies were published that focused on the issue of effects borne by the wind farms on their surroundings, such as impacts on human health (Bakker et al. 2012; Van Renterghem et al. 2013), on bird and bat populations (Drewitt and Langston 2006; Barclay, Baerwald, and Gruver 2007), deforestation and soil erosion (Dai et al. 2015), on sea ecosystems (Dolman and Simmonds 2010), visual pollution (Hurtado et al. 2004), on radar systems (de la Vega et al. 2013), on CO_2 sink (DeCarolis and Keith 2006), as well as local (Somnath Baidya Roy 2011; S. Baidya Roy, Pacala, and Walko 2004) and global (Keith et al. 2004) climatic effects.

The effect of the wind energy on the local climate can be mediated through two mechanisms: The first one is draining the kinetic energy of the wind, which reduces the velocity of the particular layer of the wind. This subsequently leads to the second mechanism – increase in the turbulent flow on the lee side of the turbine resulting from the interactions of the fast and slow wind layers. These effects were theoretically modelled (S. Baidya Roy, Pacala, and Walko 2004; Somnath Baidya Roy 2011), measured in the wind tunnels (Chamorro and Porté-Agel 2010) and through RS techniques (Zhou et al. 2013). A direct measurement of the impact of wind farms on the climatic change in their vicinity was however performed only rarely (Somnath Baidya Roy and Traiteur 2010; Daniel A. Rajewski et al. 2013).

3.3.2 Agriculture

More than 35% of the land has been already changed through human activities. The most extensive change was the transformation of the original ecosystems into agricultural landscapes (Ramankutty and Floey 1999). This change had major impact on the flow of energy and nutrients in the landscape (Foley et al. 2005). Changed water flow ratios as well as those of heat and kinetic energy between the continents and atmosphere can lead to extensive climatic consequences that can manifest both locally and in regions very distant from the source of the problems (Snyder, Delire, and Foley 2004). It is however assumed that the overall effects on the environment will grow with further development of the human population and society. Wackernagel et al. (1997), for example, estimated the average American to need 10.3 ha of land to sustain him while an average Italian 4.2 ha, an average Indian 0.8 ha and an average Bengali 0.5 ha of land. According to the estimates, current agriculture is capable of providing sustenance for approx. 8-10 billion people (Tilman et al. 2002).

A challenge for future agriculture is to cover the global demand while minimizing environmental impacts. One of the ways of minimizing the climate changes caused by agriculture could lie in increasing of the soil ability to retain water through increasing the content of soil organic matter and nutrients (Tilman et al. 2002; Foley et al. 2005), which is actually one of the aims of ecological farming (Eu 2007).

Agriculture actually means the management of the most fertile parts of the planet. The following 50 years will probably witness the final stage of the global expansion of rural activities (Tilman et al. 2002). The future agricultural practice will shape, probably irreversibly, the face of the Earth. The agricultural practice will influence both plant and animal species including humans. For a chance on the globally sustainable agriculture, fundamental understanding of techniques is needed as these could enable the increase of the ecological value of the managed areas while maintaining or even increasing production (Tilman et al. 2002; Willer and Kilcher 2010).

3.3.3 Positive anthropogenic effects

The human effect on the environment is mostly perceived negatively. It is however possible to find examples where the opposite is true. In many mountainous regions, traditional agriculture and forestry replaced the natural environment centuries ago. Low population density and nature-sensitive land management resulted in increase of the heterogeneity of such areas (Haddaway, Styles, and Pullin 2014). In the Mediterranean, generations have lived in the mountains, actively shaping the landscape for centuries (Sitzia, Semenzato, and Trentanovi 2010). Ever since 1950, however, the population dwindles constantly (Campagnaro et al. 2017). The natural forest regeneration resulting from the abandonment of the landscape brings both positive and negative effects. The negative ones include in particular a reduction of the extent of the open landscape, of landscape heterogeneity and mosaic. Such a loss of heterogeneity usually also leads to a decline of the overall biodiversity of the area as the spreading forests usually have lower biodiversity than the original landscape maintained for centuries (Gerhardt, Foster, and Forest 2002). It also leads to reduction of the area of extensive agriculture, which traditionally provided many semi-natural sites for a wide range of animals (Beaufoy, Baldock, and Clark 1994).

For example, the Apennines are a perfect example for a study of such a land cover change caused by many factors from farm abandonment, grazing by domestic animals, fires, climatic change or urbanization processes. In the past, several studies using various approaches were performed in the area of Apennines, revealing extensive changes in the land cover. Despite the primary influence of humans, these changes cannot be attributed solely to anthropogenic processes as natural processes also play a role (Symeonakis, Calvo-Cases, and Arnau-Rosalen 2007; Gatsis et al. 2006). The area was in the past also used for several botanical studies (Guarrera 1994; Petriccione and Mulder 1993; Bertoni 2012). A frequent drawback of those studies was however their local character; despite that, they can provide a unique opportunity to independently verify the trends detected through RS techniques.

3.3.4 Urban areas

Globally, urbanization is on a rise. According to the World Health Organization (WHO), the majority of people even in the less developed countries will live in the cities in 2017 (WHO 2015). Urban environment is an environment with an extreme dominance of the anthropogenic factor and the presence or persistence of natural ecosystems depends predominantly on the will of their inhabitants (Rees 1997).

The main effect of urbanization on the biodiversity is fragmentation and loss of the natural environment, which also leads to a reduction of the overall biodiversity, often resulting in biotic homogenization. The effects of the loss of heterogeneity of the environment can in turn have, through various mechanisms, a negative impact even on the human society (Newbold et al. 2016). A deeper understanding of the ecological functions in the urban developments is necessary for maintaining a high biodiversity. It is a well-known fact that the green areas in the urban environment can serve as refuges for many animal species and it is necessary to bear that in mind and care for such areas properly (Alvey 2006). For example, parks can be beneficial for maintaining and even increasing the overall biodiversity in the cities (Morelli et al. 2017). It is therefore necessary to know the environmental reactions on the structure and methods of management of such parks, and to actively act in favour of increasing the heterogeneity of the urban environment (Alvey 2006; Morelli et al. 2017).

The effect of urban areas on the local climate is another well recognized fact (Landsberg 1981). For example, people living in the urban developments are much more in danger of death or health impairment due to long-term effects of heat when compared to people living outside these areas (Kovats and Hajat 2008). This fact is also reflected in the National Programme for Reduction of the Impact of Climate Change in the Czech Republic, where an increase in the representation of the urban vegetation is recommended (MZP 2004).

4. Remote Sensing

There are many definition of remote sensing (RS). Although those definitions are all slightly different, they all share a common basis:

- Remote sensing can be defined as a collection of information about an object without physical contact with such object. Aircraft and satellites are typical platforms used for RS. The term encompasses methods utilizing electromagnetic energy as a means for measurement of target characteristics (Sabins 1978).

Or:

- RS is a science and art of acquisition of information about an object, site or phenomenon using instrumentation that does not come in to a direct contact with the observed object, site or phenomenon (Reddy 2008).

Besides those “regular” definitions, there are also unconventional, although often true, definitions:

- RS is the most expensive way to make a picture.
  (Andrew Bashfield, Intergraph Corporation)

- The art of dividing up the world into little multi-coloured squares and then playing computer games with them to release unbelievable potential that's always just out of reach.
  (Jon Huntington, CSIRO Exploration, Geoscience, Australia)

RS has a long history reaching up to 18th and 19th century. The first attempts for RS were associated with fastening cameras on balloons or even pigeons. The true remote sensing is however only connected with the first use of airborne imaging for military purposes in the 20th century (Reddy 2008).

There are two fundamental types of RS enabling us to acquire information about an object – active and passive systems. Active systems use their own source of energy, which they use to irradiate the object and acquire the information about the object from the reflected energy. This group contains in particular lidar, radar and sonar systems (Hassebo 2012). The main advantage of these systems is their independence on the intensity of irradiation from other sources, such as the Sun. The other type of data collection are passive systems, which are on the contrary dependent on the irradiation of the objects or need the object to be an emitter itself. The nature of the object is then judged by the amount and type of the reflected, diffused or emitted energy captured by a passive sensor (Reddy 2008).

4.1 Data sources

Data used in RS can be divided according to several criteria. For example, Halounová and Pavelka (2008) classify the data according to their character as image or non-image data or, based on the platform, as either airborne or satellite data. Another possible classification can be according to the sensor into digital or analogue data.

4.1.1 Direct measurements

Although direct measurements are not a part of RS as such, it is useful and often necessary for acquisition of quality results. Direct measurements is combined with RS in many instances, it is used for example for sensor calibration, determination of atmospheric parameters, measurement of the exact location of observed object or ground control points calibration (Smith and Atkinson 2001). In published studies, we also often find the need to supplement data or improve accuracy of the information acquired through RS methods (Kraus et al. 2009). As an example, we can mention the below study of detection of the bird diversity in Beijing where many park metrics were determined through RS but the presence of bird species had to be verified in situ.

Another frequent example of the need of direct measurements for supplementing RS data is the creation of training data. Those serve both for finding out the algorithms needed for identification of the objects of interest and for verification of the resulting analysis (Mishra et al. 2017). Training data can be acquired both by a direct terrestrial collection or indirectly, as demonstrated in the attached manuscript (Malavasi et al. 2018) where the secondary data collection was performed through photographs containing the information about the exact location of image acquisition – so-called geo-tagged photos (Flicker, Google Earth, Google Street View).

Last but not least, a direct continuous measurement can verify or supplement RS results that usually only reflect the state of things at the moment of the measurement. One of the parts of my thesis presents such a continuous measurement that served to verify and supplement the data acquired through RS about the impact of a wind turbine on the climate change in its vicinity over a period of several months and, based on such continuous measurement, suggested an improved experimental design of RS monitoring of that phenomenon (Moravec et al. 2018).

4.1.2. Aircraft

In RS, two types of aircraft are generally utilized. The first, more traditional, are standard manned aircraft offering a high payload, range, provide a sufficient source of electrical energy for demanding active sensors and, over the time, keep improving their resolution (Vaccari et al. 2015). These manned aircraft usually operate in the altitudes from 500 m to 8 km. In the past, airplanes were utilized for a systematic mapping of the Earth surface. At present, their use declines due to the improving resolution of satellite data on the one hand and improving payload capacity and range of cheaper unmanned aerial vehicles on the other (Tempfli et al. 2009). The principal disadvantage of the traditional aircraft is their low flexibility and high operational costs (Vaccari et al. 2015). Despite these disadvantages, traditional aircraft still remains one of important platforms for RS data acquisition (Reddy 2008).

Unmanned aerial vehicles (UAVs) are, when compared to other traditional means of RS such as aircraft or satellites, a relatively new method. They offer the highest flexibility, lowest operational costs and allow recording in the highest resolution (Vaccari et al. 2015). There are however also drawbacks when using these platforms. Legislatively, their use is limited where a potential danger to the third parties or their possession exists. Also, their load bearing capacity and range are, despite being constantly improved, still a notable limitation. However, their use by environmental protection agencies, farmers or private subjects in the future can be expected, which can lead to the needs of acquisition of high quality data at a reasonable price (Puliti et al. 2015).

4.1.3 Satellites

Satellite images represent a reliable and regularly updated source of global information (Reddy 2008). The possibilities of detecting global changes on the Earth surface and a global energy balance of the planet depend primarily on satellites as they provide a regular, calibrated, and global measurement of the surface (Chander and Markham 2003).

The possibilities of monitoring of individual satellites are to a significant degree predetermined by their orbit. The fundamental parameters of the satellite orbit are orbital altitude, predetermining to a major degree the spatial resolution and scope/extent, the inclination (angle of the orbit to equator) influencing (together with the scope width and potential inclination of the camera itself) the latitudes in which the satellite can perform imaging, and the satellite orbital time determining the period in which the satellite can observe the particular part of the global surface. The most frequent orbits are polar orbits allowing the observation of polar regions, Sun-synchronous orbits, which means orbits recording every area of the Earth always in the same Sun-time of the place in question, or geostationary satellites having a fixed position against a particular location (Tempfli et al. 2009).

Landsat series satellites are among the most frequently used for RS. In particular, Landsat 4 and 5 meant a leap forward in the entire field (Chander and Markham 2003), however even the newer satellites in that series stand out thanks to the long measurement series, to representing a suitable compromise between spectral, spatial and temporal resolution, and to free availability (Roy, Ghosh, and Ghosh 2014; G. Chen et al. 2012; Wulder et al. 2008; Xian, Homer, and Fry 2009). At present, there are tens of satellites recording data that can be used for RS purposes. To mention but a few, satellites with spatial resolution up to 0.5m (Ikonos, QuickBird, WorldView or French SPOT-6), resolution of up to 5m (Landsat, Sentinel-2) or resolution over 100m (MODIS, Sentinel-3) can be utilized for RS purposes. For radar data, KOMPSAT-5 or Sentinel-1 satellites are often used (Lu, Li, and Moran 2014; Tempfli et al. 2009).

4.2. Data types

In this chapter, the frequent data types utilized in RS will be described. With respect to the focus of my thesis, some of the more exotic data types were intentionally omitted, such as measurements using gamma rays, measurements of magnetic or gravitational anomalies or data only marginally serving for RS purposes, such as methods based on spreading of vibrations (sound) or electrical conductivity of minerals (Tempfli et al. 2009).

4.2.1 Optical data

The primary physical properties associated with the optical spectrum that can bear information about the target object include the intensity, wavelength, wave coherence and polarization. Common optical systems used at present record especially the intensity. The radiation intensity can be measured in various wavelengths. Typically, the optical sensors are classified according to the number of recorded bands into panchromatic measuring only one spectral band, multispectral with several up to tens of spectral bands and hyperspectral with up to hundreds of bands. From these spectral sensors, we can acquire the information about the distribution and type of objects in the observed area (Tyo et al. 2006).

Multispectral cameras are the most frequently used type of sensors at present. Their advantage lies in in their longer history (compared to hyperspectral), which is associated with existing experience with application of their imagery in various fields. Another advantage is their typically higher spatial resolution when compared to hyperspectral sensors. Multispectral data are generally frequently used in RS due to their sufficient information value and wide availability (Jensen 2000).

Compared to the multispectral sensors, hyperspectral sensors record up to hundreds of spectral bands. Such a number allows studying the physical/chemical properties of the surface almost at a laboratory level, which can be used for example for identification of possible mineral deposits (Papp 2002). At present, however, the availability of such data is significantly worse than that of multispectral data (Tempfli et al. 2009).

A relatively novel technique that can potentially increase the amount of available information about an optically observed object is the polarization measurement. While devices recording the intensity of radiation in individual wavelengths/bands provide us with basic information about the material, sensors recording variability in polarization provide the information about surface of that material, such as its shape, texture or structure. Polarization measurements are predominantly used in the radar spectrum but it can also apply to the visible spectrum. Polarization changes with the change of wavelength only slowly and, therefore, it provides an information uncorrelated with the spectral information, thus potentially suitably supplementing the spectral information see Fig. 2 (Tyo et al. 2006).

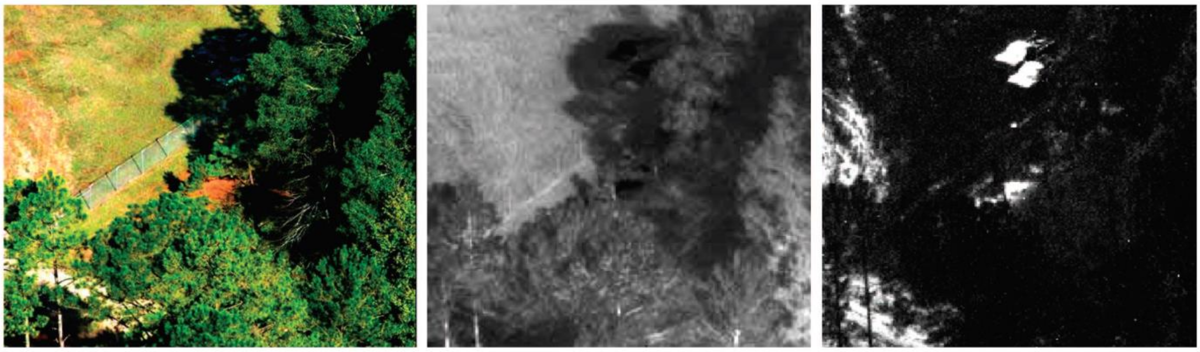


Fig. 2 A photograph of two cars in a shadow performed in visible spectrum (left), long-wave IR spectrum without polarization (middle) and with polarization (right). The high contrast of the material when compared with the original photograph demonstrates the benefit of polarization (Tyo et al. 2006)*.*

4.2.2 Radar data

Radar (Radio Detector and Ranging) is usually an active system (although passive systems are also known) sending short pulses in the microwave spectrum to the observed object and recording the characteristics of the reflected radiation. The microwave spectrum ranges from 1 mm to 1 m wavelength with radar sensors typically utilizing the wavelengths from 1 cm up to 1m, therefore much longer wavelengths than those of optical or lidar systems. These wavelengths can penetrate the atmosphere almost under any conditions and, depending on the chosen wavelength, they can “see” through clouds, smoke, mist, light rain, snow or haze (Reddy 2008).

The wavelengths are also very sensitive towards the structure and coarseness of the observed object. A surface with coarseness substantially smaller than the wavelength of the observed object acts as a smooth surface and the signal is reflected in the same angle in which it came. However, the coarser the surface, the greater is the amount of irradiation scattered in all directions and for surfaces significantly coarser than the wavelength, the scatter is almost uniform in all directions. Radar scanning can also provide information about distances, macrostructure, objects below surface or about overall chemical properties of the studied objects (Campbell 2002).

There are many possible applications of radar data. They provide an information supplementary to the spectral/optical data. For example, in forestry they provide information about the forest canopy, biomass or type of the forest. When recording the Earth surface, those data allow distinguishing different types of the surface such as urbanized areas, agricultural fields or water bodies. In agriculture, there is also an opportunity to observe the crops at any point of the season, regardless of the weather. Radar is also often used for geological mapping, hydrological modelling, oceanography, or monitoring of the ice sheets (Tempfli et al. 2009).

4.2.3 Lidar data

Lidar is an active method of data collection by the means of a laser pulse sent towards the observed object and registering the reflected radiation. From the temporal difference between the sent and received signal, the distance of the object can be determined (Lim et al. 2003). Besides the distance of the observed object, we are able to tell to some extent also the type of material from which the beam was reflected. Lidar laser beams can be of various wavelengths depending on the purpose: infrared (1500 – 2000 nm) and ultraviolet (250 nm) for meteorological purposes (Wandinger 2012; Hassebo 2012), turquoise (500 – 600 nm) for bathymetric purposes (Klemas 2012) or near infrared (1040 - 1060 nm) for Earth surface mapping (Lim et al. 2003).

Data acquired through lidar can come in various formats depending on the system used to acquire the data as well as on the degree and quality of post-processing of such data. The lowest information value we can have is one reflection per each spatial unit. That reflection is usually the first or the last depending on the settings aimed at suppressing or contrary enhancing the effects of semi-transparent structures such as vegetation. More detailed formats contain more reflection for every spatial unit, which allows us to at least partially distinguish between the vegetation cover and the bare ground. The highest quality data are in the full wave form where every spatial unit contains the information about the amount of the energy registered by the sensor for individual fixed time units. Such a format has the broadest range of possible uses, such as a detailed study of the vegetation structure in various vegetation floors or biomass volume calculations (Lim et al. 2003; Jensen 2005).

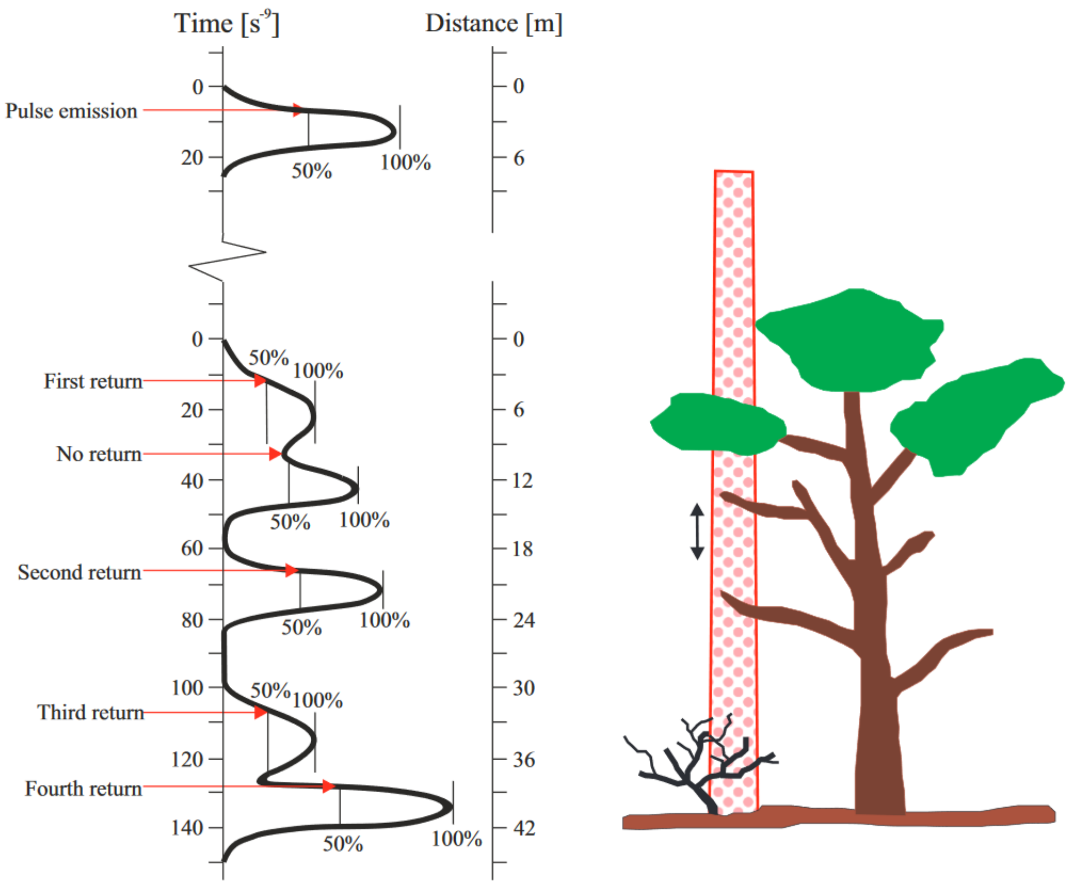


Fig. 3 Lidar – a full waveform of the reflection and analysis of individual reflections (Tempfli et al. 2009)

Lidar data can usually achieve an accuracy of ±1,5 cm at a maximum distance of about 800 – 1000 m and density of about 20 points per square meter (Jaboyedoff et al. 2012). The real-life accuracy is however often worse, especially when there are adverse conditions such as very uneven surface, parallel angle of the object with the beam, adverse weather conditions (rain, hot wind, fog), too much ambient light, too great distance, etc. (Jaboyedoff et al. 2012).

Lidar data are most frequently used in RS for acquisition of highly accurate digital surface models (DSMs), models of vegetation and buildings (Stoker et al. 2006). During lidar data processing, unlike for optical data, it is not necessary to pay attention to geometric, atmospheric or radiometric corrections. Lidar data processing consists of several steps. Those usually include automatized as well as manual work. Typically, the most crucial step is to filter the original point cloud to remove obvious errors and to distinguish the terrain from the remaining data. This step is however not always completely automatized and mostly requires repeated fine-tuning and manual edits (Q. Chen 2007). The next steps then lead to the extraction of required results. For ecological applications, these most frequently include 3D models of the surface or terrain, canopy height models or prediction of the biomass volume (Lefsky et al. 2002).

4.3 Data resolution

In RS, we encounter several types of data resolution, in particular spatial, temporal or spectral resolutions. Spatial resolution is defined as the smallest angular or linear difference of two objects distinguishable by the used data acquisition system. In practice, however, this definition is often confused with the nominal spatial resolution, which is defined as the size of one pixel projected on the surface of the Earth (Jensen 2000). Such resolution can range from tens of kilometres (typically for satellites with passive radars, for example AMSR-2 has a frequency 350MHz and resolution of 35×62 km). Contrary, the best satellite resolution can be as detailed as tens of centimetres (for example, resolution of the WorldView-4 satellite in the panchromatic channel is 31 cm).

As mentioned above, the term spatial resolution is quite frequently confused with nominal resolution and thus spatial resolution is often characterized on the basis of the nominal one. However, as pointed out by Blaschke et al. (2014), high and low resolution is not only determined by the nominal resolution of the sensor but also by the size of the object relative to the nominal resolution of the sensor. A nominal resolution of e.g. 1m can be therefore considered a fine resolution if used for detection of objects that are significantly bigger than that, e.g. buildings. When applying the same resolution for smaller objects such as smaller shrubs or herbs, however, the resolution for that particular application will be low.

One of the issues of the current RS is that it can only capture the state of the surface at the moment of recording and we can therefore not speak about a continuous recording. Still, it is possible to record a certain part of the surface with a certain periodicity and thus to observe the development of the area in question. That periodicity is called temporal resolution.

Another resolution that must be taken into account for the choice of a right sensor is the spectral resolution. Most RS are based on the relationship between the amount of reflected, scattered or emitted radiation in various spectral wavelengths and chemical, physical or biophysical parameters of the observed object (Jensen 2000). On its basis, we can classify the sensors according to the number of observed spectral bands to multispectral or hyperspectral, see more in Chapter 4.2.1 Optical data.

Along with the spectral resolution, we also have to mention radiometric resolution where we take into account the sensitivity of the sensor and its capability of distinguishing between signal strengths. For example, data depth of an older sensor Landsat 7 ETM+ was 8 bits, which allowed distinguishing of 256 signal strength values while the newer OLI sensor on Landsat-8 satellite uses a 12-bit format and can therefore distinguish between 4096 different signal strength values.

4.4. Remote sensing techniques

This chapter will briefly describe some of the principal RS techniques. Basic techniques such as georeferencing, orthorectification, vectorization or visual inspection of the images were due to the aims of the thesis omitted. The emphasis was laid especially on the use and applicability of described techniques in the own research.

4.4.1 Indices

Many RS techniques describe the observed objects on the surface of the Earth through the amount and properties of the radiation reflected from the surface and recorded by the sensor. As the amount of radiation received at the Earth surface changes over time, among other things due to atmospheric conditions, a simple recording of the amount of reflected irradiation is an insufficient way of describing the phenomena on the Earth surface. The problem lies in different results at different time points when observing the same phenomenon. This issue can however be resolved by combining values recorded in two or more spectral channels. The main benefit of spectral indices lies in providing comparable and relatively stable results over time if correct methods of computation are used (Jackson and Huete 1991).

At the beginning, ratio indices were used. Probably the first of those was the ratio vegetation index – RVI used for characterising the forest canopy measured from inside of the forest. It used the ratio of red and near infrared spectrum (0.800 / 0.675 µm) (Jordan 1969). The simple ratio however can sometimes offer just a limited range of variability. In vegetation indices, this problem was especially obvious in diffused vegetation. To overcome this issue, Rouse Jr et al. (1973) suggested to use the ratio between a difference of those channels and their sum. This vegetation index was later named NDVI (normalised difference vegetation index). It is however necessary to note that the amount of information represented by NDVI remains the same as that of the original RVI as can be shown by the simple mathematical conversion NDVI = (RVI – 1) / (RVI + 1). It however offers advantage for interpretation of the results.

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

The next step were linear combinations of two or more spectral channels. A linear combination is an orthogonal file of n independent equations calculated from n independent spectral channels. Those combinations were first described for RS purposes by Kauth and Thomas (1976) and were established under the term „Tasselled Cap". Nowadays, tens of indices describing different phenomena on the Earth surface have been developed. For example, in our study of change detection, altogether 36 vegetation indices, 10 textural characteristics, 7 components of principal component analysis and 6 components of Tasselled Cap transformation were derived from Landsat 8 data.

4.4.2 Change detection

Change detection (CD) became one of the fundamental tools of modern RS. Multispectral sensors are the most frequently used for the detection of changes on the surface of the Earth, especially due to the existence of a long series of freely available satellite images and resolution sufficient for most applications (Gupta and Shukla 2016; Chaudhuri and Mishra 2016; Kindu et al. 2013). Hyperspectral, radar or lidar data are utilized more rarely (Lu, Li, and Moran 2014). CD is performed especially on the basis of detection of differences in land use or land cover over a studied period. The principal assumption is that a change in the Earth surface results in the change of spectral characteristics of the area in question (Hussain et al. 2013). It is however necessary to beware of the detection of false changes caused for example by a change of atmospheric conditions, changes in phenological stages, different data sources or their different processing (Jensen 2005; Lu, Li, and Moran 2014; Song et al. 2000).

To be able to identify changes on the surface, it is necessary to be able to classify the surface first, which is the purpose of classification methods. There are several principal methods, such as supervised or unsupervised classification. In unsupervised classification, the surface is divided into a predetermined amount of categories based on an algorithm using differences in the spectral characteristics. Where supervised classification is concerned, user-identified categorized training data are used. The entire image is then classified into those categories based on the spectral similarities with training data (Tempfli et al. 2009).

Many CD applications have been described including study of forests (Hussain et al. 2013), grassland (Tarantino et al. 2016), landscape degradation (Symeonakis, Calvo-Cases, and Arnau-Rosalen 2007) urban developments (Weng 2001) or even global change (Lunetta et al. 2006). The results of CD can be of a binary character (changed/not changed) or including the trajectory of change, i.e. between two time points (bi-temporal) or over more time points (multi-temporal). Approaches can also be divided between a pixel approach, where each pixel is evaluated separately, and an object approach where overall characteristics of defined objects are being observed (Hussain et al. 2013). Another sorting can be between pre- and post-classification approaches. In the post-classification method, all images are first classified and the two classified images are subsequently compared. This method is easier for interpretation, it is however at the expense of greater inaccuracy caused by a higher number of classifications. The pre-classification method first compares the images and the classification of changes takes place only after that (Peiman 2011). Although many of those methods are already implemented in various software solutions, the choice of a correct method, its application and especially interpretation of the acquired results still depends on the expertise and experience of the user (Hussain et al. 2013).

4.4.3 Structure from motion

Structure from motion (SfM) is one of the subsets of photogrammetry. The full term is "structure derived from a moving sensor" (N. Micheletti, CHandler, and Lane 2015). It provides a 3D reconstruction of objects from 2D data, usually photographs. Although the method can be used for reconstruction of any object, it is most frequently used in RS for creating a 3D model of selected surface areas. Topographic data are among the basic data for RS. Their acquisition through traditional techniques such as differential GPS or laser scanning has been however often too demanding in respect of time, costs and expertise (Natan Micheletti, Chandler, and Lane 2015). However, thanks to the increase in computational performance and current possibility to use cheap and easily portable platforms such as UAVs, SfM became an effective and widely used tool for preparing high quality topographic models (Westoby et al. 2012).

The particular methods and algorithms of SfM are still developing and can differ for individual applications, the basic principle is however similar. To achieve accurate georeferencing, it is recommended to have at least 10 ground control points (GCPs) with known coordinates. For creation of a 3D model, it is then necessary to have a sufficient number of photographs of the target object. For a quality reconstruction of an object, it is recommended to have a series of photographs with an overlap of individual photographs of at least 60% (Agisoft LLC (a) 2017). In the next step, search for identical points is performed using automated algorithms and aligned. Finally, a 3D reconstruction of the object is computed from the different angles between lines connecting identical points on various photographs (Westoby et al. 2012).

SfM techniques allow us to acquire high quality topographic data in a highly automated way, which is undemanding of time, finance and expertise. These are the main reasons of the recent boom of the use of this method among the expert public (N. Micheletti, CHandler, and Lane 2015).

5. Publications

5.1 Publications within Dissertation Thesis

Article Name	Journal Type /Rank	Journal Name (IF)	Author Contribution
A. Wind turbine impact on near-ground air temperature *(**Moravec D.**, Barták V., Puš V., Wild J.)*	J_{imp} 7/33 (1Q) 20/97 (1Q)	RENEWABLE ENERGY (4,900; 2017)	60%
B. Taxonomic diversity, functional diversity and evolutionary uniqueness in bird communities of Beijing's urban parks: effects of land use and vegetation structure *(Morelli F., Benedetti Y., Su T. Zhou B., **Moravec D.**, Šímová P., Liang W.)*	J_{imp} 5/66 (1Q)	Urban Forestry and Urban Greening (2,782; 2017).	15%
C. Digital elevation models as predictors of yield: Comparison of an UAV and other elevation data sources *(**Moravec D.**, Komárek J.,Kumhálová J., Kroulík M., Prošek J., Klápště P.)*	J_{SCOPUS} 141/309	Agronomy Research (SCOPUS, SJR 0,390)	35%
D. Reforestation dynamics after land abandonment: a trajectory analysis in Mediterranean mountain landscapes *(Malavasi M., Carranza M. L., **Moravec D.**, Maurizio C.)*	J_{imp} 79/241 (2Q) 30/108 (2Q)	Regional Environmenta l Change (2,872; 2017)	20%
E. Selecting appropriate variables for detecting grassland to cropland changes using high resolution satellite data *(Klouček T., **Moravec D.**, Komárek J., Lagner O., Štych P.)*	J_{imp} 19/64 (2Q)	PeerJ (2.118; 2017)	15%

5.1 Publications out of Dissertation Thesis

F. Microclimate measurement as one of the prerequisites for successful introduction of ornamental trees (Wild J., Kirschner J., **Moravec D.**, Kohlová J.)	J_{rec}	Acta Pruhoniciana	15%

6. Supplements – Manuscripts

6.1 Wind turbine impact on near-ground air temperature: long-term field measurement

(Moravec D., Barták V., Puš V., Wild J.)

Renewable Energy 123 (2018) 627–633

Contents lists available at ScienceDirect

Renewable Energy

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

Wind turbine impact on near-ground air temperature

David Moravec [a, *], Vojtěch Barták [a], Vladimír Puš [b], Jan Wild [a, c]

[a] Department of Applied Geoinformatics and Spatial Planning, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Kamýcká 129, Prague 6, Suchdol, 165 21, Czech Republic
[b] Department of Ecology, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Kamýcká 129, Prague 6, Suchdol, 165 21, Czech Republic
[c] Institute of Botany, The Czech Academy of Sciences, Zámek 1, Průhonice, 252 43 Czech Republic

ARTICLE INFO

Article history:
Available online 19 February 2018

Keywords:
Wind farm
Surface temperature
Direct measurement
Sustainable energy
Microclimate
Topoclimate

ABSTRACT

Several aspects of wind farms' environmental impacts have been thoroughly studied. Their effect on surface temperature, however, has not been sufficiently explored. We analysed variations in land surface temperature observed over 5 months on a large wind farm (42 000 kW maximum output). To describe the near-surface microclimate variability, we measured air temperature at 15 cm above ground using 14 autonomous microclimatic stations arranged in the vicinity of 4 turbines. The observation covered various weather conditions from summer to winter. In contrast to some other recent studies, we confirmed no clear long-term, stable effect of wind turbines on near-ground temperatures. The only effect we found was a daytime warming effect at one of the four turbines. Our results suggest that in mountainous conditions the effect of turbulence caused by wind turbines can be overridden by natural wind turbulence.

1. Introduction

Wind power's installation rate was the highest among all energy-generating technologies in the EU during 2014 [1]. Production of energy from wind sources has approximately doubled about every 3 years over the past several decades. This is true despite the financial crisis, and this trend shows but minimal signs of slowing [2]. The argument for continuing to harvest wind energy is to produce energy with minimal environmental impacts. With increasing deployment of wind power plants, however, the cumulative effects of today's minor impacts could become substantial [3]. It is essential, therefore, to understand fully all impacts in order to optimize future planning and minimize possible negative effects from wind farms.

Recent papers have focused on various types of environmental impacts from wind turbines (for a review see Dai et al., 2015). These papers examine farms effect on noise and its impacts on nature or human health [5,6], bird and bat mortality or disturbance [7,8], deforestation and soil erosion [4], impacts on marine ecosystems (in the case of offshore wind farms) [9], visual pollution [10], impact on radar systems [11], reduction in carbon dioxide emissions [12], as well as local [13,14] and global climate impacts [15].

Impacts on local climate are especially crucial in situations where allocating more turbines is justified by reducing carbon emissions, because these effects could have subsequent impacts on the carbon cycle in the affected area [16]. Wind farms can affect local climates in two main ways. The first is by extracting kinetic energy, which slows wind flow. The second is by further heightening turbulence flow downwind. Turbulence can be generated in the wake of rotors [14] and also by the shear between the non-affected faster air layer below the turbine and the upper air layer slowed by the turbine [17].

The generated turbulence has a secondary effect by enhancing vertical mixing of air. Several studies showed that enhanced turbulence produced by wind farms has impact on heat and moisture exchange between the surface and the atmosphere [14,18,19]. In stable atmospheric conditions, when a warm air layer is present above cooler air, increased turbulence results in a warming near the surface by transferring thermal energy from higher levels to the lower. On the other hand, when unstable atmospheric conditions are present, i.e. cool air lying above a warmer layer, enhanced turbulence leads to mixing the layers and provides a cooling effect on the ground. These impacts depend on the ratio of natural

* Corresponding author. Department of Applied Geoinformatics and Spatial Planning, Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Kamýcká 129, Prague 6, Suchdol, 165 21, Czech Republic.
E-mail address: dmoravec@fzp.czu.cz (D. Moravec).

https://doi.org/10.1016/j.renene.2018.02.091
0960-1481/

turbulence to turbulence generated by the wind turbine. The stability of atmospheric layers can also influence a wind farm's impacts. The effect of vertical mixing can be 10–15% stronger when a wind turbine is present in the atmospheric boundary layer [20].

Theoretical models have been used to explore regional and global climatic impacts of wind farms. A three-dimensional climate model (CCM3) has been used to study the impact of a scenario wherein wind energy would supply 10% of global energy demand. The effects of increasing roughness and decreasing wind speed could cause warming of more than 1 °C across land installations. On the other hand, it can cause a 1 °C cooling effect over ocean installations [18]. Slowing wind has also been demonstrated by the Regional Atmospheric Modelling System (RAMS) [13,14].

Theoretical models have been tested in wind tunnel experiments. The outcomes of these experiments have shown that the effect of the wake can be found up to a distance of 20 rotor diameters [21]. A computational study has suggested this to be a shorter still distance of 15 diameters [22]. Maximum turbulence has been found at a distance of 4–4.5 rotor diameters above rotor hub height in neutral cases of atmospheric layers and 3–6 diameters in stable cases. Heightened turbulence intensity is associated with strong shear of layers and turbulent kinetic energy produced by regional features [21,23] or wind farm layout [19,24].

Similar results can be found in long-term remotely sensed temperature data. The Landsat 5 Thematic Mapper (resolution ca 120 m × 120 m) was used to observe the San Gorgonio Pass Wind Farm from 1984 to 2011. Daytime warming effect was confirmed [25]. A MODerate resolution Imaging Spectroradiometer (MODIS) analysis with ca 1 km resolution has been used for seasonal and diurnal variation in land surface temperature. Data show consistent warming as a night-time effect of 0.31–0.70 °C [26].

Direct measurement of near-surface temperature is much needed, however, in order to validate modelled or remotely sensed data, but such data has been collected only rarely. Two measuring towers (upwind and downwind of a farm) in San Gorgonio, California have evidenced significant impact of a wind farm on near-surface temperature [27]. Another study focused on the impact in intensely managed areas, and slight impact was observed there [17]. These results indicate the usefulness of further long-term exploration under diverse conditions. New field observations are still required to confirm numerical models and to fully understand the effects [2,18].

To fill this gap in data and knowledge, we assessed the impact of a wind farm on near-ground temperature over a period of 5 months.

2. Materials and methods

As a model area we chose the largest wind farm in the Czech Republic (Kryštofovy Hamry – Přísečnice; 50°26′ N, 13°8′ E; Fig. 1) with maximum output of 42 000 kW [28]. The wind park consists of 21 wind turbines situated on a study area with hub-height 85 m and rotor diameter 82 m. The park is located in the Ore Mountains at 817–870 m a.s.l. in a continental climate region.

We measured near-ground air temperature using 14 TMS-3 automatic climatic stations (TOMST, Prague, Czech Republic; http://www.tomst.com/tms/TMS-3.html) installed in the vicinity of 4 turbines. Air temperature was measured ca 15 cm above ground using a MAXIM/DALLAS Semiconductor DS7505U + sensor with resolution of 0.0625 °C and accuracy of ±0.5 °C over a range of 0 °C to +70 °C. Wind flow directions were measured at the nearby Měděnec meteorological station (approximately 1500 m distant).

Much greater effect of turbine is expected along the direction of prevailing wind flow [19]. Based on data from a Czech climate atlas [29], two wind directions – north-west and the opposite south-east – dominate at the locality (see Fig. 1), and we placed TMS-3 stations along this line. Local topography, land cover and land use allowed us to install two stations north-west of the turbine masts (200 m and 400 m) and one station south-east of the turbine masts (200 m). The positions of the stations were numbered from 1 to 4, starting at the south-east and ending at the north-west. Number 2 was assign to the turbine mast itself (see Fig. 1). Sensor spacing of 200 m took into account location possibilities and also previous studies. Chamorro and Porté-Agel (2010) had shown that maximum turbulence magnitude occurs at a distance of 3–6 turbine diameters, depending on atmospheric conditions. Smith et al. [30] had reported that impact on wind speed and turbulence occurs within a distance of 2.4 rotor diameters (197 m in our case). The near-ground temperatures were measured at 10 min intervals from 2 July 2014 to 30 November 2014. The chosen time period included diverse summer, autumn and winter weather conditions with temperature ranging from 29 °C to −7 °C.

We also examined wind turbines' effect on temperature during different periods of the day, because several authors have reported temperature effects to be influenced by variation through the day in air boundary level [14,26]. We therefore split the day into two parts: diurnal observation (06:00–18:00 local time) and nocturnal (18:00–06:00 local time). The data from the two time intervals were analysed separately.

To establish a benchmark for measurement in turbine vicinity at a non-affected locality, we installed two additional TMS-3 units near the wind farm at places having similar topographic (slope, altitude, orientation) and vegetation conditions but located neither downwind nor upwind from the wind farm.

From the obtained measurements, we first determined the situation when the wind was roughly flowing from the sensor at position 1 to positions 3 and 4 (from SE to NE). We considered such situation as corresponding to the measured wind speed between 90° and 150°, i.e. covering an angle of 60° around the turbine–sensor axis (see Fig. 1). We term this the "forward" direction inasmuch as it follows the dominant wind direction in the locality during the observed period. To reduce the expected temporal autocorrelation between measurements, we filtered the data so that the minimum time lag between any two subsequent measurements was 2 h. Moreover, we included only measurements successfully made on all three (resp. two for turbine B) sensors at a given turbine and time. The resulting triples or pairs of measurements – each triple or pair consisting of measurements made at the same turbine at the same time – are termed "events" through the rest of this paper.

We evaluated the effect of the sensor's position relative to the turbine on the relative temperature using mixed models. We considered sensor position (1, 3, or 4), wind turbine (A, B, C, or D), and time of day (day or night) as fixed factors, including their interactions. To consider the interdependence between measurements made in different sensors at one turbine and during one event, we included event as a random factor. Even though we designed the experiment to ensure relatively homogeneous conditions across turbines and sensors, we checked for possible effects of such additional factors as distance of the sensor from the nearest forest, as well as local elevation, slope, and aspect (categorized into 17 directions including a "flat" category). All these variables were computed in the ArcGIS 10.5 environment and using an orthophoto and digital terrain model (DMR 5 g) provided by the State Administration of Land Surveying and Cadastre of the Czech Republic. These variables were considered as additional fixed factors in the mixed models.

The significance of various fixed effects and their interactions was evaluated by comparing Akaike information criterion (AIC) values of corresponding models. The model selected as relatively

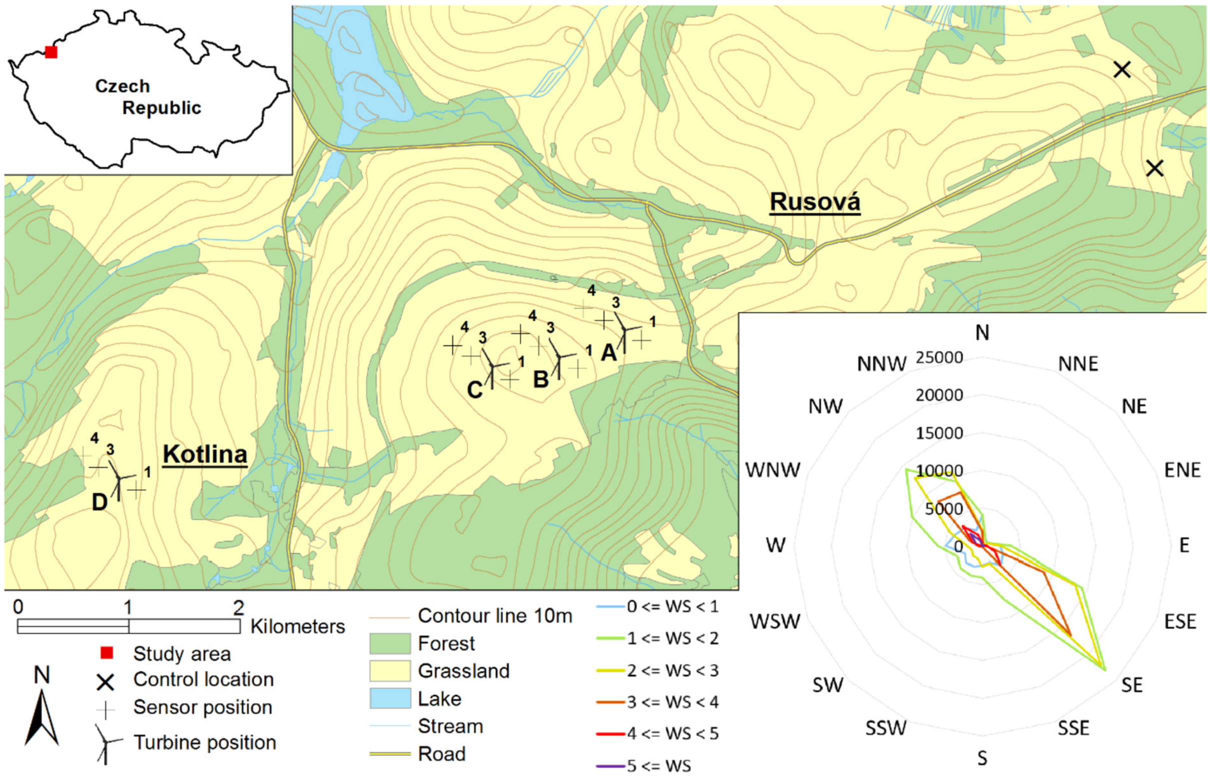


Fig. 1. Study locality of Kryštofovy Hamry wind park, with sensor positions (1, 3, 4), turbine locations (A, B, C, D), and wind direction rose showing number of wind observations and wind speed (WS) [m/s] based on the wind directions during the observation period. Base map ZABAGED®.

best was then used for computing the estimates of mean relative temperatures in various combinations of the factor levels, as well as for testing the difference between the mean relative temperature at position 1 and those at positions 3 and 4. For these tests, we used Wald confidence intervals constructed along the estimated differences between means, together with a Bonferroni correction for multiple comparisons.

To confirm whether the determined effect of sensor position can truly be attributed to the effect of turbine, we estimated the mean relative temperature also for the opposite wind direction (i.e. roughly from position 4 to positions 2 and 1), covering a 120° angle from 240° to 360° (see Fig. 1; we call this a "backward" direction), using the same kind of mixed model analysis. We then checked visually whether or not the pattern of differences between sensor positions is qualitatively different compared to the pattern obtained in the forward direction.

3. Results

The numbers of events we obtained after filtering the data for temporal autocorrelation and wind directions are summarized in Table 1. Final numbers of events were affected by sensors failure during the operating period and/or damage caused by humans or animals. This resulted in a reduced number of events especially at turbine B, where all measurements from position 4 were lost.

In the model selection procedure (see Table 2), we started with the most complex model including sensor position, time of day, and turbine, all interactions among these three, as well as distance to forest, elevation, and slope (Model 1 in Table 2). We could not include also exposure, as such a model would have too many parameters and they would not be uniquely estimable. Therefore, we fitted another model with exposure instead of elevation and slope (Model 2), as well as a model with sensor position, time of day, turbine, their interactions, and exposure (Model 3). All these models reached the same AIC value as did the model including only sensor position, time of day, turbine, and their interactions (Model 4). We thus proved the environmental and topographic factors to be irrelevant, as had been expected from the experimental design. Any further model created by excluding some of the interaction terms or main effects resulted in considerably higher AIC values, the least ΔAIC being 70.3 and 22.6 for forward and backward wind direction models, respectively. Thus, both for forward and backward wind direction, the relatively best model was Model 4 including all three main effects (i.e. sensor position, time of day, and turbine) and all interactions among them. The significance of random effect (event) was confirmed by a likelihood-ratio test comparing Model 4 with the same model but excluding the random effect (i.e. a normal linear model); the p-value was practically zero in the case of both forward and backward directions. Estimates for the standard deviation of relative temperatures among the random effect levels and the residual standard deviation were 0.61 °C and 0.37 °C, respectively, for forward wind direction and 1.08 °C and 0.66 °C, respectively, for backward wind direction.

Fig. 3 summarizes the resulting estimates of the mean relative temperatures at different sensor positions, times of day, and turbines, both for forward and backward directions. These are based on Model 4. It is clear that except in the case of turbine A the patterns do not differ qualitatively between the two wind directions, especially when the large confidence intervals are taken into account. Moreover, most of the differences in relative temperatures between sensor positions 1 and 3 and positions 1 and 4 were not statistically significant. The only significant difference was that between positions 1 and 3 at turbine A, during daytime, and in the forward wind direction (see Figs. 3 and 4).

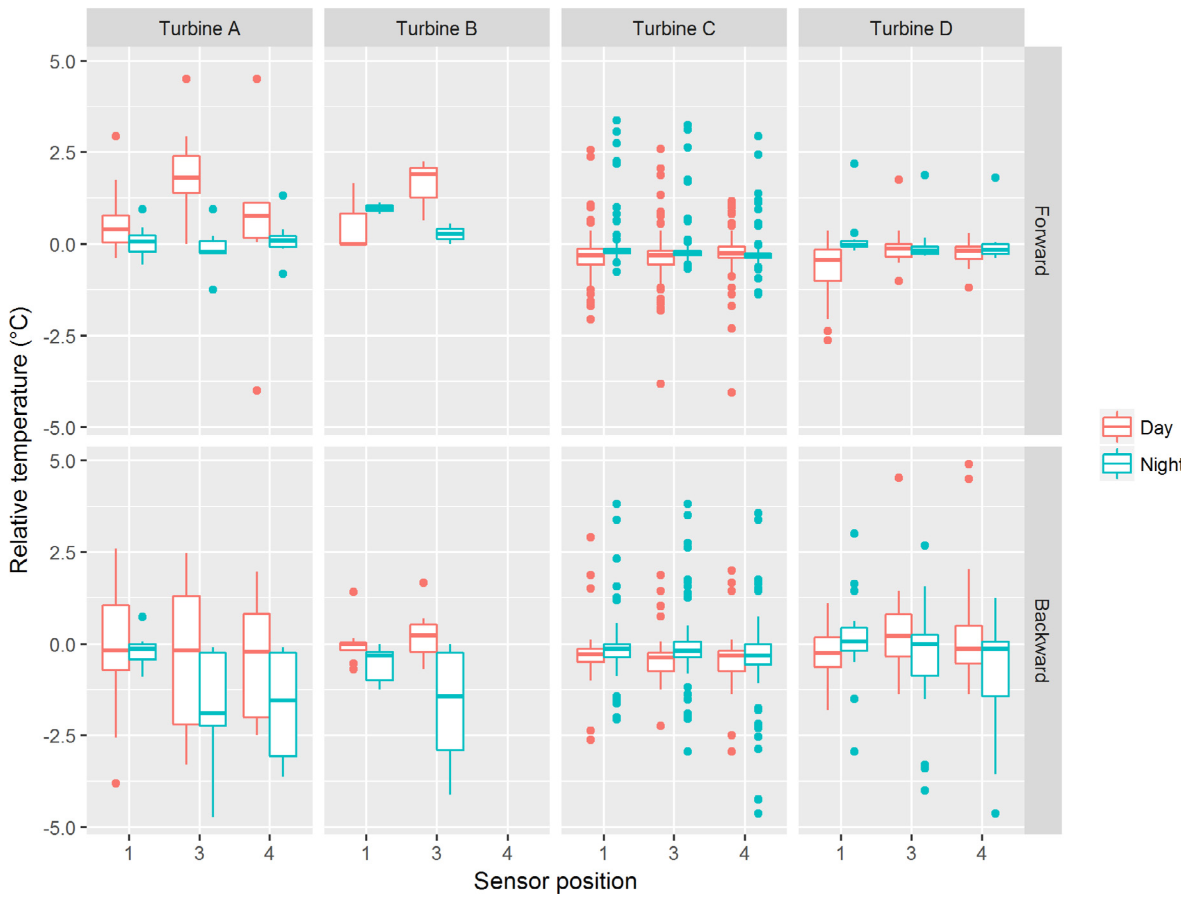


Fig. 2. Temperatures measured by the sensors and corrected by subtracting an average of control measurements made at the same time by two sensors located at an independent place with similar conditions. The original measurements are filtered so that the minimum time gap between any two subsequent measurements is 2 h. The upper panels show the measurements made when the wind blew from the sensor at position 1 through the turbine to the sensors at positions 3 and 4 (i.e. in the "forward" direction covering an angle of 60°). The lower panels show the measurements made in the opposite direction (i.e. "backward"), covering an angle of 120°. Day was defined as 06:00–18:00, night as 18:00–06:00.

Table 1
Number of events (i.e. successful measurements made on all sensors at a given turbine and time, separated by at least 2 h from each other) obtained by filtering the original data.

Time of day	Forward wind direction				Backward wind direction			
	Turb. A	Turb. B	Turb. C	Turb. D	Turb. A	Turb. B	Turb. C	Turb. D
Day	12	3	89	15	10	8	33	15
Night	8	2	93	12	13	9	49	17

The relative temperatures at different sensors, times of day, and wind directions are summarized in Fig. 2.

Table 2
Results of model selection based on Akaike information criterion (AIC) values, for both forward and backward wind directions. The "best" models (i.e. those with the lowest AIC and least parameters) are shown in bold. Note that AIC values from forward and backward wind direction models cannot be mutually compared as they are based on different data sets.

Model	Fixed effects	AIC (forward)	AIC (backward)
1	Position*TimeofDay*Turbine + DistancetoForest + Elevation + Slope	1150.2	1269.2
2	Position*TimeofDay*Turbine + DistancetoForest + Exposure	1150.2	1269.2
3	Position*TimeofDay*Turbine + Exposure	1150.2	1269.2
4	**Position*TimeofDay*Turbine**	**1150.2**	**1269.2**
5	Position*TimeofDay + Position*Turbine	1220.5	1291.8
6	Position*TimeofDay + Turbine	1249.2	1303.2
7	Position*Turbine + TimeofDay	1237.9	1312.0
8	Position + Turbine + TimeofDay	1267.3	1321.2
9	Position*TimeofDay	1278.5	1304.5
10	Position + TimeofDay	1296.5	1322.6
11	Position	1295.0	1322.5
12	No (Intercept only)	1295.0	1335.4

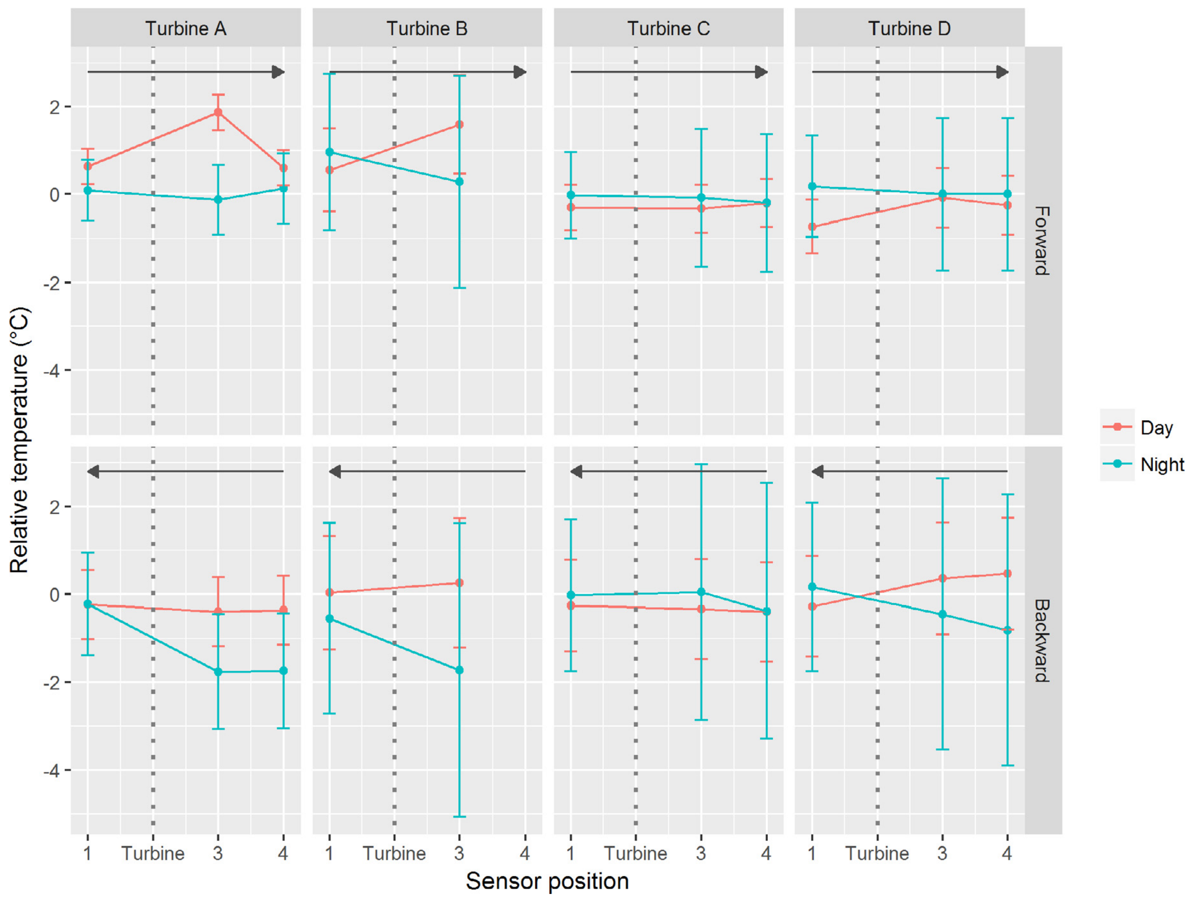


Fig. 3. Estimates of mean relative temperatures at different sensors and times of day based upon a linear mixed model with sensor position, turbine, and time of day as fixed factors (including their interactions) and event (i.e. unique time of measurement at a given turbine) as a random factor. The error bars represent 95% Wald confidence intervals. Separate models were fitted for data measured in forward and backward wind directions. Vertical dotted lines represent turbine position relative to the position of sensors. Horizontal arrows represent wind direction.

4. Discussion

Although we found various wind farm impacts on near-ground air temperature, we cannot support the spatially and temporally stable trends in relation to wind turbines referred to in several studies [13,26,27]. Only one significant result of wind farm impact was observed, that being at wind turbine A and position 3. Although the measured magnitude of 0.387–2.082 °C was similar to that reported by Baidya Roy and Traiteur (2010), the effect was inverse. In our case, daytime warming effect was observed instead of daytime cooling effect as reported by those authors. The effect of turbines is thus very likely confounded or, in our case, overridden by other environmental conditions affecting near-ground air temperature at a landscape scale, such as topography. Other studies have also pointed to the role of particular climatic and orographic conditions which could influence the final effects caused by wind [25,27,31].

On the other hand, we clearly demonstrated that the wind farm did somehow affect the near-ground temperature. The model selection (see Table 2) clearly confirms that models where wind farm is included fit better than did models without wind turbines. The potential influence of a turbine seems nevertheless to be location and/or time specific. There could be several potential causes of site-specific temperature differences, such as local hydrological, soil, or ecological conditions. Despite the apparent physiognomic homogeneity of vegetation cover (grassland) under the wind farm, it differs in species composition and therefore phenology including time of moving. It has been shown that crop type could have a greater effect on near-surface temperature than does a wind farm [17]. Our sensors were installed near the ground and the effect of vegetation cover could be more pronounced there, although we kept them unshaded by vegetation throughout the experiment. Given that crop or vegetation cover can have such an apparent effect, it is questionable whether the stable effect observed in other studies can truly be ascribed to turbines or whether other confounding factors were neglected. On the other hand, the mixing of air close to the ground where we measured is much less than that at 2 m above the surface where climate is usually measured. Though such a measurement is less standard, it is much more relevant for any biota living near the ground [32,33]. Our results thus indicate that the effect of turbines on microclimate is relatively small and can be overridden by many other environmental or anthropogenic factors.

Baidya Roy et al. (2004) described process of vertical mixing of air by wind farms. Well mixed air is subsequently capable to cool down overhead ground surface during day and warming subcooled surface during night. It is obvious that wind farms are mostly situated in places offering stable and strong wind. These locations are inclined to have strong natural turbulent flow. Hence the impact of induced turbulence could be small and/or rather limited. The resulting effect of wind farms could be different under varying conditions of natural turbulence and under different atmospheric conditions [34]. These differences could also be the reason why, in contrast with other studies [27,31], we observed no stable influence

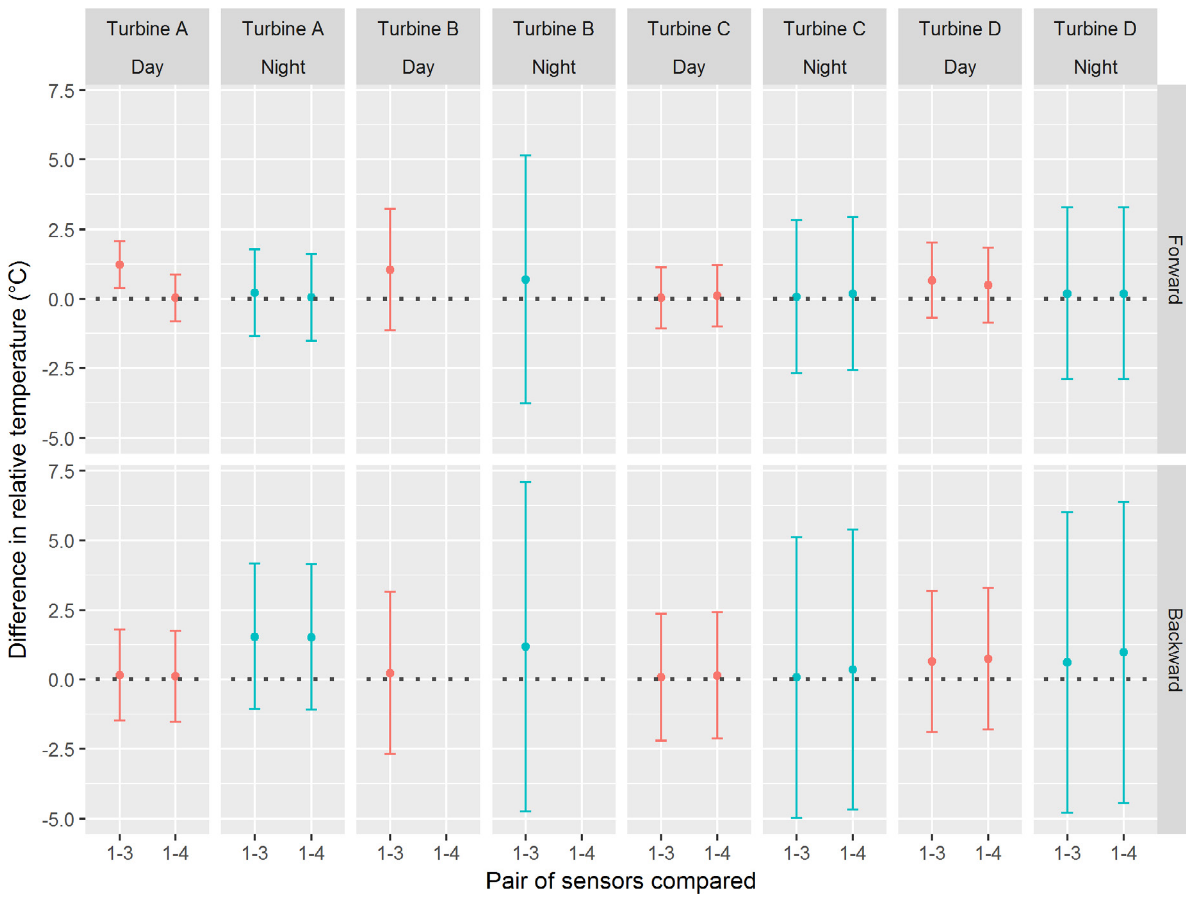


Fig. 4. Estimated differences in mean relative temperatures between sensors at positions 1 and 3 and between sensors at positions 1 and 4, together with their 95% Wald confidence intervals. Estimates are based on Model 4. Significant differences are those whose confidence intervals do not include zero.

in heterogeneous conditions either during day or night. Another explanation might be that the impact of wind turbines varies over time and hence the longer-term effects explored in this study may be different from the short-term observations presented especially in remotely sensed data [31].

The impact of wind farms is a complex issue. Our results contradicting the findings of others demonstrate the importance of following a proper field observation methodology. A cursory assessment could yield misleading results. Individual exploration of each turbine, removal of background effects, and inclusion of actual wind flow directions are key to correctly evaluating wind farm impacts on near-ground temperature. Future observations should be made to compare the effects of wind farms under different conditions.

5. Conclusion

Unlike other recent studies, ours provided no evidence of spatially and temporally stable impact of a wind farm on near-ground air temperature. Based on our measurements, such effect occurred only rarely and was locally specific. It is very likely caused by natural strong wind flow turbulence, which often occurs in places where wind farms are built. Even if a turbine effect is present, it can be of the same or lesser intensity than are effects caused by topography, land cover or land use and can be easily overridden by these environmental factors. These conclusions relate only to temperature near the ground (15 cm above the surface), where standard weather measurements only rarely are taken but where most of the organisms live. Our results thus provide relevant information about the effect of wind turbines on the microclimate and enable assessing this part of wind farms' multifaceted environmental impact.

Acknowledgements

The research was funded by the Internal Grant Agency (IGA) of the Faculty of Environmental Sciences, Czech University of Life Sciences Prague (IGA n. 42300/1312/3157).

References

[1] I. Pineda, J. Wilkes, Wind in power: 2014, European statistics, Tech. Rep. Eur. Energy Assoc. (2015) 1–12. http://www.ewea.org/fileadmin/files/library/publications/statistics/Wind_in_power_annual_statistics_2012.pdf.
[2] R. Saidur, N.A. Rahim, M.R. Islam, K.H. Solangi, Environmental impact of wind energy, Renew. Sustain. Energy Rev. 15 (2011) 2423–2430, https://doi.org/10.1016/j.rser.2011.02.024.
[3] A. Tabassum, M. Premalatha, T. Abbasi, S.A. Abbasi, Wind energy: increasing deployment, rising environmental concerns, Renew. Sustain. Energy Rev. 31 (2014) 270–288, https://doi.org/10.1016/j.rser.2013.11.019.
[4] K. Dai, A. Bergot, C. Liang, W.-N. Xiang, Z. Huang, Environmental issues associated with wind energy – a review, Renew. Energy 75 (2015) 911–921, https://doi.org/10.1016/j.renene.2014.10.074.
[5] R.H.H. Bakker, E. Pedersen, G.P.P. van den Berg, R.E.E. Stewart, W. Lok, J. Bouma, Impact of wind turbine sound on annoyance, self-reported sleep disturbance and psychological distress, Sci. Total Environ. 425 (2012) 42–51, https://doi.org/10.1016/j.scitotenv.2012.03.005.
[6] T. Van Renterghem, A. Bockstael, V. De Weirt, D. Botteldooren, Annoyance, detection and recognition of wind turbine noise, Sci. Total Environ. 456–457 (2013) 333–345, https://doi.org/10.1016/j.scitotenv.2013.03.095.
[7] A.L. Drewitt, R.H.W. Langston, Assessing the impacts of wind farms on birds,

Ibis (Lond. 1859) 148 (2006) 29–42, https://doi.org/10.1111/j.1474-919X.2006.00516.x.
[8] R.M.R. Barclay, E.F. Baerwald, J.C. Gruver, Variation in bat and bird fatalities at wind energy facilities: assessing the effects of rotor size and tower height, Can. J. Zool. Can. Zool. 85 (2007) 381–387, https://doi.org/10.1139/Z07-011.
[9] S. Dolman, M. Simmonds, Towards best environmental practice for cetacean conservation in developing Scotland's marine renewable energy, Mar. Pol. 34 (2010) 1021–1027, https://doi.org/10.1016/j.marpol.2010.02.009.
[10] J.P. Hurtado, J. Fernández, J.L. Parrondo, E. Blanco, Spanish method of visual impact evaluation in wind farms, Renew. Sustain. Energy Rev. 8 (2004) 483–491, https://doi.org/10.1016/j.rser.2003.12.009.
[11] D. de la Vega, J. Matthews, L. Norin, I. Angulo, Mitigation techniques to reduce the impact ofWind turbines on radar services, Energies 6 (2013) 2859–2873, https://doi.org/10.3390/en6062859.
[12] J.F. DeCarolis, D.W. Keith, The economics of large-scale wind power in a carbon constrained world, Energy Pol. 34 (2006) 395–410, https://doi.org/10.1016/j.enpol.2004.06.007.
[13] S. Baidya Roy, Simulating impacts of wind farms on local hydrometeorology, J. Wind Eng. Ind. Aerod. 99 (2011) 491–498, https://doi.org/10.1016/j.jweia.2010.12.013.
[14] S. Baidya Roy, S.W. Pacala, R.L. Walko, Can large wind farms affect local meteorology? J. Geophys. Res. Atmos. 109 (2004) D19101, https://doi.org/10.1029/2004JD004763.
[15] D.W. Keith, J.F. Decarolis, D.C. Denkenberger, D.H. Lenschow, S.L. Malyshev, S. Pacala, P.J. Rasch, The influence of large-scale wind power on global climate, Proc. Natl. Acad. Sci. U. S. A 101 (2004) 16115–16120, https://doi.org/10.1073/pnas.0406930101.
[16] A. Armstrong, S. Waldron, J. Whitaker, N.J. Ostle, Wind farm and solar park effects on plant-soil carbon cycling: uncertain impacts of changes in ground-level microclimate, Global Change Biol. 20 (2014) 1699–1706, https://doi.org/10.1111/gcb.12437.
[17] D.A. Rajewski, E.S. Takle, J.K. Lundquist, S. Oncley, J.H. Prueger, T.W. Horst, M.E. Rhodes, R. Pfeiffer, J.L. Hatfield, K.K. Spoth, R.K. Doorenbos, Crop wind energy experiment (CWEX): observations of surface-layer, boundary layer, and mesoscale interactions with a wind farm, Bull. Am. Meteorol. Soc. 94 (2013) 655–672, https://doi.org/10.1175/BAMS-D-11-00240.1.
[18] C. Wang, R.G. Prinn, Potential climatic impacts and reliability of very large-scale wind farms, Atmos. Chem. Phys. Discuss. 9 (2009) 19081–19102, https://doi.org/10.5194/acpd-9-19081-2009.
[19] F. Porté-Agel, H. Lu, Y.-T. Wu, Interaction between large wind farms and the atmospheric boundary layer, Procedia IUTAM 10 (2014) 307–318, https://doi.org/10.1016/j.piutam.2014.01.026.
[20] M. Calaf, M.B. Parlange, C. Meneveau, Large eddy simulation study of scalar transport in fully developed wind-turbine array boundary layers, Phys. Fluids 23 (2011) 126603, https://doi.org/10.1063/1.3663376.
[21] L.P. Chamorro, F. Porté-Agel, Effects of thermal stability and incoming boundary-layer flow characteristics on wind-turbine wakes: a wind-tunnel study, Boundary-Layer Meteorol. 136 (2010) 515–533, https://doi.org/10.1007/s10546-010-9512-1.
[22] J. Meyers, C. Meneveau, Optimal turbine spacing in fully developed wind farm boundary layers, Wind Energy 15 (2012) 305–317, https://doi.org/10.1002/we.469.
[23] F. Porté-Agel, Y.-T. Wu, H. Lu, R.J. Conzemius, Large-eddy simulation of atmospheric boundary layer flow through wind turbines and wind farms, J. Wind Eng. Ind. Aerod. 99 (2011) 154–168, https://doi.org/10.1016/j.jweia.2011.01.011.
[24] W. Zhang, C.D. Markfort, F. Porté-Agel, Experimental study of the impact of large-scale wind farms on land–atmosphere exchanges, Environ. Res. Lett. 8 (2013) 15002, https://doi.org/10.1088/1748-9326/8/1/015002.
[25] J.M. Walsh-Thomas, G. Cervone, P. Agouris, G. Manca, Further evidence of impacts of large-scale wind farms on land surface temperature, Renew. Sustain. Energy Rev. 16 (2012) 6432–6437, https://doi.org/10.1016/j.rser.2012.07.004.
[26] L. Zhou, Y. Tian, S. Baidya Roy, Y. Dai, H. Chen, Diurnal and seasonal variations of wind farm impacts on land surface temperature over western Texas, Clim. Dynam. 41 (2013) 307–326, https://doi.org/10.1007/s00382-012-1485-y.
[27] S. Baidya Roy, J.J. Traiteur, Impacts of wind farms on surface air temperatures, Proc. Natl. Acad. Sci. U. S. A 107 (2010) 17899–17904, https://doi.org/10.1073/pnas.1000493107.
[28] ČSVE, Česká společnost pro větrnou energii, 2013. http://www.csve.cz/clanky/aktualni-instalace-vte-cr/120. (Accessed 3 February 2016).
[29] R. Tolasz, T. Míková, A. Valeriánová, V. Voženílek, Atlas Podnebí Česka, Praha/Olomouc, 2007.
[30] C.M. Smith, R.J. Barthelmie, S.C. Pryor, In situ observations of the influence of a large onshore wind farm on near-surface temperature, turbulence intensity and wind speed profiles, Environ. Res. Lett. 8 (2013) 34006, https://doi.org/10.1088/1748-9326/8/3/034006.
[31] R.A. Harris, L. Zhou, G. Xia, Satellite observations of wind farm impacts on nocturnal land surface temperature in Iowa, Rem. Sens. 6 (2014) 12234–12246, https://doi.org/10.3390/rs61212234.
[32] R. Geiger, R. Aron H, P. Todhunter, The Climate Near the Ground, seventh ed., Rowman & Littlefield Publishers, 2009.
[33] K.A. Potter, A.H. Woods, S. Pincebourde, Microclimatic challenges in global change biology, Global Change Biol. 19 (2013) 2932–2939, https://doi.org/10.1111/gcb.12257.
[34] G. Xia, L. Zhou, J.M. Freedman, S.B. Roy, R.A. Harris, M.C. Cervarich, A case study of effects of atmospheric boundary layer turbulence, wind speed, and stability on wind farm induced temperature changes using observations from a field campaign, Clim. Dynam. 46 (2016) 2179–2196, https://doi.org/10.1007/s00382-015-2696-9.

6.2 Taxonomic diversity, functional diversity and evolutionary uniqueness in bird communities of Beijing’s urban parks: effects of land use and vegetation structure

(Morelli F., Benedetti Y., Su T. Zhou B., Moravec D., Šímová P., Liang W.)

Urban Forestry & Urban Greening 23 (2017) 84–92

Contents lists available at ScienceDirect

Urban Forestry & Urban Greening

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

Original article

Taxonomic diversity, functional diversity and evolutionary uniqueness in bird communities of Beijing's urban parks: Effects of land use and vegetation structure

Federico Morelli[a,*], Yanina Benedetti[a], Tongping Su[b,c], Bo Zhou[b], David Moravec[a], Petra Šímová[a], Wei Liang[b]

[a] Czech University of Life Sciences Prague, Faculty of Environmental Sciences, Department of Applied Geoinformatics and Spatial Planning, Kamýcká 129, CZ-165 00 Prague 6, Czech Republic
[b] Ministry of Education Key Laboratory for Tropical Plant and Animal Ecology, College of Life Sciences, Hainan Normal University, Haikou 571158, PR China
[c] School of Nature Conservation, Beijing Forestry University, Beijing 100083, PR China

ARTICLE INFO

Article history:
Received 27 January 2017
Received in revised form 6 March 2017
Accepted 6 March 2017
Available online 12 March 2017

Keywords:
Biodiversity
Evolutionary distinctiveness
Functional diversity
Species richness
Urban parks
Vegetation structure

ABSTRACT

The importance of biodiversity conservation is well recognized, and the loss of biodiversity is particularly evident in highly urbanized areas. On the other hand, green spaces inside cities, as parks, can provide a resource for maintaining and increasing biodiversity, especially for bird species. However, only a few studies have addressed the effects of vegetation structure and land use composition on different components of biodiversity.

Here, we explored the response of bird community composition to environmental differences related to land use composition and vegetation structure in green spaces in the city of Beijing, China. We compared the values of taxonomic diversity, functional diversity and community evolutionary distinctiveness in breeding bird communities, among ten urban parks of the world's third most populous city. Variation partitioning analysis and generalized linear mixed models were used to explore the unique and shared effects of land use composition and vegetation structure on each biodiversity metric.

Park size was not associated with the diversity of bird communities in Beijing. Land use composition was the best predictor of change in bird community composition, followed by vegetation structure at ground level and the intersection between land use and vegetation structure at tree level. Water coverage increased bird species richness, while the presence of large trees increased both taxonomic diversity and bird functional richness in urban parks. Finally, the presence of patches of deciduous trees showed a positive effect on the average score of evolutionary distinctiveness of bird communities. In conclusion, we highlight that different elements of the environment are supporting different components of bird community diversity.

1. Introduction

Urbanization has increased rapidly across the globe (McDonald, 2008), so understanding the ecological mechanisms supporting biodiversity in urban areas is becoming essential for maintenance of ecosystem functioning (Groombridge and Jenkins, 2002; Kang et al., 2015; Pereira et al., 2012). The main effects of urbanization on biodiversity have been assessed in many studies: fragmentation and loss of natural habitat for many species in highly urbanized areas carry out strong negative effects on biodiversity (Cardinale et al., 2012; McKinney, 2002; Newbold et al., 2016; Shochat et al., 2010) also leading to biotic (Devictor et al., 2007; McKinney, 2006). The biotic homogenization is characterized by similar communities, with few dominant species among different urban locations (Møller et al., 2012). Furthermore, the loss of biodiversity can negatively impact on human populations in many different ways (Cardinale et al., 2012; Newbold et al., 2016).

Even if some species are able to use the urban environment by exploiting the available resources or niches (Aronson et al., 2014; Zerbe et al., 2003), it is generally accepted that urbanization has a detrimental effect on wildlife (Sol et al., 2014). However, green urban spaces constitute important refuges for wildlife in urbanized environments and thus should be maintained (Alvey, 2006). Furthermore, green spaces can help to create less dense urban set-

* Corresponding author.
E-mail address: fmorellius@gmail.com (F. Morelli).

http://dx.doi.org/10.1016/j.ufug.2017.03.009
1618-8667/

tlements, such that an intermediate level of urbanization should have less negative impact on overall biodiversity (Chace and Walsh, 2006; Jokimäki et al., 1996). For example, city parks can provide a resource for maintaining or increasing urban biodiversity, especially for bird species (Chiesura, 2004; Schütz and Schulze, 2015; Strohbach et al., 2009). Nevertheless, urban parks in general are not necessarily hotspots of urban bird diversity (Strohbach et al., 2009).

Birds are potentially useful bioindicator in the cities, because it is relatively easy to assess their responses to urbanization and environmental changes (Koskimies, 1989; Minor and Urban, 2010). Some characteristics like park size, vegetation structure and patch connectivity have been shown to be important factors for the maintenance of avian diversity in urban landscapes (Fernández-Juricic and Jokimäki, 2001; Zhang et al., 2013). However, the effects of urbanization have mostly been studied on species richness and functional diversity (Devictor et al., 2008, 2007; Godet et al., 2016) than on other components such as phylogenetic diversity and evolutionary uniqueness of bird communities (Ibáñez-Álamo et al., 2016; Morelli et al., 2016).

Some aspects of bird diversity have already been studied in Beijing's urban parks, mainly focusing on taxonomic diversity and the diet guild of bird species in each community (Huang et al., 2015). Beijing is an interesting case study, because it has been particularly affected by rapid urbanization process when compared with other cities; in 10 years the population has increased from 13.9 million to more than 20 million (Xia, 2013). However, in order to assess the effects of habitat, vegetation structure and land use composition on the biodiversity of urban parks we must explore these effects on each different component of diversity of bird communities. For instance, a study to assess phylogenetic diversity and evolutionary uniqueness of Beijing's urban parks is still absent. Even an explicit exploration trying to quantify the relative effect of each environmental characteristic of green spaces on functional diversity of bird communities can lead to a better understanding the impacts of fast urbanization processes as well as bird adaptation and potential associated ecological changes.

The aim of this study is to explore the effects of land use and vegetation structure on different components of biodiversity on Beijing's urban parks: species richness, functional diversity and evolutionary uniqueness of bird communities. In addition, we investigate the environmental characteristics driving the change on each diversity metric and ecological score in these parks.

2. Methods

2.1. Study area, environmental variables and bird data collection

The study was carried out in ten urban parks of the city of Beijing, the capital of the People's Republic of China and third most populous city in the world, with more than 21.7 millions people (http://www.stats.gov.cn) in 2670.83 ± 103.62 km^2 of urban area (Li et al., 2015). These parks were selected because they can be considered representative of the main types of urban parks of the city. Park borders were vectorized using World Imagery maps (ESRI, 2009) in ArcGis 10.4 for Desktop as well as geographical metrics calculations. The city center was selected in the middle of the Forbidden City. Limits to the border of Beijing's urban areas were based on maps of China's urban areas (Yang et al., 2013).

The land-use composition of sampling sites was quantified in a 100 m radius buffer zone around each sampling site. The selection of 100 m radius is suggested by the results of previous studies (Morelli et al., 2013, 2014). Land-use categories were classified in 7 land-use types: roads, building (which includes residential building, built with infrastructure and processing areas), cropland (which includes all cultivated and farmland categories), uncultivated, forest, water and shrubs (ESM Table A). For each sampling site, we calculated the distance to the center of the city and the distance to the nearest urban park of the city.

To characterize the vegetation in Beijing's urban parks we described eight vegetation structural attributes (VGS) around each sampling site (100 m radius area). The measures were estimated based on ground level and tree level. Each stratum was assessed independently of the other. The structural variables of VGS at ground level were visually estimated percentage cover of bare soil, grass and leaf litter. For VGS at tree level, we estimated visually the percentages of tree layout (rows, scattered, patches), leaf typology (perennial, deciduous), bark typology (wrinkled, smooth), estimated height (above and below 30 m) and crown width (above and below 5 m).

Data on bird species were collected using standardized bird point counts, carried out during the 2016 breeding season (June). Point counts provide highly reliable estimates of relative population density, constituting a standardized method in ecology (Bibby et al., 1992). All points, separated by at least 200 m, were visited once between 06:00 and 10:00 for 10 min, only under favorable weather conditions. All diurnal bird species detected visually and acoustically were recorded by the observer in a radius of 100 m.

2.2. Biodiversity metrics and evolutionary distinctiveness in bird communities

In this study we used three different measures of biodiversity, calculated for each bird community (sampling site): (a) one related to taxonomic diversity, (b) one related to functional diversity and (c) one related to phylogenetic uniqueness.

(a) The bird species richness (BSR) was used as a measure of taxonomic diversity (Magurran, 2004). Species richness was expressed as the number of recorded bird species at each sampling site.
(b) The biodiversity metrics based on species-trait approaches are focused on functional aspects of biodiversity, and constitute an additional tool to the traditional taxonomic approach (de Bello et al., 2010). In this study, a functional diversity (FD) index was calculated using the avian niche traits, based on foraging and breeding ecology for all species (Huang et al., 2015; MacKinnon et al., 2000). The traits table consists of: resident type (resident or summer migrant), diet (granivorous, seed-eater, omnivorous, insectivorous, carnivorous), foraging substrate (foliage, ground), nesting substrate (tree, ground), nesting parasitism (yes or not). All variables, except resident type, are binomial (scored as either 0 or 1) (ESM Table A). In this study, Functional Richness (FRic) was used to describe the overall functional diversity in an assemblage. FRic represents the amount of functional space occupied by a species assemblage (Villéger et al., 2008). The FRic index was calculated using the 'FD' package for R (Laliberté et al., 2015).
(c) In order to explore changes in bird communities in terms of phylogenetic diversity, we used the evolutionary distinctiveness (ED) score as a measure of the species uniqueness (Frishkoff et al., 2014; Isaac et al., 2007). Using the ED score, we calculated the community evolutionary distinctiveness (CED) as the average ED for the entire assemblage (Morelli et al., 2016; Tucker et al., 2016).

2.3. Statistical analysis

In order to avoid redundancy variables, we performed principal components analysis (PCA) of measured land use and vegetation attributes. For graphical purposes, land use and vegetation structure variables were also classified on quartiles classes.

A variation partitioning by partial regression analysis was used to isolate the proportion of the variation explained by each of the two sets of factors exclusively (vegetation structure at ground level, vegetation structure at tree level and land use composition), and the proportions attributable to interactions between factors, accounting for variation in bird community composition (Borcard et al., 1992; Perez-Neto et al., 2006). The Pearson's product-moment correlations for all relationships were calculated during the preliminary exploration of the dataset. Pearson's product-moment correlations between predictors included in models were all below 0.6, to avoid multicollinearity between predictors (Graham, 2003). To test whether explanatory variables account for a significant variance, we used function 'rda' to test for fractions. Variation partitioning was performed using the 'vegan' package for R (Oksanen et al., 2016).

We used GLMMs, accounting for variation in bird species richness, functional richness and community evolutionary distinctiveness in relation to land use composition, vegetation structure and connectivity measures in the ten urban parks in Beijing. The names of the parks were added as random factors in the statistical models. Models were fitted assuming a Poisson distribution for bird species richness, and normal distribution for functional richness and community evolutionary distinctiveness, after having explored the distribution of variables (Box and Cox, 1964) using the package 'MASS' (Venables and Ripley, 2002), and 'glmmADMB' in R (Fournier et al., 2012; Skaug et al., 2013). The Akaike's Information Criterion (AIC) was used to determine the model that 'best' explained variation in the data (Burnham and Anderson, 2002).

All statistical tests were performed with R software (R Development Core Team, 2017).

3. Results

From the ten Beijing's urban parks, surveyed by means of 102 sampling sites (Fig. 1; Table A, ESM), 39 breeding bird species were recorded (Table B, ESM). The bird species richness in sampling sites ranged from a minimum of 1 species to a maximum of 13 species (Table B, ESM). The highest values of average species richness was recorded in Minghe Park (8 ± 3.34 species), and the lowest in Jingshan Park (3.25 ± 1.26 species) (Fig. 2). The highest average functional diversity (FRic) estimated on bird traits (Table C, ESM) was calculated in bird communities from Chaoyang Park (0.18 ± 0.07), while the lowest values were obtained for Heaven Park and Jingshan Park (0.09 ± 0.06) (Fig. 2). Finally, the highest values of community evolutionary distinctiveness (CED) was estimated in Minghe Park (9.29 ± 1.71), and the lowest values was estimated in Yuyuantan Park (6.27 ± 1.34) (Fig. 2). The values recorded in Zizhuyuan Park were excluded from this comparison as they were obtained from only two sampling sites.

Nine environmental descriptors were found to be suitable to describe urban parks. Three land use types: shrubs, forest and water (%); three categories of VGS at ground level: i.e. bare soil, grass and litter (%); and three categories of VGS at tree level: leaf typology (deciduous), tree height (above 30 m) and crown width (above 5 m).

The three categories of environmental descriptors were significantly correlated with bird species composition (all $p < 0.05$). However, the large effect on bird composition was found for land

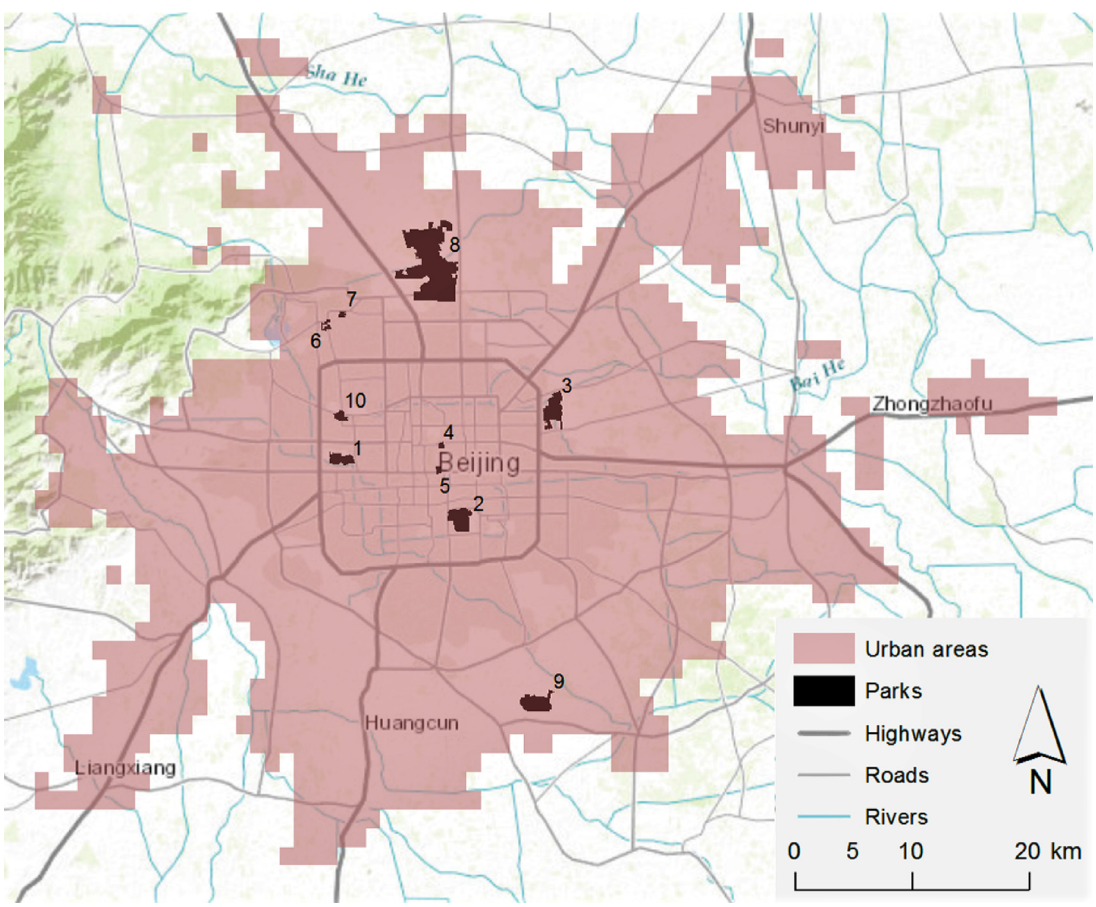


Fig. 1. Map of the ten Beijing parks surveyed during the breeding season 2016 in this study. Park names: 1: Yuyuantan Park; 2: Heaven Park; 3: Chaoyang Park; 4: Jingshan Park; 5: Zhongshan Park; 6: Minghe Park; 7: Yuanmingyuan Park; 8: Olympic Forest North Park; 9: Sanhaizi Country Park; 10: Zizhuyuan Park. ESRI, DeLorme, MapmyIndia, © OpenStreetMap contributors, and the GIS user community. The urban zones were taken from Yang et al. (2013).

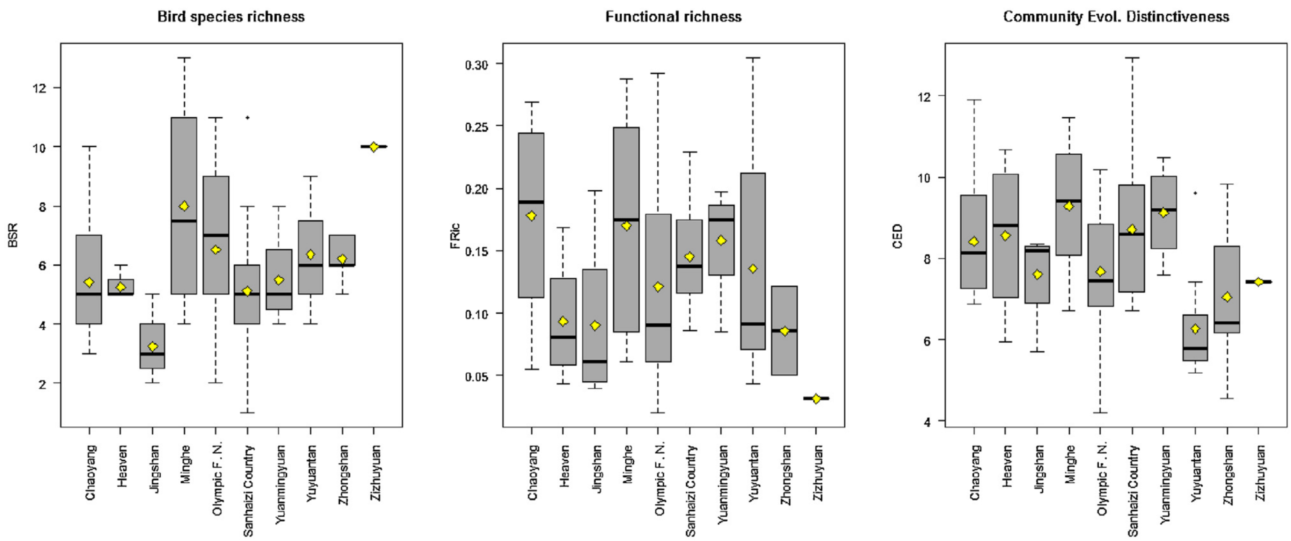


Fig. 2. Comparison of bird species richness, functional diversity and community evolutionary distinctiveness among Beijing's urban parks. The *y*-axis represents the estimated variable. The box plots show the median (bar in the middle of rectangles), mean (yellow rhombus), upper and lower quartiles, maximum and minimum values (vertical dashed lines) and outliers. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

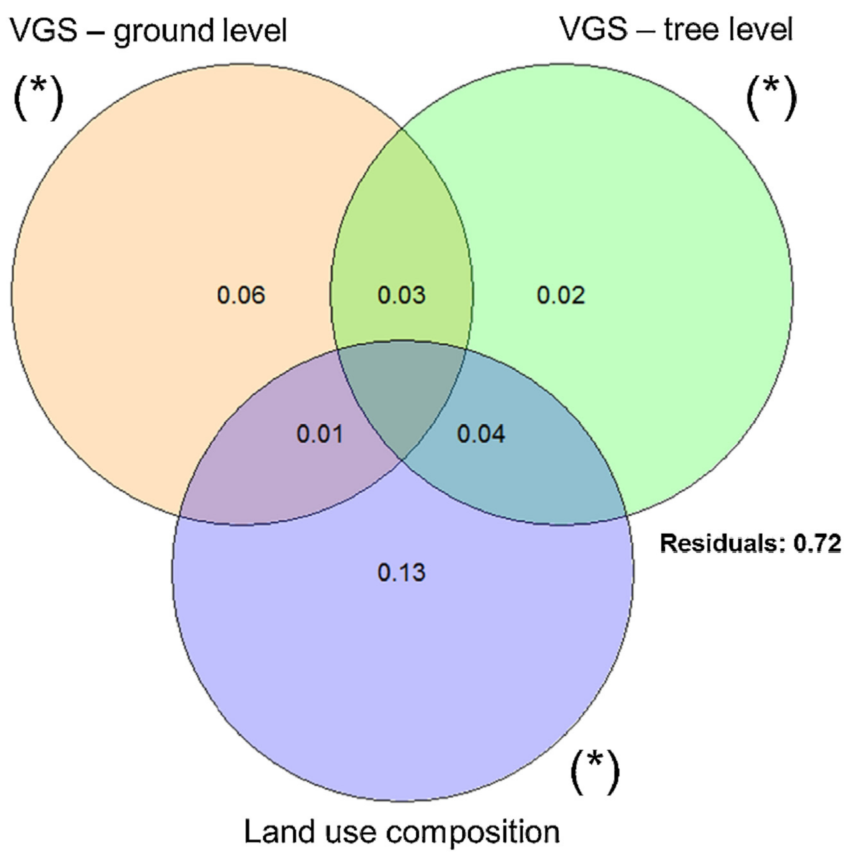


Fig. 3. Venn diagram showing the results of variation partitioning analysis on bird community composition. The diagrams represent the adjusted percentages of unique contribution of vegetation structure (VGS) at ground level, tree level and land use composition on bird species composition in parks of Beijing, China. The fraction between two overlapped circles represents the variation explained between the components while the residuals are the variation left unexplained by the canonical model. The fractions of variation displayed in the diagram are computed from adjusted r^2. All unique contributions were statistically significant (*).

use composition, followed by vegetation structure at the ground level, and the intersection between land use composition with vegetation structure at the tree level (Fig. 3).

Considering separately each bird diversity metric and evolutionary distinctiveness, the effects of land use and vegetation structure were significantly associated with different measures. Among the candidate predictors, connectivity measures (distance from the city center and the distance from the nearest park) were not included in the best models. Water coverage increased the values of bird species richness (Table 1, Fig. 4), while shrub coverage was negatively associated with functional richness of bird communities (Table 1, Fig. 4). Bird species richness increased with grass coverage,

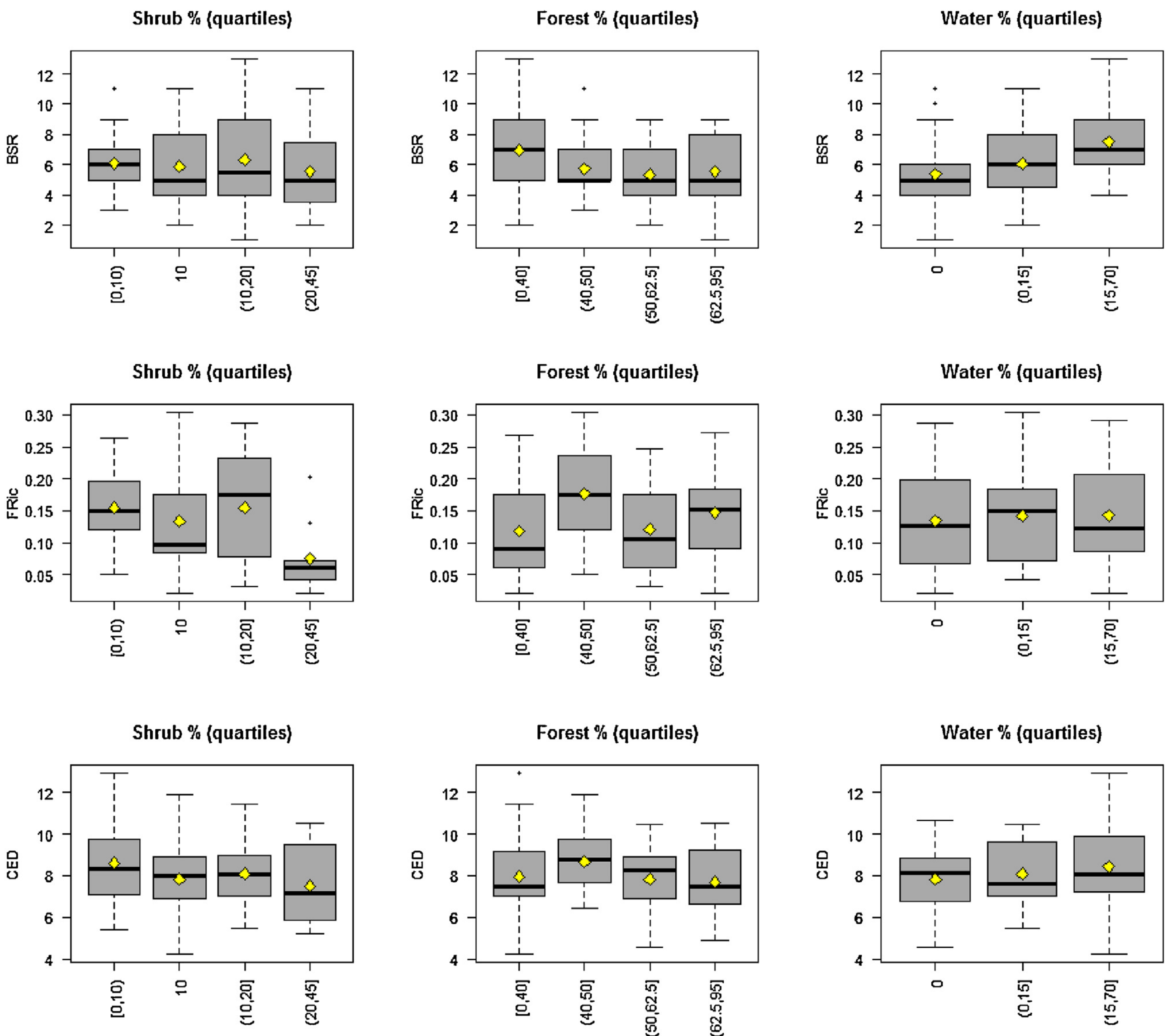


Fig. 4. Differences of bird species richness, functional diversity and community evolutionary distinctiveness in relation to land use composition (shrub, forest and water coverage) classified in quartiles, in Beijing's urban parks. The *y*-axis represents the estimated variable. The box plots show the median (bar in the middle of rectangles), mean (yellow rhombus), upper and lower quartiles, maximum and minimum values (vertical dashed lines) and outliers. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

Table 1
Results of fixed-effect parameters in a GLMM, accounting for variation in bird species richness, functional richness and community evolutionary distinctiveness in relation to land use composition and vegetation structure in Beijing's urban parks. The parks were added as random factors in the models. Only significant variables are shown in the table. ES, estimate; SE, standard error.

Variable/(model)	ES	SE	*z*/*t*	*P*
(Bird species richness)				
Intercept	2.707	0.885	3.06	<0.05
Water	0.010	0.003	1.98	<0.05
Crown width > 5 m	0.042	0.014	2.88	<0.05
(Functional richness)				
Intercept	0.002	0.168	0.01	>0.05
Shrub	−0.019	0.011	−1.98	<0.05
Crown width > 5 m	0.005	0.003	1.93	<0.05
(Community evolutionary distinctiveness)				
Intercept	8.378	3.883	2.16	<0.05
Tree deciduous	0.014	0.006	2.34	<0.05

and showed a U-shaped response to litter coverage, however these effects were not statistically significant (Table 1, Fig. 5). Finally, the presence of large trees with crown width larger than 5 m slightly increased both species richness and functional richness of bird communities. The coverage of deciduous trees was also associated with a slight increase in average scores of evolutionary distinctiveness in bird communities in Beijing's urban parks (Table 1, Fig. 6).

4. Discussion

In an interesting study, Huang et al. (2015) explored the relationships between the size of parks, plant and insects richness in relation to birds in many Beijing urban parks. It highlighted how green spaces around urban parks increase breeding bird richness, and also indicated the importance of connectivity. In addition, Huang et al. (2015) showed how important coniferous trees are for the settlement of many species, such as omnivorous birds. Green spaces, such as urban parks, can play a key role in conservation of biodiversity, especially under scenarios of densification processes as exhibited in many major cities (Haaland and van den Bosch, 2015; Xie et al., 2016).

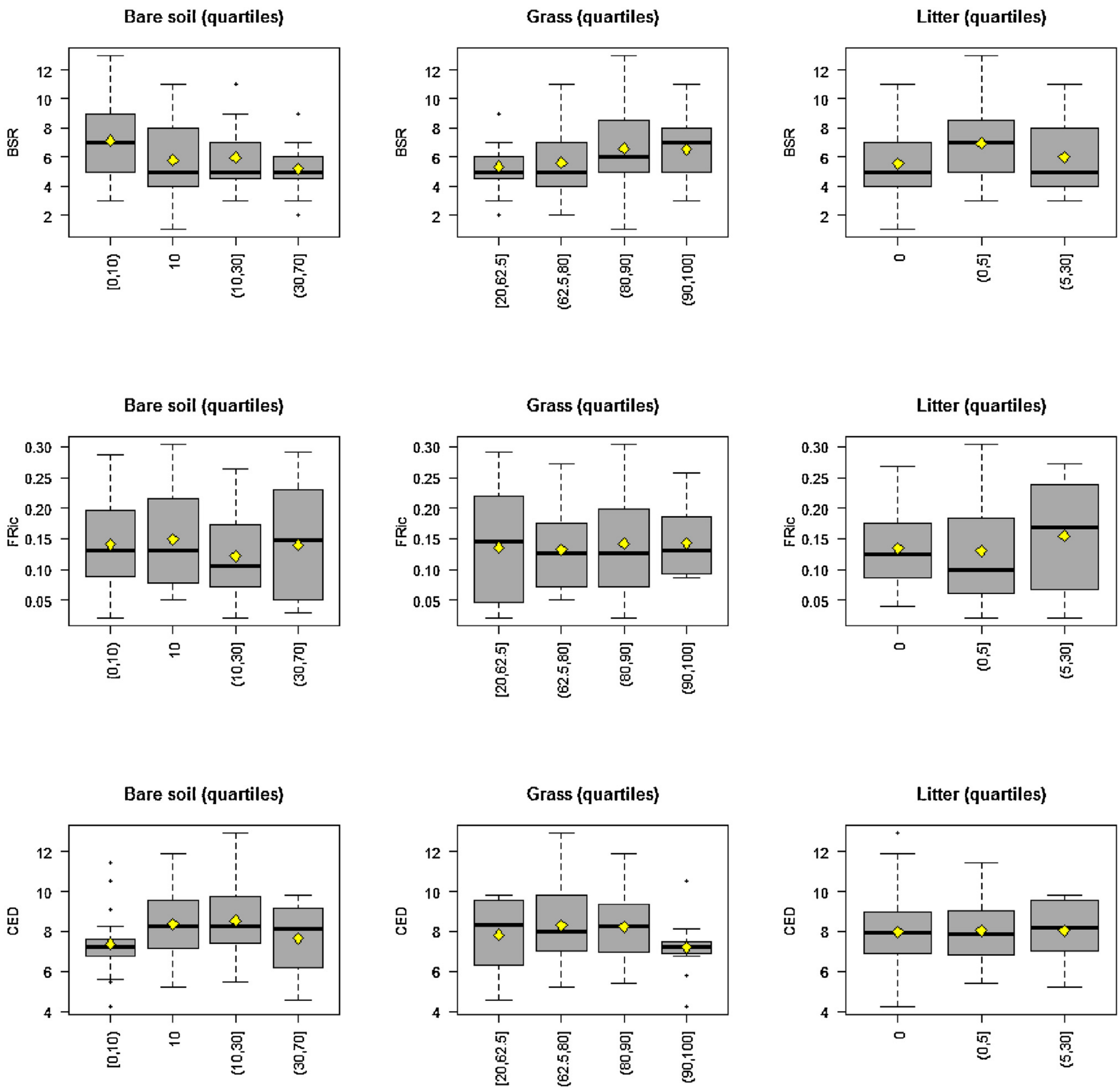


Fig. 5. Differences of bird species richness, functional diversity and community evolutionary distinctiveness in relation to the vegetation structure at ground level (bare soil, grass and litter coverage) classified in quartiles, in Beijing's urban parks. The *y*-axis represents the estimated variable. The box plots show the median (bar in the middle of rectangles), mean (yellow rhombus), upper and lower quartiles, maximum and minimum values (vertical dashed lines) and outliers. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

Our findings provide new data on bird community composition and bird diversity metrics in some urban parks of the metropolis of Beijing. Furthermore, our study provides a first assessment of the relative effects of land use and vegetation structure on each component of diversity and evolutionary distinctiveness of bird communities, analyzed separately. Land use composition was the main predictor of bird community composition, followed by vegetation structure at ground level and the intersection between land use and vegetation structure at tree level. Water surface was associated with an increase in bird species richness, while the percentage of shrubs, was surprisingly only slightly negatively correlated with the number of bird species in communities. However, examining the data collected, we hypothesize that this was a statistical artifact due to a strong correlation between built areas and shrub features in the surveyed parks.

At the ground level of vegetation structure, the balance between availability of bare soil and coverage of grass, can be important for the foraging strategies of insectivorous birds, as demonstrated in other studies in Europe (Fonderflick et al., 2010; Morelli, 2013, 2012). Another interesting result, although not statistically significant, was the inverse U-shape relationship found between litter coverage and bird species richness (Fig. 5). We know that bird species can respond to variations in the soil composition and the presence of litter (Myers et al., 2015). Based on this evidence, we can hypothesize that bird communities achieve the highest values of richness in habitat where the litter is present (but not at extreme values), corresponding to more heterogeneous environments.

In this study, we found higher values of bird taxonomic diversity in Minghe Park and Olympic Forest North Park, the smallest and largest parks surveyed in Beijing respectively. However, even

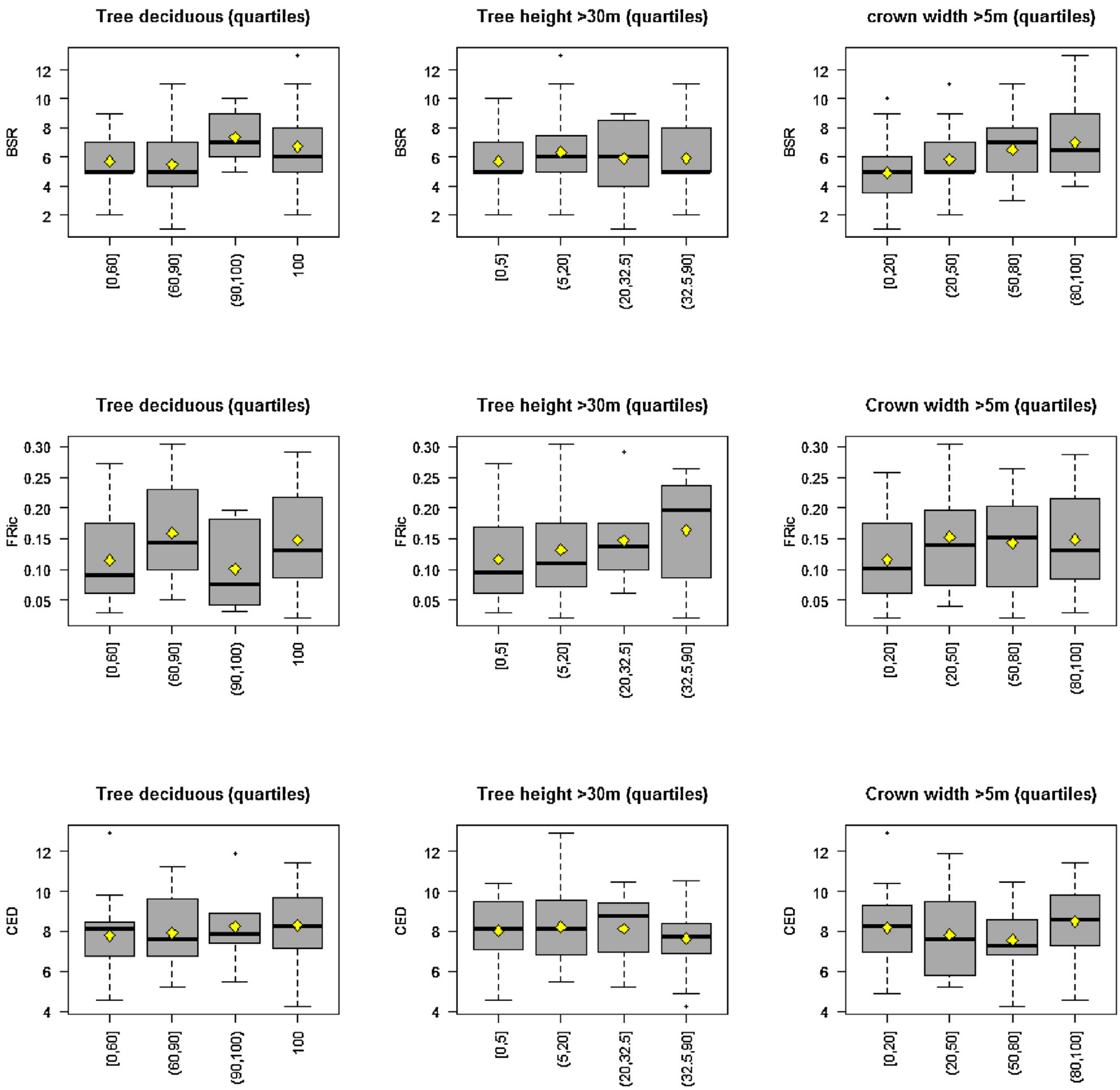


Fig. 6. Differences of bird species richness, functional diversity and community evolutionary distinctiveness in relation to the vegetation structure at tree level (coverage of deciduous tree, tree height above 30 m and tree with crown width above 5 m) classified in quartiles, in Beijing's urban parks. The *y*-axis represents the estimated variable. The box plots show the median (bar in the middle of rectangles), mean (yellow rhombus), upper and lower quartiles, maximum and minimum values (vertical dashed lines) and outliers. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

considering Zizhuyuan Park, a medium-size park where the data came from only one sampling site, the size of the parks seems not to be the key-stone factor for bird diversity. Furthermore, the small Minghe Park, with a surface of only 48 ha, was the first park for community evolutionary distinctiveness and the second park for functional richness (after Chaoyang Park, a medium-size park). Our findings support the statement that park size is more important for bird abundance than for bird species diversity, in agreement with a recent study, where authors suggest that vegetation foliage is an important factor influencing avian species diversity in Beijing's parks (Xie et al., 2016).

The results of mixed model approach highlighted how the percentage of large trees can increase bird functional richness in urban parks. In fact, our findings support the theory that large and old trees (represented by trees with crown width >5 m in this study) are key-stones for biodiversity conservation, providing refuge and required resources for many species (Le Roux et al., 2014; Stagoll et al., 2012).

One of the reasons why Minghe Park presented higher values of community evolutionary distinctiveness, constituting an important target for the conservation of birds evolutionary uniqueness, is related to the presence and abundance of two species with high ED scores: *Cyanopica cyanus*, the Azure-winged Magpie, with ED score of 17.139 and *Stigmatopelia chinensis*, the Spotted Dove, with ED score of 11.523. Both values are relatively high if compared with the average ED score for all bird species monitored in this study, ED score: 8.56 (see the values of ED for bird species in the EDGE website, Zoological Society of London, 2008). Furthermore, the presence of patches of deciduous forest and small patches of deciduous trees were positively associated with average score of evolutionary distinctiveness of bird communities in urban parks.

In conclusion, we have shown how different environmental characteristics of urban parks can improve different components of bird community as taxonomic or functional diversity and evolutionary distinctiveness. Water surface can increase bird species richness and large trees can enhance both species richness and functional diversity of bird communities in the ecosystem. Finally, increasing the surface of patches of deciduous trees in green spaces, it is possible to attract bird species characterized by evolutionary uniqueness, supporting more evolutionary history in bird assemblages. Each biodiversity component needs to be considered, in order to establish better ecological planning, and future biodiversity conservation in urban parks.

Acknowledgements

We are very grateful to Dr. Emma Nelson, from the Liverpool University (UK), for assistance with English language editing and valuable comments on the manuscript. This work was supported by the National Natural Science Foundation of China (Nos. 31472013 to WL).

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ufug.2017.03.009.

References

Alvey, A.A., 2006. Promoting and preserving biodiversity in the urban forest. Urban For. Urban Green. 5, 195–201, http://dx.doi.org/10.1016/j.ufug.2006.09.003.
Aronson, M.F.J., La Sorte, F.A., Nilon, C.H., Katti, M., Goddard, M.A., Lepczyk, C.A., Warren, P.S., Williams, N.S.G., Cilliers, S., Clarkson, B., Dobbs, C., Dolan, R., Hedblom, M., Klotz, S., Kooijmans, J.L., Kühn, I., Macgregor-Fors, I., McDonnell, M., Mörtberg, U., Pysek, P., Siebert, S., Sushinsky, J., Werner, P., Winter, M., 2014. A global analysis of the impacts of urbanization on bird and plant diversity reveals key anthropogenic drivers. Proc. R. Soc. Lond. B: Biol. Sci. 281, 20133330, http://dx.doi.org/10.1098/rspb.2013.3330.
Bibby, C.J., Burgess, N.D., Hill, D.A., 1992. Bird Census Techniques (Google eBook). Academic Press.
Borcard, D., Legendre, P., Drapeau, P., 1992. Partialling out the spatial component of ecological variation. Ecology 73, 1045–1055, http://dx.doi.org/10.2307/1940179.
Box, G.E.P., Cox, D.R., 1964. An analysis of transformations. J. R. Stat. Soc. B 26, 211–252.
Burnham, K.P., Anderson, D.R., 2002. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach, 2nd edition. Springer Verlag, New York, NY, USA.
Cardinale, B.J., Duffy, J.E., Gonzalez, A., Hooper, D.U., Perrings, C., Venail, P., Narwani, A., Mace, G.M., Tilman, D., Wardle, D.A., Kinzig, A.P., Daily, G.C., Loreau, M., Grace, J.B., Larigauderie, A., Srivastava, D.S., Naeem, S., 2012. Biodiversity loss and its impact on humanity. Nature 486, 59–67, http://dx.doi.org/10.1038/nature11148.
Chace, J.F., Walsh, J.J., 2006. Urban effects on native avifauna: a review. Landsc. Urban Plan. 74, 46–69.
Chiesura, A., 2004. The role of urban parks for the sustainable city. Landsc. Urban Plan. 68, 129–138, http://dx.doi.org/10.1016/j.landurbplan.2003.08.003.
de Bello, F., Lavorel, S., Gerhold, P., Reier, Ü., Pärtel, M., 2010. A biodiversity monitoring framework for practical conservation of grasslands and shrublands. Biol. Conserv. 143, 9–17, http://dx.doi.org/10.1016/j.biocon.2009.04.022.
Devictor, V., Julliard, R., Clavel, J., Jiguet, F., Lee, A., Couvet, D., 2008. Functional biotic homogenization of bird communities in disturbed landscapes. Glob. Ecol. Biogeogr. 17, 252–261, http://dx.doi.org/10.1111/j.1466-8238.2007.00364.x.
Devictor, V., Julliard, R., Couvet, D., Lee, A., Jiguet, F., 2007. Functional homogenization effect of urbanization on bird communities. Conserv. Biol. 21, 741–751, http://dx.doi.org/10.1111/j.1523-1739.2007.00671.x.
ESRI, 2009. World Imagery [WWW Document], ArcGIS Online.
Fernández-Juricic, E., Jokimäki, J., 2001. A habitat island approach to conserving birds in urban landscapes: case studies from southern and northern Europe. Biodivers. Conserv. 10, 2023–2043, http://dx.doi.org/10.1023/A:1013133308987.
Fonderflick, J., Caplat, P., Lovaty, F., Thévenot, M., Prodon, R., 2010. Avifauna trends following changes in a Mediterranean upland pastoral system. Agric. Ecosyst. Environ. 137, 337–347, http://dx.doi.org/10.1016/j.agee.2010.03.004.
Fournier, D.A., Skaug, H.J., Ancheta, J., Ianelli, J., Magnusson, A., Maunder, M., Nielsen, A., Sibert, J., 2012. AD Model Builder: using automatic differentiation for statistical inference of highly parameterized complex nonlinear models. Optim. Methods Softw. 27, 233–249.
Frishkoff, L.O., Karp, D.S., M'Gonigle, L.K., Mendenhall, C.D., Zook, J., Kremen, C., Hadly, E.A., Daily, G.C., 2014. Loss of avian phylogenetic diversity in neotropical agricultural systems. Science 345, 1343–1346, http://dx.doi.org/10.7910/DVN/26910.
Godet, L., Devictor, V., Burel, F., Robin, J.-G., Ménanteau, L., Fournier, J., 2016. Extreme landscapes decrease taxonomic and functional bird diversity but promote the presence of rare species. Acta Ornithol. 51, 23–38, http://dx.doi.org/10.3161/00016454AO2016.51.1.003.
Graham, M.H., 2003. Confronting multicollinearity in ecological multiple regression. Ecology 84, 2809–2815, http://dx.doi.org/10.1890/02-3114.
Groombridge, B., Jenkins, M.D.D., 2002. World Atlas of Biodiversity: Earth's Living Resources in the 21st Century. University of California Press, Berkeley, CA.
Haaland, C., van den Bosch, C.K., 2015. Challenges and strategies for urban green-space planning in cities undergoing densification: a review. Urban For. Urban Green. 14, 760–771, http://dx.doi.org/10.1016/j.ufug.2015.07.009.
Huang, Y., Zhao, Y., Li, S., von Gadow, K., 2015. The effects of habitat area, vegetation structure and insect richness on breeding bird populations in Beijing urban parks. Urban For. Urban Green. 14, 1027–1039, http://dx.doi.org/10.1016/j.ufug.2015.09.010.
Ibáñez-Álamo, J.D., Rubio, E., Benedetti, Y., Morelli, F., 2016. Global loss of avian evolutionary uniqueness in urban areas. Glob. Change Biol., http://dx.doi.org/10.1111/gcb.13567.
Isaac, N.J.B., Turvey, S.T., Collen, B., Waterman, C., Baillie, J.E.M., 2007. Mammals on the EDGE: conservation priorities based on threat and phylogeny. PLoS ONE 2, e296, http://dx.doi.org/10.1371/journal.pone.0000296.
Jokimäki, J., Suhonen, J., Inki, K., Jokinen, S., 1996. Biogeographical comparison of winter bird assemblages in urban environments in Finland. J. Biogeogr. 23, 379–386, http://dx.doi.org/10.1046/j.1365-2699.1996.00033.x.
Kang, W., Minor, E.S., Park, C., Lee, D., 2015. Effects of habitat structure, human disturbance, and habitat connectivity on urban forest bird communities. Urban Ecosyst. 18, 857–870, http://dx.doi.org/10.1007/s11252-014-0433-5.
Koskimies, P., 1989. Birds as a tool in environmental monitoring. Ann. Entomol. Fenn. 26, 153–166.
Laliberté, E., Legendre, P., Shipley, B., 2015. Measuring Functional Diversity (FD) from Multiple Traits, and Other Tools for Functional Ecology: R Package Version 1.0-12.
Le Roux, D.S., Ikin, K., Lindenmayer, D.B., Manning, A.D., Gibbons, P., 2014. The future of large old trees in urban landscapes. PLOS ONE 9, http://dx.doi.org/10.1371/journal.pone.0099403.
Li, X., Gong, P., Liang, L., 2015. A 30-year (1984–2013) record of annual urban dynamics of Beijing City derived from Landsat data. Remote Sens. Environ. 166, 78–90, http://dx.doi.org/10.1016/j.rse.2015.06.007.
MacKinnon, J., Phillipps, K., Showler, D., 2000. A Field Guide to the Birds of China.
Magurran, A., 2004. Measuring Biological Diversity. Blackwell Science, Oxford, UK.
McDonald, R.I., 2008. Global urbanization: can ecologists identify a sustainable way forward? Front. Ecol. Environ. 6, 99–104.
McKinney, M.L., 2006. Urbanization as a major cause of biotic homogenization. Biol. Conserv. 127, 247–260, http://dx.doi.org/10.1016/j.biocon.2005.09.005.
McKinney, M.L., 2002. Urbanization, biodiversity, and conservation. Bioscience 52, 883, http://dx.doi.org/10.1641/0006-3568(2002)052[0883:UBAC]2.0.CO;2.
Minor, E., Urban, D., 2010. Forest bird communities across a gradient of urban development. Urban Ecosyst. 13, 51–71.
Møller, A.P., Diaz, M., Flensted-Jensen, E., Grim, T., Ibáñez-Álamo, J.D., Jokimäki, J., Mänd, R., Markó, G., Tryjanowski, P., 2012. High urban population density of birds reflects their timing of urbanization. Oecologia 170, 867–875, http://dx.doi.org/10.1007/s00442-012-2355-3.
Morelli, F., 2012. Correlations between landscape features and crop type and the occurrence of the Ortolan Bunting *Emberiza hortulana* in farmlands of Central Italy. Ornis Fenn. 89, 264–272.
Morelli, F., 2013. Are the nesting probabilities of the red-backed shrike related to proximity to roads? Nat. Conserv. 5, 1–11, http://dx.doi.org/10.3897/natureconservation.5.4511.
Morelli, F., Benedetti, Y., Ibáñez-Álamo, J.D., Jokimaki, J., Mänd, R., Tryjanowski, P., Møller, A.P., 2016. Evidence of evolutionary homogenization of bird communities in urban environments across Europe. Glob. Ecol. Biogeogr. 25, 1284–1293, http://dx.doi.org/10.1111/geb.12486.
Morelli, F., Jerzak, L., Tryjanowski, P., 2014. Birds as useful indicators of high nature value (HNV) farmland in Central Italy. Ecol. Indic. 38, 236–242.
Morelli, F., Pruscini, F., Santolini, R., Perna, P., Benedetti, Y., Sisti, D., 2013. Landscape heterogeneity metrics as indicators of bird diversity: determining the optimal spatial scales in different landscapes. Ecol. Indic. 34, 372–379, http://dx.doi.org/10.1016/j.ecolind.2013.05.021.
Myers, M.C., Mason, J.T., Hoksch, B.J., Cambardella, C.A., Pfrimmer, J.D., 2015. Birds and butterflies respond to soil-induced habitat heterogeneity in experimental plantings of tallgrass prairie species managed as agroenergy crops in Iowa, USA. J. Appl. Ecol. 52, 1176–1187, http://dx.doi.org/10.1111/1365-2664.12503.
Newbold, T., Hudson, L.N., Arnell, A.P., Contu, S., De Palma, A., Ferrier, S., Hill, S.L.L., Hoskins, A.J., Lysenko, I., Phillips, H.R.P., Burton, V.J., Chng, C.W.T., Emerson, S., Gao, D., Pask-Hale, G., Hutton, J., Jung, M., Sanchez-Ortiz, K., Simmons, B.I., Whitmee, S., Zhang, H., Scharlemann, J.P.W., Purvis, A., 2016. Has land use pushed terrestrial biodiversity beyond the planetary boundary? A global assessment. Science 353, 45–50, http://dx.doi.org/10.1126/science.aaf2201.

Oksanen, J., Guillaume Blanchet, F., Kindt, R., Legendre, P., Minchin, P.R., O'Hara, B.R., Simpson, G.L., Solymos, P., Stevens, M.H.H., Wagner, H., 2016. vegan: Community Ecology Package. R Package Version 2.3-4.
Pereira, H.M., Navarro, L.M., Martins, I.S., 2012. Global biodiversity change: the bad, the good, and the unknown. Annu. Rev. Environ. Resour. 37, 25–50, http://dx.doi.org/10.1146/annurev-environ-042911-093511.
Perez-Neto, P., Legendre, P., Dray, S., Borcard, D., 2006. Variation partitioning of species data matrices: estimation and comparison of fractions. Ecology 87, 2614–2625.
R Development Core Team, 2017. R: A Language and Environment for Statistical Computing.
Schütz, C., Schulze, C.H., 2015. Functional diversity of urban bird communities: effects of landscape composition, green space area and vegetation cover. Ecol. Evol. 5, 5230–5239, http://dx.doi.org/10.1002/ece3.1778.
Shochat, E., Lerman, S.B., Anderies, J.M., Warren, P.S., Faeth, S.H., Nilon, C.H., 2010. Invasion, competition, and biodiversity loss in urban ecosystems. Bioscience 60, 199–208, http://dx.doi.org/10.1525/bio.2010.60.3.6.
Skaug, H., Fournier, D., Nielsen, A., 2013. glmmADMB: Generalized Linear Mixed Models Using AD Model Builder – R Package.
Sol, D., González-Lagos, C., Moreira, D., Maspons, J., Lapiedra, O., 2014. Urbanisation tolerance and the loss of avian diversity. Ecol. Lett. 17, 942–950, http://dx.doi.org/10.1111/ele.12297.
Stagoll, K., Lindenmayer, D.B., Knight, E., Fischer, J., Manning, A.D., 2012. Large trees are keystone structures in urban parks. Conserv. Lett. 5, 115–122, http://dx.doi.org/10.1111/j.1755-263X.2011.00216.x.
Strohbach, M.W., Haase, D., Kabisch, N., 2009. Birds and the city: urban biodiversity, land use, and socioeconomics. Ecol. Soc. 14, 31.
Tucker, C.M., Cadotte, M.W., Carvalho, S.B., Davies, T.J., Ferrier, S., Fritz, S.A., Grenyer, R., Helmus, M.R., Jin, L.S., Mooers, A.Ø., Pavoine, S., Purschke, O., Redding, D.W., Rosauer, D.F., Winter, M., Mazel, F., 2016. A guide to phylogenetic metrics for conservation, community ecology and macroecology. Biol. Rev., http://dx.doi.org/10.1111/brv.12252.
Venables, W.N., Ripley, B.D., 2002. Modern Applied Statistics with S, 4th ed. Springer, New York, NY, USA.
Villéger, S., Mason, N.W.H., Mouillot, D., 2008. New multidimensional functional diversity indices for a multifaceted framework in functional ecology. Ecology 89, 2290–2301, http://dx.doi.org/10.1890/07-1206.1.
Xia, Q.F., 2013. Beijing Statistical Yearbook 2013. China Statistics Press, Beijing.
Xie, S., Lu, F., Cao, L., Zhou, W., Ouyang, Z., 2016. Multi-scale factors influencing the characteristics of avian communities in urban parks across Beijing during the breeding season. Sci. Rep. 6, 29350, http://dx.doi.org/10.1038/srep29350.
Yang, Y., He, C., Zhang, Q., Han, L., Du, S., 2013. Timely and accurate national-scale mapping of urban land in China using Defense Meteorological Satellite Program's Operational Linescan System nighttime stable light data. J. Appl. Remote Sens. 7, 73535, http://dx.doi.org/10.1117/1.JRS.7.073535.
Zerbe, S., Maurer, U., Schmitz, S., Sukopp, H., 2003. Biodiversity in Berlin and its potential for nature conservation. Landsc. Urban Plan. 62, 139–148.
Zhang, S., Suo, M., Liu, S., Liang, W., 2013. Do major roads reduce gene flow in urban bird populations? PLoS ONE 8, e77026, http://dx.doi.org/10.1371/journal.pone.0077026.
Zoological Society of London, 2008. Edge of Existence Programme [WWW Document], http://www.edgeofexistence.org.

6.3 Digital elevation models as predictors of yield: Comparison of an UAV and other elevation data sources

(MoravecD., KomárekJ., KumhálováJ., KroulíkM., ProšekJ., KlápštěP.)

Agronomy Research **15**(1), 249–255, 2017

Digital elevation models as predictors of yield: Comparison of an UAV and other elevation data sources

D. Moravec[1,*], J. Komárek[1], J. Kumhálová[2], M. Kroulík[3], J. Prošek[1] and P. Klápště[1]

[1]Czech University of Life Sciences Prague, Faculty of Environmental Sciences, Department of Applied Geoinformatics and Spatial Planning, Kamýcká 129, CZ165 21 Prague, Czech Republic
[2]Czech University of Life Sciences Prague, Faculty of Engineering, Department of Machinery Utilization, Kamýcká 129, CZ165 21 Prague, Czech Republic
[3]Czech University of Life Sciences Prague, Faculty of Engineering, Department of Agricultural Machines, Kamýcká 129, CZ165 21 Prague, Czech Republic
*Correspondence: dmoravec@fzp.czu.cz

Abstract. Topography usually plays an important role for yield variability assessment. This study provides insight into the use of surface models from different sources for agriculture purposes: unmanned aerial vehicle imagery, LiDAR data and elevation data acquired from a harvester. The dataset from an aerial vehicle was obtained in the form of ortho-mosaics and digital surface model using casual camera. The LiDAR data was provided by the State Administration of Land Surveying and Cadastre in the form of Digital Terrain Model of the 4th and 5th generation. The data of yield together with its coordinates were gained from a combine harvester in the form of a regular grid. Yield data was interpolated by kriging geostatistical method. Position data including an altitude was used for modelling the last digital surface model. All gained surface models were correlated with the spring barley yield. Results show correlation similarity across all tested models with the yield; no significant differences were sighted. Free available coarser scale data is able to predict a yield sufficiently. The study indicates less effectivity of using very detailed scale data sources due to its time-consumption or expensive data gathering and processing process.

Key words: Unmanned aerial vehicle, structure from motion, spatial resolution.

INTRODUCTION

Elevation data can be acquired from three main sources: ground surveys, existing topographic maps and remote sensing techniques (Ouédraogo et al., 2014). Imagery acquisition using unmanned aerial vehicles (UAV) is very popular elevation data gathering technique within the last years. Besides other advantages, consumer grade cameras can perform high spatial resolution and high temporal frequency imagery. It is possible to get sufficient-accuracy ortho-mosaic and elevation model of large areas. UAV-based data became a promising tool for many agronomic applications during last few years (Schmale et al., 2008; Zhang & Kovacs, 2012; Gómez-Candón et al., 2014). These systems become an effective complement for conventional agricultural approaches, especially in precision agriculture or site-specific management respectively (Primicerio et al., 2012; Honkavaara et al., 2013; Rokhmana, 2015). UAV could be less expensive and more practical in contrast with satellite and airborne systems for high resolution remotely sensed data (Zhang & Kovacs, 2012). That is why it is possible to use UAV for the creation of topography model for agricultural purposes. Moreover, it is possible to capture actual micro-topography in any time using UAV. The Digital Elevation Model (DEM) is a stable factor compared to other variables (Schmidt & Persson, 2003), and it is generally known that spatial variability of yield can be explained by topography as one of several variables (Zhang et al., 2002). For example, Kumhálová & Moudrý (2014) used RTK-GPS, harvester yield monitor with DGPS and Airborne Laser Scanning (ALS) in their study. Using aerial systems, high spatial scale data are gained. Use of low-cost cameras and specialized software solutions make the generation of ortho-mosaic and elevation models quite easy. UAV based models usually reach resolutions within centimetres. On the other hand, there is still the question of justification of accurate digital surface models in comparison with free available coarse datasets.

The aim of this study was to discuss the effectiveness of Digital Elevation Models from different sources with different spatial resolution for explanation of yield on large agricultural plots.

MATERIALS AND METHODS

The experimental field is located near to Vendoli in Eastern Bohemia (49°43' 47.94"N, 16°24' 14.21"E) and its size is 26.4 ha large. A 15.55 ha section of the field was chosen for our experiment. The terrain of the plot is undulated with an average slope of approximately 6%. The elevation ranges from 555.3 to 571.6 m above average sea level (565.4 m on average). The soil can be classified as modal cambisoils lying on calcareous sandstone. Some parts, on sloped terrain especially, are strongly eroded. The average precipitation is 700 mm per year and the average temperature is between 6–7 °C. Conventional arable soil tillage technology based on ploughing and crop rotation system based on wheat, barley and oilseed rape crops alternation were applied on the plot.

The topographic data were obtained from four sources. The first data set was obtained from perpendicular images taken by an unmanned aerial vehicle using the photogrammetry approach. Aerial photographs were taken on September 11, 2015 by a fixed 16 mm focal length lens at consumer-grade RGB camera Sony NEX5. The camera was mounted on the Falcon 8 V-form octocopter platform manufactured by Ascending Technologies GmbH, Germany. The aerial system and the camera were managed manually by a pilot. Photoscan software solution (version 1.2.6., Agisoft LLC, Russia) was used for aligning imagery and dense cloud generation. Images were aligned using 74 ground control points, which were measured by real time kinematic GPS method using Trimble device with VRS Now corrections. Digital elevation model with its final spatial resolution of 0.05 m was created from 285 overlapping images using Structure from Motion method (Fig. 1a). More than 80 million dense cloud points were gained by this approach. The next sources of elevation data, Digital Terrain Model of the Czech Republic of the 5th generation (DMR 5G) and Digital Terrain Model of the Czech Republic of the 4th generation (DMR 4G), Airborne Laser Scanning data sets were kindly provided by the State Administration of Land Surveying and Cadastre. Both models represent natural man-modelled terrain in digital form from the year of 2013. DMR 4G was distributed in a grid of 5×5 m with total mean elevation error of 0.3 m in open areas, while DMR 5G was distributed in a grid of 2 × 2 m with a total mean elevation error of 0.18 m (Brázdil & Dušánek, 2010; 2012).

Yield and the fourth terrain model has been measured by axial combine harvester New Holland CR9080. The harvester was equipped with a yield monitor and differential GPS receiver. The precision of this system is ± 0.1 to 0.3 m horizontally and ± 0.2 to 0.6 m vertically. The yield and elevation data were stored with the coordinates every second. The yield values of spring barley were corrected using a common statistical procedure; all values that exceeded the range defined as mean ± 3 standard deviations were removed. Because of the large amount of data for every year studied (more than 18 thousand), the MoM (Method of Moments) was used to compute the experimental variograms. Experimental variograms of yield were computed and modelled by weighted least squares approximation in GS+ (Gamma Design Software LLC, USA). Ordinary punctual kriging was done using the relevant data and variogram model parameters for yield data visualization. For detailed description of the data sets see Table 1. All spatial data were processed using ArcGIS solution (version 10.3.1., ESRI, USA).

Table 1. Summary of statistics for data sets used (m)

Source	Yield harvester	DEM harvester	DEM UAV	DEM DMR 4G	DEM DMR 5G
Count	18,537	18,537	62,188,439	6,118	38,811
Resolution			0.05 × 0.05	5 × 5	2 × 2
Mean	4.049	566.8	566.2	565.7	565.1
Median	4.111	567.0	566.7	566.0	565.0
Std	1.377	3.178	3.797	2.994	3.064
Minimum	0.204	557.0	554.0	556.6	556.0
Maximum	8.733	578.0	573.3	571.6	571.0
Skewness	-0.025	-0.310	-0.432	-0.458	-0.449

Statistical data was counted in R free software (version 3.2.2., R Core Development Team, Austria). The number of 23 random sampling points were created for the plot. At each point, the yield and altitude from all four digital elevation models were estimated. The yield spatial autocorrelation was verified by Moran's Index where presence of autocorrelation was not revealed. The estimated altitude from each model in each point was then tested for correlation with yield. R-squared error was also determined by fitting individual linear models for each digital elevation model as predictor of yield. A Hot Spot map of yield was finally created by using the Getis-Ord Gi* statistic for supporting our results.

RESULTS AND DISCUSSION

The results of the evaluation are shown in Table1. DMR 4G and DMR 5G models had similar median and also minimum and maximum values. Slightly different values can be observed in the digital model obtained by UAV (Fig. 1a). This is due to a better resolution which can capture different local roughness. Standard deviation is also slightly higher in UAV (4.15) compared to DMR 5G (3.43) and DMR 4G (3.34). The elevation models used are highly correlated (between ≈0.98 and ≈1.00, Pearson R), see Fig. 2. To evaluate differences in the models, we provide Tests of significance for correlations (r.test). The results show that input models are equivalent as predictor of yield with probability of ≈ 100%. For a better understanding of heterogeneity of yield at the field we have created a hot spot map where statistically significant high (red colour) and low (blue colour) yields can be observed, Fig. 1b. It also reveals relative homogeneity of field yields.

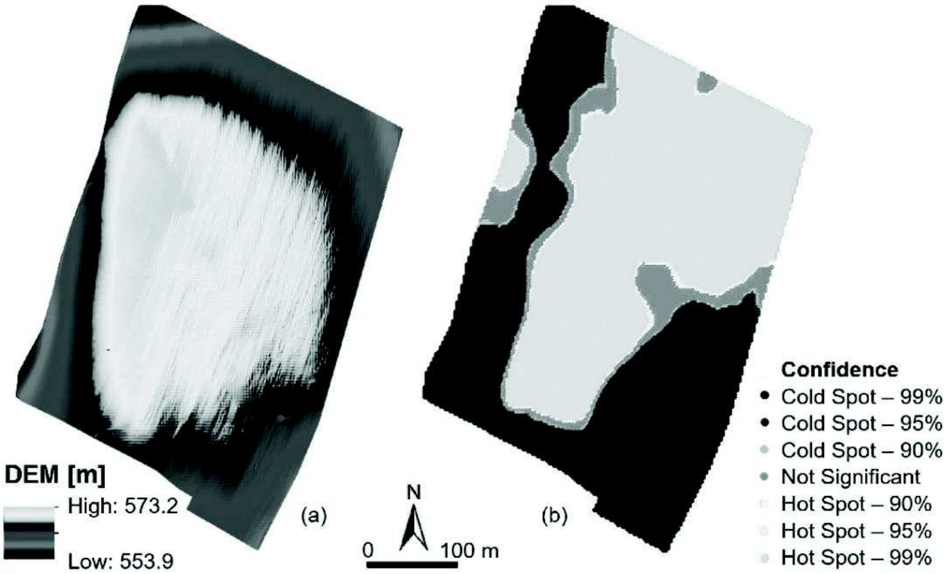


Figure 1. Elevation model using photo-reconstruction methods (a) and yield hotspot map (b) of the field study.

Elevation models were compared according to yield data using the correlation method (Table 2). The best model for yield prediction was DMR 4G explained 22.08% of yield variation followed by DEM from the UAV and DEM from the combine harvester. But all models can equally predict yield. The ability for predicting yield varies from 19% to 22% depending on the model.

Table 2. Statistics of correlation between models; yield and amount of variability in yield

Source	DEM harvester	DEM UAV	DEM DMR 4G	DEM DMR 5G
Pearson's correlation coefficient	0.480	0.502	0.477	0.506
Correlation significance (p-value)	0.020	0.015	0.021	0.014
Adjusted R-squared	0.194	0.217	0.221	0.191

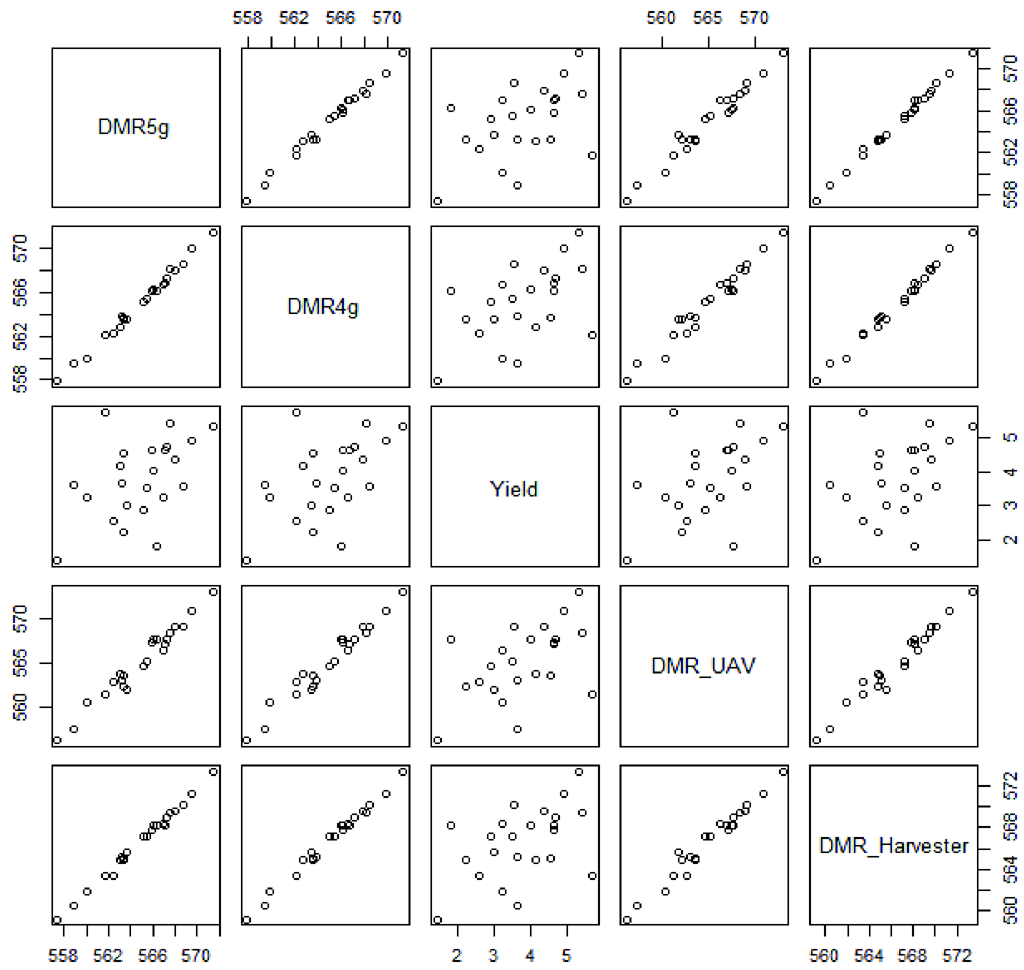


Figure 2. Matrix of input scatterplots showing dependence of input variables.

There is an effort in recent studies (Ristorto et al., 2015; Rokhmana, 2015) to use the most accurate data with the finest resolution as possible. As we show in this study, a field's yield can be relatively homogenous (Fig. 1b). In fact, using the finest resolution for prediction of yield does not necessarily bring additional information and furthermore, can have similar information value as models with coarse resolution. Uysal et al. (2015) discussed in their study the advantages of UAV systems utilization, such as low-cost, real time, high temporal or spatial resolution data. These conclusions are in accordance with our study. The UAV campaign was planned to early spring after sowing the spring barley, when the soil was bare. Belka et al. (2012) stated that the Airborne Laser Scanning was made during the spring or autumn. A large part of the Czech Republic was scanned regardless of vegetation on the fields. The flexibility in time is why the UAV possibility is suitable for monitoring the agriculture plot in different time.

Comparatively, acquisition of DEM from UAV is quite time consuming. To benefit from accurate UAV based DEM, 74 ground control points were necessary in our study. All of the points had to be measured by accurate GPS method. Moreover, special software has been used for computation of DEM from acquired photos. As we can see from the results, the ability to predict yield is similar across our models. In this point of view, the free available DEM models (DMR 5G or DMR 4G) could be better due to less time consumption. The digital model acquired by harvester is also a better choice than UAV in this case; nevertheless, some interpolating technics have to be made in GIS software to achieve final DEM.

The explained variability of yield reached at maximum only 22% in the DMR 4G model. It can be assumed that we could obtain similar results with other predictors, i.e. amount of soil meter, fertilization distribution, distribution of water, solar radiation etc. Using coarse data for predicting future yield or plant health could bring similar information value as the more accurate ones.

CONCLUSION

In this study we compare different digital terrain models obtained from different sources. Despite the fact of different resolution and accuracy of the data (from course 5×5 m to 0.05×0.05 m UAC model), the ability of models to predict the final yield were almost the same. We did not observe any statistically significant difference between input models.

As our results show, to use the most precise data is not necessary in every case. Less accurate, free available data could be equally sufficient to data with high costs or high time consumption. UAV based data can be used for DEM generation as a low-cost and real time source.

ACKNOWLEDGEMENTS. The project was supported by the Grant Agency of the Czech University of Life Sciences Prague (CIGA Nos. 20163005, 20174208) and by the Internal Grant Agency of the Faculty of Environmental Sciences, Czech University of Life Sciences Prague (IGA Nos. 42300/1312/3157, 42300/1312/3168).

REFERENCES

Belka, L., Dusanek, P., Fiala, R., Gamrat, J., Kafka, O., Peichl, J. & Sima, J. 2012. Technical report to the 4th generation Digital Elevation Model - DEM 4G (in Czech).

Brázdil, K. & Dušánek, P. 2010. Technical report for digital elevation model of the 4th generation (DMR 4G) (in Czech).

Brázdil, K. & Dušánek, P. 2012. Technical report for digital elevation model of the 5th generation (DMR 5G) (in Czech).

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**(1), 44–56.

Honkavaara, E., Saari, H., Kaivosoja, J., Pölönen, I., Hakala, T., Litkey, P., Mäkynen, J. & Pesonen, L. 2013. Processing and assessment of spectrometric, stereoscopic imagery collected using a lightweight UAV spectral camera for precision agriculture. *Remote Sensing* **5**(10), 5006–5039.

Kumhálová, J. & Moudrý, V. 2014. Topographical characteristics for precision agriculture in conditions of the Czech Republic. *Applied Geography* **50**, 90–98.

Ouédraogo, M.M., Degré, A., Debouche, C. & Lisein, J. 2014. The evaluation of unmanned aerial system-based photogrammetry and terrestrial laser scanning to generate DEMs of agricultural watersheds. *Geomorphology* **214**, 339–355.

Primicerio, J., Di Gennaro, S.F., Fiorillo, E., Genesio, L., Lugato, E., Matese, A. & Vaccari, F.P. 2012. A flexible unmanned aerial vehicle for precision agriculture. *Precision Agriculture* **13**(4), 517–523.

Ristorto, G., Mazzetto, F., Guglieri, G. & Quagliotti, F. 2015. Monitoring performances and cost estimation of multirotor Unmanned Aerial Systems in precision farming. 2015 *International Conference of Unmanned Aircraft Systems* ICUAS 2015, 502–509.

Rokhmana, C.A. 2015. The Potential of UAV-based Remote Sensing for Supporting Precision Agriculture in Indonesia. *Procedia Environmental Sciences* **24**, 245–253.

Schmale, D.G., Dingus, B.R. & Reinholtz, C. 2008. Development and application of an autonomous unmanned aerial vehicle for precise aerobiological sampling above agricultural fields. *Journal of Field Robotics* **25**(3), 133–147.

Schmidt, F. & Persson, A. 2003. Comparison of DEM data capture and topographic wetness indices. *Precision Agriculture* **4**, 179–192.

Uysal, M., Toprak, A.S. & Polat, N. 2015. DEM generation with UAV Photogrammetry and accuracy analysis in Sahitler hill. *Measurement* **73**, 539–543.

Zhang, C. & Kovacs, J.M. 2012. The application of small unmanned aerial systems for precision agriculture: A review. *Precision Agriculture* **13**(6), 693–712.

Zhang, N., Wang, M. & Wang, N. 2002. Precision agriculture a worldwide overview. *Computers and Electronics in Agriculture* **36**(2–3), 113–132.

6.4. Reforestation dynamics after land abandonment: a trajectory analysis in Mediterranean mountain landscapes

(Malavasi M., Carranza M. L., Moravec D., Maurizio C.)

Regional Environmental Change
https://doi.org/10.1007/s10113-018-1368-9

ORIGINAL ARTICLE

Reforestation dynamics after land abandonment: a trajectory analysis in Mediterranean mountain landscapes

Marco Malavasi[1] · Maria Laura Carranza[2] · David Moravec[1] · Maurizio Cutini[3]

Received: 21 February 2018 / Accepted: 9 June 2018

Abstract

Reforestation after land abandonment across Mediterranean mountains, together with the related landscape pattern dynamics and its possible impacts on the natural flora and fauna are issues that need further research efforts. This research, based on multi-temporal land cover maps derived from remotely sensed data (1987, 2003, 2016) of the Central Apennines, sets out to (i) quantify land cover changes and (ii) explore forest re-growth accounting for the interdependencies between forest gain and spatial configuration through trajectory analyses. Landscape change was assessed by transition matrix. Forest composition and configuration over time were analyzed by trajectory analysis based on random sampling techniques. This approach, implemented here for the first time for analyzing forest re-growth, allows us to explore the relationship between forest gain (the percentage of landscape covered by forests) and changes in spatial pattern (patch density, edge density, and mean patch area). An increase in forest cover over the past 30 years underlined the intense process of natural re-colonization, which started after World War II, at the expense of the typical heterogeneity of Mediterranean cultural landscapes. The change in the spatial pattern of forested areas highlighted a significant transformation which is related to two processes: the centrifugal development of existing patches and the establishment of new nuclei. The trajectory analysis highlighted non-linear relationships between forest gain and spatial pattern, offering the basis envisage of their effects on biodiversity. Conservation-oriented management of Mediterranean mountain forests must acknowledge both the role of natural succession in generating complex mosaics and the importance of maintaining forest patches of different dimensions and configuration.

Keywords Landscape change · Transition matrix · Spatial pattern · Landscape composition and configuration metrics · Vegetation dynamics

Introduction

Human activity has shaped natural landscapes across the world since ancient times (Munteanu et al. 2015). In several mountain and hilly areas of Europe, landscapes were historically dominated by pastures and agriculture cover types; in fact, grazing pressure and agricultural practices were the most important man-induced selection forces on the environment

Editor: Wolfgang Cramer

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s10113-018-1368-9) contains supplementary material, which is available to authorized users.

✉ Maria Laura Carranza
carranza@unimol.it

Marco Malavasi
malavasi@fzp.czu.cz

David Moravec
dmoravec@fzp.czu.cz

Maurizio Cutini
maurizio.cutini@uniroma3.it

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

[2] EnvixLab. Department of Bioscienze e Territorio, University of Molise, Contrada Fonte Lappone, 86090 Pesche, IS, Italy

[3] Department of Sciences, University of Roma Tre, viale Guglielmo Marconi 446, 00146 Rome, Italy

Published online: 19 June 2018

(Plieninger et al. 2010). In the Mediterranean basin, broad mountain areas were deforested in order to gain new space for grazing and agriculture, while forests were maintained and managed for the provision of timber or non-timber products, and to prevent soil erosion or avalanches (Furher 2000). With increased human colonization of the Mediterranean mountains from 1700 to 1900, pastoralism became the prevalent human activity (De Arabanzabal et al. 2008; Papanastasis 2012), contributing to the formation of a typical “cultural landscape” (sensu Antrop 2005) characterized by a mosaic of sparse open areas and woodland patches (Rosati et al. 2010). Conversely, in recent decades, widespread abandonment of agricultural land and traditional cultivation practices has occurred (Lasanta et al. 2017). The consistent rural exodus, which started after World War II and persisted over time, triggered the process of natural vegetation re-growth (Rocchini et al. 2006): the abandonment of grazing activities, followed by the onset of natural succession processes, promoted shrub and woodland encroachment (Falcucci et al. 2007; Campagnaro et al. 2017) and, in a few decades, allowed forests to recover in wide areas in which they were present a long time ago (Sitzia et al. 2010; Bracchetti et al. 2012).

Throughout the Mediterranean basin, the ecological consequences of land abandonment and forest recovery may be disparate (Plieninger et al. 2014). Natural reforestation on Italian mountains, as highlighted by Falcucci et al. (2007), can promote recolonization by large vertebrates (wolf, ungulates, brown bear) or may limit the effect of water runoff and soil erosion (Tasser et al. 2003), control the sediment yield and improvement the soil properties (Seeber and Seeber 2005). On the other hand, changes occurring after land abandonment and forest recovery are generally accompanied by a simplification and homogenization of these landscapes (Ricotta et al. 2000; Carranza et al. 2007; Sitzia et al. 2010), resulting in a decrease in biodiversity typically sheltered by traditional anthropogenic landscapes (Mazzoleni et al. 2004; Kleijn et al. 2011; Lasanta et al. 2017).

Landscape change after land abandonment is of particular concern on Mediterranean mountains, since many of the species and plant communities that characterize traditional cultural landscapes are also of concern for the conservation of natural biodiversity in Europe (e.g., protected by the European Commission (1992) network and European protected areas) (Tsiafouli et al. 2013).

There is a growing consensus that the landscape is the most important level for the management of biodiversity and that conservation strategies should be implemented at this scale to have the highest probability of success (With 2005; Malavasi et al. 2018). Indeed, given the widely documented relationship between natural biodiversity and landscape patterns (Fahrig 2003; Walz 2011), improving the actual understanding concerning the ongoing landscape processes affecting traditional rural landscapes after land abandonments is still crucial for defining appropriate conservation policies (Dahlström et al. 2013). However, there is no “one-size-fits-all” biodiversity conservation approach, since any effect on biodiversity is dependent on the environmental characteristics of the analyzed region (Plieninger et al. 2014).

Still, in the Mediterranean mountain ecosystems, natural reforestation after land abandonments is responsible for the greater environmental and landscape transformation (Lasanta et al. 2017). Within the context of this investigation, reforestation (sensu Sitzia et al. 2010) can be defined as natural reestablishment of a forested landscape on disused agricultural lands and grasslands following land abandonment in regions where the potential natural vegetation (sensu Zerbe 1998) is forest. The reforestation process entails changes in the spatial pattern of forested land cover type that can be described by two landscape components (Uuemaa et al. 2009): (a) composition changes, such as forest loss or gain, and (b) configuration changes or changes in the arrangement of forest patches. Forest compositional and configurational changes occur simultaneously, but the effects on biodiversity of such changes (e.g., Noss, 1999) are different, calling for the need to isolate these diverse components. Besides, contrary to the well-known process of forest loss and fragmentation affecting tropical and subtropical ecosystems (e.g., Wade et al. 2003; Frate et al. 2015; Carranza et al. 2015), which is one of the most important causes of biodiversity loss (see Fahrig 2003), findings about landscape dynamics of natural reforestation and the related natural biodiversity after abandonment are controversial. In a comprehensive review study about natural forest recovery on rural mountain landscapes, Sitzia et al. (2010) found diverse and fragmentary results concerning configurational changes of forested land cover types in relation to forest gain (compositional change).

In consideration of the above, this research sets out to analyze temporal landscape changes which occurred over the last three decades in Mediterranean mountain landscapes and provide reliable temporal trajectories of forest composition and configuration changes accounting for their possible effects on natural flora and fauna. Based on multi-temporal land cover maps derived from remotely sensed data of the Central Apennines, landscape change was analyzed by the implementation of traditionally used transition matrices (Turner 1990); forest composition and configuration changes were analyzed by trajectory analysis based on random sampling of the landscape. Trajectory analysis, previously used to describe the process of forest loss and fragmentation (Long et al. 2010; Carranza et al. 2014), is here adopted for the first time to explore the configurational changes of forested land cover type in relation to forest gain. In addition, the random sampling approach allows us to obtain statistically valid descriptions of each map (Hassett et al. 2012) and comparisons between the different time steps (Carranza et al. 2015).

By identifying the role of forest cover and configuration changes, we contribute to the exhaustive description of the process of mountain forest re-growth, offering the basis to envisage their effects on natural flora and fauna.

Material and methods

Study area

The study area is located in the Central Apennines on a limestone massif ranging from 450 to 2486 m asl and covering 62,500 ha in total. It is characterized by a transition zone between temperate and submediterranean bioclimate (Pesaresi et al. 2017). This territory host two protected areas (Montagne della Duchessa Natural Regional Reserve; Sirente-Velino Natural Regional Park; see online resource 1) and is part of the E-LTER (European Long Term Ecological Research) network, thus representing a worthwhile training ground to assess landscape changes in mountain ecosystems.

This area is representative of the landscape dynamics occurring in the Mediterranean mountains that over recent centuries were mainly shaped by grazing activities. Still, before the 1950s, the abandonment of transhumance practices and pastoralism took place with a consequent reduction in natural grasslands. During the last few decades, human population in the study area declined by 10% and major changes in grazing activities occurred with a steep decrease of sheep units (online resources 2 and 3).

The Apennine area hosts high levels of biodiversity, with more than 1000 species and subspecies of vascular plants recorded above 1400 m asl, 12.7% of which are endemic (Lucchese and De Simone 2000), and several habitats of European conservation concern (92/43/EEC) (European Commission 1992; Biondi et al. 2009) (for a complete list of habitats of European concern, see online resource 4).

Land cover maps

In order to analyze changes in landscape composition and configuration, we used land cover maps derived from a multitemporal sequence of remotely sensed satellite data. Three vegetation maps were produced relying on three dates of Landsat imagery. We used three different satellites due to a total span of 29 years: Landsat 5 with Thematic Mapper (TM) sensor, Landsat 7 with Enhanced Thematic Mapper (ETM+), and Landsat 8 Operational Land Imager (OLI) sensor for 14 August 1987, 25 August 2003, 29 August 2016 (path 190, row 031). All the satellite images have a spatial resolution of 30 m (15 m for panchromatic band in ETM+ and OLI). Each satellite image was selected with respect to a cloud-free study area. The satellite data were downloaded from USGS (online: https://earthexplorer.usgs.gov/) in the format of Level 1 product which are processed with standard radiometric, geometric, and terrain correction using digital elevation model and ground control points. The accuracy of geo-registration was visually confirmed for all images. Image to image registration was not necessary.

First, pixel-based unsupervised classification was performed on each image to analyze the number of distinguishable classes. Particular attention was given to natural and semi-natural land cover types. Artificial structures were not considered in the classification because of their low extent in the area. Six land cover types were identified and mapped according to CORINE Land Cover classification, with a fourth level of detail for forests and semi-natural formations. A description of these cover types is included in Table 1. Then, more than 16 km^2 (0.5–8 km^2 depending on class) of training data were vectorized on basic visual inspection of images, knowledge of the local vegetation, and ground truth data (Google Earth satellite images and geo-tagged Flickr pictures) (for details, see Arsanjani et al. 2016). Using these training data, we created final maps using pixel-based supervised classification with maximum likelihood method. The whole classification process was done in ENVI 5.3. The overall accuracy of classification was calculated using 488 points. All the points were distributed by stratified random sampling method, where each class has a randomly distributed number of points proportional to the area of the class. Practical verification of the points was done by comparison of the classified image from 2016 with Google Earth images. The overall accuracy of the recent map has reached 85.4%.

Land cover change

Data on general land cover changes which occurred over the last 29 years was derived by comparing the cover maps at two time periods t and t + τ. In particular, after describing the extent of each cover type in 1987 and 2016, we build a transition matrix that summarizes the percentage of each land cover type extent which changed into each other during the time interval τ (Turner 1990). The temporal dynamics of the analyzed landscape over the selected time period (1987–2016) were displayed as percentage (%) of landscape change using a Chord-Diagram. The Chord-Diagram is a graphical method for displaying the inter-relationships between data in a contingency matrix, and it is very appropriate to represent confusion or transition matrices (Rajbhandari et al. 2017; Komarek et al. 2018).

Spatial pattern analysis of forest over time

The dynamics of forest spatial pattern over time were analyzed by trajectory analysis (Cushman and McGarigal 2007; Long et al. 2010). Trajectory analysis, introduced by Cushman and McGarigal (2007), relies on the documented relationship between landscape composition and landscape configuration and allows to inspect both aspects of change simultaneously.

Table 1 CORINE land cover types present in the study area with a fourth level of detail for natural and semi-natural categories. A brief vegetation description and the EC habitat types (92/43/EEC) and EUNIS 2007 Code (in brackets) are also reported. A synthetic land cover name is reported in capital letters and brackets. All the mapped categories belong to category 3 of the first level of CORINE: forest and semi natural areas

Level 2	Level 3	Land-cover types	Most significant vegetation formations, EC habitat types, and EUNIS code
3.1 Forests	3.1.1. Broad-leaved forests	3.1.1.1. Mixed deciduous woods (Forest)	- *Fagus sylvatica* forests and woodlands (9210*: Apennine beech forests with *Taxus* and *Ilex*) (G1.681; G1.685; G1.686). - Mixed thermophilous woods with *Quercus cerris*, *Q. pubescens*, *Ostrya carpinifolia, Acer obtusatum*; locally *Corylus avellana* e *Populus tremula* (91AA*: Eastern white oak woods) (G1.7371; G1.7372).
	3.1.2. Coniferous forests	3.1.2.2. *Pinus spp* plantations (Pinus)	- *Pinus nigra* (and other coniferous species) plantations.
3.2. Scrub and/or herbaceous vegetation associations	3.2.1. Natural grasslands	3.2.1.1. Xeric grassland (Arid grass)	- Xerophytic grassland dominated by *Bromus erectus*, *Sesleria nitida*, *Globularia meridionalis*, *Helianthemum* sp.pl.; generally discontinuous coverage, includes facies with *Brachypodium rupestre* and those of rocky outcrops (*Stipa appenninicola* ssp. *dasyvaginata*) (6210*: Semi-natural dry grasslands and scrubland facies on calcareous substrates (*Festuco-Brometalia*) (*important orchid sites). - Primary (and secondary) alpine and subalpine grasslands dominated by genus *Carex, Festuca, Sesleria*, generally above 2000 m (6170: Alpine and subalpine calcareous grasslands) (E4.4).
		3.2.1.2. Mesophytic grasslands (Wet grass)	- Mesophytic grassland with continuous coverage dominated by *Brachypodium genuense, Sesleria uliginosa, Nardus stricta*. Generally in depressions (dolines) and on poor slopes with deep soils (6510: Lowland hay meadows (*Alopecurus pratensis, Sanguisorba officinalis*) (E2.2).
	3.2.4. Transitional woodland--shrub	3.2.4.1. Scattered trees embedded in grassland and shrubs (Shrub)	- Isolated trees or small groups (*Quercus cerris*, *Q. pubescens*, *Ostrya carpinifolia*, *Acer obtusatum*) mixed with low scrubls (*Juniperus oxycedrus* and *J. communis*) and residual grassland (5130: *Juniperus communis* formations on heaths or calcareous grasslands) (F3.1; F3.16). - Heath with *Juniperus communis ssp. nana* and *Arctostaphylos uva-ursi* (generally at higher altitude but also at intermediate altitude on steep slopes) with isolated *Fagus* tree (sometimes *Ostrya carpinifolia*) (4060: Alpine and Boreal heaths) (F2.2).
3.3. Open spaces with little or no vegetation	3.3.2. Bare rocks	3.3.2.1. Bare areas (Rock)	- Bare soil without vegetation, rocky outcrops. Rock communities with very low coverage also with *Primula auricula* and *Saxifraga* sp.pl. and *Potentilla* sp.pl.; scree vegetation dominated by *Festuca dimorpha* and *Silene acaulis* at higher altitude (8120 Calcareous and calcshist screes at the montane to alpine levels (*Thlaspietea rotundifolii*) (H2.4) and 8210 Calcareous rocky slopes with chasmophytic vegetation (H3.2).

Trajectory analysis offers the framework to correctly interpret and model the configurational changes of each habitat (i.e., spatial arrangement of forest patches) in relation to changes in its composition (i.e., forest amount) at landscape scale. Because this relationship could be non-linear, similar forest configuration values could be related to different landscapes in terms of forest amount (e.g., Long et al. 2010; Carranza et al. 2014). Within this context, we considered the trajectory analysis approach as a very appropriate one for dealing with forest changes over time and we implemented it for the first time for describing reforestation dynamics as follows. First, a set of non-redundant landscape metrics and adequate for sample-based estimations of landscape pattern (Hassett et al. 2012) were selected, relying on the pre-existing literature (Long et al. 2010; Carranza et al. 2015; Uuemaa et al., 2009). Specifically, a composition metric, the percentage of landscape covered by forests (PLAND), and three configuration metrics, patch density (PD), edge density (ED), and mean patch area (AREA_MN) were calculated for the different dates using FRAGSTAT (McGarigal and Marks 1995). Pattern metrics were calculated within a set of non-overlapping and randomly sampled square grids within the whole set of land cover maps (1987, 2003, 2016), covering a total of 10% of the total study area. Since the square grid dimension must be at least twice as large as the landscape grain (O'Neill et al. 1996), a 250 × 250-m grid was used, representing an adequate dimension for describing landscape changes in Italian mountains (Campagnaro et al. 2017).

Then, after a Shapiro normality test, the set of values of the landscape parameters of each date were statistically compared through Kruskal-Wallis rank test and the mean values with confidence intervals (95%) were calculated. To examine thedifferences between coupled dates, Dunn's paired comparison test was used (R package FSA; Ogle 2016).

Finally, the relationship between forest gain (composition) and spatial pattern changes (configuration) over time was explored by trajectory analysis. Specific relationship space for each configuration metric (PD, ED, AREA_MN) was built by plotting the metric values computed for each sampled grid against the respective composition value (percentage of forest cover: PLAND). The construction of a multi-temporal relationship space derived from sampled landscapes offered sound insight for spatial configuration metrics analysis and was used here in the assessment of forest change. Then, the means of the pattern metrics for each year were plotted in the relationship space, and the chronological trajectories were drawn by connecting such means with arrows (Carranza et al. 2015).

Results

Land cover change

The percent of each cover type in the analyzed mountain landscape largely varied through time. A consistent increment of natural woodlands (Forest) occurred over the last three decades, as clearly revealed by the expansion of broad-leaved forests, initially covering 15.6% of the total area and 20.4% in 2016 (Fig. 1a). On the other hand, the cover amount of the other cover categories looks quite constant, except for arid grasslands (Arid grass), which decreased from 31.2% of the landscape in 1987 to the 26.6% in 2016 (Fig. 1a).

As regards the observed major changes, the transition matrix displayed by chord diagram (Fig. 1b) highlighted that forest re-growth has mainly occurred at the expenses of scattered trees (4.9% of Shrub went into Forest) which, in turn, maintained the same overall extent in time because it substituted xeric grassland (6.4% of Arid grass went into Shrub). For absolute values of the transition matrix, see online resource 5.

Spatial pattern analysis of forests over time

Kruskal-Wallis rank test ($p < 0.05$) comparing the three different dates shows significant change for the whole set of landscape parameters, highlighting a significant transformation of the pattern of forested areas (Fig. 2a). Specifically, the percentage of landscape covered by forest (PLAND) increased during the considered time period, as did patch density (PD), edge density (ED), and mean patch area. Forests, initially occupying 17.1% of the sampled landscaped, now occupy more than 21.6% of the sample. The density of the patches per sample also increased from 5.1 patches per sample to 8.3 per sample, resulting in an increase in edge density. The mean area of forest patches also increased, but only considering the second time period (2003–2016), while it remained stable during the first one (1987–2003).

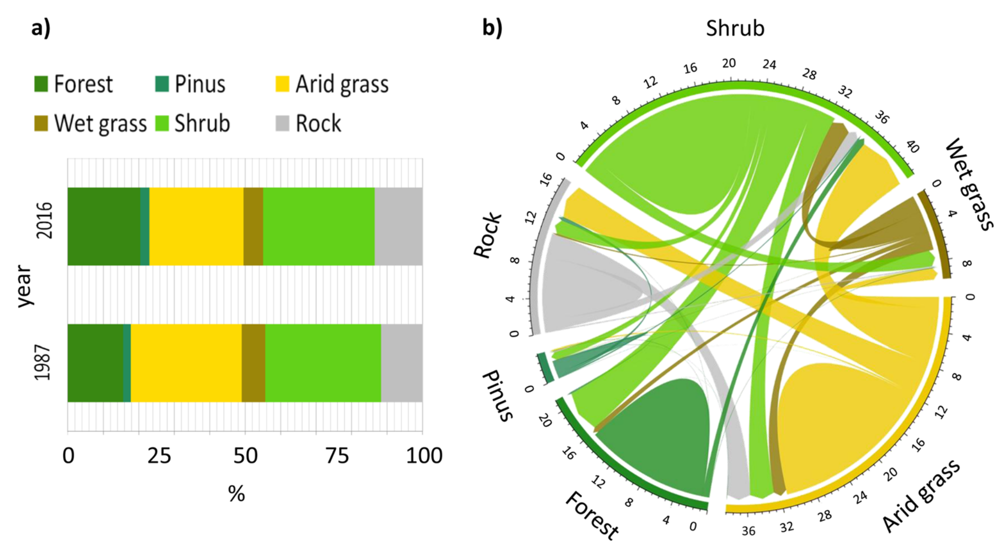
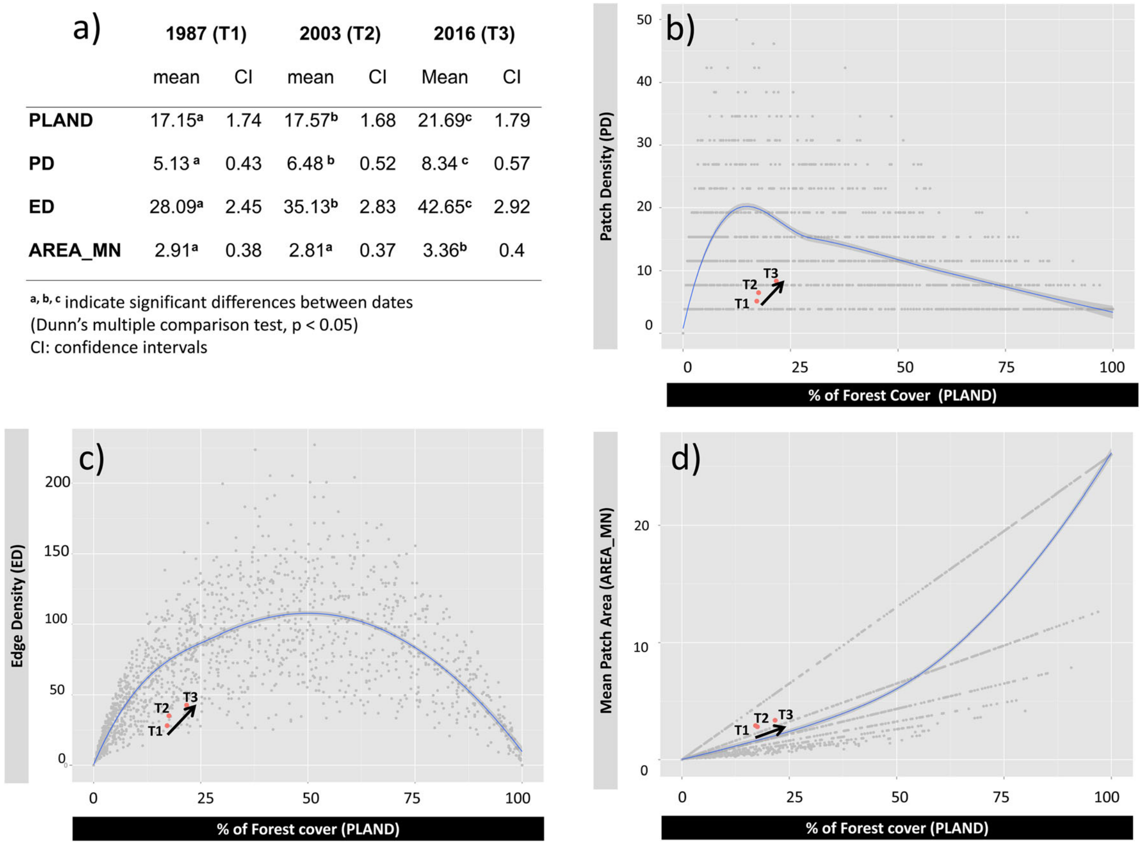


Fig. 1 **a** Percentage (%) of mapped land cover types for 1987 and 2016. **b** Chord Diagram summarizing the percentage (%) of each land cover type which changed into each other during the time interval (1987–2016). To show transitions, the arrows represent the direction of change, while the width of the arrow represents the extent (%) of the transition. The internal colored ring indicates the extent (%) of each land cover type that remained stable over time. For a detailed description of cover types, see Table 1. For absolute values of the transition matrix, see online resource 5



	1987 (T1)		2003 (T2)		2016 (T3)	
	mean	CI	mean	CI	Mean	CI
PLAND	17.15[a]	1.74	17.57[b]	1.68	21.69[c]	1.79
PD	5.13[a]	0.43	6.48[b]	0.52	8.34[c]	0.57
ED	28.09[a]	2.45	35.13[b]	2.83	42.65[c]	2.92
AREA_MN	2.91[a]	0.38	2.81[a]	0.37	3.36[b]	0.4

[a, b, c] indicate significant differences between dates (Dunn's multiple comparison test, p < 0.05)
CI: confidence intervals

Fig. 2 **a** Means and confidence intervals (CI) for each year (1987, 2003, 2016) for forest pattern metrics (PLAND: percentage of forest cover, PD: patch density, ED: edge density, AREA_MN: mean patch area). Different superscripted letters indicate significant differences between dates (Dunn's multiple comparison test, $p < 0.05$). PLAND: percent of landscape covered by forests, PD: patch density, ED: edge density, AREA_MN: mean patch area. Trajectories of forests in the relationship space described by plotting the percentage (%) of forest cover (PLAND) against forest configuration metrics: **b** PD, **c** ED, **d** AREA_MN are also reported. Gray dots represent the observed values of pattern metrics within the whole set of samples (250 × 250-m random sampled grids). The blue line represents the fitted curves describing the configuration vs composition metrics relationship. Red dots indicate the mean values of forest cover (%) and configuration metrics for each date (T1: 1987, T2: 2003, T3: 2016). The arrows display the direction of temporal change

Visual inspection of the relationship spaces (Fig. 2a) evidences that during the reforestation process, spatial pattern metrics are characterized by index-specific behaviors in relation to forest cover. Mean patch size tends to be very low for low forest cover values and exponentially increases when forest cover exceeds 50%. In contrast, edge density is characterized by a symmetric parabolic relationship, assuming a positive peak at intermediate values of forest cover (~ 50%) and low values at the upper and lower curve tails. Patch density has an asymmetric parabolic shape along the forest cover gradient, assuming a positive peak when forest reaches almost 20% of the landscape area, and low values for both landscapes dominated by forests or landscapes where forest cover is very low (close to 0%).

The projection of mean metric values of each year (1987, 2003, 2016) into the respective relationship spaces, and the relative trajectories over time, show important changes in forest pattern which begun during the first time period (1987–2003) and accelerated in the second one (2003–2016). In conjunction with the increment of forest cover, changes in forest configuration also occurred (Fig. 2b–d). Patch density (PD) significantly increased (Fig. 2b), even though it is in the lower tile of the relationship curve (forest cover above 20%). Edge density (ED) has also been increasing and it is coherently included in the increasing left side of the parabolic relationship curve (up to 50% of forest cover) (Fig. 2c). Mean values of mean patch area (AREA_MN) have been increasing and they will clearly increase as long as the reforestation process occurs (Fig. 2d).

Discussion

Land cover change

During recent decades, as in other mountain areas in Europe (Gellrich et al. 2007; Verburg et al. 2010), we have observed a consistent process of natural forest recolonization at the expense of the typical heterogeneity of such cultural landscapes.

The observed changes reflect wider socioeconomic transformations occurring in Europe (Cernusca et al. 1999; MacDonald et al. 2000) and specifically in the Mediterranean basin, which evolved from a post-war rural economy to an industrial one (Lasanta-Martinez et al. 2005; Mottet et al. 2006; Petanidou et al. 2008). Indeed, during recent decades, in the Central Apennines, the human population moved to industrialized areas causing a reduction in mountain inhabitants in association with an increment in forested lands (Pelorosso et al. 2009). On the other hand, grazing activities (mainly sheep livestock numbers) that in the past ensured wide and widespread secondary grasses have recently dropped with a consequent reduction in open areas and grasslands (Evangelista et al. 2016; Frate et al. 2018).

Across the investigated area, the reduction and cessation of mountain cropping and livestock grazing have allowed the onset of natural succession processes. Abandonment of meadows and pastures (Arid grass) growing in areas where the potential natural vegetation is forest has allowed shrublands (Shrub) to take over, and in turn to evolve into woodlands (Forest). While the total amount of grassland decreased and forest increased, the total extent of shrubland kept constant over time. Although different models of succession were detected in the temperate mountains (Mazzoleni et al. 2004; Bracchetti et al. 2012), these results differ from previous studies where, together with forest expansion, shrub expansion is listed among the main effects of land abandonment (Rocchini et al. 2006; Campagnaro et al. 2017). Shrublands kept similar cover over time, most likely because of the turnover, which balances losses (transition to forest) and gains (areas gained from grassland). Such a peculiarity may be due to the dispersal and growth features that the tree species of the analyzed habitats (EC 9210*: Apennine beech forests with *Taxus* and *Ilex* and EC 91AA*: Eastern white oak woods) tend to adopt in mountain environments. There are two particular issues to be noted in Italian mountains (Canullo 1991; Cutini and Blasi 2002): the capacity of some trees (*Fagus sylvatica* and *Ostrya carpinifolia*) to constitute shrub-low arboreal formations that ensure fast dynamism and forest advancement and the fact that on grazed and impervious areas, thanks to the easy movement of propagules (anemophilous entities), the reforestation process is also initiated by tree pioneer species (*Fraxinus ornus*, *Ostrya carpinifolia*, *Acer campestre*, and *A. obtusatum*).

Spatial pattern of forests over time

The statistical comparison of landscape pattern metrics over time and the trajectory analysis show a significant transformation in the composition and configuration of forested areas, highlighting an ongoing reforestation process. Specifically, in concomitance with the rise in the percentage of landscape covered by forest, an increase in the spatial configuration metrics of forested land (patch density, edge density, and the mean patch area) also occurred.

The observed changes in forest configuration is most likely related to two natural mechanisms involved in the reforestation process: (1) the centrifugal development of existing forest patches ("frontal" colonization, Rameau 1993) that promotes the increment in edge density and mean patch area (Geri et al. 2010; Frate and Carranza, 2013) and (2) the settlement of new isolated nuclei ("nucleation" process; Decocq, 2005) with a consequent rise in the number of patches (Rocchini et al. 2006).

However, Sitzia et al. (2010), in a review paper collecting the behavior of landscape metrics related to natural reforestation process, found a common trend as regards forest mean patch size, which usually tends to increase, while data on the number of patches (or patch density) and boundary length (i.e., edge density) are fragmentary and diverse. Such a dilemma can be solved by inspecting the, here adopted, relationship space of the trajectory analyses. In this context, while the relationship of forest cover with forest mean patch size is linear, allowing us to envisage a further linear increment of forest mean patch size over time, the relationship with patch density and edge density is not (Neel et al. 2004). In the light of this, the detected temporal growth of forest edge density mean values (ED) should continue over time until forest area reaches 50% of the landscape, after which a further increase in forest cover should drive to a decline in edge density values (Long et al. 2010; Carranza et al. 2015). Similarly, patch density (PD) has been significantly increasing, even though these mean values are included in the lower tile of the relationship curve (forest cover above 20%), suggesting that patch density will slowly start to decline in the coming years with the increase of forested land that goes over the 20% of the landscape.

Implications for conservation of forested habitats

Trajectory analysis, allowing us to relate changes in spatial pattern metrics to different levels of forest cover, offered a basis to envisage the effects of such changes on native flora and fauna. Since the directions and intensities of response in biodiversity to land abandonment are heterogeneous across the Mediterranean basin (Plieninger et al. 2014), we specifically focused our discussion on some conservation issues of the Central Apennines. However, it must be noted that such implications have been inferred from existing literature connecting landscape pattern to biodiversity field data of the study area.

The "linear" increment of forest mean patch size (AREA_MN) concurrently with forest cover (PLAND) highlighted how forest patches expanded and joined into larger ones (Geri et al. 2010; Frate and Carranza 2013). Prior studies illustrated that the presence of big and well-connected patches of natural forest help wildlife survival and conservation by ensuring habitat availability (Fahrig 1997) and offer opportunities for organisms to move across the landscape (Saura and Rubio 2010). Concerning temperate mountain forests, mainly represented in the area by natural *Fagus sylvatica* forests (Habitat 9210*: Apennine beech forests with *Taxus* and *Ilex*), the size of fragments is correlated with plant species diversity: bigger fragments generally host higher numbers of rare, nemoral, and specialist species (Rosati et al. 2010; Carranza et al. 2012; Scolastri et al. 2017a). Furthermore, large and well-connected forest patches have ensured optimal conditions for forest specialist vertebrates (Di Febbraro et al. 2015), forest birds (Tellini-Florenzano 2004), and large vertebrates that during recent decades increased both in numbers and distribution (Falcucci et al. 2007).

As the percentage of cover in the prior and new situation is under 50%, forest edges tend to increase and, in the absence of disturbance, should further increase in the coming years. Many authors agree that edge habitats have micro-environmental conditions that differ from those of interior forest habitats, such as more light availability and lower moisture (Forman and Moore 1992). The implications of long edges for the conservation of native temperate forest flora and fauna could promote the presence of generalist and clearing species, as observed in some Italian temperate forests (Rosati et al. 2010; Carranza et al. 2012; Scolastri et al. 2017b). Furthermore, forest edges are efficient corridors for vertebrates, thus allowing the movement of natural fauna over long distances across the landscape (Roscioni et al. 2014).

The temporal trends observed in the density of forest patches (PD) is primarily related to a process of colonization of open formations by many isolated woody vegetation patches occurring in the former stages of reforestation (Rocchini et al. 2006) and to the expansion and coalescence of wooded nuclei in a few patches in the advanced stages (Sitzia et al. 2010; Frate et al. 2014). The presence of several small patches across the landscape that may serve as stepping stones for the movement of fauna should be considered as an important factor promoting positive effects on species richness and dispersal (Fahrig 2003; Saura et al. 2014).

Conclusions

Over the past 30 years, the analyzed Mediterranean mountain area has undergone an intense process of natural forest recolonization that began after World War II and that is still in progress. Management abandonment led to natural succession: meadows and pastures were abandoned in a region where the potential natural vegetation is forest. In contrast to previous studies listing shrub expansion among the main effects of land abandonment, the total extent of shrubland remained constant over time because of the fast dynamism and forest advancement of the involved species, which balance losses (transition to forest) and gains (areas gained from grassland).

The significant transformation of the landscape pattern of forested areas is related to two processes: the centrifugal development of existing patches and the establishment of new nuclei. Trajectory analysis allowed us to draw general conclusions about the spatial pattern dynamics occurring with forest re-growth, highlighting the non-linear relationship between forest gain and spatial pattern change over time. Although previous studies reported fragmentary and diverse observations about the behavior of landscape metrics related to natural reforestation process, the trajectory approach revealed that such observation mainly depends on the stage of reforestation process, thus on the time at which the reforestation process was analyzed and recorded.

From our results, sound implications for habitat and species conservation in Mediterranean mountain forests also emerged. Forest advancement is likely to provide higher opportunity for organisms to move across the landscape and an increase in nemoral and specialist species for *Fagus sylvatica* forests. Simultaneously, more edges could promote the presence of generalist and clearing species until forest cover reaches 50% of the local landscape.

A conservation-oriented management of Mediterranean mountain forests must contemplate both the role of natural succession in generating complex and heterogeneous mosaics, and the importance of maintaining forest patches of different dimensions and configuration. Management practices such as moderate grazing activities and harvesting should have a crucial role for mountain landscapes to preserve long-term persistence of native species and they could represent important measures to be implemented in the definition of landscape management policies able to fulfill Habitat Directive demands and legal obligations.

Acknowledgments The project was supported by the Grant Agency of the Czech University of Life Sciences Prague (CIGA No. 20174208) and by the Internal Grant Agency of the Faculty of Environmental Sciences, Czech University of Life Sciences Prague (IGA No. 42300/1312/3128). Furthermore, we would like to thank Annarita Frattaroli for the information about local habitats and Daniele Di Giacomo for data on local population and livestock units.

References

Antrop M (2005) Why landscapes of the past are important for the future. Land Urban Plan 70(1–2):21–34. https://doi.org/10.1016/j.landurbplan.2003.10.002

Arsanjani JJ, See L, Tayyebi A (2016) Assessing the suitability of GlobeLand30 for mapping land cover in Germany. Int J Digital Earth 9(9):873–891. https://doi.org/10.1080/17538947.2016.1151956

Biondi E, Blasi C, Burrascano S, Casavecchia S, Copiz R, Del Vico E, Galdenzi D, Gigante D, Lasen C, Spampinato G, Venanzoni R, Zivkovic L (2009) Manuale Italiano di Interpretazione degli habitat della Direttiva 92/43/CEE. SBI, MATTM, DPN. [available online at http://vnr.unipg.it/habitat/index.jsp].

Bracchetti L, Carotenuto L, Catorci A (2012) Land-cover changes in a remote area of central Apennines (Italy) and management directions. Land Urb Plan 104:157–170. https://doi.org/10.1016/j.landurbplan.2011.09.005

Campagnaro T, Frate L, Carranza ML, Sitzia T (2017) Multi-scale detection of spatial pattern change in alpine cultural landscapes: implications for biodiversity conservation. Ecol Indic 74:147–159. https://doi.org/10.1016/j.ecolind.2016.11.017

Canullo R (1991) L'evolution de la vegetaion vers la Foret: etudes des popolations. Coll Phyt XX:121–140

Carranza ML, Acosta A, Ricotta C (2007) Analyzing landscape diversity in time: the use of Rènyi's generalized entropy function. Ecol Indic 7:505–510. https://doi.org/10.1016/j.ecolind.2006.05.005

Carranza ML, Frate L, Paura B (2012) Structure, ecology and plant richness patterns in fragmented beech forests. Pl Ecol Div 5(4):541–551. https://doi.org/10.1080/17550874.2012.740509

Carranza ML, Frate L, Acosta ATR, Hoyos L, Ricotta C, Cabido M (2014) Measuring forest fragmentation using multitemporal remotely sensed data: three decades of change in the dry Chaco. Eur J Remote Sensing 47:793–804. https://doi.org/10.5721/EuJRS20144745

Carranza ML, Hoyos L, Frate L, Acosta ATR, Cabido M (2015) Measuring forest fragmentation using multitemporal forest cover maps: forest loss and spatial pattern analysis in the gran Chaco, Central Argentina. Land Urb Plan 143:23–247. https://doi.org/10.1016/j.landurbplan.2015.08.006

Cernusca A, Tappeiner U, Bayfield N (eds) (1999) land-use changes in European Mountain ecosystems. ECOMONT – concepts and results, Blackwell, berlin, DE

Cutini M, Blasi C (2002) Contributo alla definizione sintassonomica e sindinamica dei mantelli di vegetazione dell'Appennino centrale. Fitosociologia 39(suppl. 2):97–120

Cushman SA, McGarigal K (2007) Multivariate landscape trajectory analysis: an example using simulation modeling of American marten habitat change under four timber harvest scenarios. In: Bissonette, JA and Storch I (ed) Temporal dimensions in landscape ecology: Wildlife responses to variable resources, Springer US, NewYork, pp. 119–140.

Dahlström A, Iuga A, Lennartsson T (2013) Managing biodiversity rich hay meadows in the EU: a comparison of Swedish and Romanian grasslands. Envir Cons 40:194–205. https://doi.org/10.1017/S0376892912000458

De Aranzabal I, Schmitz MF, Aguilera P, Pineda FD (2008) Modelling of landscape changes derived from the dynamics of socio-ecological systems: a case of study in a semiarid Mediterranean landscape. Ecol Ind 8(5):672–685. https://doi.org/10.1016/j.ecolind.2007.11.003

Decocq G (2005) Mécanismes de la dynamique naturelle des végétations forèstieres de montagne: essai de synthese et consequences en phytosociologie. Act Bot Gall 52(4):581–594. https://doi.org/10.1080/12538078.2005.10515516

Di Febbraro M, Roscioni F, Frate L, Carranza ML, De Lisio L, De Rosa D, Marchetti M, Loy A (2015) Long-term effects of traditional and conservation-oriented forest management on the distribution of vertebrates in Mediterranean forests: a hierarchical hybrid modelling approach. Div Distr 21(10):1141–1154. https://doi.org/10.1111/ddi.12362

European Commission (1992) Council directive 92/43/EEC of 21 may 1992 on the conservation of natural habitats and of wild fauna and flora. Official Journal L 206, 22/07/1992. P. 0007–0050.

Evangelista A, Frate L, Carranza ML, Attorre F, Pelino G, Stanisci A (2016) Changes in composition, ecology and structure of high-mountain vegetation: a re-visitation study over 42 years. AoB Plants 8:plw004. https://doi.org/10.1093/aobpla/plw004

Fahrig L (1997) Relative effects of habitat loss and fragmentation on species extinction. J Wild Manag 61(3):603–610. https://doi.org/10.2307/3802168

Fahrig L (2003) Effects of habitat fragmentation on biodiversity. Ann Rev Ecol Evol Syst 34:487–515. https://doi.org/10.1146/annurev.ecolsys.34.011802.132419

Falcucci A, Maiorano L, Boitani L (2007) Changes in land-use/land-cover patterns in Italy and their implications for biodiversity conservation. Landsc Ecol 22(4):617–631. https://doi.org/10.1007/s10980-006-9056-4

Forman RTT, Moore PN (1992) Theoretical foundations for understanding boundaries. In: Hansen AJ, Di Castri F (eds) Landscape boundaries: consequences for biotic diversity and ecological flows. Springer-Verlag, New York, pp 236–258

Frate L, Carranza ML (2013) Quantifying landscape-scale patterns of temperate forests over time by means of neutral simulation models. Int J Geo-Inf 2:94–109. https://doi.org/10.3390/ijgi2010094

Frate L, Saura S, Minotti M, Di Martino P, Giancola G, Carranza ML (2014) Quantifying forest spatial pattern trends at multiple extents: an approach to detect significant changes at different scales. Rem Sens 6(10):9298–9315. https://doi.org/10.3390/rs6109298

Frate L, Acosta ATR, Cabido M, Hoyos L, Carranza ML (2015) Temporal changes in forest fragmentation contexts at multiple extents: patch, perforated, edge and interior forests in the gran Chaco. Central Argentina Plos One 10(12):e0142855. https://doi.org/10.1371/journal.pone.0142855.

Frate L, Carranza ML, Evangelista A, Stinca A, Schaminée JHJ, Stanisci A (2018) Climate and land use change impacts on Mediterranean high-mountain vegetation in the Apennines since the 1950s. Plant Ecol Divers:1–13. https://doi.org/10.1080/17550874.2018.1473521

Fuhrer E (2000) Forest functions, ecosystem stability and management. For Ecol Manag 132:29–38. https://doi.org/10.1016/S0378-1127(00)00377-7

Gellrich M, Baur P, Koch B, Zimmermann NE (2007) Agricultural land abandonment and natural forest re-growth in the Swiss mountains: a spatially explicit economic analysis. Agr Ecos Envir 118:93–108. https://doi.org/10.1016/j.agee.2006.05.001

Geri F, Rocchini D, Chiarucci A (2010) Landscape metrics and topographical determinants of large-scale forest dynamics in a Mediterranean landscape. Land Urb Plan 95:46–53. https://doi.org/10.1016/j.landurbplan.2009.12.001

Hassett EM, Stehman SV, Wickham JD (2012) Estimating landscape pattern metrics from a sample of land cover. Landsc Ecol 27:133–149. https://doi.org/10.1007/s10980-011-9657-4

Kleijn D, Rundlo FM, Scheper J, Smith HG, Tscharntke T (2011) Does conservation on farmland contribute to halting the biodiversity decline? Trends Ecol Evol 26:474–481. https://doi.org/10.1016/j.tree.2011.05.009

Komarek J, Klouček T, Prošek J (2018) The potential of unmanned aerial systems: a tool towards precision classification of hard-to-distinguish vegetation types? Int J Appl Earth Obs Geoinformation 71:9–19. https://doi.org/10.1016/j.jag.2018.05.003

Lasanta T, Arnáez J, Pascual N, Ruiz-Flaño P, Errea MP, Lana-Renault N (2017) Space-time process and drivers of land abandonment in Europe. Catena 149:810–823. https://doi.org/10.1016/j.catena.2016.02.024

Lasanta-Martinez T, Vicente-Serranob SM, Cuadrat-Pratscet JM (2005) Mountain Mediterranean landscape evolution caused by the abandonment of traditional primary activities: a study of the Spanish central Pyrenees. Appl Geogr 25:47–65. https://doi.org/10.1016/j.apgeog.2004.11.001

Long JA, Nelson TA, Wulder MA (2010) Characterizing forest fragmentation: distinguishing change in composition from configuration.

Appl Geogr 30:426–435. https://doi.org/10.1016/j.apgeog.2009.12.002
Lucchese F, De Simone M (2000) Confronto tra flore d'altitudine nell'Appennino centrale. Metodi di rilevamento, risultati e analisi di una caratterizzazione fitogeografica. Ann Musei Civ Rovereto 14:113–145
Malavasi M, Bartak V, Carranza ML, Simova P, Conti L, Acosta ATR (2018) Landscape pattern and plant biodiversity in Mediterranean coastal dune ecosystems: do habitat loss and fragmentation really matter? J Biogeogr. https://doi.org/10.1111/jbi.13215
Mazzoleni S, Di Pasquale G, Mulligan M, Di Martino P, Rego F (2004) Recent dynamics of the mediterranean vegetation and landscape. Wiley & Sons Ltd, Chichester
MacDonald D, Crabtree JR, Wiesinger G, Dax T, Stamou N, Fleury P, Gutierrez Lazpita J, Gibon A (2000) Agricultural abandonment in mountain areas of Europe: environmental consequences and policy response. J Env Manag 59:47–69. https://doi.org/10.1006/jema.1999.0335
McGarigal K, Marks BJ (1995) Fragstats: spatial pattern analysis program for quantifying landscape structure (user guidelines general technical reportPNW-GTR-351). USDA, Forest Service, Pacific, Northwest Research Station, Portland, OR
Mottet A, Ladet S, Coqué N, Gibon A (2006) Agricultural land-use change and its drivers in mountain landscapes: a case study in the Pyrenees. Agr Ecos Env 114(2–4):296–310. https://doi.org/10.1016/j.agee.2005.11.017
Munteanu C, Kuemmerle T, Keuler NS, Müller D, Balazs P, Dobosz M, Griffiths P, Halada L, Kaim D, Király G, Konkoly-Gyuró É, Kozak J, Lieskovský J, Ostafin K, Ostapowicz K, Shandra O, Radeloff VC (2015) Legacies of 19th century land use shapes contemporary forest cover. Gl Env Ch 34:83–94. https://doi.org/10.1016/j.gloenvcha.2015.06.015
Neel MC, Mc Garigal K, Cushman SA (2004) Behavior of class-level landscape metrics across gradients of class aggregation and area. Landsc Ecol 19:435–455. https://doi.org/10.1023/B:LAND.0000030521.19856.cb
Noss RF (1999) Assessing and monitoring forest biodiversity: a suggested framework and indicators. For Ecol Manag 115(2–3):135–146. https://doi.org/10.1016/S0378-1127(98)00394-6
Ogle, D.H. 2016. Introductory Fisheries Analyses with R. Chapman & Hall/CRC, Boca Raton
O'Neill RV, Hunsaker CT, Timmins SP, Jackson BL, Jones KB, Riitters KH, Wickham JD (1996) Scale problems in reporting landscape pattern at the regional scale. Landsc Ecol 11:169–180. https://doi.org/10.1007/BF02447515
Papanastasis VP (2012) Land Use Changes. In: Vogiatzakis (ed) Mediterranean Mountain Environments. Wiley-Blackwell, London, pp 159–184
Pelorosso R, Leone A, Boccia L (2009) Land cover and land use change in the Italian central Apennines: a comparison of assessment methods. Appl Geogr 29:35–48
Pesaresi S, Biondi E, Casavecchia S (2017) Bioclimates of Italy. J Maps 14:955–960. https://doi.org/10.1080/17445647.2017.1413017
Petanidou T, Kizos T, Soulakellis N (2008) Socioeconomic dimensions of changes in the agricultural landscape of the Mediterranean basin: a case study of the abandonment of cultivation terraces on Nisyros Island, Greece. Environ Manag 41(2):250–266. https://doi.org/10.1007/s00267-007-9054-6
Plieninger T, Schaich H, Kizos T (2010) Land-use legacies in the forest structure of silvopastoral oak woodlands in the eastern Mediterranean. Reg Environ Chang 11:603–615. https://doi.org/10.1007/s10113-010-0192-7
Plieninger T, Cang H, Gaertner M, Huntsinger L (2014) The impact of land abandonment on species richness and abundance in the Mediterranean Basin: a meta-analysis. PLoS One 9:e98355. https://doi.org/10.1371/journal.pone.0098355
Rajbhandari S, Aryal J, Osborn J, Musk R, Lucieer M (2017) Benchmarking the applicability of ontology in geographic object-based image analysis. Int J Geo-Information 6(12):386. https://doi.org/10.3390/ijgi6120386
Rameau JC (1993) Phytodinamique forestiere: l'approche du phytoecologue forestier. Objectifs, concepts, methodes, problemes rencontres. Coll Phyt XX:29–71
Ricotta C, Carranza ML, Avena G, Blasi C (2000) Quantitative comparison of the diversity of landscapes with actual vs. potential natural vegetation. Appl Veg Sci 3:157–162. https://doi.org/10.2307/1478994
Rocchini D, Perry GLW, Salerno M, Maccherini S, Chiarucci A (2006) Landscape change and the dynamics of open formations in a natural reserve. Land Urb Plan 77:167–177. https://doi.org/10.1016/j.landurbplan.2005.02.008
Rosati L, Fipaldini M, Marignani M, Blasi C (2010) Effects of fragmentation on vascular plant biodiversity in a Mediterranean forest archipelago. Pl Bios 144:38–46. https://doi.org/10.1080/11263500903429213
Roscioni F, Rebelo H, Russo D, Carranza ML, Di Febbraro M, Loy A (2014) A modelling approach to infer the effects of wind farms on landscape connectivity for bats. Landsc Ecol 29(5):891–903. https://doi.org/10.1007/s10980-014-0030-2
Saura S, Rubio L (2010) A common currency for the different ways in which patches and links can contribute to habitat availability and connectivity in the landscape. Ecograpy 33:523–537. https://doi.org/10.1111/j.1600-0587.2009.05760.x
Saura S, Bodin O, Fortin MJ (2014) Stepping stones are crucial for species' long-distance dispersal and range expansion through habitat networks. J Appl Ecol 51:171–182. https://doi.org/10.1111/1365-2664.12179
Seeber J, Seeber GUH (2005) Effects of land-use changes on humus forms on alpine pastureland (central alps Tyrol). Geod 124(3–4):215–222. https://doi.org/10.1016/j.geoderma.2004.05.002
Scolastri A, Cancellieri L, Iocchi M, Cutini M (2017a) Old coppice vs high Forest: the impact of beech forest management on plant species diversity. J Plant Ecol 10(2):271–280. https://doi.org/10.1093/jpe/rtw034
Scolastri A, Bricca A, Cancellieri L, Cutini M (2017b) Understory functional response to different management in the Mediterranean beech forest (central Apennine, Italy). For Ecol Manag 400:665–676. https://doi.org/10.1016/j.foreco.2017.06.049
Sitzia T, Semenzato P, Trentanovi G (2010) Natural reforestation is changing spatial patterns of rural mountain and hill landscapes: a global overview. For Ecol Manag 259:1354–1362. https://doi.org/10.1016/j.foreco.2010.01.048
Tasser E, Mader M, Tappeiner U (2003) Effects of land use in alpine grasslands on the probability of landslides. Bas Appl Ecol 4(3):271–280. https://doi.org/10.1078/1439-1791-00153
Tellini-Florenzano G (2004) Birds as indicators of recent environmental changes in the Apennines (Foreste Casentinesi National Park, Central Italy). Ital J Zool 71:317–324. https://doi.org/10.1080/11250000409356589
Tsiafouli MA, Apostolopoulou E, Mazaris AD, Kallimanis AS, Drakou EG, Pantis JD (2013) Human activities in Natura 2000 sites: a highly diversified conservation network. Env Manag 51:1025–1033. https://doi.org/10.1007/s00267-013-0036-6
Turner M (1990) Spatial and temporal analysis of landscape pattern. Landsc Ecol 4:21–30
Uuemaa E, Antrop M, Roosaare J, Marja R, Mander Ü (2009) Landscape metrics and indices: an overview of their use in landscape research. Liv Rev Land Res 3:1. https://doi.org/10.12942/lrlr-2009-1
Verburg PH, van Berkel DB, van Doorn AM, van Eupen M, Harm v d H (2010) Trajectories of land use change in Europe: a model-based exploration of rural futures. Landsc Ecol 25(2):217–232. https://doi.org/10.1007/s10980-009-9347-7

Wade TG, Riitters KH, Wickham JD, Jones KB (2003) Distribution and causes of global forest fragmentation. Conserv Ecol 7(2). http://www.consecol.org/vol7/iss2/art7

Walz U (2011) Landscape structure, landscape metrics and biodiversity. Liv Rev Land Res 5:1–35. https://doi.org/10.12942/lrlr-2011-3

With KA (2005) Landscape conservation: a new paradigm for the conservation of biodiversity. In: Wiens JA, Moss MR (eds) Issues and perspectives in landscape ecology. Cambridge University press, UK, pp 238–247

Zerbe S (1998) Potential natural vegetation: validity and applicability in landscape planning and nature conservation. Appl Veg Sci 1:165–172. https://doi.org/10.2307/1478945

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

(Klouček T., Moravec D., Komárek J., Lagner O., Štych P.)

Q1

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

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

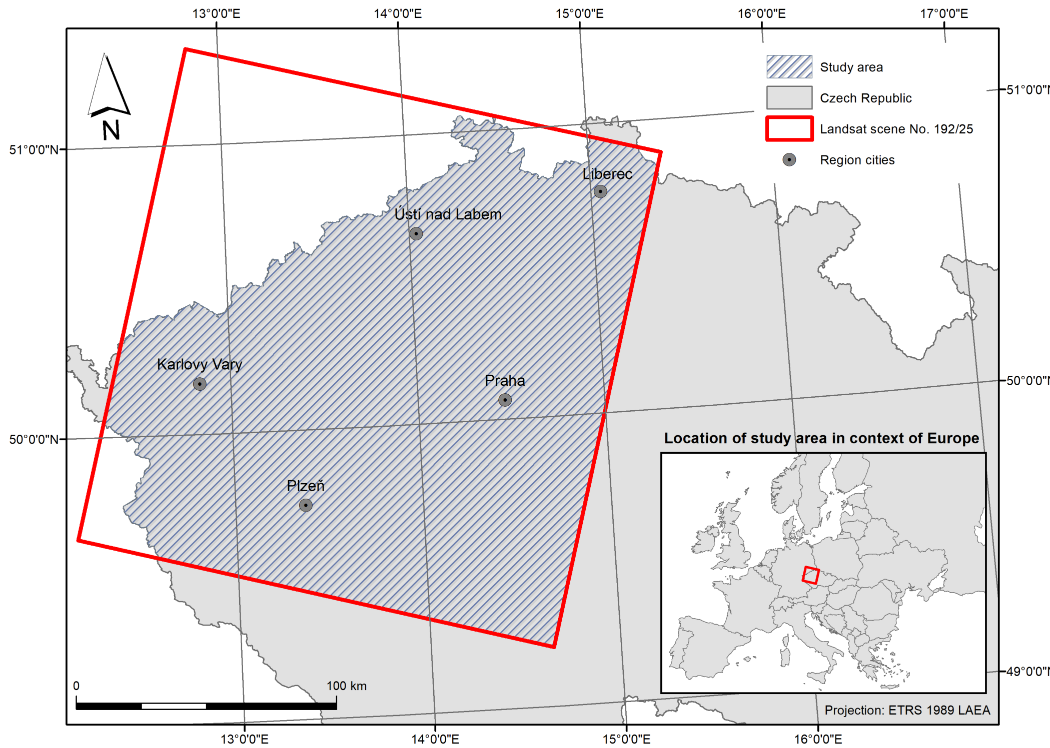


Figure 1 **The study area is (located in the Czech Republic, specifically) comprising a part of Landsat 8 scene Path 192 Row 25.**

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

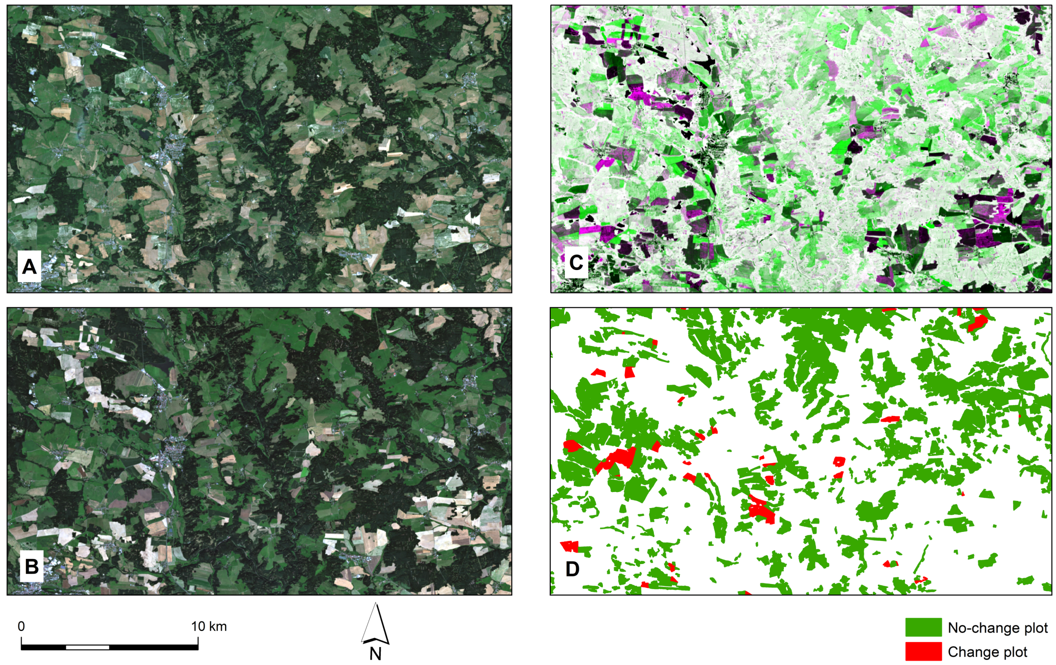


Figure 2 An example of used datasets. Landsat 8 images, NDVI vegetation index, and (no-)change grassland to cropland plots (LPIS database) from 2013 and 2016. (A) Landsat 8 image from 2013. (B) Landsat 8 image from 2016. (C) NDVI RGB composite (R = NDVI 2013, G = NDVI 2016, B = NDVI 2013). (D) (No-)change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

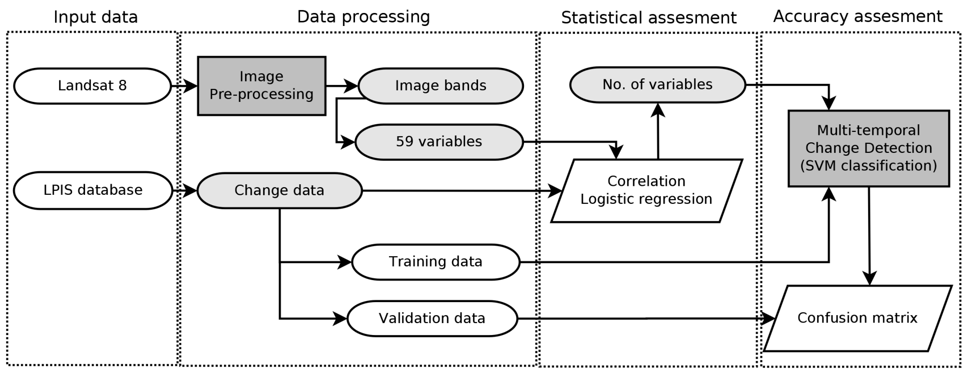


Figure 3 A scheme of the study methods describing data processing workflow. For validation of models was used multi-temporal change detection based on object-based classification using Support Vector Machine algorithm.

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

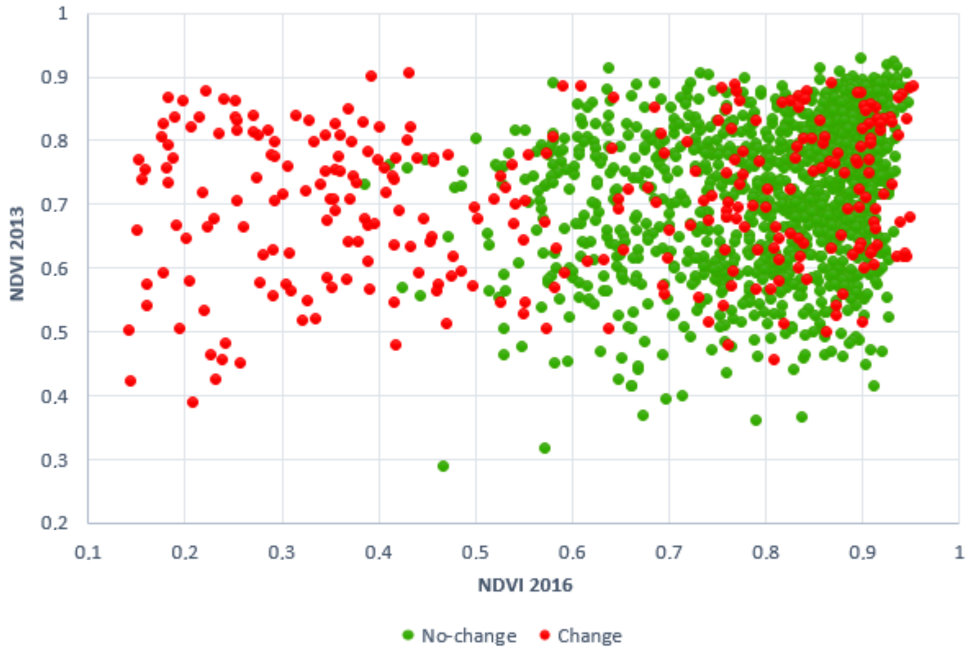


Figure 4 2D scatter plot created from NDVI average values of change and no-change plots. Points represent training data (300 change, 1,200 no-change plots). *X*-axis belongs to NDVI 2016 and *Y*-axis belongs to NDVI 2013 (one-variable model).

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

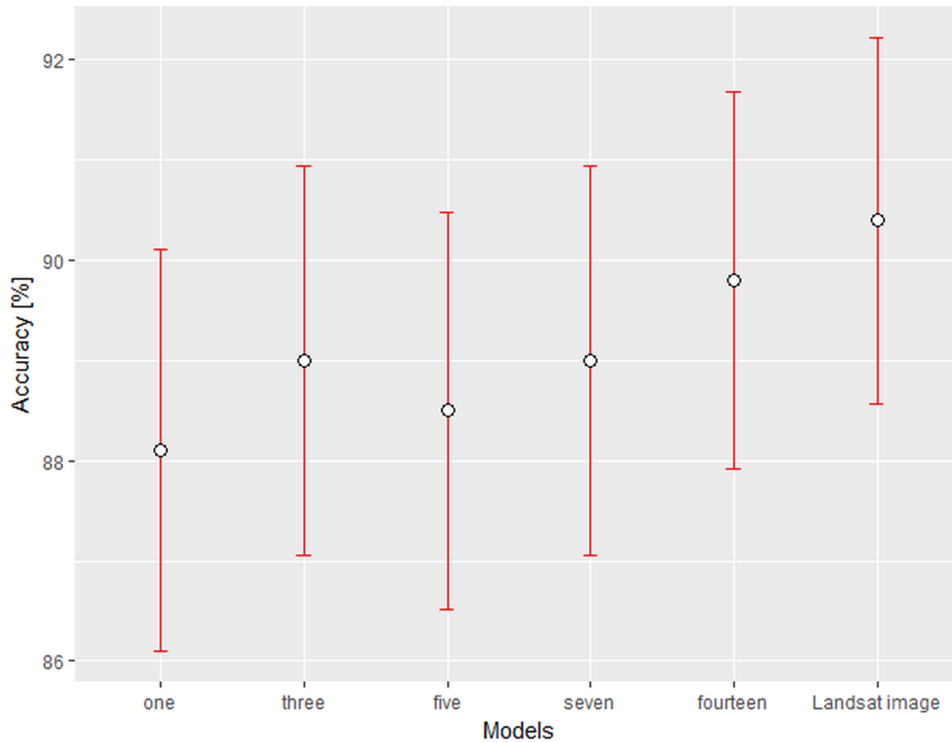


Figure 5 **Overall accuracy (%) of calculated models with 95% confidence intervals.**
Full-size DOI: 10.7717/peerj.5487/fig-5

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

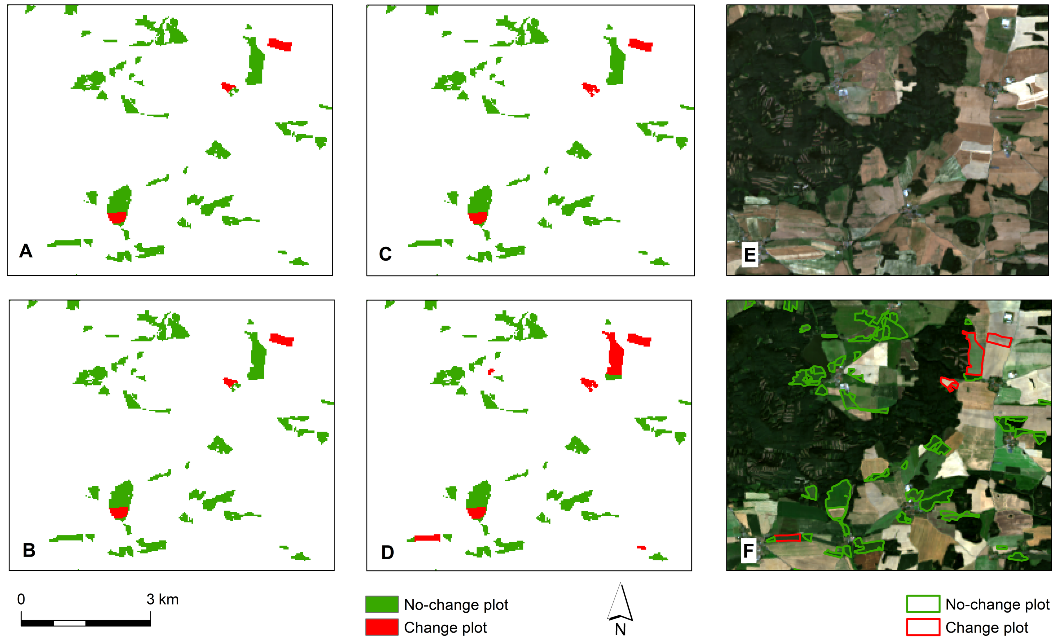


Figure 6 Comparison of created change maps with Landsat 8 images and LPIS database. (A) One-variable model. (B) Three-variable model. (C) Fourteen-variable model. (D) Landsat 8 images only model. (E) Landsat 8 image from 2013. (F) Landsat 8 image from 2018 with (no-)change plots from LPIS database.

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* *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.

Q4 **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..

Q5 **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.

Q6 **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, Oaheľ 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.

7. Comments on Results

As the discussion and comments on the results are already present in the published papers, this chapter has a different goal than that typical in scientific publications. In the first part of this chapter, I will present my subjective and personal views on the individual studies. I will explain why the particular methods were chosen, clarify my contribution to these studies and focus on the problems that arose during my work on these studies. In the conclusion and outlook part, I will shortly present general comments valid across all presented studies.

7.1 Wind turbine impact on near-ground air temperature: a long-term field measurement

In this paper, we observed in a long term the temperature in the vicinity of wind farms. Reviewing available literature revealed that the effect of wind farms on the temperature in their vicinity can vary throughout the day and the season. There was also a certain ambiguity in respect of different effects of the wind farms during the day and at night. All of these reasons led us to the conclusion that to be able to monitor the real effects, it will be necessary to perform measurements on hourly basis over the period of several months. At present, however, there are no satellites providing the requested temporal and spatial resolution. The needed nominal resolution was 200m, which would provide a clean pixel with a temperature affected by the wind turbine. A sufficient spatial resolution would be provided by Landsat satellites, those, however, with their periodicity of 16 days, cannot meet the other condition of temporal resolution in the order of hours.

Another factor supporting the use of direct measurement was the fact that RS only provides so-called skin temperature values. That means that the radiation registered at the satellite originates predominantly from the top layer of molecules (more about skin temperature can be found e.g. in Jin and Dickinson (2010)). The skin temperature is however very susceptible to the actual direction and velocity of the wind while the directly measured temperature is more accurate, more stable over time and at the same time better reflecting the effect of the wind farm on the surrounding environment.

Despite these advantages, direct measurement also has its drawbacks. The susceptibility of the sensors to microclimatic conditions turned out to be the greatest disadvantage. A typical feature of RS-detected temperatures is averaging – the temperature in the particular pixel is a sum of partial contributions of all surfaces in the given pixel. Contrary, direct measurements can be affected by specific conditions found in a very small (in the case of our TMS sensor, several centimetres) surroundings. If, for example, the sensor is placed in a small hollow, its immediate surroundings is likely to be damper, which will result in a more stable temperature curve. Another drawback is the susceptibility of the sensors to damage or break-ups. In our experiment, I originally had 26 TMS TOMSR sensors at my disposal. They however gradually succumbed to malfunction, especially due to a frequent ice forming and thawing, which caused a gradual increase of fine gaps resulting in a subsequent destruction of the sensor. This affected 7 sensors over the course of the study. Another, unexpected and perhaps even worse by that, was an ordinary human curiosity, ignorance or even maliciousness. Before the experiment started, an agreement was reached with the plot owner allowing us to place the sensors on the premises. Each sensor was labelled with a leaflet explaining the purpose and explanation of the experiment, thanks for consideration and personal contact. Unfortunately, despite these measures, 5 more sensors where (un?)intentionally ran over by a tractor. For these reasons, I had to wrap up the experiment, originally designed to last 12 months, after 5 months already as even after that period, I was left with only 14 out of original 26 functional sensors.

Fig. 4 A sensor destroyed after being ran over by a tractor.

Despite the above mentioned problems, we managed to acquire a sufficient amount of data from different weather conditions to be able to perform an assessment of the results. The results were quite surprising when compared to those of previously published studies, e.g. those of Baidya Roy (2011) or Zhou et al. (2013). There, a cooling effect of the turbine on the surroundings was observed during the day and warming during night. In our study, contrary, none of that was proved (with one exception). Personally, I tend to explain the discrepancy predominantly by different conditions. Unlike in other studies, our turbine was located in a mountainous area. The area is susceptible to a natural occurrence of turbulent flow on itself. It is however the turbulent flow generated by the wind farm that is typically used as an explanation of the effects of the wind farm on the surrounding climate (Baidya Roy and Traiteur 2010). As in our environment, the turbulent flow was probably to a great extent present naturally, we were unable to show a consistent effect of the wind farm on the surroundings. Another possible reason may lie in the direct temperature measurement while Zhou et al. (2013) only measured the skin temperature. The study was published in a prestigious journal Renewable Energy.

7.2 Taxonomic diversity, functional diversity and evolutionary uniqueness in bird communities of Beijing's urban parks: effects of land use and vegetation structure

In this paper, my task was predominantly to use simple classification techniques and vectorization to find out the size of water bodies and parks, to delineate edges of urbanized areas and to measure a distance of each directly measured point from those. All these tasks were relatively simple and straightforward apart from the delineation of the edge of the city of Beijing. To facilitate a simple statistical evaluation and due to limitations of the intended statistical approaches, it was necessary to specify a definite number, without any uncertainty.

The efforts to determine a definite number however can lead to substantial uncertainties. As mentioned for example by Rocchini et al. (2013), classification methods used in the RS often lead to creating a limited number of discrete categories, which however often does not reflect on the reality and natural substance of the phenomena on the surface of the Earth where the categories are only gradually changing into one another. Such classification approaches therefore may not reflect the real state of the phenomenon and in effect can lead to a loss of information contained in the original images.

In this study, it was no different. The real borders of the city of Beijing gradually dissipate into the surrounding countryside and a dense mosaic of developments becomes first an area with more sparsely scattered buildings, which subsequently turns into an open landscape. At first, I attempted to overcome this lack of existence of a firm border by determining a firm threshold in the spectral channels of the landscape reflectance or through derived indices (NDVI or Built-Up Area Index). None of those approaches was however satisfactory over the entire border. Another approach that could have resolved the issue was to use one of fuzzy/soft classification methods instead of hard classification techniques. In those methods, the area in question does not necessarily have to be assigned into one of the two categories, they leave the room for "unclear" pixels. Fuzzy classifications can mimic human thinking and allow the expression of probability with which the pixel belongs to a given category (e.g., the pixel is with a 70% probability a water body and with 30% probability a grassland). Spectral unmixing is another soft classification method with the resulting spectral curve of a pixel in question being thought of as of a combination of n spectral curves with a uniform surface (so-called endmembers). In the resulting product, it can be said how much of the surface in the particular pixel is covered by the user-defined land cover types (Jones and Vaughan 2010). Such results would however not be fully satisfactory for subsequent analyses. For those reasons, I opted in the end for the use of a raster from the study of Yang et al. (2013) who defined a sharp border of Beijing (although on a coarse raster).

7.3 Digital elevation models as predictors of yield: Comparison of UAV and other elevation data sources

This paper was prepared in a little unusual way. Thanks to our cooperation with the Faculty of Engineering, we performed together one of the first UAV flights with the purpose of acquiring data for creation of a detailed digital model using the structure from motion technique. As our Faculty lacked both the necessary know-how and technologies at the time, that flight had to be performed by an external subject. As it turned out, however, the overlap of the acquired photos was relatively low for processing using the required method. The resulting model had therefore a high number of "holes" and was therefore unsuitable for the original study purpose, i.e. the effect of precision farming on microtopography.

We have therefore acquired a dataset/digital model of a field that could not have been used for the original purpose. For that reason, we (in particular with my colleagues Komárek and Kumhálová) came up with a new study concept where we correlated the data on crop on that field with detailed SfM data and freely available laser scanning models. Despite an interesting result, namely that our significantly more detailed data have not resulted in a significant improvement for such models, the main purpose of the study was accomplished through presenting/publishing the information at a conference and in conference proceedings and thus introducing the capabilities of SfM technique to the experts in the field of agriculture as a novel method in the field.

7.4 Reforestation dynamics after land abandonment: a trajectory analysis in Mediterranean mountain landscapes

In this study, we were observing the development of land cover in the region of Apennines, central Italy, namely in two protected areas. Ever since World War II, a notable decline of population due to migration from the mountainous areas to the lowland urban regions is apparent there. RS brought in this area an independent verification of many observations previously made directly by ground sampling. The main benefit of the use of RS when compared to ground sampling lied in a possibility of the quantification of all processes over the entire area as well as in the opportunity to utilize an extensive database of archived images.

My tasks in the study included in particular processing of Landsat satellite imagery (namely Landsat 5, 7 and 8) and subsequent change detection analysis. Thanks to the long-term database of Landsat images, I was able to perform an analysis of a period of over 29 years (1987 till 2016).

The biggest complication of this analysis rested in the missing direct data from the site. Due to the extent of the area, along with high financial and time demands, I had no opportunity to collect the data directly in the area of interest. The collection of real-life data is however crucial for such a study for two reasons. The first reason is the need to create a land cover database that can be used as training data for algorithms for the automated classification. Secondly, it is necessary to verify the accuracy of each classification method. We managed to overcome this problem through the use of available data from other sources. The primary source was Google Street View where individual land cover types used in our study could be relatively well distinguished. Additional auxiliary information was extracted from geo-tagged photographs from Flicker. These two sources enabled us to find 488 calibration points in total for accuracy assessment. The accuracy was 85.4 %.

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

This paper built on the Master's thesis by Tomáš Klouček. My involvement rested predominantly in the experimental design, its statistical evaluation and manuscript preparation. The original idea of the research was to detect the change of the arable land to grassland. That phenomenon has been described, mainly due to the return to the market economy, restitutions, land abandonment or abandonment of cultivation where there were adverse natural conditions (Boučníková and Kučera 2005). Unfortunately, as the first experiments showed, the process of arable land succession is very slow and it can take several years till the former fields begin to show the spectral characteristics of the original grassland. For this reason, we decided to take a different route, i.e., to detect the opposite change of grassland to cropland. This is a very abrupt process and, therefore, easier to detect in a short time horizon. As training data, we used LPIS database, which contains annual data about type of farming on individual plots of land. The aim of this research was to create a potential tool of automatic inspection of land management on the agricultural land in the Czech Republic.

After finding an agreement, we opted for a method of search for various combinations of predictors (spectral or textural indices) until a proper combination facilitating the grassland to cropland change detection is found. Despite this approach being scientifically sound, I would not use it again. It became soon apparent that many indices are closely correlated, often more than r=0.98 (see manuscript supplement), which led to an immense amount of redundant work. In my opinion (supported by the opinion of one of the manuscript reviewers), a far more elegant approach would lie in observation of spectral profiles of the given phenomena and to select spectral bands for detection only based on such knowledge. Thereafter, it is possible to focus on spectral indices working within those bands.

Another significant issue of the study was a major heterogeneity of the study area. As we selected an area containing both lowlands in the vicinity of major rivers and mountainous border regions, climate conditions and therefore stages of agricultural process differed throughout the study area. It is obvious that the change of grassland to cropland is best detectable at the moment of ploughing up the cropland. However, due to different climate conditions across the area, this moment was at different times in different locations, which significantly complicated a selection of a suitable time point.

Despite those issues, we managed to find suitable indices and time points and to publish the research in a prestigious journal.

8. Conclusion and outlook

In this thesis, I have described and successfully used several types of ground measurement and remote sensing techniques to study environment and its changes. The main advantages and disadvantages of each study can be seen either in the scientific papers or in the comment part above. When we decide to use remote sensing data, then we usually have to choose between temporal and spatial resolution. There is trade-off present in the systems, and with increasing temporal resolution we usually end with coarse spatial resolution and vice versa. For example, sensors MODIS on the TERRA and AQUA satellites has the temporal resolution from one to two days, but their best spatial resolution is only 250 m. In contrast, Sentinel-2 satellite has 10 m resolution however temporal resolution of five days.

To choose the appropriate sensor for observing of different aspects of the environment, we have to consider the specific parameters of the satellite. In the areas of geology, forestry or land cover and land change detection the appropriate periodicity is around month or years and the nominal spatial resolution in the order of tenth meters. On the other end, there are areas (i.e. emergency response, Precision Agriculture) where the demands on the spatial and temporal resolution are significantly higher.

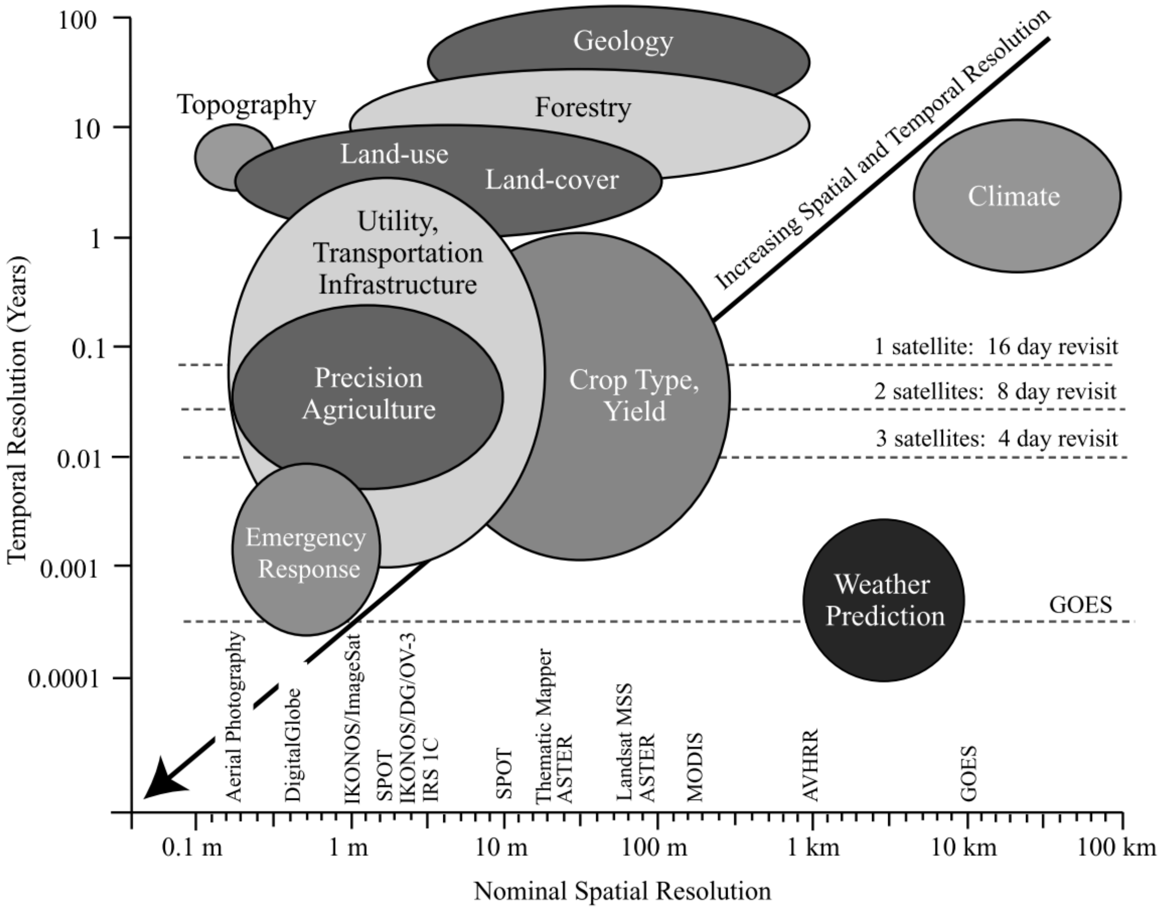


Fig. 5 Spatial and temporal resolution for selected applications (Jensen 2000).

Alternatively, ground measurement is preferred in cases where one of the resolutions of the remote sensing systems are insufficient or in cases where acquisition costs are too high.

Very interesting and perspective approach of remote sensing is UAV. They offer higher flexibility, lower operational costs and allow recording in the higher temporal and spatial resolutions in contrast to satellites or aircraft (Vaccari et al. 2015). With UAV we can overcome the factor of clouds, which is limiting for satellite observation, especially in conditions of Central Europe. On the other hand, there are still some limitations especially due to weather conditions (rain or strong wind) or legislation restrains.

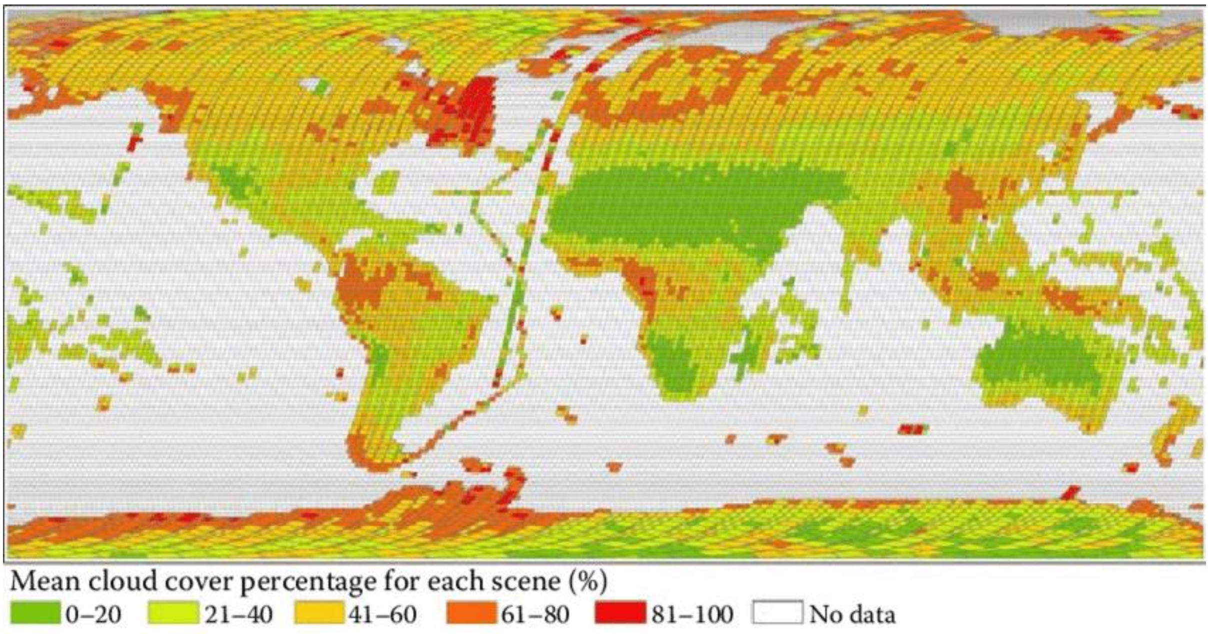


Fig. 6 Mean global cloud cover in all available Landsat 8 scenes between September 2013 and August 2017 (Zhu et al. 2018).

The amount of the cloud cover over some areas such as central Europe is also rising importance of radar data. Their main advantage is ability to penetrate signal through clouds. The main free source of such data is nowadays Sentinel 1 satellite.

In the near future, we can expect several improvements of the earth observation capacity. One of the milestones is the LIDAR on the international space station (ISS). This LIDAR system called Global Ecosystem Dynamics Investigation – or GEDI is first of its kind and should increase the capability of observing of forest structure, carbon recourses and biodiversity of the world. Similar aim have also first of its king P-band polarimetric SAR satellite called BIOMASS. The satellite antenna will be the first earth observing SAR satellite observing in P-band which could penetrate forest canopy with the spatial resolution of 200m.

Several improvements could be expected also in the non-space remote sensing. One of the most progressive technology is UAV. We can expect further improvements of the flight duration and payload capabilities. Another promising technology (but still not fully available yet) is the High Altitude Pseudo-Satellites (HAPS). These technology is filling the gap between satellites and a drones. These unmanned aircraft are able to fly in very high altitudes (even in the stratosphere) for a long time (few months nowadays) and make an almost continual investigation of the requested areas.

9. References

Agisoft LLC (a). 2017. “Agisoft Photoscan.” http://www.agisoft.com.

Alvey, A. Alexis. 2006. “Promoting and Preserving Biodiversity in the Urban Forest.” *Urban Forestry & Urban Greening* 5: 195–201. doi:10.1016/j.ufug.2006.09.003.

Baidya Roy, S., S. W. Pacala, and R. L. Walko. 2004. “Can Large Wind Farms Affect Local Meteorology?” *Journal of Geophysical Research D: Atmospheres* 109 (19): D19101. doi:10.1029/2004JD004763.

Baidya Roy, Somnath. 2011. “Simulating Impacts of Wind Farms on Local Hydrometeorology.” *Journal of Wind Engineering and Industrial Aerodynamics* 99 (4). Elsevier: 491–98. doi:10.1016/j.jweia.2010.12.013.

Baidya Roy, Somnath, and Justin J Traiteur. 2010. “Impacts of Wind Farms on Surface Air Temperatures.” *Proceedings of the National Academy of Sciences of the United States of America* 107 (42): 17899–904. doi:10.1073/pnas.1000493107.

Bakker, R.H. H., E. Pedersen, G.P. P. van den Berg, R.E. E. Stewart, W. Lok, and J. Bouma. 2012. “Impact of Wind Turbine Sound on Annoyance, Self-Reported Sleep Disturbance and Psychological Distress.” *Science of the Total Environment* 425 (May). Elsevier B.V.: 42–51. doi:10.1016/j.scitotenv.2012.03.005.

Barclay, Robert M R, E F Baerwald, and J C Gruver. 2007. “Variation in Bat and Bird Fatalities at Wind Energy Facilities: Assessing the Effects of Rotor Size and Tower Height.” *Canadian Journal of Zoology-Revue Canadienne De Zoologie* 85 (3): 381–87. doi:10.1139/Z07-011.

Beaufoy, G., D. Baldock, and J. Clark. 1994. “The Nature of Farming: Low Intensity Farming Systems in Nine European Countries.” London.

Bertoni, Roberto. 2012. “La Rete Italiana per La Ricerca Ecologica a Lungo Termine (LTER–Italia).” *Aracne Editrice*. Roma.

Blake, R.a., F. Moshary, and R.M. Khanbilvardi. 1999. “Remote Sensing as a Tool for Assessing and Monitoring Environmental Impacts: Integration of Research and Education.” *IEEE 1999 International Geoscience and Remote Sensing Symposium. IGARSS’99 (Cat. No.99CH36293)* 1: 53–55. doi:10.1109/IGARSS.1999.773398.

Blaschke, Thomas, Geoffrey J. Hay, Maggi Kelly, Stefan Lang, Peter Hofmann, Elisabeth Addink, Raul Queiroz Feitosa, et al. 2014. “Geographic Object-Based Image Analysis - Towards a New

Paradigm.” *ISPRS Journal of Photogrammetry and Remote Sensing* 87. International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS): 180–91. doi:10.1016/j.isprsjprs.2013.09.014.

Boučníková, Eva, and Tomáš Kučera. 2005. “How Natural and Cultural Aspects Influence Land Cover Changes in the Czech Republic.” *Ekológia* 24 (Supp. 1): 1–24. http://www.usbe.cas.cz/people/kucera/PAPERS/boucnikova_kucera.pdf.

Campagnaro, Thomas, Ludovico Frate, Maria Laura Carranza, and Tommaso Sitzia. 2017. “Multi-Scale Analysis of Alpine Landscapes with Different Intensities of Abandonment Reveals Similar Spatial Pattern Changes: Implications for Habitat Conservation.” *Ecological Indicators* 74. Elsevier Ltd: 147–59. doi:10.1016/j.ecolind.2016.11.017.

Campbell, Bruce A. 2002. *Radar Remote Sensing of Planetary Surfaces*. *Ultramicroscopy*. Vol. 75. Cambridge University Press. doi:10.1016/S0304-3991(98)00068-0.

Chamorro, Leonardo P., and Fernando Porté-Agel. 2010. “Effects of Thermal Stability and Incoming Boundary-Layer Flow Characteristics on Wind-Turbine Wakes: A Wind-Tunnel Study.” *Boundary-Layer Meteorology* 136 (3): 515–33. doi:10.1007/s10546-010-9512-1.

Chander, Gyanesh, and Brian Markham. 2003. “Revised Landsat-5 TM Radiometric Calibration Procedures and Postcalibration Dynamic Ranges.” *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING* 41 (11): 2674–77.

Chaudhuri, Gargi, and Niti B. Mishra. 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. Elsevier Ltd: 68–83. doi:10.1016/j.apgeog.2016.01.002.

Chen, Gang, Geoffrey J. Hay, Luis M. T. Carvalho, and Michael a. Wulder. 2012. “Object-Based Change Detection.” *International Journal of Remote Sensing* 33 (14): 4434–57.

Chen, Qi. 2007. “Airborne Lidar Data Processing and Information Extraction.” *Photogrammetric Engineering and Remote Sensing* 73 (2). ASPRS AMERICAN SOCIETY FOR PHOTOGRAMMETRY AND: 109.

Clark, J.S., and J Robinson. 1993. “Paleoecology of Fire.” In *Fire in the Environment: The Ecological, Atmospheric and Climatic Importance of Vegetation Fires.*, 193–214.

Dai, Kaoshan, Anthony Bergot, Chao Liang, Wei-Ning Xiang, and Zhenhua Huang. 2015. “Environmental Issues Associated with Wind Energy – A Review.” *Renewable Energy* 75: 911–21. doi:10.1016/j.renene.2014.10.074.

DeCarolis, Joseph F., and David W. Keith. 2006. “The Economics of Large-Scale Wind Power in a Carbon Constrained World.” *Energy Policy* 34 (4): 395–410. doi:10.1016/j.enpol.2004.06.007.

Dolman, Sarah, and Mark Simmonds. 2010. “Towards Best Environmental Practice for Cetacean Conservation in Developing Scotland’s Marine Renewable Energy.” *Marine Policy* 34 (5). Elsevier: 1021–27. doi:10.1016/j.marpol.2010.02.009.

Drewitt, A L, and R H W Langston. 2006. “Assessing the Impacts of Wind Farms on Birds.” *Ibis* 148: 29–42. doi:10.1111/j.1474-919X.2006.00516.x.

Eu. 2007. “Council Directive 834/2007 on Organic Production and Labelling of Organic Products.” *Official Journal of the European Communities L 189* 2007 (394): 1–23.

Foley, Jonathan a, Ruth Defries, Gregory P Asner, Carol Barford, Gordon Bonan, Stephen R Carpenter, F Stuart Chapin, et al. 2005. “Global Consequences of Land Use.” *Science (New York, N.Y.)* 309 (2005): 570–74. doi:10.1126/science.1111772.

Gatsis, I, S Koukoulas, A Vafeidis, E Lagoudakis, and K Gkoltsiou. 2006. “MONITORING AND MAPPING OF LAND COVER / USE CHANGES IN AN AGRICULTURAL AND NATURAL ENVIRONMENT , USING MULTITEMPORAL SATELLITE DATA AND GIS (LESVOS ISLAND , GREECE).” In . RSPSoc Annual Conference, Understanding a Changing World.

Gerhardt, Fritz, David R Foster, and Harvard Forest. 2002. “Physiographical and Historical Effects on Forest Vegetation in Central New England , USA” 29 (10): 1421–37.

Guarrera, P M. 1994. “Il Patrimonio Etnobotanico Del Lazio.” *Giornale Botanico Italiano* 128 (1). Taylor & Francis: 446. doi:10.1080/11263509409437253.

Gupta, Sharad Kumar, and Dericks Praise Shukla. 2016. “Assessment of Land Use / Land Cover Dynamics of Tso Moriri Lake , a Ramsar Site in India.” *Environmental Monitoring and Assessment*, no. 201. Environmental Monitoring and Assessment. doi:10.1007/s10661-016-5707-3.

Haddaway, Neal R., David Styles, and Andrew S. Pullin. 2014. “Environmental Impacts of Farm Land Abandonment in High Altitude/Mountain Regions: A Systematic Map of the Evidence.” *Environmental Evidence* 2 (1): 18. doi:10.1186/2047-2382-2-18.

Halounová, Lenka, and Karel Pavelka. 2008. *DÁLKOVÝ PRŮZKUM ZEMĚ*. Ceské vysoké učení technické v Praze.

Hassebo, Yasser. 2012. “Remote Sensing - Advanced Techniques and Platforms.” In , edited by Boris

Escalante, 696. InTech.

Hurtado, Juan Pablo, Joaquín Fernández, Jorge L. Parrondo, and Eduardo Blanco. 2004. "Spanish Method of Visual Impact Evaluation in Wind Farms." *Renewable and Sustainable Energy Reviews* 8 (5): 483–91. doi:10.1016/j.rser.2003.12.009.

Hussain, Masroor, Dongmei Chen, Angela Cheng, Hui Wei, and David Stanley. 2013. "Change Detection from Remotely Sensed Images: From Pixel-Based to Object-Based Approaches." *ISPRS Journal of Photogrammetry and Remote Sensing* 80 (June). International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS): 91–106.

IPCC. 2014. *Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner,. Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, United Kingdom and New York k, NY, USA: Cambridge University Press. doi:10.1017/CBO9781107415416.

Jaboyedoff, Michel, Thierry Oppikofer, Antonio Abellán, Marc Henri Derron, Alex Loye, Richard Metzger, and Andrea Pedrazzini. 2012. "Use of LIDAR in Landslide Investigations: A Review." *Natural Hazards* 61 (1): 5–28. doi:10.1007/s11069-010-9634-2.

Jackson, D. Ray, and R. Alfredo Huete. 1991. "Interpreting Vegetation Indices." *Prev. Vet. Med.* 11: 185–200.

Jensen, J.R. 2005. *Introductory Digital Image Processing: A Remote Sensing Perspective*. Toronto: Prentice Hall.

Jensen, J R. 2000. *Remote Sensing of the Environment: An Earth Resource Perspective*. *Prentice Hall, Upper Saddle River, NJ*. Vol. 1.

Jin, Menglin, and Robert E. Dickinson. 2010. "Land Surface Skin Temperature Climatology: Benefitting from the Strengths of Satellite Observations." *Environmental Research Letters* 5 (4). doi:10.1088/1748-9326/5/4/044004.

Jones, Hamlyn G, and Robin A Vaughan. 2010. *Remote Sensing of Vegetation: Principles, Techniques, and Applications*. Oxford university press.

Jordan, Carl F. 1969. "Derivation of Leaf-area Index from Quality of Light on the Forest Floor." *Ecology* 50 (4). Wiley Online Library: 663–66.

Kalis, Arie J., Josef Merkt, and Jürgen Wunderlich. 2003. “Environmental Changes during the Holocene Climatic Optimum in Central Europe - Human Impact and Natural Causes.” *Quaternary Science Reviews* 22 (1): 33–79. doi:10.1016/S0277-3791(02)00181-6.

Kalnay, Eugenia, and Ming Cai. 2003. “Impact of Urbanization and Land-Use Change on Climate.” *Nature* 423 (May): 528–31. doi:10.1038/nature01649.1.

Kauth, Richard J, and G S Thomas. 1976. “The Tasselled Cap--a Graphic Description of the Spectral-Temporal Development of Agricultural Crops as Seen by Landsat.” In *LARS Symposia*, 159.

Keith, David W., Joseph F. Decarolis, David C. Denkenberger, Donald H. Lenschow, Sergey L. Malyshev, Stephen Pacala, and Philip J. Rasch. 2004. “The Influence of Large-Scale Wind Power on Global Climate.” *Proceedings of the National Academy of Sciences of the United States of America* 101 (46): 16115–20. doi:10.1073/pnas.0406930101.

Kindu, Mengistie, Thomas Schneider, Demel Teketay, and Thomas Knoke. 2013. “Land Use/Land Cover Change Analysis Using Object-Based Classification Approach in Munessa-Shashemene Landscape of the Ethiopian Highlands.” *Remote Sensing* 5 (5): 2411–35. doi:10.3390/rs5052411.

Klemas, Victor. 2012. “Beach Profiling and LIDAR Bathymetry: An Overview with Case Studies.” *Journal of Coastal Research* 27 (6): 1019–28. doi:10.2112/JCOASTRES-D-11-00017.1.

Kovats, R Sari, and Shakoor Hajat. 2008. “Heat Stress and Public Health: A Critical Review.” *Annual Review of Public Health* 29 (October): 41–55. doi:10.1146/annurev.publhealth.29.020907.090843.

Kraus, Tanja, Michael Schmidt, Stefan Dech, and Cyrus Samimi. 2009. “Combination of Remote Sensing and in Situ Measurements for a Detailed Assessment of Biophysical Properties of East African Rainforests: A Case Study for Kakamega Forest, Kenya, and Budongo Forest, Uganda.” *International Geoscience and Remote Sensing Symposium (IGARSS)* 3: 326–29. doi:10.1109/IGARSS.2009.5417766.

la Vega, David de, James Matthews, Lars Norin, and Itziar Angulo. 2013. “Mitigation Techniques to Reduce the Impact OfWind Turbines on Radar Services.” *Energies* 6 (6): 2859–73. doi:10.3390/en6062859.

Landsberg, H E. 1981. *The Urban Climate*. International Geophysics. Elsevier Science.

Lefsky, Michael A, Warren B Cohen, Geoffrey G Parker, and David J Harding. 2002. “Lidar Remote Sensing for Ecosystem Studies: Lidar, an Emerging Remote Sensing Technology That Directly

Measures the Three-Dimensional Distribution of Plant Canopies, Can Accurately Estimate Vegetation Structural Attributes and Should Be of Particular Inte.” *BioScience* 52 (1). BioOne: 19–30.

Lim, K., P. Treitz, M. Wulder, B. St-Ongé, and M. Flood. 2003. “LiDAR Remote Sensing of Forest Structure.” *Progress in Physical Geography* 27 (1): 88–106. doi:10.1191/0309133303pp360ra.

Ložek, Vojen. 1973. “Příroda ve Čtvrtohorách.” Academia.

Lu, Dengsheng, Guiying Li, and Emilio Moran. 2014. “Current Situation and Needs of Change Detection Techniques.” *International Journal of Image and Data Fusion* 5 (1). Taylor & Francis: 13–38. doi:10.1080/19479832.2013.868372.

Lunetta, Ross S., Joseph F. Knight, Jayantha Ediriwickrema, John G. Lyon, and L. Dorsey Worthy. 2006. “Land-Cover Change Detection Using Multi-Temporal MODIS NDVI Data.” *Remote Sensing of Environment* 105 (2): 142–54.

Magny, Michel. 2004. “Holocene Climate Variability as Reflected by Mid-European Lake-Level Fluctuations and Its Probable Impact on Prehistoric Human Settlements.” *Quaternary International* 113: 65–79. doi:10.1016/S1040-6182(03)00080-6.

Malavasi, M., M.L. Carranza, D. Moravec, and M. Cutini. 2018. “Reforestation Dynamics after Land Abandonment: A Trajectory Analysis in Mediterranean Mountain Landscapes.” *Regional Environmental Change*. doi:10.1007/s10113-018-1368-9.

Micheletti, N., J.H. CHandler, and S.N. Lane. 2015. “Structure from Motion (SFM) Photogrammetry.” In *Geomorphological Techniques*. London: British Society for Geomorphology.

Micheletti, Natan, Jim H Chandler, and Stuart N Lane. 2015. “Structure from Motion (SFM) Photogrammetry.” British Society for Geomorphology.

Mishra, Varun Narayan, Rajendra Prasad, Pradeep Kumar, Dileep Kumar Gupta, and Prashant K. Srivastava. 2017. “Dual-Polarimetric C-Band SAR Data for Land Use/Land Cover Classification by Incorporating Textural Information.” *Environmental Earth Sciences* 76 (1). Springer Berlin Heidelberg: 26. doi:10.1007/s12665-016-6341-7.

Moravec, David, Vojtěch Barták, Vladimír Puš, and Jan Wild. 2018. “Wind Turbine Impact on Near-Ground Air Temperature.” *Renewable Energy* 123: 627–33. doi:https://doi.org/10.1016/j.renene.2018.02.091.

Morelli, Federico, Yanina Benedetti, Bo Su Zhou, David Moravec, Petra Šímová, and Wei Liang. 2017. "Taxonomic Diversity, Functional Diversity and Evolutionary Uniqueness in Bird Communities of Beijing's Urban Parks: Effects of Land Use and Vegetation Structure." *Urban Forestry & Urban Greening*. doi:http://dx.doi.org/doi:10.1016/j.ufug.2017.03.009.

MZP. 2004. "Národní Program Na Zmírnění Dopadů Změny Klimatu."

Newbold, Tim, Lawrence N Hudson, Andrew P Arnell, Sara Contu, Adriana De Palma, Simon Ferrier, Samantha L L Hill, et al. 2016. "Has Land Use Pushed Terrestrial Biodiversity beyond the Planetary Boundary? A Global Assessment." *Science* 353: 288–91. doi:10.1126/science.aaf2201.

Panwar, N L, S C Kaushik, and Surendra Kothari. 2015. "Role of Renewable Energy Sources in Environmental Protection : A Review." *Renewable and Sustainable Energy Reviews* 15 (3). Elsevier Ltd: 1513–24. doi:10.1016/j.rser.2010.11.037.

Papp, Eva. 2002. "Geophysical and Remote Sensing Methods for Regolith Exploration." *CRC LEME Open File Report 144. ISSN*. Canberra. doi:10.1109/5.338072.

Peiman, Reihaneh. 2011. "Pre-Classification and Post-Classification Change-Detection Techniques to Monitor Land-Cover and Land-Use Change Using Multi-Temporal Landsat Imagery: A Case Study on Pisa Province in Italy." *International Journal of Remote Sensing* 32 (15). Taylor & Francis: 4365–81. doi:10.1080/01431161.2010.486806.

Petriccione, B, and C Mulder. 1993. *Flora e Vegetazione Del Massiccio Del Monte Velino (Appennino Centrale): Comprendente Il Territorio Della Riserva Naturale Orientata "Monte Velino" e Della Foresta Demaniale "Montagna Della Duchessa" (Con Carta Della Vegetazione in Scala 1:10.000)*. Collana Verde. Ministero della Risorse Agricole, Alimentari e Forestali. https://books.google.cz/books?id=_Z0VtwAACAAJ.

Pimm, S L, C N Jenkins, R Abell, T M Brooks, J L Gittleman, L N Joppa, P H Raven, C M Roberts, and J O Sexton. 2014. "The Biodiversity of Species and Their Rates of Extinction, Distribution, and Protection." *Science (New York, N.Y.)* 344 (6187): 1246752. doi:10.1126/science.1246752.

Pineda, Ivan, and Justin Wilkes. 2015. "Wind in Power: 2014, European Statistics." *Technical Report The European Energy Association*, no. February: 1–12. doi:http://www.ewea.org/fileadmin/files/library/publications/statistics/Wind_in_power_annual_statistics_2012.pdf.

Puliti, Stefano, Hans Olerka, Terje Gobakken, and Erik Næsset. 2015. "Inventory of Small Forest Areas

Using an Unmanned Aerial System.” *Remote Sensing* 7 (8): 9632–54. doi:10.3390/rs70809632.

Rajewski, Daniel A., Eugene S. Takle, Julie K. Lundquist, Steven Oncley, John H. Prueger, Thomas W. Horst, Michael E. Rhodes, et al. 2013. “Crop Wind Energy Experiment (CWEX): Observations of Surface-Layer, Boundary Layer, and Mesoscale Interactions with a Wind Farm.” *Bulletin of the American Meteorological Society* 94 (5): 655–72. doi:10.1175/BAMS-D-11-00240.1.

Rajewski, Daniel Andrew. 2013. “CWEX (Crop/Wind-Energy Experiment): Measurements of the Interaction between Crop Agriculture and Wind Power,” 182.

Ramankutty, Navin, and A. Jonathan Floey. 1999. “Estimating Historical Changes in Global Land Cover : Croplands Historical Have Converted Areas.” *Global Biogeochemical Cycles* 13 (4): 997–1027. doi:10.1029/1999GB900046.

Raupach, Michael R, Gregg Marland, Philippe Ciais, Corinne Le Quéré, Josep G Canadell, Gernot Klepper, and Christopher B Field. 2007. “Global and Regional Drivers of Accelerating CO2 Emissions.” *Proceedings of the National Academy of Sciences of the United States of America* 104 (24): 10288–93. doi:10.1073/pnas.0700609104.

Reddy, M. Anji. 2008. *Remote Sensing and Geographical Information Systems*. Third Edit. Hyderabad: BS Publications.

Rees, Wili. 1997. “Urban Ecosystems: The Human Dimension.” *Urban Ecosystems* 1: 63–75.

Renterghem, Timothy Van, Annelies Bockstael, Valentine De Weirt, and Dick Botteldooren. 2013. “Annoyance, Detection and Recognition of Wind Turbine Noise.” *Science of the Total Environment* 456–457. Elsevier B.V.: 333–45. doi:10.1016/j.scitotenv.2013.03.095.

Reviews, Sustainable Energy. 2008. “Energy Production , Consumption , and Environmental Pollution for Sustainable Development : A Case Study in Turkey Environmental Pollution for Sustainable,” no. January 2016. doi:10.1016/j.rser.2007.03.003.

Rocchini, Duccio, Giles M. Foody, Harini Nagendra, Carlo Ricotta, Madhur Anand, Kate S. He, Valerio Amici, et al. 2013. “Uncertainty in Ecosystem Mapping by Remote Sensing.” *Computers and Geosciences* 50: 128–35. doi:10.1016/j.cageo.2012.05.022.

Rouse Jr, John W, R Hect Haas, J A Schell, and D W Deering. 1973. “Monitoring the Vernal Advancement and Retrogradation (Green Wave Effect) of Natural Vegetation.” Maryland.

Roy, Moumita, Susmita Ghosh, and Ashish Ghosh. 2014. “A Novel Approach for Change Detection of

Remotely Sensed Images Using Semi-Supervised Multiple Classifier System." *Information Sciences* 269 (June). Elsevier Inc.: 35–47. doi:10.1016/j.ins.2014.01.037.

Sabins, F F. 1978. *Remote Sensing: Principles and Interpretation*. Earth Sciences Series. W. H. Freeman.

Saidur, R., N. A. Rahim, M. R. Islam, and K. H. Solangi. 2011. "Environmental Impact of Wind Energy." *Renewable and Sustainable Energy Reviews* 15 (5): 2423–30. doi:10.1016/j.rser.2011.02.024.

Sitzia, Tommaso, Paolo Semenzato, and Giovanni Trentanovi. 2010. "Natural Reforestation Is Changing Spatial Patterns of Rural Mountain and Hill Landscapes: A Global Overview." *Forest Ecology and Management* 259 (8). Elsevier B.V.: 1354–62. doi:10.1016/j.foreco.2010.01.048.

Smith, David P, and Samuel F Atkinson. 2001. "Accuracy of Rectification Using Topographic Map versus GPS Ground Control Points." *Photogrammetric Engineering & Remote Sensing* 67 (5). Citeseer: 565–70.

Snyder, P. K., C. Delire, and J. a. Foley. 2004. "Evaluating the Influence of Different Vegetation Biomes on the Global Climate." *Climate Dynamics* 23: 279–302. doi:10.1007/s00382-004-0430-0.

Song, Conghe, Curtis E Woodcock, Karen C Seto, Mary Pax Lenney, and Scott A Macomber. 2000. "Classification and Change Detection Using Landsat TM Data : When and How to Correct Atmospheric Effects ?" 4257 (00).

Stoker, Jason M, Susan K Greenlee, Dean B Gesch, and Jordan C Menig. 2006. "CLICK: The New USGS Center for Lidar Information Coordination and Knowledge." *Photogrammetric Engineering and Remote Sensing* 72 (6): 613–16.

Symeonakis, Elias, Adolfo Calvo-Cases, and Eva Arnau-Rosalen. 2007. "Land Use Change and Land Degradation in Southeastern Mediterranean Spain." *Environmental Management* 40 (1): 80–94. doi:10.1007/s00267-004-0059-0.

Takebayashi, Hideki, and Masakazu Moriyama. 2007. "Surface Heat Budget on Green Roof and High Reflection Roof for Mitigation of Urban Heat Island." *Building and Environment* 42 (8): 2971–79. doi:10.1016/j.buildenv.2006.06.017.

Tarantino, Cristina, Maria Adamo, Richard Lucas, and Palma Blonda. 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. The Authors: 65–72. doi:10.1016/j.rse.2015.12.031.

Tempfli, K, G C Huurneman, W H Bakker, L L F Janssen, W F Feringa, A S M Gieske, K A Grabmaier, C A Hecker, and J A van der Horn. 2009. *Principles of Remote Sensing: An Introductory Textbook*. ITC Educational Textbook Series. ITC. https://books.google.it/books?id=sk1bAQAACAAJ.

Tilman, David, Kenneth G Cassman, Pamela a Matson, Rosamond Naylor, and Stephen Polasky. 2002. “Agricultural Sustainability and Intensive Production Practices.” *Nature* 418 (August): 671–77. doi:10.1038/nature01014.

Treml, V. 2009. “Středoevropská Krajina v Holocénu.” *Geografické Rozhledy* 18 (5): 6–7.

Tyo, J Scott, Dennis L Goldstein, David B Chenault, and Joseph a Shaw. 2006. “Review of Passive Imaging Polarimetry for Remote Sensing Applications.” *Applied Optics* 45 (22): 5453–69. doi:10.1364/AO.45.005453.

Vaccari, Francesco Primo, Jacopo Primicerio, Claudio Belli, and Alessandro Zaldei. 2015. “Platforms for Precision Viticulture.” *Remote Sensing* 7: 2971–90. doi:10.3390/rs70302971.

Wackernagel, Marthis, Larry Onisto, Alejandro Linares Callejas, Ina SusanaFalfán López, Jesus Méndez García, Ana Isabel Suárez Guerrero, and Ma. Guadalupe Suárez Guerrero. 1997. “ECOLOGICAL FOOTPRINTS OF NATIONS.” MEXICO.

Wandinger, Ulla. 2012. “Introduction to Lidar,” 1–18. http://www.forestry.gov.uk/forestry/infd-6rvc9j.

Weng, Q. 2001. “A Remote Sensing – GIS Evaluation of Urban Expansion and Its Impact on Surface Temperature in the Zhujiang Delta , China.” *Int. J. Remote Sensing* 22 (10): 1999–2014. doi:10.1080/713860788.

Westoby, M. J., J. Brasington, N. F. Glasser, M. J. Hambrey, and J. M. Reynolds. 2012. “‘Structure-from-Motion’ Photogrammetry: A Low-Cost, Effective Tool for Geoscience Applications.” *Geomorphology* 179. Elsevier B.V.: 300–314. doi:10.1016/j.geomorph.2012.08.021.

WHO. 2015. “WHO | World Health Statistics 2015.” http://www.who.int/gho/publications/world_health_statistics/2015/en/.

Willer, H, and L Kilcher. 2010. *The World of Organic Agriculture Training Manuals for Organic Agriculture. Statistics and Emerging Trends 2010*. http://www.organic-world.net/fileadmin/documents/yearbook/2010/world-of-organic-agriculture-2010.pdf.

Wulder, Michael A., Joanne C. White, Samuel N. Goward, Jeffrey G. Masek, James R. Irons, Martin

Herold, Warren B. Cohen, Thomas R. Loveland, and Curtis E. Woodcock. 2008. “Landsat Continuity: Issues and Opportunities for Land Cover Monitoring.” *Remote Sensing of Environment* 112 (3): 955–69. doi:10.1016/j.rse.2007.07.004.

Xian, George, Collin Homer, and Joyce Fry. 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 (6). Elsevier Inc.: 1133–47. doi:10.1016/j.rse.2009.02.004.

Yang, Yang, Chunyang He, Qiaofeng Zhang, Lijian Han, and Shiqiang Du. 2013. “Timely and Accurate National-Scale Mapping of Urban Land in China Using Defense Meteorological Satellite Program’s Operational Linescan System Nighttime Stable Light Data.” *Journal of Applied Remote Sensing* 7: 073535. doi:10.1117/1.JRS.7.073535.

Zhou, Liming, Yuhong Tian, Somnath Baidya Roy, Yongjiu Dai, and Haishan Chen. 2013. “Diurnal and Seasonal Variations of Wind Farm Impacts on Land Surface Temperature over Western Texas.” *Climate Dynamics* 41 (2): 307–26. doi:10.1007/s00382-012-1485-y.

Zhu, Zhe, Shi Qiu, Binbin He, and Chengbin Deng. 2018. “Cloud and Cloud Shadow Detection for Landsat Images : The Fundamental Basis for Analyzing Landsat Time Series.” *Remote Sensing Time Series Image Processsing*, no. December 2017: 3–24. doi:10.1201/9781315166636-10.

Zolitschka, Bernd, Karl Ernst Behre, and Jürgen Schneider. 2003. “Human and Climatic Impact on the Environment as Derived from Colluvial, Fluvial and Lacustrine Archives - Examples from the Bronze Age to the Migration Period, Germany.” *Quaternary Science Reviews* 22 (1): 81–100. doi:10.1016/S0277-3791(02)00182-8.

10. Appendix - Biography

PERSONAL

Name David Moravec
Citizenship Czech

BELONGING

Since 2013 Department of Applied Geoinformatics and Spatial Planning,
Since 2017 Spatial Science in Environment and Ecology Research Group

EDUCATION

Czech University of Life Sciences Prague, Faculty of Environmental Sciences

2013 – Present PhD (Doctoral) degree - Applied and Landscape Ecology
2011 – 2013 Master's degree - Landscape Engineering
2008 – 2011 Bachelor's degree - Landscaping

TRAININGS

2017 Trans-Atlantic Training, Pécs, HU
2016 ENVI ESRI ARCDATA PRAHA CZ

ACADEMIC VISITS

2018 Universidad Politécnica de Madrid, Spain (5 weeks)
2017 Università degli studi Roma Tre, Rome (5 weeks)

TEACHING EXPERIENCES

Since 2013 Seminars of GIS, Computer Basics
Since 2016 Seminars of Remote Sensing

PROJECTS

2017 Urbanization impact on different aspects of bird diversity - Czech Science Foundation.

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

2017 influence of remote sensing data resolution in evaluating ecological measures - Czech University of Life Sciences Prague.

2017 Multitemporal analysis of change detection in central Italy - Czech University of Life Sciences Prague.

2015 Mitigation of impacts of wind farms on local climate - Czech University of Life Sciences Prague.

2014 Wind turbine impacts on near ground air temperature - Czech University of Life Sciences Prague.

2013 Design and calibration of modular autonomous station for the measurement of soil moisture and temperature conditions in vast point clusters - Technology Agency of the Czech Republic.