ISPRS Journal of Photogrammetry and Remote Sensing 115 (2016) 3–21

Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

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

Information from imagery: ISPRS scientific vision and research agenda

Jun Chen [a], Ian Dowman [b], Songnian Li [c], Zhilin Li [d], Marguerite Madden [e], Jon Mills [f], Nicolas Paparoditis [g], Franz Rottensteiner [h], Monika Sester [i], Charles Toth [j], John Trinder [k], Christian Heipke [h,*]

[a] National Geomatics Center of China, Beijing 100830, China
[b] Department of Geomatic Engineering, University College London, Gower Street, WC1E 6BT London, United Kingdom
[c] Department of Civil Engineering, Ryerson University, Toronto, Ontario M5B 2K3, Canada
[d] Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hong Kong
[e] Center for Remote Sensing and Mapping Science, Department of Geography, The University of Georgia, Athens, GA, USA
[f] School of Civil Engineering and Geosciences, Newcastle University, Newcastle upon Tyne NE1 7RU, United Kingdom
[g] IGN Research and Education, Institut National de l'Information Géographique et Forestière, Saint-Mandé Cedex, France
[h] Institute for Photogrammetry and GeoInformation, Leibniz Universität Hannover, 30167 Hannover, Germany
[i] Institute for Cartography and Geoinformatics, Leibniz Universität Hannover, 30167 Hannover, Germany
[j] Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, USA
[k] School of Civil and Environmental Engineering, University of New South Wales, Sydney, NSW 2052, Australia

ARTICLE INFO

Article history:
Received 15 May 2015
Received in revised form 18 September 2015
Accepted 21 September 2015
Available online 9 October 2015

Keywords:
Research agenda
Photogrammetry
Remote sensing
Spatial information science
ISPRS

ABSTRACT

With the increased availability of very high-resolution satellite imagery, terrain based imaging and participatory sensing, inexpensive platforms, and advanced information and communication technologies, the application of imagery is now ubiquitous, playing an important role in many aspects of life and work today. As a leading organisation in this field, the International Society for Photogrammetry and Remote Sensing (ISPRS) has been devoted to effectively and efficiently obtaining and utilising information from imagery since its foundation in the year 1910. This paper examines the significant challenges currently facing ISPRS and its communities, such as providing high-quality information, enabling advanced geospatial computing, and supporting collaborative problem solving. The state-of-the-art in ISPRS related research and development is reviewed and the trends and topics for future work are identified. By providing an overarching scientific vision and research agenda, we hope to call on and mobilise all ISPRS scientists, practitioners and other stakeholders to continue improving our understanding and capacity on information from imagery and to deliver advanced geospatial knowledge that enables humankind to better deal with the challenges ahead, posed for example by global change, ubiquitous sensing, and a demand for real-time information generation.

1. Introduction

1.1. Background

Information from Imagery was adopted as the tagline of the International Society for Photogrammetry and Remote Sensing (ISPRS) at its 19th Congress in Amsterdam in 2000. The ISPRS promotes the extraction and utilisation of information from imagery by encouraging and facilitating research and development in its areas of scientific activity, advancing knowledge through scientific networking, stimulating international cooperation, pursuing interdisciplinary integration, facilitating education and training, enhancing and exploring new applications, and developing public recognition of photogrammetry, remote sensing and spatial information science. Information from imagery, in ISPRS parlance, is obtained using the principles of remote sensing, photogrammetry and spatial information science:

Remote sensing *is the science and technology of capturing, processing and analysing imagery, in conjunction with other physical data of the Earth and the planets, from sensors in space, in the air and on the ground.* Remotely sensed observations of the Earth from airborne and space-borne sensors, in synergy with in-situ and hand-held measurements, provide the basis for mapping human and natural activities; for physical and empirically based process monitoring; for assessing and mitigating disasters; for identifying and assessing non-renewable resources; for monitoring temporal changes in weather, land and sea cover; and for many other

* Corresponding author.

http://dx.doi.org/10.1016/j.isprsjprs.2015.09.008
0924-2716/

applications. Spatial and semantic descriptions of objects, features and processes are derived from one-, two- and three-dimensional (3D) measurements, and the interpretation of their electromagnetic and acoustic signal attributes using active and passive optical, thermal and microwave instruments and sounding devices.

Photogrammetry *is the science and technology of extracting reliable three-dimensional geometric and thematic information, often over time, of objects and scenes from image and range data*. Resultant data can be used for the development of spatial databases and spatial information systems (SIS) in digital, graphical and image forms. The technology is employed for image-based three-dimensional measurements in mapping, engineering, heritage recording, forensic analysis, robotics, driver assistance systems, medical applications, computer gaming and other fields, where it provides geometric and semantic object information for populating spatial databases and for creating virtual reality scenes with real-life textured models.

Spatial Information Science *is concerned with the modelling, storage, processing, retrieval, application and communication of information with a spatial reference*. Employing concepts and methods from spatial information science is an essential step in the process of obtaining useful information from images, since typically the description and location of objects and processes, as well as temporal relationships between these physical objects, need to be integrated with socio-economic and other data for analysis, simulation, prediction and visualisation purposes. Spatial information science deals with, for example, spatial data mining, interoperability and data integration, visual analytics, spatio-temporal perspectives on big data, visualisation and generalisation, the Internet of Things, social networks, and human–computer interaction. It is applied in transportation planning and management, urban and infrastructure planning, land and resource management, smart cities, disaster management, environmental monitoring, public health, security, and in understanding many other natural and anthropogenic processes and phenomena.

It should be noted that the three topics overlap. Firstly, while photogrammetry is longer established, it is today regarded as part of the wider field of remote sensing. Nevertheless, for the sake of continuity, we will discuss both subjects separately in this paper with an emphasis on terrestrial and airborne images when referring to photogrammetry, and on satellite data when referring to remote sensing. Moreover, photogrammetry forms one of the foundations of modern computer vision (Förstner, 2009). Secondly, while spatial information science is sometimes understood to include data capture, and thus photogrammetry and remote sensing, we take the view here that spatial information science is mainly concerned with making use of the information acquired from images and stored in a database, in order to emphasise our focus on imagery and image exploitation. The spatial database can thus be perceived to form an interface between photogrammetry and remote sensing, on the one side, and spatial information science on the other.

1.2. Information from imagery

The importance of information from imagery has been widely recognised in the last decade (Li et al., 2008; Zell et al., 2012). The application of imagery is now ubiquitous, with the increased availability of very high-resolution satellite imagery, terrain based imaging and scanning, inexpensive sensors (e.g., smartphones) and platforms (e.g., unmanned aircraft systems), complemented by rapidly growing processing capacity and advancement in information and communications technology (ICT).

Aerial and satellite imagery has successfully been utilised in a variety of areas such as topographic mapping, urban planning, environmental assessment, forestry, precision agriculture, water resources and disaster monitoring. An increasing demand for reliable and current information from imagery has also been manifested in many societal benefits areas (SBAs), such as national mapping programs (Kelmelis et al., 2003), disaster and risk management (Altan et al., 2012), global environmental change studies (Reid et al., 2010; Pereira et al., 2013), and sustainability development (Hecht et al., 2012).

Terrain based imagery (also referred to as close-range or terrestrial imagery) have seen a similar increase in prominence, making major inroads into mobile mapping, industrial metrology, forensics, cultural heritage preservation, medical imaging, underwater measurement and the gaming and movie industries (Grün, 2008), in particular since the advent of unmanned aircraft systems (UAS) as new and flexible platforms. Such images are not used exclusively in the photogrammetric community, but also in many neighbouring disciplines, in particular in computer science and electrical engineering, and typically under different nomenclature, such as computer vision (Hartley and Zisserman, 2003) and robotics (Thrun et al., 2005). Today, the field is also linked to diverse applications such as automatic real-time visual perception, visual navigation, autonomous driving and ambient assisted living which use visual clues to tackle societal challenges such as mobility, health and ageing; it is an extremely active area of research and development.

Crowdsourcing, also known as volunteered geographic information (VGI), has added a new dimension to data acquisition. The Internet, and in particular the Geospatial (or Spatial) Data Infrastructure (GDI or SDI), has become key to nearly all aspects of geospatial data, from acquisition to processing, management and analysis in federated databases and data sharing via standardised web services. Digital globes such as NASA World Wind, Google Earth and Microsoft Bing Maps 3D are prominent evidence of these developments.

There are a number of scientific, technological and organisational issues related to information from imagery (Fig. 1). First of all, the *scientific issues* include an understanding of the properties of electromagnetic radiation and its interaction with the atmosphere and with objects, the fundamental principles and models for understanding and recognising spatio-temporal patterns in images, as well as the abstraction, modelling and representation of spatio-temporal objects and phenomena and their relationships. Concepts, theories and algorithms are continuously being developed and refined to tackle these scientific issues. Secondly, *technological issues* relate to a variety of instrumentation, tools and systems required to realise image acquisition, information extraction and spatial information services. Active and passive sensors, imaging platforms, digital photogrammetric workstations (DPWS), image processing and geographical information systems (GIS), and web-based services taking advantage of a fully developed SDI are among the modern day technologies employed to this end. Many technical issues remain to be solved for the design, testing, fabrication, and commercialisation of novel tools and systems, with increasing numbers of organisations and enterprises becoming involved in such activities. Thirdly, *organisational issues* need to be addressed to ensure that the aforementioned science and technology are applied to meet societal or domain needs, such as topographic mapping, civil engineering, heritage documentation and protection, resource inventory, disaster and environmental monitoring, autonomous driving, visual navigation, robotics, industrial measurement and medical imaging. Significant efforts have been, and should continuously be, devoted to socio-economic and operational aspects to ensure that the information derived from imagery is being firmly embedded in policy-making processes, public uptake and commercial exploitation. Such issues include the formulation of technical standards, the development and re-engineering of workflows, the collection, processing, quality

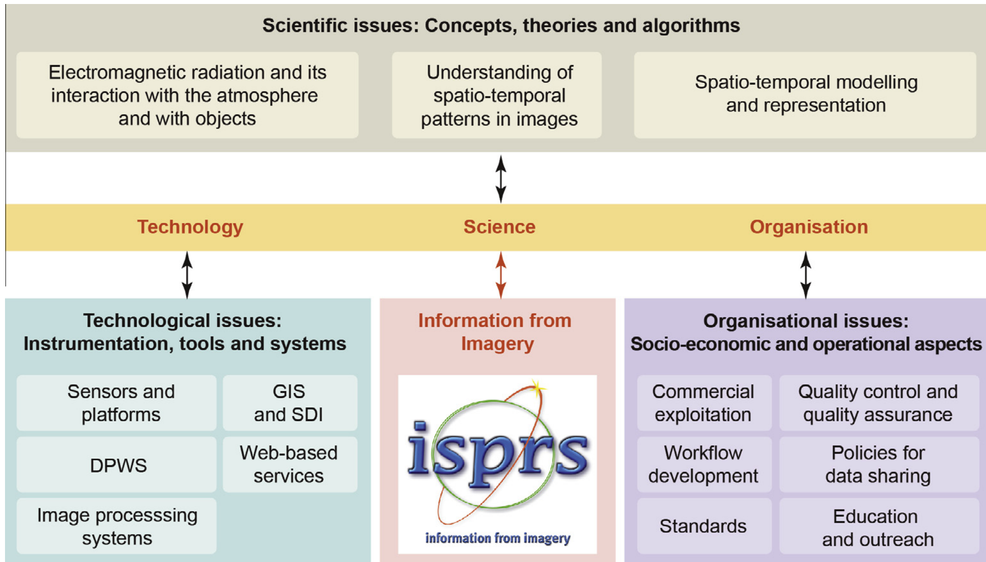

Fig. 1. Scientific, technological and organisational issues relating to information from imagery.

control and quality assurance of massive datasets, and policies for data usage, sharing and dissemination, as well as education and outreach.

1.3. Role of the ISPRS

It is beneficial to closely examine recent developments in these scientific, technological, social and organisational aspects from time to time, so as to provide a relevant scientific vision for the community. Indeed, the ISPRS has had a long tradition in doing so. During each quadrennial Congress, a number of resolutions have been formulated and approved by the ISPRS General Assembly (GA) to set the course of scientific activities for the succeeding four-year term (Konecny, 1985; Trinder and Fritz, 2008). Such resolutions normally address new or rapidly evolving topics and are succinctly enunciated for reference on the ISPRS website. For the areas of scientific activity within ISPRS, a set of Terms of Reference (ToR) is also developed to guide ISPRS Commissions and Working Groups. In 2008, the ISPRS published a Congress Book with approximately 40 review and overview papers to summarise the latest progress in scientific activities and to project future directions (Li et al., 2008). In 2010, in parallel with its Centenary celebrations, the ISPRS reviewed its strategic plan to ensure that the role of imagery is understood and that the derived information is used to its best advantages for all of society. As a result of the strategic review, the continuous identification of new challenges and the development of a clearer scientific vision has been emphasised as one of the primary objectives and tasks for the ISPRS and its officers.

This paper continues the traditions, presenting an overarching scientific vision for information from imagery and setting out a forward research agenda for the Society. The contents are based on the synthesis of the resolutions from the 22nd ISPRS Congress in 2012, the ToR of the Technical Commissions for the period 2012–2016, keynote presentations from the 2012 Congress, 2014 mid-term Symposia and other recent ISPRS meetings, as well as further materials published in relevant disciplines. The vision and strategies articulated here are also derived from numerous discussions within ISPRS Council and consultation with Commission Presidents, the International Science Advisory Committee, the International Policy Advisory Committee, as well as numerous experts in the international community.

The remainder of this paper is organised as follows: Section 2 examines new demands and challenges facing our field with an emphasis on earth observation from space, noting that similar requirements exist also for the other areas of photogrammetry, remote sensing and spatial information science. The state-of-the-art of information from imagery and current trends are reviewed in Section 3. Scientific research topics for the future are discussed in Section 4. Section 5 summarises the conclusions reached in the paper.

2. Major challenges

Humankind is currently in an era in which the spatial sciences play a prominent role in preparing information for the general public. There are increasing demands on the fitness for purpose of spatial information, as humankind faces a number of unprecedented grand challenges, for example in climate change (Schiermeier, 2013) and sustainable development (Hecht et al., 2012), but also in mobility, health and safety and security. Key factors in dealing with these grand challenges are to provide high-quality information, to enable advanced geospatial computing, and to support collaborative problem solving (Fig. 2). These factors are further discussed in this section, focussing on an earth observation perspective. As the first two factors have a scientific and technical background, they are also the focus of Sections 3 and 4 of this scientific vision paper.

2.1. High-quality spatial information

High-quality (i.e., timely, complete, thematically correct as well as geometrically accurate and reliable) information from imagery has always been a key requirement for any application. For instance, the understanding and forecasting of earth system processes require a variety of reliable information from imagery about the Earth, its environment and other physical objects and processes (Suresh, 2012). Such information may concern topography, land cover and land use, cadastre, population and pollution distribution, etc. (UN-GGIM, 2013). Different user communities generally have their own specific sets of variables to be derived from imagery, for example, the Essential Biodiversity Variables (EBVs) for the ecological community, land cover changes for the climate change community and detailed topographic and semantic infor-

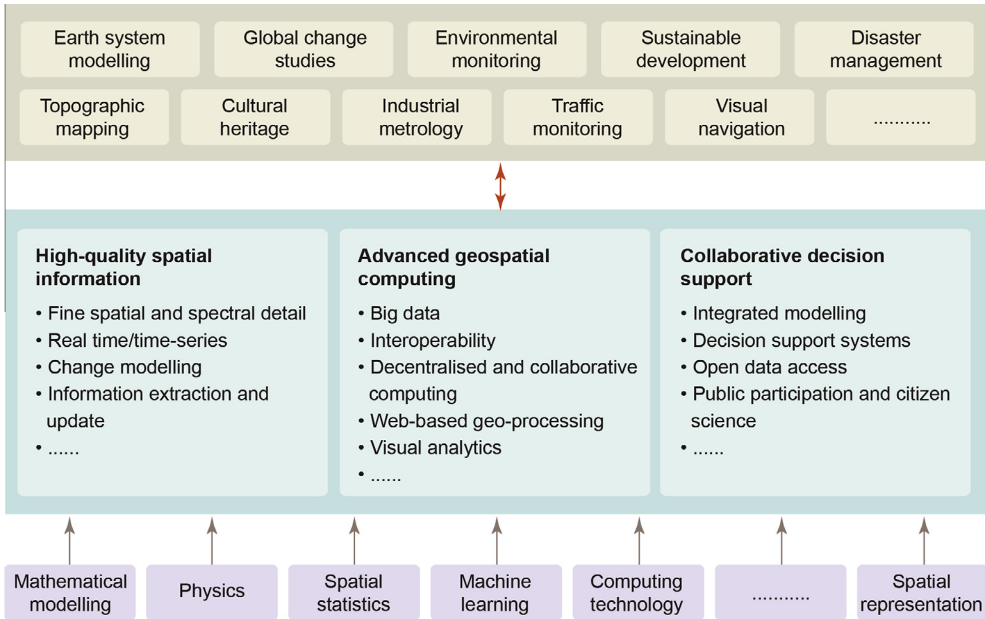

Fig. 2. Major challenges faced by the ISPRS community, with applications at the top of the figure, challenges in the middle and supporting disciplines below.

mation for national mapping agencies and government. A number of national, regional and international programs and initiatives have been launched to optimise the exploitation of imagery. Such initiatives aim to provide the right information, in the right place, at the right time, to the right people to make appropriate decisions (Pereira et al., 2013; Whitcraft et al., 2015).

High-quality and high-resolution information is needed for various applications such as coastal monitoring (Addo et al., 2008) and glacier studies (Kunz et al., 2012). This data is often used not only for monitoring but also for calibrating and validating environmental models. Spatial resolution in earth observation from space has been continuously improved, i.e., from 80 m for Landsat 1 in 1970s, to 30 m for Landsat 7 in 1990s, and to the current 0.31 m for WorldView 3 in 2015; from aircrafts and UAS cm-level images can be obtained. As a result, higher-resolution geospatial data products have been developed at local, national and global scale. One recent example for a global dataset is Globaland30 (global land cover dataset of 30 m resolution, Chen et al., 2014a), donated by China to the United Nations in 2014. Similar goals are being pursued with the European INSPIRE initiative which strives to harmonise high-resolution topographic data across the continent. Further, land cover information at 1–2 m resolution has been requested for urban studies (Belgiu et al., 2014). Such a shift to fine resolution represents a major challenge scientifically, technically and organisationally.

The Earth is a dynamic planet with changes taking place at different time scales. Monitoring such changes and mapping their impacts requires image sequences so as to collect time-series information (Kuenzel et al., 2015). For example, from a weather–climate-hazards viewpoint, a seamless prediction system should be able to use imagery from recent hours, seasons and decades, from local to global, for all kinds of hazards (McBean, 2014). Some new observation systems have come into operation, and many more are planned, for the monitoring and modelling of the dynamic planet. Extraction of change information in time-series from the copious amounts and types of data to assess impacts on a range of social, economic, political, and environmental issues at all scales leads, and thus using all available imaging platforms, to questions which today do not have a reliable answer and thus need further research to be carried out.

The same is true for processing and analysing terrestrial data. With the advent of multi-sensor systems, including digital frame and video cameras, laser scanners and positioning/navigation devices, high-frequency image sequences are now captured from UAS and mobile mapping vans at normal traffic speed. In particular UAS, which constitute a genuine enabling technology, promise to offer innovative and flexible solutions to many of the issues raised in this paragraph, as long as the project area is not too large. At the same time they have their own research challenges, e.g., when it comes to constellation flights and decentralised computing, but also in terms of security and data privacy. While automatically interpreting images is a formidable task in its own right (see also Section 3), deriving meaningful and high-quality information from these large datasets presents additional specific research problems which are being tackled using principles from, for example, pattern recognition and machine learning.

2.2. Advanced geospatial computing

With the rapid advances in remote sensing and crowdsourcing, as well as ground-based sensor networks and computational simulation, highly heterogeneous data of very different origins are being produced, accessed, analysed, integrated, stored and retrieved daily (Conti et al., 2012). This implies that we are entering a data-intensive world or an era of so-called big data, and are facing another challenge – advanced geospatial computing (Bryan, 2013). Since analysis must often make use of different datasets, geometric and semantic interoperability of these datasets needs to be ensured (McInerney et al., 2012). Ideally, a web-based spatial information platform able to access federated databases would facilitate the use of these diverse and distributed datasets. In this regard, research and development are needed to solve such key issues as automated cross-ontology translation and interoperable web services.

New computational techniques and tools are in demand for filtering extraneous information and revealing hidden patterns. Often, this challenge needs to be solved in a collaborative setting, calling for decentralised computing. One critical issue is whether or not the algorithms and models already developed could meet with the operational or experimental setting (Hansen and

Loveland, 2012). The other is whether or not we can have a flexible deployment and integration of existing data analysis algorithms and models. Based on open standards such as those of OGC, the processing algorithms and models can be encapsulated and exposed as Web Services in a flexible, distributed architecture. An example is the Group on Earth Observation (GEO) Model Web initiative (Nativi et al., 2013). This makes it possible to discover the desired algorithms and models from web service registries and repositories, and to re-use them by combining them into complex workflows through service composition and executing them over a distributed architecture (McInerney et al., 2012; Zhao et al., 2012).

Many current visualisation systems are domain- or application-specific and require a certain commitment to understand and to learn how to use them, which sometimes hampers their use. New animation and interaction tools such as those being developed in visual analytics (Andrienko et al., 2014) are needed to enable better analysis and enhanced understanding of the massive and dynamic datasets (Hey and Trefethen, 2005).

2.3. Collaborative decision support

As many problems involving spatial information are rather complex, inter-disciplinary and cross-border cooperation, as well as advanced decision support systems are in demand. An example of inter-disciplinary collaboration is the preparation of a post-2015 development agenda, led by the UN, for implementing a set of Sustainable Development Goals (SDGs) (Hecht et al., 2012). Since sustainable development has economic, environmental and social dimensions, a mix of disciplinary and interdisciplinary research on "the future we want" has witnessed a transition from being dominated by the natural sciences towards involving the full range of natural, engineering and social sciences (Pereira et al., 2013; Kauffman and Arico, 2014). Another example is the Future Earth program of the International Council of Science (ICSU), which aims to mobilise the international scientific community around a focused decade of research to support sustainable development in the context of global environmental change (Reid et al., 2010; O'Riordan, 2013). ISPRS works with sister societies, particularly through ICSU and the Joint Board of Geospatial Information Societies (JBGIS) to contribute to this goal.

From the technical point of view, systems are in demand for presenting observational evidence, generating policy narratives, and framing sets of assumptions during policy decision making (Pielke et al., 2011; Schubert et al., 2015). It is often necessary to discuss policy issues in the context of spatially referenced information, empowered by computer-supported cooperative work (CSCW) technologies, or groupware, to enable policy makers and the public (or citizens) to present their perspectives, solve spatial disputes, and take and implement decisions. In many cases, an integration of sensors, domain specific analysis models and monitoring capabilities is needed.

3. State-of-the-art in information from imagery

In the last few years, we have witnessed significant scientific and technological progress in extracting information from imagery. Key topics include the development of digital aerial cameras, unmanned aircraft systems (UAS) as new flexible platforms, automatic orientation and dense matching of multi-view images, image sequence analysis, automated processing of airborne, terrestrial and mobile laser scanning (lidar) data, very high-resolution optical and radar space sensors, small satellites and satellite constellations, as well as geosensor networks. Other relevant developments include crowdsourcing, linked and big data, federated spatial databases, visual analytics, distributed web-based information services, spatial data infrastructures, as well as open spatial science. These core topics have been augmented by developments in related technologies such as global navigation satellite systems (GNSS) and inertial surveying.

In this section, we summarise the state-of-the-art in research into the extraction of information from imagery. We start with image acquisition, followed by image orientation, surface reconstruction and thematic information extraction, change detection, global mapping, and then come to spatial data modelling and analysis, visualisation and web-based services (Fig. 3). Parts of this sequence constitute the traditional processing chain of topographic data acquisition from images, while other processing sequences are obviously also feasible.

3.1. Image acquisition

Image acquisition has experienced phenomenal developments in the past two decades, evidenced by an unprecedented proliferation of imaging sensors as well as platforms. Until the millennium, large format film-based aerial cameras represented the workhorse of airborne photogrammetry; today, a large variety of active and passive imaging sensors is used in production on platforms, ranging from tripods, through UAS to satellites. Furthermore, there has been a paradigm shift in image acquisition, as the model of integrated sensors has replaced the long-standing single imaging sensor based approaches. Georeferencing sensors, including integrated GNSS and inertial measurement unit (IMU) systems, are widely used devices to support the orientation of either one or, more typically, multiple imaging sensors.

With the advancement of imaging sensor technologies and general hardware developments, faster image acquisition rates are easily available and the recording of large amounts of data is feasible, producing excellent quality geospatial data (Cramer, 2011). Combined with an increasing number of platforms, image data can be acquired with higher repetition rates, providing better temporal resolution, as shown by the tendency to move from three to four dimensional (3D plus time) spatial data structures. For example, UAS can provide products that meet all the requirements of national mapping (Cramer, 2013), as well as applications such as coastal and glacial monitoring, and monitoring of vegetation growth on a daily basis. Similarly, new satellite constellations can provide daily (or even multiple times a day) image coverage, for example, to monitor natural disasters or traffic flow. In addition, higher imaging rates allow for increased image overlap, thus resulting in better feature extraction performance, such as point cloud generation from multi-stereo imagery. High-speed mono and stereo cameras are increasingly being used in the automotive industry to record dynamic scenes, e.g., for car safety investigations; they are also in use in sports.

Following the introduction of active sensors some decades ago, we now find that active and passive imaging sensors have more or less the same market share of airborne imaging, characterised by large format digital aerial cameras and lidar systems, while airborne interferometric SAR (InSAR/IfSAR) represents a niche market. On satellite platforms, passive multispectral sensing is the dominant player, though SAR systems have shown remarkable developments and provide a rapidly increasing volume of global geospatial data (Krieger et al., 2007; Zink et al., 2014).

A recent trend in image acquisition has been the increasing use of consumer-grade imaging sensors, such as webcams and smartphone cameras. Whilst these sensors have been around for more than a decade, their performance level, in terms of image quality and transfer speed, was too modest to support massive use until a few years ago. Since these devices are ubiquitous, and often quite accurately georeferenced, the volunteered geographic information

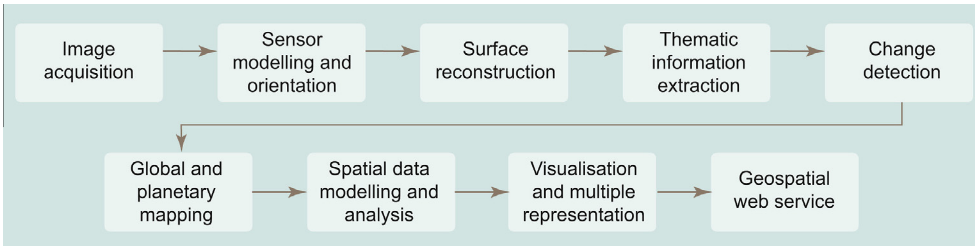

Fig. 3. Active research areas for information from imagery.

(VGI, Sui et al., 2013) they gather arguably forms the largest volume of current geospatial data today. While these crowdsourcing approaches are far from mainstream mapping, such data streams are already becoming a prime source of imagery for emergency situation monitoring and management, as well as applications such as cultural heritage documentation (Goodchild and Glennon, 2010). Similarly, the number of surveillance cameras is steadily growing, and they can also effectively support human geography related applications. This raises challenges in handling the vast quantities of data, extracting useful information from such sources, taking into account the differences in data quality and also in data privacy.

The separation between close-range and aerial/space photogrammetry, which was very clear a few decades ago, has become increasingly blurred, primarily due to two factors. First, aerial and space campaigns have become much more diverse with less- or non-standardised sensors including oblique imagery, multiple (and changing) overlap, and direct sensor orientation. Second, imagery is increasingly combined with range information from lidar, since integration happens along similar lines for close-range and aerial approaches.

Another notable tendency is that the differences in the characteristics between airborne and satellite optical imagery are decreasing, as recently launched high-resolution commercial satellites can acquire data at spatial resolutions as high as 30 cm ground sampling distance (GSD, Dowman et al., 2012), which was once the typical resolution for the majority of airborne imagery. In a similar trend, high-performance aerial cameras can deliver images at the 5 cm GSD level (Sandau, 2009). Yet the use of satellite imagery is gradually increasing at the cost of passive airborne imagery, as many applications do not necessarily require high-spatial resolution imagery.

3.2. Sensor modelling and orientation

The rapid development of digital sensors in recent years has significantly improved the quality of image and range data (much higher signal to noise ratio and much larger dynamic range), and has dramatically increased the capacity to acquire highly overlapping stereo images, leading to a higher level of redundancy in observations. These advantages have resulted in the development of much more robust algorithms and methods for the orientation of image and range sensors (also called pose estimation) and for surface reconstruction.

Sensor modelling and geometric calibration is generally well understood (Remondino and Fraser, 2006), while radiometric calibration (Honkavaara et al., 2009) and a detailed consideration of environmental effects still hold a number of unsolved questions, the latter in particular for range sensors, since atmospheric conditions influence the speed of light much more than the direction of light rays. Image sequence exploitation in 3D requires also temporal synchronisation; a solution is, for example, given by Raguse and Heipke (2009). Generalised cameras, i.e., those that do not follow the laws of perspective, have long been employed for rigorous geometric modelling in photogrammetry and remote sensing, an example is the use of multiple line cameras for topographic (Hofmann et al., 1982) and planetary work (Spiegel, 2007); models for fisheye lenses were, for example, described in Abraham and Förstner (2005). Models for generalised cameras are also discussed in the computer vision literature (Grossberg and Nayar, 2001).

Automatic image orientation has been a very active field in the photogrammetric community for a long time. Image orientation aims at reconstructing the coordinates of the perspective centre and the viewing direction during image capture (and sometimes also the interior orientation parameters) of a potentially very large set of unordered or ordered images with short or wide base lines. Different approaches have been proposed and developed, including bespoke, precise automated solutions of the type adopted by vision metrology systems in industrial measurement. More recently, it has also become very prominent in the computer vision (structure from motion, or SFM) and the robotics (simultaneous localisation and mapping, or SLAM) communities with various strategies now commonplace. Such approaches have generated renewed interest and stimulated activity in imaging methods within a wide variety of application areas ranging from cultural heritage to earth sciences.

Different noticeable advancements in automated image orientation can be distinguished: one is the development of invariant feature detectors, also called interest point operators, such as the Förstner and Gülch (1987) and Harris and Stephens (1988) operators, scale-invariant feature transform (SIFT, Lowe, 2004) and speeded up robust features (SURF, Bay et al., 2008). Another is the development of new matching strategies for interest points across images, and closed-form techniques to estimate an initial relative pose between pairs of images (Nistér, 2004; Frahm et al., 2010; Mayer, 2014). Blunders typically occurring in automatic matching are detected using random sample consensus (RANSAC)-type algorithms (Fischler and Bolles, 1981). For homogeneous and high-accuracy requirements, a bundle adjustment is usually performed as the final step of image orientation.

Range sensor orientation utilises the same mathematical concept of 3D coordinate transformations, but the pose is computed based on matching individual 3D point clouds, potentially augmented by signalised ground control features, typically spheres or planar surfaces (Brenner et al., 2008). Calibration of range sensors can be challenging for high-precision, but in general solutions are available (Lichti et al., 2011). A popular algorithm for point cloud matching is the iterative closest point algorithm (ICP, Besl and McKay, 1992) and its derivatives; different solutions exist for automatically measuring the positions of the ground control features in the point cloud dataset. Solutions for the combined pose estimation of image and range data have also been suggested and are in use today.

3.3. Surface reconstruction

After bundle adjustment, a sparse set of 3D coordinates of the matched interest points across the views is available. This point set is often then used as an initial solution for a pixel-wise surface reconstruction (also called "dense" reconstruction, i.e., one depth or one elevation is generated per pixel) by matching the images employing constraints derived from epipolar geometry. Various reconstruction approaches have been developed, with energy-based methods (Pierrot-Deseilligny and Paparoditis, 2006; Hirschmüller, 2008; Furukawa and Ponce, 2010; Strecha et al., 2010; Bulatov et al., 2011) providing the best results to date. Such methods aim at finding the best global solution (i.e., the best surface) by minimising the weighted sum between a data term describing the local matching costs and a regularisation term evaluating the global plausibility of the surface shape, e.g., in terms of smoothness and piecewise continuity. The solutions are typically derived using algorithms from graph theory or dynamic programming. In particular, semi-global matching (SGM, Hirschmüller, 2008) has been widely adopted, both in the photogrammetric community and beyond (Gehrig et al., 2009). The majority of such methods were developed for close-range applications with large depth differences and are, therefore, also particularly well suited for aerial and satellite imagery of urban scenes with significant height discontinuities (Haala, 2011).

The reconstructed surfaces are often used together with image brightness information to ease the 3D understanding of the scene and for thematic information extraction. The optimisation-based surface reconstruction methods allow the reconstruction of 3D details as small as the size of the structuring elements on which the similarity scores are calculated. For instance, when very high-resolution (e.g., 5–10 cm) aerial imagery is used, the superstructures of roof tops (such as dormer windows, chimneys or terraces) can be reconstructed (Brédif, 2010). From such high-quality Digital Surface Models (DSMs), true orthophotos can be generated by merging the centre parts of the rectified images. Quite often, optimisation-based techniques are employed to find the best combination and stitching between all centre parts of corresponding images. The remaining artefacts of this process are often erased by blending techniques applied to the stitching areas. However, the quality of such orthophotos can be inferior in areas close to 3D discontinuities (e.g., building limits), since pixel-based matching techniques cannot render 3D discontinuities in a clean way without explicitly taking these discontinuities into account in the matching process.

3.4. Thematic information extraction

Thematic information extraction has a long history in photogrammetry and remote sensing (Mayer, 2008; Vosselman, 2009). On the one hand, detection and reconstruction schemes for individual objects, mostly topographic, from high-resolution images and 3D point clouds have been developed, e.g., for buildings (Rottensteiner et al., 2014) and roads (Gerke and Heipke, 2008). Image and point clouds have often been processed separately (partly because only one dataset was available), but approaches for combined processing strategies exist. On the other hand, classification methodologies using, e.g., maximum likelihood classification for satellite images, dating back to the 1970s, have been employed for this task. While classification does not deliver objects per se, the results typically serve as the basis for the detection and delineation of individual objects. More recently, modern discriminative methods for classification such as AdaBoost (Chan and Paelinckx, 2008), Support Vector Machines (SVM, Mountrakis et al., 2011) and Random Forests (RF, Gislason et al., 2006) have been applied in photogrammetry and remote sensing. Probabilistic approaches based on graphical models such as Markov Random Fields or Conditional Random Fields (CRF) have been adopted for context-based classification with such applications as façade classification (Yang and Förstner, 2011), point cloud labelling (Niemeyer et al., 2014a), segmentation for 3D building reconstruction (Lafarge and Mallet, 2012) and multi-temporal classification of remote sensing images (Hoberg et al., 2015). The behaviour of these classification methods is well understood, and they deliver reasonable accuracy in a wide range of applications.

High-level vision tasks for scene understanding can also rely on graphical models, but they require other object representation schemes and/or a more complex layout of the underlying graph. For instance, part-based models decompose an object into its components, whose relative alignment can be learned from images (Felzenszwalb et al., 2010) when taking into account 3D CAD models (Zia et al., 2013). Object parts detected in an image can mutually support each other and thus give clues for the detection and localisation of the entire object, which results in a correct detection of objects even if they are partly occluded. Hierarchical models (Yang and Förstner, 2011) integrate the scale-space behaviour of objects. Marked point processes can consider a strong object model in a stochastic framework based on statistical sampling. They try to find the most probable object configuration according to the models of the shape and relative alignment of the individual objects (Tournaire et al., 2010; Brédif et al., 2013). In procedural-based modelling methods, the model knowledge about the objects can also be represented by grammars, used in combination with statistical sampling, for instance, to understand the structure of a façade (Ripperda, 2008) and to model deciduous trees in image sequences (Huang and Mayer, 2007). Procedural-based modelling can also be used to accelerate the productivity of semi-automatic image-based modelling, where the model knowledge allows the reconstruction of further parts of an object based on a minimal set of measurements made by the human operator. This approach is particularly useful for on-line checking and refinement by superimposing the reconstruction result to the images (Cura et al., 2015).

The analysis of image sequences has rendered possible the detection and tracking of moving objects from images of static or moving cameras, single or in stereo camera systems. Very dense motion fields can be derived from mono or stereo image sequences in real-time (Rabe et al., 2010) using an Extended Kalman Filter (EKF) to connect different scenes over time. Segmentation of such motion fields can be employed to detect moving objects in image sequences from moving platforms, e.g., cars (Kitt et al., 2010). This methodology has achieved such a degree of maturity that it is implemented by the car industry in driver assistance systems. An alternative approach is to follow the tracking by detection paradigm, where object detectors are applied to single frames to track them over time. Examples include pedestrian detection from a moving stereo rig (Schindler et al., 2010) and the detection of moving objects in monocular image sequences (Wojek et al., 2010; Klinger et al., 2014). Particle filters can be used as an alternative to an EKF to model the temporal behaviour of objects (Breitenstein et al., 2011). Again, graphical models provide a probabilistic framework for many of these applications.

3.5. Change detection

The value of geospatial information depends critically on its consistency with respect to the real world, and this has stimulated intensive research on change mapping and monitoring, as well as their applications at both national and global scales. New change detection techniques continue to be developed (Lu et al., 2014). Examples include integrated change detection and classification methods (Chen et al., 2012), spectral gradient difference based (SGD-based) approaches (Chen et al., 2013a), object-based change detection (Hussain et al., 2013), 3D change detection (Qin and Grün, 2014), phenology-based seasonal trend analysis (Li and Wu, 2014; Parmentier and Eastman, 2014), and random field model-based approaches (Helmholz et al., 2012; Benedek et al., 2015). These all aim at effectively employing different features inherent in the images and ancillary data for reducing so-called pseudo changes, i.e., changes in appearance which are not relevant for the task at hand.

Crowdsourcing data collection is another active research topic (Goodchild and Glennon, 2010; Heipke, 2010), often employed for change detection. Both volunteers and professionals can collect and analyse change information using web-based platforms. Geo-Wiki is such an on-line platform for collecting land cover information from crowdsourced images (Fritz et al., 2012) and it has been applied in the generation of land cover maps (See et al., 2015). Crowdsourcing geographic information has been collected for early response and crisis management (Stange and Bothe, 2013). GNSS trajectory data from car navigation systems and smartphones has been used to predict urban traffic conditions, extract road network geometry (Zhang et al., 2010; Cao and Sun, 2014) and perform human mobility analysis (Huang et al., 2015). In this context, images (e.g., from Flickr or Instagram) are often used in terms of their metadata (namely, the coordinates and the annotation text) and not necessarily with respect to the image content, which would require image interpretation.

At the national level, rapid updating of geospatial databases has become a top priority of national mapping agencies (Heipke et al., 2008; Chen et al., 2014b). A recent survey conducted by ISPRS with the help of the United Nations Global Geospatial Information Management group (UN-GGIM) shows that some UN member states update their geospatial databases once per year and many other countries have succeeded in completing or updating their mapping requirements at the critical scales 1:5000 to 1:50 000 (Konecny, 2013). There are, however, many other countries that need to improve their cycle of national mapping database updating.

3.6. Global and planetary mapping

Global (Ban et al., 2015) and planetary (Heipke et al., 2007; van Gasselt and Nass, 2011) mapping and monitoring are other current topics. Efforts have been expended on the derivation and supply of global geoinformation, such as global digital elevation models (DEMs, Robinson et al., 2014), burned area mapping (Mouillot et al., 2014), surface roughness (Chen et al., 2014c), forest cover change (Hansen et al., 2013), and ecosystem service values (Li and Fang, 2014). Several global monitoring initiatives have been launched or discussed, e.g., for terrestrial species (Schmeller et al., 2015), habitat (Lucas et al., 2015), agriculture (Whitcraft et al., 2015) and climate-induced vegetation disturbances (McDowell et al., 2015), along with the related monitoring technologies (Aschbacher and Milagro-Pérez, 2012; El-Sheimy et al., 2015). A noticeable development is the Globeland30 product (Chen et al., 2015) which constitutes the world's first 30 m global land cover data for the years 2000 and 2010 and comprises ten types of land cover. A so called pixel-object-knowledge based approach was developed to achieve a compromise between effectiveness (accuracy) and efficiency (level of automation) with the overall classification accuracy being higher than 80%.

3.7. Spatial data modelling and analysis

Modelling geographical reality and spatial phenomena of interest in digital form is the basis for the construction of geospatial databases, the development of digital earth, virtual globes and smart cities (Wise, 2000; Craglia et al., 2012). Spatial analysis is the further interpretation of the digital model to derive meaningful knowledge or to explain the geographic phenomena linked to locations on the Earth surface (Miller, 2004). The characteristics of geographic space have significant impact on the content and performance of spatial data modelling and analysis.

During the past few years, 3D modelling has become common practice for many larger cities in the world. Many algorithms and data structures were developed for improving the efficiency and quality of city modelling. These include CityGML for semantic queries (Kolbe, 2009; Gröger and Plümer, 2012), octrees for huge point clouds (Elseberg et al., 2013) and flexible primitives for 3D building modelling (Xiong et al., 2015).

Spatio-temporal data modelling aims at representing objects and events with continuous movements and status changes (van de Weghe et al., 2014), and to manipulate dynamic processes such as traffic vehicle flow or individual person movement (Fang et al., 2012). These approaches have been applied in many fields, such as identifying sources and spatial patterns of disease and injuries (Cusimano et al., 2010), real-time disaster response, mitigation and prevention (Ren et al., 2007), monitoring of natural resources and pollutants (Obradovic et al., 2010), landmark-based pedestrian navigation (Fang et al., 2012) and other location-based services (Conti et al., 2012).

Scale is another fundamental topic in spatial data modelling. Techniques have been developed for multi-scale modelling of various types of spatio-temporal data such as trajectories and point process data (Bereuter and Weibel, 2013; Popa et al., 2015). Scale effects have also been modelled for terrain analysis based on DEMs (Gao et al., 2012), geographic analysis of health data (Lee et al., 2014), species distribution analysis (Moudrý and Šímová, 2012), the measurement of landscape structure (Ricotta and Carranza, 2013) and dynamic land use change simulations (Kim, 2013).

Geospatial big data has become a focus of spatio-temporal analysis in the past few years, because of the large amounts of data being acquired by new sensors and new data sources such as social media, GNSS-trajectories gathered by mobile phones (Sester et al., 2014; Hahmann and Burghardt, 2013) and sensor networks (Devaraju et al., 2015). The data collected with such systems has the properties of being abundant, streaming, continuously changing, mostly geo-referenced, and being (partially) unstructured. Exploitation of the implicit information in data from these sources is a challenge, which offers huge opportunities due to its real-time characteristics. Mining techniques have been developed particularly for VGI (Hagenauer and Helbich, 2012), trajectories (Liu et al., 2012), social media data (Majid et al., 2013), road networks (Niu et al., 2011) and movement data (Bleisch et al., 2014). A particular focus lies on spatio-temporal big data. These included probabilistic space–time prisms of moving objects; time uncertainty for activity-travel scheduling, detection and description of dynamic activity patterns with large-volume trajectory data; and modelling and exploring spatio-temporal big data.

Spatial relations have been another topic of interest. Discussions on topological and direction relations have been noticed, such as decentralized querying of topological relations between regions (Jeong and Duckham, 2013) and identification of a unifying framework for directional relations and frames of reference (Clementini, 2013), a complete classification of spatial relations using the Voronoi-based nine-intersection model (Long and Li, 2013), an Euler number-based computation model for topological relations (Zhou et al., 2013), and temporal logic and operation relations for representing change knowledge (Chen et al., 2013b).

3.8. Visualisation and multiple representation

Visualisation has always been an important aspect of spatial information. On-line 3D atlases have been discussed by, for example Sieber et al. (2012), these merge the big trends of 3D mapping, on-line and mobile applications with cartographic design and atlas-specific functionality. Multi-perspective 3D panoramas (Pasewaldt et al., 2014) and interactive focus maps (van Dijk and Haunert, 2014) have been developed. Visualisation techniques have been applied to explore various types of spatial data such as human mobility data (Kwan et al., 2013), Hepatitis A and E outbreaks (Hughes et al., 2014), land use change (Vaz and Aversa, 2013), and urban heat island data (Danahy et al., 2015).

The design of effective maps has recaptured research attention in recent years (Li, 2012). Information theory (Bjørke, 2012; Ruiz et al., 2012) and multi-objective optimisation (Xiao and Armstrong, 2012) have been employed for map design. Usability is another issue in visualisation (Joshi et al., 2014), which includes the effectiveness and efficiency of visualisation techniques. With effectiveness in mind, map-alike representations such as schematic maps and cartograms (Buchin et al., 2014) are emerging. In particular, a number of methods for the automated generation of schematic maps (Ti and Li, 2014) have been developed.

In multi-scale representation of maps, research is centred on the "scale-driven" paradigm (Li, 1996). Noticeable developments are fully automatic generalisation processes for map production (Stoter et al., 2014), 3D-generalisation, progressive transmission (Sester and Brenner, 2009; Kada, 2014), integration of data of different scales, and hierarchical techniques for representation of road networks (Li and Zhou, 2012; Zhou and Li, 2014; Benz and Weibel, 2014).

3.9. Geospatial web services

Geospatial web services allow on-line access to, and processing of, maps and geospatial data stored on one or more geospatial data servers. Their utilisation has already had a profound impact on managing geospatial knowledge, structuring and automating workflows within and across organizations that deal with location-based information and intelligence, and bringing geospatial data into people's daily life through geobrowsing or the geospatial web. Recent research efforts have been directed towards smart or intelligent geoprocessing on the web, which involves semantics-enabled web services, intelligent service discovery, dynamic and automatic service chaining and composite workflows, and service load balancing, ideally based on personalised user or application preferences (Li et al., 2011; Veenendaal et al., 2014).

Numerous developments have exemplified the advances in the field. Mapping services have emerged as the new platform to allow a multitude of users to post, consume, compare and analyse data collaboratively, facilitating the process of geospatial data crowdsourcing or VGI (Han et al., 2015; Liu et al., 2015). This has provided automatic, analytical, shared and open source web and cloud services for geospatial information. In handling geoprocessing services, both syntactic and semantic approaches, and web service and process modelling languages have been studied. The emergence of the 3D internet, with a wide availability of accessible web-based solutions (that exploit aforementioned developments in sensor orientation, surface reconstruction, etc.) such as Microsoft Photosynth, Autodesk 123d Catch, and virtual globes (e.g., Google Earth, Microsoft Bing Maps 3D), has enabled easy generation and visualisation of 3D data from various data sources. Cloud computing has played an active role in web mapping and GIS because it links disparate computers to form one large infrastructure, harnessing unused resources and forming an integral platform (Yang et al., 2014). The concept of linked data, which is often considered as part of the semantic web, has been explored to connect geospatial data as well as other related data that were not previously linked using Uniform Resource Identifier (URI) and Resource Description Framework (RDF) over the web (Bizer et al., 2009; Abbas and Ojo, 2013).

Despite the rapid development of geospatial web services, there remains a variety of issues pertinent to data, technology and organisational aspects that challenge researchers, developers, professionals and public users in the field (Li et al., 2011). As more and more geospatial data are accessed and collected on-line in the form of web services, a higher demand for the quality of data and services has been placed on both providers and consumers. Clear measures of quality that help identify, visualise, evaluate and select appropriate geospatial information and services for dedicated applications via the Internet are needed. On the technology side, the main challenges are related to appropriate and efficient distributed components and data architectures, lack of sufficient geoprocessing power, lack of semantic aspects of web services, service orchestration (service selection, relationship, interaction and composition), and performance management and dynamic service load balancing. Also, more attention needs to be paid to some often-forgotten yet important issues related to data ownership, copyright and privacy, data and service use policies, and the implications of data and service quality (Li and Yan, 2010; Blatt, 2014).

4. Scientific research agenda

In this section, we provide a vision on the future development in information from imagery. In doing so we follow the new commission structure of ISPRS, adopted in 2015 for implementation 2016 (Fig. 4), which comprises five commissions:

Commission I Sensor systems
Commission II Photogrammetry
Commission III Remote Sensing
Commission IV Spatial Information Science
Commission V Education and Outreach

The research challenges of Commission V, being a non-technical commission, will be discussed further in Section 5.

4.1. Sensor systems

Commission I is concerned with the design, construction, characterisation, calibration and use of imaging sensors, sensor systems and sensor networks for photogrammetry, remote sensing and spatial information science, such as air- and space-borne digital cameras (frame and video) and laser scanners, and thermal, hyperspectral and radar sensors. It investigates the different platforms for data acquisition, including, but not restricted to, UAS, mobile mapping systems, aircraft, satellites including small satellites and satellite constellations. Commission I also cooperates with the related industrial sector.

4.1.1. Optical imaging sensors

Imaging sensors are expected to continue evolving at a fast pace in the foreseeable future. Advances in CCD/CMOS technologies are mainly driven by the large consumer market and camera system developments will be strong in the coming years. The number of pixels per image acquisition will continue increasing and camera systems with multi-view configurations, providing simultaneously acquired images from different directions, are expected to rapidly increase their market share (Gruber and Walcher, 2014). This development and the expected increase in the data available emphasises the need for improved processing of big data and concepts for data integration. While the radiometric performance of cameras is likely to improve, the typical RGB and RGB-NIR spectral resolution is unlikely to change in the short term (Honkavaara et al., 2009), though interest in hyperspectral imaging from air and space is growing and this data can be used for generating 3D scenes. However, work is needed on calibration and on the handling of the large volumes of data. Also, there is an increasing interest in thermal imaging. For terrestrial work multi-camera sensors will increasingly be used due to their advantages in 3D data cap-

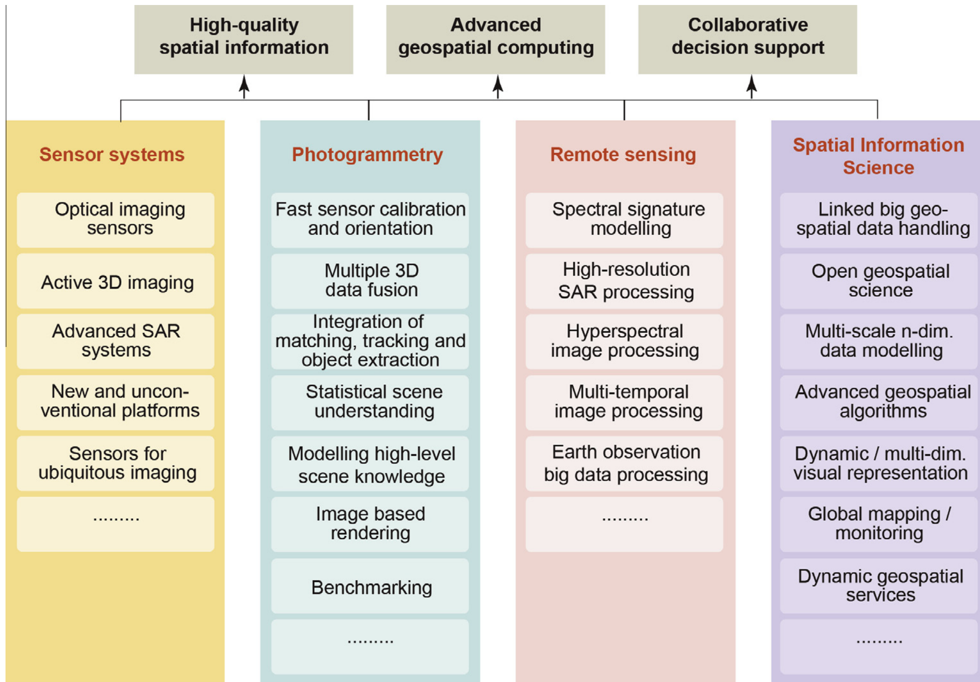

Fig. 4. Challenging research topics for ISPRS.

ture, e.g., for medical applications. The frame acquisition rate for capturing image sequences is expected to see improvements, allowing for a higher image overlap and better object space observation from the ground, air and space. If designed as PTZ (pan, tilt, zoom) cameras, such sensors can also be used for surveillance and monitoring tasks, involving highly dynamic processes. For such processes, 3D data capture from image sequences needs high-precision time synchronisation, which can be an issue. The boundary between professional and consumer imaging sensors will be further blurred. A challenge lies in setting and monitoring standards to distinguish high-precision photogrammetric products from consumer type images.

4.1.2. Active 3D imaging

Laser-based 3D active imaging technologies are relatively expensive, yet rapidly advancing, currently at a 15% annual development rate (Hyyppä et al., 2013). They thus provide the basis for significant future system developments (Mallet and Bretar, 2009). Airborne lidar systems are approaching a pulse rate of 1 MHz, as multiple pulses in the air and multi-sensor (multiple laser sensor-based) systems are further developed on all platforms (Nagai et al., 2009). Mobile lidar is currently the strongest growing segment of the direct 3D data acquisition market, and the trend is likely to continue for a while. In particular, rapid developments are expected in the low-end category. Time-of-flight cameras, which deliver a depth measurement for each pixel simultaneously, have appeared on the market and are being used in human–machine interfaces and computer games, for driver assistance systems and also for measurement tasks. Nevertheless, their potential is still largely untapped. Flash lidar technology has reached maturity and is about to enter into mainstream production (Stettner, 2010). Indoor mapping will likely be the first application to benefit from this powerful technology. In addition, while high-energy pulsed lidar systems will continue to dominate the market, single-photon or Geiger-mode lidar systems are also expected to approach the necessary performance for commercial applications (Abdullah, 2012). Finally, multi-wavelength lidar systems are being actively researched, and they will likely be widely introduced as market demand develops. Currently, dual wavelength, green and red lidar systems are increasingly used for shoreline and bathymetric mapping (Allouis et al., 2010; Niemeyer et al., 2014b) and four-wavelength systems have been tested in forestry applications (Bo et al., 2011).

4.1.3. Advanced SAR systems

SAR has made major inroads into our field, in particular since the availability of high-resolution data from space, e.g., from Cosmo-SkyMed, TerraSAR-X and TanDEM-X (Eineder et al., 2009; Zink et al., 2014). A particular challenge is flying these satellites in a very close formation. Other sensor innovations comprise bi- and multi-static SAR, digital beam forming and super resolution SAR; terahertz (THz) imaging promises to allow for extremely precise range measurements. Images of a geometric resolution in the dm range from aerial systems show great potential, in particular when used in multi-aspect mode (Palm et al., 2015). Also ground-based radar is gaining importance, e.g., for geo-monitoring tasks.

4.1.4. New and unconventional platforms

In recent years, a clear trend could be observed to use small satellites (Sandau et al., 2011) and satellite constellations such as RapidEye or Skybox for different kinds of applications. A comparison of these flexible systems with more comprehensive and partly monolithic systems will yield an interesting insight into the potential and limitations of this new technology for mapping and remote sensing. Another type of platform which has become very popular in recent years, is UAS (Colomina and Molina, 2014; Pajeres, 2015). For the geospatial community the challenge is how to deal with the larger platform motion variation and the use of non-metric sensors. Specialists from neighbouring disciplines in particular have shown a tremendous interest in using these systems for applications ranging from television to homeland security and traffic monitoring. The initial hype seems to be over, and we now need to both systematically assess the merits of these platforms and improve them according to industry needs. There is also a move to use geostationary platforms for mapping purposes (Joseph, 2015). This offers the possibility of fast revisit and real-time image acquisition, while challenging instrument developers to provide a sensor which will indeed generate high-resolution imagery from high earth orbit.

4.1.5. Sensors for ubiquitous imaging

In general terms, imaging is ubiquitous and, in fact, becoming pervasive, in particular when used in sensor networks, as an exponentially growing number of imaging sensors provide highly redundant data at increasing temporal resolution. Clearly, redundancy is growing, as multiple sensors simultaneously capture the object space and sensor platforms cooperatively observe the same area (Hyde et al., 2006). The increasing variety of platforms, including smart devices equipped with cameras and GNSS, as well as UAS, is another key aspect to be noted. Due to the competitiveness of the consumer market, research and development is very strong in this category and advances are being rapidly transferred into the professional market. There are concerns in this area over legal and privacy issues, and also in the establishment of standards governing the quality of products.

In conclusion, it can be seen that developments in technology are producing new data acquisition systems and the challenge for ISPRS is to match this with adequate scientific methods and tools for assessment, processing and analysis.

4.2. Photogrammetry

Commission II deals with the theory and methodology for extracting and analysing spatio-temporal information of objects from terrestrial, aerial and satellite images, image sequences and point clouds, by using approaches from photogrammetry, image analysis and computer vision, with emphasis on accurate and reliable geometric information. Applications include image-based 3D measurement in geospatial data acquisition, extra-terrestrial mapping, engineering and industrial metrology, heritage recording, forensic analysis, robotics, driver assistance systems, surveillance, medical applications, gaming and movie industries, and other fields.

4.2.1. Fast sensor calibration and orientation

As part of photogrammetric processing sensor modelling and calibration needs more attention for precise geometric measurement tasks in image metrology, and for unconventional imaging devices such as fisheye lenses, plenoptic and other generalised cameras. Automatic image orientation (pose estimation) has developed to a certain degree of maturity over the last decade. Further research directions are, on the one hand, the simultaneous orientation of images with very different perspective and/or from different sensors and the orientation of a new source of data relative to already oriented imagery or 3D models such as 3D visual landmarks generated from imagery. On the other hand, incremental solutions to cope with massive amounts of images, solutions based on convex optimisation (Boyd and Vandenberghe, 2004) and the integration of different imaging sensors with additional information on position and viewing direction, such as from GNSS and IMU, are increasingly important topics.

In particular in navigation, robotics and surveillance, real-time solutions for processing image sequences are necessary, e.g., for obstacle avoidance in autonomous driving and driver assistance systems and for pedestrian tracking and for SLAM. The focus should be on the development of algorithms that are scalable across many orders of magnitude and can be easily parallelized (Klingner et al., 2013).

4.2.2. Multiple 3D data fusion

Another field which will gain importance is the fusion of multiple complementary data for 3D applications. Newly developed acquisition systems are integrating more and more multiple imaging sensors in addition to lidar sensors. For example, a combined use of optical imagery and lidar in the context of street view imaging (Paparoditis et al., 2012) has many advantages for 3D processing. To give another example, lidar point clouds with a much smaller density (with respect to the 3D point clouds that can be generated from optical processing) can be used to identify focused areas and cut down the combinatorial effort for scene analysis purposes, in addition to providing an initial surface reconstruction to predict the occlusions and to normalise the reconstruction of 3D point clouds and meshes from optical images.

In a similar vein, the simultaneous use of multiple images for image classification can help to overcome the problems of occlusion to obtain a classification of an entire scene (Roig et al., 2011). The availability of aerial images with high overlaps without any extra costs, along with the trend to obtain oblique aerial views, may provide the background for making such applications also possible for the aerial case.

4.2.3. Integration of matching, tracking and object extraction

3D surface and object reconstruction from images and point clouds has reached an encouraging status in research, but problems still persist, e.g., in the presence of multiple occlusions, poor texture, and significant depth discontinuities. As a consequence, although the detection of moving objects for driver assistance systems has found its way into practical applications, it is arguably not yet robust against challenging imaging conditions such as sudden brightness changes, rain or snow.

The integration of image matching, tracking of patterns and object extraction in the same process is a potential solution to these problems, which needs to be explored more deeply. Currently, these tasks are usually solved independently from each other, so the errors in the solution of one task propagate to the next; a simultaneous solution can help to overcome some of the limitations of current methods. A first solution for integrating image matching and classification has been developed by Ladický et al. (2012), but the problem still requires further research efforts. A further important extension of dense matching is dynamic scene flow, i.e., the estimation of spatially and temporally consistent dense depth and velocity vector fields (Vogel et al., 2013; Menze and Geiger, 2015), which can also be used to identify individual (moving) objects (Menze et al., 2015).

4.2.4. Statistical scene understanding

Much of the current work on robust scene understanding by image classification and tracking is based on a statistical problem formulation, in many cases in a supervised setting to make the respective applications more easily adaptable to different scenes. Graphical models have proven to provide a flexible framework well suited to solving these problems. Classifiers based on graphical models such as conditional random fields (CRF) are rather well understood today, and they should become the method of choice for classification tasks (Schindler, 2012). However, the provision of training data is a limiting factor for practical applications, in particular if sophisticated context models are to be learned in training. This problem can be overcome by adapting techniques for transfer learning (Pan and Yang, 2010) to image classification problems. Transfer learning can help to adapt a classifier trained on an image set to another dataset having different underlying distributions, or it can help to solve new tasks based on the existing solution of a similar task. Both types of transfer learning should find their way into photogrammetry and remote sensing. Another possibility to cope with too few training data, in particular for mapping applications, is the use of potentially outdated database information. The challenge is to deal with partly wrong information. This issue is referred to the "label noise" problem (Frénay and Verleysen, 2014).

For many applications, it is also important that the algorithms "come to know where they fail" in order, on the one hand, to pilot an operator to control and potentially edit and correct the failure, or on the other hand, to swap to an alternative algorithm (Paparoditis et al., 2007). Possibilities for self-diagnosis based on reliable quality measures (Boudet et al., 2006) are needed to achieve integrity measures such as those used in the aircraft industry.

4.2.5. Modelling high-level scene knowledge

The incorporation of high-level scene knowledge for object detection and scene understanding is one of the most important directions of research. CRF and related models work well at a very local level, combining the classification of neighbouring pixels of an image. As pointed out in the section on the state-of-the-art, there are a variety of strategies to pursue this problem. Not all of them can easily be transferred to aerial and satellite imagery, and it is not yet entirely clear which is the best strategy to follow when trying to tackle this problem. Examples for considering high-level knowledge include the use of multiple layers of object labels as in part-based models, the definition of high-order cliques combining the labels of multiple pixels, the use of hierarchical models taking into account class labels at different scales, and other ways of considering long-range interactions such as relative location priors (Gould et al., 2008). Some of these techniques involve a multi-stage procedure where classification at a local level and high-level procedures interact. Marked point processes (MPPs, Lafarge et al., 2008) and particularly multi-object MPPs are another promising possibility to integrate high-level scene knowledge; these might potentially succeed where expert systems failed in the 1980s. An interesting and challenging perspective could also be to unify MPPs and graphical models in the same framework to yield complementary advantages. The optimal way of considering high-level knowledge, as well as the best way of integrating multiple processing stages in this context, still needs to be investigated. This provides a rather wide field of research that needs to be tackled by the scientific community.

4.2.6. Image-based rendering

This consists in navigating continuously in 3D for a higher level of immersion, "in between" the closest oriented images by warping and blending these images given a 3D model (already existing or generated off-line or on-the-fly from the imagery) to generate a synthetic but realistic rendering for any view, thus avoiding the need to texture the 3D models before navigation, which is not a well-posed problem. This would, for example, avoid the need for the generation of orthophotos off-line and lead to the generation of on-the-fly orthophotos. Some open research issues are the consideration and management of uncertainty of both the image orientations and the 3D model in the rendering process and radiometric equalisation of the images (physical, empirical, or halfway between the two) before the blending of textures.

4.2.7. Benchmarking

Last, but not least, the ISPRS community should increase their efforts to provide benchmarks for specific tasks (Rottensteiner et al., 2014; Nex et al., 2015; Vallet et al., 2015). Whereas benchmark datasets from the computer vision and robotics community may be sufficient in many cases, there are some applications that they do not cover, in particular those requiring near-vertical views. It may be difficult to overcome copyright and security issues, but providing a common test bed for new algorithms is nevertheless important to make different approaches comparable and to be able to identify promising strategies, as against those that are less promising. As a consequence, benchmarking can considerably speed up research progress.

4.3. Remote sensing

Commission III is concerned with research, development, investigation and operational use of methods and systems for the analysis of remotely sensed observations of the Earth from air- and space-borne sensors, in synergy with in-situ and hand-held measurements. Examples include physical modelling of electromagnetic radiation, the analysis of spectral signatures, image classification, data fusion and pattern recognition. Applications dealt with in Commission III include environmental monitoring for sustainable development and global change; mapping of human and natural activities including land cover, land use and biodiversity; physical and empirically based process monitoring; assessment and mitigation of disasters; identification and assessment of renewable and non-renewable resources; and the monitoring of temporal changes in weather and in land and sea cover.

4.3.1. Spectral signature modelling

A key element in remote sensing remains physical modelling of electromagnetic waves and their interaction with the atmosphere, as well as with the imaged surfaces and objects. With the increasing number of spectral bands available in many satellite sensors, e.g., WorldView 3 with a total of 28 bands, and in particular the hyperspectral missions such as the German ENMAP with more than 240 bands, modelling the spectral signatures of different materials reaches a higher level of complexity and comprises many new challenges.

4.3.2. High-resolution SAR processing

Synthetic aperture radar (SAR) remote sensing will play an important role in future remote sensing applications. The fact that radar is an active system and can penetrate clouds makes it a very useful tool for continuous monitoring tasks in earth observation. Specific research challenges lie in high-resolution imaging in all three dimensions, possibly through tomographic SAR, combined with compressive sensing (Zhu and Bamler, 2012). Also polarimetric SAR and simplifications of tomographic SAR, such as InSAR/IfSAR and permanent scatterer interferometry (PSI), still provide many unsolved challenges, in particular when employed with the now available high-resolution SAR image stacks and multi-aspect SAR data. Along-track mode interferometric provides possibilities for monitoring moving objects, e.g., in ship traffic monitoring, the measurement of ocean currents and the monitoring of icebergs. Another area of increased interest is the fusion of optical and SAR data, since in many instances these two data sources are complementary.

4.3.3. Hyperspectral image processing

Interpretation of satellite images in an automatic fashion makes use of image classification and image analysis approaches (see discussions in Section 4.2). Hyperspectral images provide an additional challenge, since a proper band selection and feature definition is often necessary to be able to handle the large amounts of data and to escape the "curse of dimensionality" (Hughes, 1968) that can easily arise due to a lack of sufficient training data. One other important research issue is the elaboration of classification methods which only need a minimum of difficult and expensive-to-collect in-situ measurements.

4.3.4. Multi-temporal image processing

Satellite constellations such as RapidEye, with five satellites, and more so the Skybox system, which is capable of capturing high-resolution videos from space and is planned to have 24 satellites in its final constellation, deliver an increased amount of repeated observations which can be used in multi-temporal processing to model dynamic processes, e.g., growth patterns of plants in agriculture. Obviously, for smaller areas such time series can also be acquired using fixed wing and rotary wing UAS. In exploiting such time series, the images will play the role of a snapshot, documenting a specific state of the underlying, observed processes that are inducing change. Whilst these processes can be natural (e.g., geoscientific and biological) or anthropogenic (i.e., man-made), the emphasis will be on estimating the parameters governing the processes for an improved understanding and predictive power. Obviously, such studies require an interdisciplinary approach.

4.3.5. Earth observation big data processing

The volumes of data currently acquired by remote sensing systems from space, and also from the air and by ground-based mobile mapping systems, present a challenge not only in terms of storage and pre-processing of the imagery, but also in terms of information extraction (especially in 3D) and information mining (Quartulli and Olaizola, 2013). This topic thus relates also to the other ISPRS commissions. The new paradigm is to fully extract, at night, information from data that has traditionally been acquired only during daytime. New technologies for the processing of big data such as Hadoop and MapReduce on the cloud or high-performance computing (HPC) solutions should advantageously be investigated and applied to such imagery (Nativi et al., 2015). Moreover, the factorised pre-processing of the data to extract 2D or 3D low-level or medium-level features is necessary to avoid redundant processing and to streamline data exploitation.

4.4. Spatial information science

Commission IV deals with theoretical and practical aspects of modelling, management, analysis, dissemination and visualisation of geospatial data, including interoperability, web services and geospatial data infrastructure. It is also concerned with applications and operational use of spatio-temporal information in areas such as transportation, environmental monitoring, disaster management, mobility, 3D city models, Building Information Systems (BIM), social media, location-based services and health.

4.4.1. Linked big geospatial data handling

Linked big geospatial data achieved through the combination of linked data technology with geospatial big data, refers to the construction and publishing of structured and unstructured high-volume geospatial data, to allow more useful semantic queries and permit better re-use of knowledge embedded in different data sources (Kuhn et al., 2014; Lee and Kang, 2015). A number of issues need to be explored, such as the semantic aggregation and publishing of massive amounts of spatial data with domain-specific and social media data, the retrieval and browsing of linked spatio-temporal data, the development of innovative and capable tools for processing (big or linked) geospatial data, the connecting and publishing of geospatial big data and the mining and visualisation of linked geospatial big data, as well as their application in navigation, public health, urban management, environmental monitoring and other societal benefit areas.

4.4.2. Open geospatial science

With the significant increases in open geospatial data, the rapid advancement of free and open source software for geoinformation (FOSS4G) and the open access to research publications, we will see dramatic development in open geospatial science (Steiniger and Hunter, 2013; Jeffery et al., 2014; Simón et al., 2014; Harris and Baumann, 2015; Swain et al., 2015). It will promote large-scale collaboration of scientists and citizens in various stages of the information from imagery process, including data sharing, software code re-use, science reproducibility and collaborative processing and validation. The critical research issues include open data standards, quality evaluation and control of open data, semantic interoperability, VGI, architectures and frameworks for open source software, conceptualisation and creation of open source software, human computer interfaces and usability in and around open GI systems, the combination and integration of open source geospatial software and data, a cost and benefit analysis of open source applications, and open source business models.

4.4.3. Multi-scale n-dimensional data modelling

Even after twenty-years of investigation, there is still a lack of well-established approaches for sophisticated modelling of large amounts of multi-dimensional data, multi-scale phenomena and man-made structures, including their temporal changes (Craglia et al., 2012; Long and Li, 2013; Xiong et al., 2015). A variety of issues remain to be solved for developing new methodologies, algorithms and applications related to the representation of n-dimensional spatial data at multiple scales. Typical examples are (a) the representation and computation of 3D and temporal relationships, and spatio-temporal ontologies, as well as their use for representing 3D and higher dimensional geographic and environmental phenomena, (b) spatial data structures and spatial indexing for multi-dimensional models, (c) automated multi-dimensional data generalisation of different levels of detail for various purposes, and (d) complete sets of atomic algorithms for multi-dimensional modelling.

4.4.4. Advanced geospatial algorithms

More and more spatial datasets are available which have to be analysed and combined in an intelligent way. To do so, interpretation methods are needed, which are able to find higher level information in the given structured geodata. To this end, similar techniques can be applied as in image analysis, (spatial) data mining and machine learning methods being very powerful techniques (Miller and Han, 2009). As the data is acquired by several sensors, it is obvious that it can also be processed separately, i.e., in a decentralized way. This has several benefits, e.g., parallel processing, local computing with advantages concerning data privacy, as well as a reduction in data communication (Duckham, 2012). Finally, methods and models are needed which are able to incrementally update and refine geospatial datasets and explicitly allow the descriptions to have different states: e.g., parts of the object might be completely captured, other parts only coarsely or not at all. It must then still be possible to store the (preliminary) information, mark it as such, and incrementally refine and complete it at a later stage.

4.4.5. Dynamic and multi-dimensional visual representation

Geovisualisation will retain a strong link with geospatial big data and 3D data. Visualisation of mobility and dynamics in urban environments will continue to attract attention. Visual analytics allows interactive visual inspection of potentially large and high-dimensional data (Andrienko and Andrienko, 2013). Visualisation for 3D indoor navigation and underground infrastructure is gaining more ground. Continuous zooming will become a critical function for digital earth and spatial analysis systems. Theoretical issues include the perception by the human brain of structures of visual representations, design principles of maps and other visual representations, and usability of visual representation. Based on metric, thematic and topological information (Li and Huang, 2002), information theory will be widely employed as a theoretical basis for the effective design of information transmission systems and for the evaluation of visual representations. As the usability of maps will be more emphasised by users in the future, particularly by the general public, map-alike representations such as schematic maps, variable-scale maps and other personalised maps will become more popular.

4.4.6. Global mapping and monitoring

With open access to global datasets, more efforts will be devoted to their validation, updating and application (Li et al., 2011; Giri et al., 2013; Chen et al., 2015; Ban et al., 2015). It is necessary to develop internationally agreed technical specifications defining overall strategy, sampling and approaches to quality assessment, and to establish a corresponding web-based validation platform. Operational updating approaches for the generation of more current products and time-series of datasets through a combination of robust change detection, citizen crowdsourcing and ancillary data collation remain to be developed. A number of dynamic monitoring networks to operate at local, regional, national and continental scales will need to be set up for timely delivery of land cover change and other facts, relevant essential variables and trends for decisions makers and relevant users. In order to integrate fine-scale monitoring and analysis with global coverage, it is essential to integrate or connect all existing information sources at a variety of spatial scales, distributed locally to globally, to form widely accessible knowledge portals and to provide a 'one-stop' information service for land cover, snow and ice and other land-related information. As a result, incremental update and refinement will remain a topic deserving research attention. It is also critical to incorporate domain specific knowledge and principles into the monitoring process to understand the reasons for and consequences of observed changes and to predict future trends.

4.4.7. Dynamic geospatial services

Recent advances in cyber-infrastructure network and communications technologies, especially the more recent cloud computing technologies, have created both great potential for web-based services and demand for new types of services for disseminating spatial information and accessing massively scaled computing infrastructures, and for new web and cloud services for on-line processing of static and dynamic geospatial and spatio-temporal information and data-intensive problems. The fast transition from Web 2.0 to Web 3.0 shifts the web from "content creation" and "participation" to "means and connected knowledge", requiring a semantic web rather than just one that is interactive. Web 3.0 calls for an "intelligent web" with linked geospatial datasets for more effective discovery, analysis, automation, integration, re-use and visualisation of geospatial information across various applications. New standards and interoperability specifications are needed for services, system architectures and geospatial information, processes and workflows. Future research will focus more on the intelligent retrieval and processing of distributed computing resources, on the provenance and metadata for spatial analytical methods, and on grid and cloud computing for a functionally rich and collaborative geospatial web based on geospatial services (Li, 2008; Li et al., 2011; Evangelidis et al., 2014). This will move us towards the web as a platform that provides traditional GIS capabilities in a non-traditional way.

5. Conclusion

As a society concerned with *Information from Imagery*, the ISPRS is facing significant scientific challenges, with some of its sub-disciplines evolving gradually and some moving at a very fast pace. The major trends can be summarised as follows:

- *Image acquisition:* The model of integrated sensors has replaced the traditional model of a single imaging sensor. New data sources such as Urthcast and cameras on UAS are widely used and raise issues of calibration and data quality. Ubiquitous sensing and public participation is gaining weight leading to "citizen sensing" or "participatory sensing". While this development opens up many new applications, e.g., in updating and disaster monitoring, scientists are challenged to ensure aspects of data quality, trustworthiness and data privacy.
- *Satellite constellations:* In the near future, constellations comprising multiple satellites will provide high-resolution imagery up to multiple times per day of every corner of the globe in near real-time. It will thus become possible to monitor dynamic processes on the Earth surface. Challenges comprise multi-temporal data processing and modelling of the dynamic processes as well as multi-temporal data processing and information mining.
- *Information extraction:* The integration of image matching, tracking and object extraction is replacing the traditional model of independent processing of individual objects. Real-time scalable solutions will become more and more important, while high geometric accuracy, coupled with the highest degree of automation, remains a core requirement and a core challenge, in particular in industrial metrology. The use of multiple images promises to offer a solution for image classification and object reconstruction to overcome the problem of occlusion. Large area monitoring is moving from research-based experimental settings to operational procedures.
- *Data modelling:* The modelling and understanding of real world and on-line communities and their interaction are becoming crucial for the emerging convergent cyber–physical world (CPW). Spatial data structures tend to move from three to four dimensions (3D plus time). Spatial data infrastructure will be a dynamic framework to share information globally, to include both indoor and outdoor environments, and to navigate across space and time.
- *Geospatial service:* The key concerns have shifted from information provision to geospatial knowledge delivery, from chance mapping to dynamic monitoring and the prediction of future trends, and from traditional desktop solutions to cloud platforms using web services. Geospatial big data is here to stay and calls for re-examination of what existing geospatial theory, methods and application systems are capable of handling. There is an immense challenge to provide spatial data infrastructures and related services which are robust and can serve the need to provide information to decision makers in a way which is useful, understandable and user friendly.
- *Disciplinary interaction:* The separation between close-range and aerial photogrammetry has become increasingly blurred. Remote sensing and spatial information science are more closely integrated in many operational systems, and more domain specific knowledge and principles will be incorporated into traditional geometry-dominant geospatial data processing and analysis.

This paper has identified and discussed research topics for the ISPRS community to tackle in the future. Our major objective has been to call upon and mobilise all ISPRS scientists, practitioners and stakeholders to continue improving our understanding and capacity related to the generation of information from imagery, and to deliver geospatial knowledge that will enable humankind to confront the challenges ahead, posed, for example, by global change, ubiquitous sensing and demand for real-time information.

The implementation of this ISPRS scientific vision and research agenda requires more education and outreach effort, as well as international and inter-disciplinary collaboration. We need to promote the use of imagery to other professions, to attract young scientists and practitioners, to engage a new generation of researchers and users, to educate our partners about our strengths, and to develop innovative international partnerships between researchers and operational agencies. This is where the ISPRS Commission V on Education and Outreach will play a central role. Commission V deals with education, training, capacity building and outreach in all areas related to the ISPRS. It is also the home commission for the ISPRS Student Consortium.

Some of the scientific developments and challenges discussed also raise legal and policy issues. For example, the use of UAS raises issues relating to safety and privacy. High-resolution satellite data also creates concerns about privacy and national security, as do surveillance cameras combined with tracking algorithms. Another major policy issue is access to data and software, and whether data and tools collected and developed with taxpayers' money should be free of charge. These issues must continue to be addressed in the future and ISPRS can play a role in such discussions. With this overarching scientific vision and the new Commission structure, ISPRS is well positioned as a relevant, vibrant and forward-looking scientific organisation dedicated to obtaining and utilising information from imagery in the 21st Century.

Acknowledgements

The authors would like to thank ISPRS First Vice President Orhan Altan, Congress Director Lena Halounová, IPAC Chair Gunter Schreier and Professor Wenzhong Shi (The Hong Kong Polytechnic University), Professor Stephan Winter (University of Melbourne), for their contributions to the paper. We also acknowledge ISPRS Honorary Members, Fellows, Technical Commission Presidents and other ISPRS officers for their valuable comments and suggestions. Finally, the authors thank Christine Jeans of Newcastle University for her assistance in preparing the figures.

References

Abbas, S., Ojo, A., 2013. Towards a linked geospatial data infrastructure. In: Technology-Enabled Innovation for Democracy, Government and Governance, LNCS, vol. 8061, pp. 196–210.

Abdullah, Q.A., 2012. Mapping matters. Photogramm. Eng. Rem. Sens. 78 (7), 664–665.

Abraham, S., Förstner, W., 2005. Fish-eye-stereo calibration and epipolar rectification. ISPRS J. Photogramm. Rem. Sens. 59 (5), 278–288.

Addo, K.A., Walkden, M., Mills, J.P., 2008. Detection, measurement and prediction of coastal recession in Accra, Ghana. ISPRS J. Photogramm. Rem. Sens. 63 (5), 543–558.

Allouis, T., Bailly, J.S., Pastol, Y., Le Roux, C., 2010. Comparison of lidar waveform processing methods for very shallow water bathymetry using Raman, near infrared and green signals. Earth Surf. Process. Land. 35 (6), 640–650.

Altan, O., Backhaus, R., Boccardo, P., Zlatanova, S., 2012. Best practices in disaster management. Geospatial TODAY 12, 36–40.

Andrienko, N., Andrienko, G., 2013. Visual analytics of movement: an overview of methods, tools and procedures. Inform. Visual. 12 (1), 3–24.

Andrienko, G., Fabrikant, S., Griffin, A., Dykes, J., Schiewe, J., 2014. GeoViz: interactive maps that help people think. Int. J. Geogr. Inform. Sci. 28 (10), 2009–2012.

Aschbacher, J., Milagro-Pérez, M., 2012. The European Earth monitoring (GMES) programme: status and perspectives. Rem. Sens. Environ. 120, 3–8.

Ban, Y.-F., Gong, P., Giri, C., 2015. Global land cover mapping using Earth observation satellite data: recent progresses and challenges. ISPRS J. Photogramm. Rem. Sens. 103, 1–6.

Bay, H., Ess, A., Tuytelaars, T., van Gool, L., 2008. SURF: speeded up robust features. Comput. Vis. Image Und. 110 (3), 346–359.

Belgiu, M., Dragut, L., Strobl, J., 2014. Quantitative evaluation of variations in rule-based classifications of land cover in urban neighbourhoods using WorldView-2 imagery. ISPRS J. Photogramm. Rem. Sens. 87, 205–215.

Benedek, C., Shadaydeh, M., Kato, Z., Szirányi, T., Zerubia, J., 2015. Multilayer Markov Random Field models for change detection in optical remote sensing images. ISPRS J. Photogramm. Rem. Sens. 107 (9), 22–37.

Benz, S., Weibel, R., 2014. Road network selection for medium scales using an extended stroke-mesh combination algorithm. Cartogr. Geogr. Inform. Sci. 41 (4), 323–339.

Bereuter, P., Weibel, R., 2013. Real-time generalization of point data in mobile and web mapping using quadtrees. Cartogr. Geogr. Inform. Sci. 40 (4), 271–281.

Besl, P., McKay, N., 1992. A method for registration of 3-D shapes. IEEE Trans. Pattern Anal. Mach. Intell. 14 (2), 239–256.

Bizer, C., Heath, T., Berners-Lee, T., 2009. Linked data – the story so far. Int. J. Semantic Web Inform. Syst. 5 (3), 1–22.

Bjørke, J., 2012. Exploration of information theoretic arguments for the limited amount of information in a map, theories of map design in the digital era. Cartogr. Geogr. Inform. Sci. 39 (2), 88–97.

Blatt, A.J., 2014. Data privacy and ethical uses of volunteered geographic information. Geotechnol. Environ. 12, 49–59.

Bleisch, S., Duckham, M., Galton, A., Laube, P., Lyon, J., 2014. Mining candidate causal relationships in movement patterns. Int. J. Geogr. Inform. Sci. 28 (2), 363–382.

Bo, Z., Wei, G., Shuo, S., Shalei, S., 2011. A multi-wavelength canopy lidar for vegetation monitoring: system implementation and laboratory-based tests. Proc. Environ. Sci. 10, 2775–2782.

Boudet, L., Paparoditis, N., Jung, F., Martinoty, G., Pierrot-Deseilligny, M., 2006. A supervised classification approach towards quality self-diagnosis of 3D building models using digital aerial imagery. In: The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI-3, pp. 136–141.

Boyd, S.P., Vandenberghe, L., 2004. Convex Optimization. Cambridge University Press.

Brédif, M., 2010. Modélisation 3D de bâtiments: reconstruction automatique de superstructures de toits et recalage cinétique de toits polyédriques prenant en compte la topologie, Thèse de doctorat de Télécom ParisTech.

Brédif, M., Tournaire, O., Vallet, B., Champion, N., 2013. Extracting polygonal building footprints from digital surface models: a fully-automatic global optimization framework. ISPRS J. Photogramm. Rem. Sens. 77, 57–65.

Breitenstein, M.D., Reichlin, F., Leibe, B., Koller-Meier, E., van Gool, L., 2011. Online multiperson tracking-by-detection from a single, uncalibrated camera. IEEE Trans. Pattern Anal. Mach. Intell. 33 (9), 1820–1833.

Brenner, C., Dold, C., Ripperda, N., 2008. Coarse orientation of terrestrial laser scans in urban environments. ISPRS J. Photogramm. Rem. Sens. 63 (1), 4–18.

Bryan, B., 2013. High-performance computing tools for the integrated assessment and modelling of social ecological systems. Environ. Model. Softw. 39, 295–303.

Buchin, K., van Goethem, A., Hoffmann, M., van Kreveld, M., Speckmann, B., 2014. Travel-time maps: linear cartograms with fixed vertex locations. In: Duckham, M., Pebesma, E., Stewart, K., Frank, A. (Eds.), GI Science (LNCS 8728). Springer, Berlin, pp. 18–33.

Bulatov, D., Wernerus, P., Heipke, C., 2011. Multi view dense matching supported by triangular meshes. ISPRS J. Photogramm. Rem. Sens. 66 (6), 907–918.

Cao, C., Sun, Y., 2014. Automatic road centerline extraction from imagery using road GPS data. Rem. Sens. 6, 9014–9033.

Chan, J., Paelinckx, D., 2008. Evaluation of random forest and adaboost tree-based ensemble classification and spectral band selection for ecotope mapping using airborne hyperspectral imagery. Rem. Sens. Environ. 112 (6), 2999–3011.

Chen, J., Lu, M., Chen, X., Chen, J., Chen, L., 2013a. A spectral gradient difference based approach for land cover change detection. ISPRS J. Photogramm. Rem. Sens. 85, 1–12.

Chen, J., Wu, H., Li, S., Liao, A., He, C., Cheng, D., 2013b. Temporal logic and operation relations based knowledge representation for land cover change web service. ISPRS J. Photogramm. Rem. Sens. 83, 140–150.

Chen, J., Ban, Y., Li, S., 2014a. China: open access to Earth land-cover map. Nature 514 (434), 23.

Chen, J., Wang, D., Zhao, R., Zhang, H., Liao, A., Liu, J., 2014b. Fast updating of national geo-spatial databases with high resolution imagery: China's methodology and experiences. In: The International Archives of the Photogrammetry Remote Sensing and Spatial Information Sciences, vol. XL-4, pp. 41–50.

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

Chen, X., Chen, J., Shi, Y., Yamaguchi, Y., 2012. An automated approach for updating land cover maps based on integrated change detection and classification methods. ISPRS J. Photogramm. Rem. Sens. 71, 86–95.

Chen, X., Li, Y., Su, Y., Han, L., Liao, J., Yang, S., 2014c. Mapping global surface roughness using AMSR-E passive microwave remote sensing. Geoderma 235–236, 308–315.

Clementini, E., 2013. Directional relations and frames of reference. GeoInformatica 17 (2), 235–255.

Colomina, I., Molina, P., 2014. Unmanned aerial systems for photogrammetry and remote sensing: a review. ISPRS J. Photogramm. Rem. Sens. 92, 79–97.

Conti, M., Das, S., Bisdikian, C., Kumar, M., Ni, L., Passarella, A., Roussos, G., Troster, G., Tsudik, G., Zambonelli, F., 2012. Looking ahead in pervasive computing: challenges and opportunities in the era of cyber–physical convergence. Pervasive Mobile Comput. 8, 2–21.

Craglia, M., de Bie, K., Jackson, D., Pesaresi, M., Remetey-Fülöpp, G., Wang, C., Annoni, A., Bian, L., Campbell, F., Ehlers, M., van Genderen, J., Goodchild, M., Guo, H., Lewis, A., Simpson, R., Skidmore, A., Woodgate, P., 2012. Digital earth 2020: towards the vision for the next decade. Int. J. Digit. Earth 5 (1), 4–21.

Cramer, M., 2011. Digital Camera Calibration, EuroSDR, Publication No 55, 262p.
Cramer, M., 2013. The UAV@LGL BW project – a NMCA case study. In: Fritsch, D. (Ed.), Photogrammetric Week 2013. Wichmann, Heidelberg, pp. 151–163.
Cura, R., Perret, J., Paparoditis, N., 2015. Streetgen: in-base procedural-based street generation. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. II-3/W5, pp. 409–416.
Cusimano, M., Marshall, S., Rinner, C., Jiang, D., Chipman, M., 2010. Patterns of urban violent injury: a spatio-temporal analysis. PLoS ONE 5 (1), e8669.
Danahy, J., Mitchell, J., Feick, R., Wrigh, R., 2015. Multi-scale 3D geovisualization of urban heat island data for planning dialogue in Toronto. In: Nunes Silva, C. (Ed.), Emerging Issues, Challenges and Opportunities in Urban E-Planning. University of Lisbon, Portugal, pp. 166–187.
Devaraju, A., Kuhn, W., Renschler, C., 2015. A formal model to infer geographic events from sensor observations. Int. J. Geogr. Inform. Sci. 29 (1), 1–27.
Dowman, I., Jacobsen, K., Konecny, G., Sandau, R., 2012. High Resolution Optical Satellite Imagery. Whittles Publishing, 230p.
Duckham, M., 2012. Decentralized Spatial Computing: Foundations of Geosensor Networks. Springer, Berlin.
Eineder, M., Adam, N., Bamler, R., Yague-Martinez, N., Breit, H., 2009. Spaceborne Spotlight SAR Interferometry With TerraSAR-X. IEEE Trans. Geosci. Rem. Sens. 47 (5), 1524–1535.
El-Sheimy, N., Liang, S., Toth, C., 2015. Integrated imaging and sensor fusion for rapid response and monitoring applications. ISPRS J. Photogramm. Rem. Sens. 104, 174.
Elseberg, J., Borrmann, D., Nüchter, A., 2013. One billion points in the cloud – an octree for efficient processing of 3D laser scans. ISPRS J. Photogramm. Rem. Sens. 76 (2), 76–88.
Evangelidis, K., Ntouros, K., Makridis, S., Papatheodorou, C., 2014. Geospatial services in the cloud. Comput. Geosci. 63, 116–122.
Fang, Z., Li, Q., Zhang, X., Shaw, S., 2012. A GIS data model for landmark-based pedestrian navigation. Int. J. Geogr. Inform. Sci. 26 (5), 817–838.
Felzenszwalb, P.F., Girshick, R.B., McAllester, D., Ramanan, D., 2010. Object detection with discriminatively trained part based models. IEEE Trans. Pattern Anal. Mach. Intell. 32 (9), 1627–1645.
Fischler, M., Bolles, R., 1981. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Commun. ACM 24 (6), 381–395.
Förstner, W., 2009. Computer vision and remote sensing – lessons learned. In: Fritsch, D. (Ed.), Photogrammetric Week, Heidelberg, pp. 241–249.
Förstner, W., Gülch, E., 1987. A fast operator for detection and precise location of distinct points, corners and centres of circular features. In: Proc., ISPRS Intercommission Conference on Fast Processing of Photogrammetric Data, pp. 281–305.
Frahm, J.M., Gallup, D., Johnson, T., Raguram, R., Wu, C., Jen, Y.H., Dunn, E., Clipp, B., Lazebnik, S., Pollefeys, M., 2010. Building Rome on a cloudless day. In: European Conference on Computer Vision, pp. 368–381.
Frénay, B., Verleysen, M., 2014. Classification in the presence of label noise: a survey. IEEE Trans. Neural Networks Learn. Syst. 25 (5), 845–869.
Fritz, S., McCallum, I., Schill, C., Perger, C., See, L., Schepaschenko, D., van der Velde, M., Kraxner, F., Obersteiner, M., 2012. Geo-Wiki: an online platform for improving global land cover. Environ. Model. Softw. 31, 110–123.
Furukawa, Y., Ponce, J., 2010. Accurate, dense and robust multi-view stereoopsis. IEEE Trans. Pattern Anal. Mach. Intell. 32 (8), 1362–1376.
Gao, J., Burt, J., Zhu, A.X., 2012. Neighborhood size and spatial scale in raster-based slope calculations. Int. J. Geogr. Inform. Sci. 26 (10), 1959–1978.
Gehrig, S., Eberli, F., Meyer, T., 2009. A real-time low-power stereo vision engine using semi-global matching. In: International Conference on Computer Vision Systems (LNCS 5815), pp. 134–143.
Gerke, M., Heipke, C., 2008. Image based quality assessment of road databases. Int. J. Geoinform. Sci. 22 (8), 871–894.
Giri, C., Pengra, B., Long, J., Loveland, T., 2013. Next generation of global land cover characterization, mapping, and monitoring. Int. J. Appl. Earth Observation Geoinform. 25, 30–37.
Gislason, P.O., Benediktsson, J.A., Sveinsson, J.R., 2006. Random forests for land cover classification. Pattern Recogn. Lett. 27 (4), 294–300.
Goodchild, M., Glennon, J., 2010. Crowdsourcing geographic information for disaster response: a research frontier. Int. J. Digit. Earth 3 (3), 231–241.
Gould, S., Rodgers, J., Cohen, D., Elidan, G., Koller, D., 2008. Multi-class segmentation with relative location prior. Int. J. Comput. Vis. 80 (3), 300–316.
Gröger, G., Plümer, L., 2012. CityGML – interoperable semantic 3D city models. ISPRS J. Photogramm. Rem. Sens. 71, 12–33.
Grossberg, M.D., Nayar, K.S., 2001. A general imaging model and a method for finding its parameters. In: International Conference on Computer Vision, pp. 108–115.
Gruber, M., Walcher, W., 2014. Calibrating the new ultracam osprey oblique aerial sensor. In: The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XL-3/W1, pp. 47–52.
Grün, A., 2008. Scientific-technological development in photogrammetry and remote sensing between 2004 and 2008. In: Li, Z., Chen, J., Baltsavias, M. (Eds.), Advances in Photogrammetry, Remote Sensing and Spatial Information Sciences. Taylor & Francis, London, pp. 21–25.
Haala, N., 2011. Multiray photogrammetry and dense image matching. In: Fritsch, D. (Ed.), Photogrammetric Week 2011. Wichmann, Heidelberg, pp. 185–195.
Hagenauer, J., Helbich, M., 2012. Mining urban land-use patterns from volunteered geographic information by means of genetic algorithms and artificial neural networks. Int. J. Geogr. Inform. Sci. 26 (6), 963–982.
Hahmann, S., Burghardt, D., 2013. How much information is geospatially referenced? Networks and cognition. Int. J. Geogr. Inform. Sci. 27 (6), 1171–1189.
Han, G., Chen, J., He, C., Li, S., Wu, H., Liao, A., Peng, S., 2015. A web-based system for supporting global land cover data production. ISPRS J. Photogramm. Rem. Sens. 103, 66–80.
Hansen, M.C., Loveland, T., 2012. A review of large area monitoring of land cover change using landsat data. Rem. Sens. Environ. 122, 66–74.
Hansen, M., Potapov, P., Moore, R., Hancher, M., Turubanova, S., Tyukavina, A., Thau, D., Stehman, S., Goetz, S., Loveland, T., Kommareddy, A., Egorov, A., Chini, L., Justice, C., Townshend, J., 2013. High-resolution global maps of 21st-century forest cover change. Science 342, 850–853.
Harris, C., Stephens, M., 1988. A combined corner and edge detector. In: Alvey Conference, pp. 147–152.
Harris, R., Baumann, I., 2015. Open data policies and satellite Earth observation. Space Policy 32, 44–53.
Hartley, R., Zisserman, A., 2003. Multiple View Geometry in Computer Vision, 2nd ed. Cambridge University Press, Cambridge.
Hecht, A.D., Fiksel, J., Fulton, S., Yosie, T., Hawkins, N., Leuenberger, H., Golden, J., Lovejoy, T., 2012. Creating the future we want. Sustain.: Sci. Pract. Policy 8 (2), 62–75.
Heipke, C., Oberst, J., Albertz, J., Attwenger, M., Dorninger, P., Dorrer, E., Ewe, M., Gehrke, S., Gwinner, K., Hirschmüller, H., Kim, J.R., Kirk, R.L., Mayer, H., Muller, J.-P., Rengarajan, R., Rentsch, M., Schmidt, R., Scholten, F., Shan, J., Spiegel, M., Wählisch, M., Neukum, G., the HRSC Co-Investigator Team, 2007. Evaluating planetary digital terrain models – the HRSC DTM test. Planet. Space Sci. 55 (14), 2173–2191.
Heipke, C., Woodsford, P.A., Gerke, M., 2008. Updating geospatial databases from images. In: Li, Z., Chen, J., Baltsavias, M. (Eds.), Advances in Photogrammetry, Remote Sensing and Spatial Information Sciences. Taylor & Francis, London, pp. 355–362.
Heipke, C., 2010. Crowdsourcing geospatial data. ISPRS J. Photogramm. Rem. Sens. 65 (6), 550–557.
Helmholz, P., Becker, C., Breitkopf, U., Büschenfeld, T., Busch, A., Braun, C., Grünreich, D., Müller, S., Ostermann, J., Pahl, M., Rottensteiner, F., Vogt, K., Ziems, M., Heipke, C., 2012. Semi-automatic quality control of topographic data sets. Photogramm. Eng. Rem. Sens. 78 (9), 959–972.
Hey, T., Trefethen, A., 2005. Cyberinfrastructure for e-Science. Science 308, 817–821.
Hirschmüller, H., 2008. Stereo processing by semi-global matching and mutual information. IEEE Trans. Pattern Anal. Mach. Intell. 30 (2), 328–341.
Hoberg, T., Rottensteiner, F., Feitosa, R.Q., Heipke, C., 2015. Conditional random fields for multitemporal and multiscale classification of optical satellite imagery. IEEE Trans. Geosci. Rem. Sens. 53 (2), 659–673.
Hofmann, O., Nave, P., Ebner, H., 1982. DPS – a digital photogrammetric system for producing digital elevation models and orthophotos by means of linear array scanner imagery. In: The International Archives of Photogrammetry and Remote Sensing, vol. XXIV-B3, pp. 216–227.
Honkavaara, E., Arbiol, R., Markelin, L., Martinez, L., Cramer, M., Bovet, S., Veje, N., 2009. Digital airborne photogrammetry – a new tool for quantitative remote sensing? – A state-of-the-art review on radiometric aspects of digital photogrammetric images. Rem. Sens. 1 (3), 577–605.
Huang, H., Mayer, H., 2007. Extraction of the 3D branching structure of unfoliaged deciduous trees from image sequences. Photogrammetrie – Fernerkundung – Geoinform. (6), 429–436
Huang, W., Li, S., Liu, X., Ban, Y., 2015. Predicting human mobility with activity changes. Int. J. Geogr. Inform. Sci. 29 (9), 1569–1587.
Hughes, C., Sengupta, R., Naik, V., Saxena, D., 2014. Geovisualization for cluster detection of Hepatitis A & E outbreaks in Ahmedabad, Gujarat, India. In: Proceedings of the 3rd ACM SIGSPATIAL International Workshop on the use of GIS in Public Health, Dallas, TX.
Hughes, G.F., 1968. On the mean accuracy of statistical pattern recognizers. IEEE Trans. Inform. Theory 14 (1), 55–63.
Hussain, M., Chen, D., Cheng, A., Wei, H., Stanley, D., 2013. Change detection from remotely sensed images: from pixel-based to object-based approaches. ISPRS J. Photogramm. Rem. Sens. 80, 91–106.
Hyde, P., Dubayah, R., Walker, W., Blair, J.B., Hofton, M., Hunsaker, C., 2006. Mapping forest structure for wildlife habitat analysis using multi-sensor (Lidar, SAR/InSAR, ETM+, Quickbird) synergy. Rem. Sens. Environ. 102 (1), 63–73.
Hyyppä, J., Jaakola, A., Chen, Y., Kukko, A., Kaartinen, H., Zhu, L., Alho, P., Hyyppä, H., 2013. Unconventional lidar mapping from air, terrestrial and mobile. In: Fritsch, D. (Ed.), Photogrammetric Week 2013. Wichmann, Heidelberg, pp. 205–214.
Jeffery, K., Asserson, A., Houssos, N., Brasse, V., Jörg, B., 2014. From open data to data-intensive science through CERIF. Proc. Comput. Sci. 33, 191–198.
Jeong, M., Duckham, M., 2013. Decentralized querying of topological relations between regions monitored by a coordinate-free geosensor network. GeoInformatica 17 (4), 669–696.
Joseph, G., 2015. Building Earth Observation Cameras. CRC Press, Taylor & Francis Group, Boca Raton, USA, 350 p.
Joshi, A., Josiane, M., Sriram, I., Robert, V., Craig, J., Jiajie, Z., 2014. Usability evaluations of an interactive, internet enabled human centered sanaviz geovisualization application. In: HCI in Business, LNCS, vol. 8527, pp. 723–734.
Kada, M., 2014. Progressive transmission of 3D building models based on string grammars and planar half-spaces. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. II-2, pp. 9–14.

Kauffman, J., Arico, S., 2014. New directions in sustainability science: promoting integration and cooperation. Sustain. Sci. 9, 413–418.
Kelmelis, J., DeMulder, M., Ogrosky, C., van Driel, N., Ryan, B., 2003. The national map from geography to mapping and back again. Photogramm. Eng. Rem. Sens. 69 (10), 1109–1118.
Kim, J.H., 2013. Spatiotemporal scale dependency and other sensitivities in dynamic land-use change simulations. Int. J. Geogr. Inform. Sci. 27 (9), 1782–1803.
Kitt, B., Ranft, B., Lategahn, H., 2010. Detection and tracking of independently moving objects in urban environments. In: Proceedings of the 13th IEEE Conference on Intelligent Transportation Systems, pp. 1396–1401.
Klinger, T., Rottensteiner, F., Heipke, C., 2014. Pedestrian recognition and localisation in image sequences as bayesian inference. In: Kukelová, Z., Heller, J. (Eds.), Computer Vision Winter Workshop 2014. Czech Society for Cybernetics and Informatics, pp. 51–58.
Klingner, B., Martin, D., Roseborough, J., 2013. Street view motion-from-structure-from-motion. In: International Conference on Computer Vision, pp. 953–960.
Kolbe, T., 2009. Representing and exchanging 3D City models with CityGML-2. In: Lee, J., Zlatanova, S. (Eds.), 3D Geo-Information Sciences. Springer, Berlin, pp. 15–31.
Konecny, G., 1985. The international society for photogrammetry and remote sensing – 75 years old, or 75 years young. Photogramm. Eng. Rem. Sens. 51 (7), 919–933.
Konecny, G., 2013. Survey of the current status of mapping and map updating in the world. In: UN-GGIM Conference, Cambridge, UK, 24–26 July 2013.
Krieger, G., Moreira, A., Fiedler, H., Hajnsek, I., Werner, M., Younis, M., Zink, M., 2007. TanDEM-X: a satellite formation for high-resolution SAR interferometry. IEEE Trans. Geosci. Rem. Sens. 45 (11), 3317–3341.
Kuenzel, C., Dech, S., Wagner, W. (Eds.), 2015. Remote Sensing Time Series – Revealing Land Surface Dynamics. Springer, Berlin, 441p.
Kuhn, W., Kauppinen, T., Janowicz, K., 2014. Linked data – a paradigm shift for geographic information science. In: Duckham, M., Pebesma, E., Stewart, K., Frank, A. (Eds.), GI Science (LNCS 8728). Springer, Berlin, pp. 173–186.
Kunz, M., King, M.A., Mills, J.P., Miller, P.E., Fox, A.J., Vaughan, D.G., Marsh, S.H., 2012. Multi-decadal glacier surface lowering in the Antarctic Peninsula. Geophys. Res. Lett. 39, L19502. http://dx.doi.org/10.1029/2012GL052823.3.
Kwan, M., Shen, Y., Chai, Y., 2013. Investigating commuting flexibility with GPS data and 3D geovisualization: a case study of Beijing, China. J. Trans. Geogr. 32, 1–11.
Ladický, L., Sturgess, P., Russell, C., Sengupta, S., Bastanlar, Y., Clocksin, W., Torr, P.H. S., 2012. Joint optimization for object class segmentation and dense stereo reconstruction. Int. J. Comput. Vis. 100 (2), 122–133.
Lafarge, F., Descombes, X., Zerubia, J., Pierrot-Deseilligny, M., 2008. Building reconstruction from a single DEM. In: IEEE Conference on Computer Vision and Pattern Recognition, pp. 1–8.
Lafarge, F., Mallet, C., 2012. Creating large-scale city models from 3D-point clouds: a robust approach with hybrid representation. Int. J. Comput. Vis. 99 (1), 69–85.
Lee, J., Alnasrallah, M., Wong, D., Beaird, H., Logue, E., 2014. Impacts of scale on geographic analysis of health data: an example of obesity prevalence. ISPRS Int. J. Geo-Inform. 3 (4), 1198–1210.
Lee, J.-G., Kang, M., 2015. Geospatial big data: challenges and opportunities. Big Data Res. 2 (2), 74–81.
Li, G., Fang, C., 2014. Global mapping and estimation of ecosystem services values and gross domestic product: a spatially explicit integration of national 'green GDP' accounting. Ecol. Indic. 46, 293–314.
Li, S., 2008. Web mapping/GIS services and applications. In: Li, Z., Chen, J., Baltsavias, M. (Eds.), Advances in Photogrammetry, Remote Sensing and Spatial Information Sciences. Taylor & Francis, London, pp. 335–354.
Li, S., Yan, W., 2010. Mashing up geospatial data services: implications of acceptable use policies. Geomatica 64 (1), 111–122.
Li, S., Dragićević, S., Veenendaal, B. (Eds.), 2011. Advances in Web-based GIS, Mapping Services and Applications. CRC Press.
Li, W., Wu, C., 2014. Phenology-based temporal mixture analysis for estimating large-scale impervious surface distributions. Int. J. Rem. Sens. 35 (2), 779–795.
Li, Z., 1996. Transformation of spatial representation in scale dimension: a new paradigm for digital generalization of spatial data. In: The International Archives for Photogrammetry and Remote Sensing, vol. XXXI-B3, pp. 453–458.
Li, Z., 2012. Theories of map design in the digital era. Cartogr. Geogr. Inform. Sci. 39 (2), 71–75.
Li, Z., Chen, J., Baltsavias, M. (Eds.), 2008. Advances in Photogrammmetry, Remote Sensing and Spatial Information Sciences. Taylor & Francis, London.
Li, Z., Huang, P., 2002. Quantitative measures for spatial information of maps. Int. J. Geogr. Inform. Sci. 16 (7), 699–709.
Li, Z., Zhou, Q., 2012. Integration of linear- and areal-hierarchies for continuous multi-scale representation of road networks. Int. J. Geogr. Inform. Sci. 46 (5), 855–880.
Lichti, D.D., Chow, J., Lahamy, H., 2011. Parameter decorrelation and model-identification in hybrid-style terrestrial laser scanner self-calibration. ISPRS J. Photogramm. Rem. Sens. 66 (3), 317–332.
Liu, L., Qiao, S., Zhang, Y., Hu, J., 2012. An efficient outlying trajectories mining approach based on relative distance. Int. J. Geogr. Inform. Sci. 26 (10), 1789–1810.
Liu, X., Li, S., Huang, W., Gong, J., 2015. Designing sea ice web APIs for ice information services. Earth Sci. Inform. 8 (3), 483–497.
Long, Z., Li, S., 2013. A complete classification of spatial relations using the Voronoi-based nine-intersection model. Int. J. Geogr. Inform. Sci. 15 (3), 201–220.
Lowe, D., 2004. Distinctive image features from scale-invariant keypoints. Int. J. Comput. Vis. 60 (2), 91–110.
Lu, D., Li, G., Moran, E., 2014. Current situation and needs of change detection techniques. Int. J. Image Data Fusion 5 (1), 13–38.
Lucas, R., Blonda, P., Bunting, P., Jones, G., Inglada, J., Arias, M., Kosmidou, V., Petrou, Z., Manakos, I., Adamo, M., Charnock, R., Tarantino, C., Mücher, C., Jongman, R., Kramer, H., Arvor, D., Pradinho-Honrado, J., Mairota, P., 2015. The earth observation data for habitat Monitoring (EODHaM) system. Int. J. Appl. Earth Observation Geoinform. 37, 17–28.
Majid, A., Chen, L., Chen, G., Mirza, H.T., Hussain, I., Woodward, J., 2013. A context-aware personalized travel recommendation system based on geotagged social media data mining. Int. J. Geogr. Inform. Sci. 27 (4), 662–684.
Mallet, C., Bretar, F., 2009. Full-waveform topographic lidar: state-of-the-art. ISPRS J. Photogramm. Rem. Sens. 64 (1), 1–16.
Mayer, H., 2008. Object extraction in photogrammetric computer vision. ISPRS J. Photogramm. Rem. Sens. (63), 213–222
Mayer, H., 2014. Efficient hierarchical triplet merging for camera pose estimation. In: German Conference on Pattern Recognition – GCPR 2014. Springer, Berlin, pp. 99–409.
McBean, G A., 2014. The grand challenges of integrated research on disaster risk. In: Extreme Natural Hazards, Disaster Risks and Societal Implications, (1), pp. 15.
McDowell, N., Coops, N., Beck, P., Chamers, J., Gangodagamage, C., Hicke, J., Huang, C., Kennedy, R., Krofcheck, D., Litvak, M., Medens, A., Muss, J., Negron-Juarez, R., Peng, C., Schwantes, A., Swenson, J., Vernon, L., Williams, A., Xu, C., Zhao, M., Running, S., Allen, C., 2015. Global satellite monitoring of climate-induced vegetation disturbances. Trends Plant Sci. 20 (2), 114–123.
McInerney, D., Bastin, L., Díaz, L., Figueiredo, C., Barredo, J., San-Miguel, Ayanz J., 2012. Developing a forest data portal to support multi-scale decision making. IEEE J. Selec. Top. Appl. Earth Observations Rem. Sens. 5 (6), 1692–1699.
Menze, M., Geiger, A., 2015. Object scene flow for autonomous vehicles. In: IEEE Conference on Computer Vision and Pattern Recognition, pp. 3061–3070.
Menze, M., Heipke, C., Geiger, A., 2015. Joint 3D estimation of vehicles and scene flow. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. II-3/W5, pp. 427–434.
Miller, H.J., 2004. Tobler's first law and spatial analysis. Ann. Assoc. Am. Geogr. 94 (2), 284–289.
Miller, H.J., Han, J. (Eds.), 2009. Geographic Data Mining and Knowledge Discovery. CRC Press.
Mouillot, F., Schultz, M., Yue, C., Cadule, P., Tansey, K., Ciais, P., Chuvieco, E., 2014. Ten years of global burned area products from spaceborne remote sensing—a review: analysis of user needs and recommendations for future developments. Int. J. Appl. Earth Observation Geoinform. 26, 64–79.
Mountrakis, G., Im, J., Ogole, C., 2011. Support vector machines in remote sensing: a review. ISPRS J. Photogramm. Rem. Sens. 66 (3), 247–259.
Moudrý, V., Šímová, P., 2012. Influence of positional accuracy, sample size and scale on modelling species distributions: a review. Int. J. Geogr. Inform. Sci. 26 (11), 2083–2095.
Nagai, M., Chen, T., Shibasaki, R., Kumagai, H., Ahmed, A., 2009. UAV-borne 3-D mapping system by multisensor integration. IEEE Trans. Geosci. Rem. Sens. 47 (3), 701–708.
Nativi, S., Mazzettia, P., Gellerb, G.N., 2013. Environmental model access and interoperability: the GEO Model Web initiative. Environ. Modell. Softw. 39, 214–228.
Nativi, S., Mazzetti, P., Santoro, M., Papeschi, F., Craglia, M., Ochiai, O., 2015. Big data challenges in building the global earth observation system of systems. Environ. Modell. Softw. 68, 1–26.
Nex, F., Gerke, M., Remondino, F., Przybilla, H.J., Bäumker, M., Zurhorst, A., 2015. ISPRS Benchmark for multi-platform photogrammetry. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. II-3/W4, pp. 135–142.
Niemeyer, J., Rottensteiner, F., Soergel, U., 2014a. Contextual classification of lidar data and building object detection in urban areas. ISPRS J. Photogramm. Rem. Sens. 87 (1), 152–165.
Niemeyer, J., Kogut, T., Heipke, C., 2014b. Airborne laser bathymetry for monitoring the german baltic sea coast. In: Seyfert, E., Gülch, E., Heipke, C., Schiewe, J., Sester, M. (Eds.), DGPF Annual Meeting Nr. 23, München, 10p.
Nistér, D., 2004. An efficient solution to the five-point relative pose problem. IEEE Trans. Pattern Anal. Mach. Intell. 26 (6), 756–770.
Niu, Z., Li, S., Pousaeid, N., 2011. Road extraction using smart phones GPS. In: 2nd ACM International Conference on Computing for Geospatial Research & Applications, pp. 1–6.
Obradovic, Z., Das, D., Radosavljevic, V., Ristovski, K., Vucetic, S., 2010. Spatio-temporal characterization of aerosols through active use of data from multiple sensors. In: The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVIII-7B, pp. 424–429.
O'Riordan, T., 2013. Future earth: a refreshed sustainability science. Environ.: Sci. Policy Sustain. Dev. 55 (3), 2.
Pajeres, G., 2015. Overview and current status of remote sensing applications based on unmanned aerial vehicles. Photogramm. Eng. Rem. Sens. 81 (4), 281–329.
Palm, S., Pohl, N., Stilla, U., 2015. Challenges and potentials using multi aspect coverage of urban scenes by airborne SAR on circular trajectories. In: The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XL-3/W2, pp. 149–154.
Pan, S.J., Yang, Q., 2010. A survey on transfer learning. IEEE Trans. Knowl. Data Eng. 22 (10), 1345–1359.
Paparoditis, N., Boudet, L., Tournaire, O., 2007. Automatic man-made object extraction and scene reconstruction from geomatic images. In: URBAN, GRSS/

ISPRS Joint Workshop on Data Fusion and Remote Sensing over Urban Areas, Paris, France, pp. 1–6.
Paparoditis, N., Papelard, J.-P., Cannelle, B., Devaux, A., Soheilian, B., David, N., Houzay, E., 2012. Stereopolis II: a multi-purpose and multi-sensor 3D mobile mapping system for street visualisation and 3D metrology. Revue Française de Photogrammétrie et de Télédétection 200, 69–79.
Parmentier, B., Eastman, J.R., 2014. Land transitions from multivariate time series: using seasonal trend analysis and segmentation to detect land-cover changes. Int. J. Rem. Sens. 35 (2), 671–692.
Pasewaldt, S., Semmo, A., Trapp, M., Döllner, J., 2014. Multi-perspective 3D panoramas. Int. J. Geogr. Inform. Sci. 28 (10), 2030–2051.
Pereira, H.M., Ferrier, S., Walters, M., Geller, G., Jongman, R., Scholes, R., Bruford, M., Brummitt, N., Butchart, S., Cardoso, A., Coops, N., Dulloo, E., Faith, D., Freyhof, J., Gregory, R., Heip, C., Höft, R., Hurtt, G., Jetz, W., Karp, D., McGeoch, M., Obura, D., Onoda, Y., Pettorelli, N., Reyers, B., Sayre, R., Scharlemann, J., Stuart, S., Turak, Walpole, M., Wegmann, M., 2013. Essential biodiversity variables. Sci. Mag. 339 (6117), 277–278.
Pielke Sr., R., Pitman, A., Niyogi, D., Mahmood, R., McAlpine, C., Hossain, F., Goldewijk, K., Nair, U., Betts, R., Fall, S., Reichstein, M., Kabat, P., de Noblet, N., 2011. Land use/land cover changes and climate: modeling analysis and observational evidence. Wires Clim. Change 2 (6), 828–850.
Pierrot-Deseilligny, M., Paparoditis, N., 2006. A multiresolution and optimization-based image matching approach: an application to surface reconstruction from SPOT5-HRS stereo imagery. In; The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI-1/W41, 5p.
Popa, I.S., Zeitouni, K., Oria, V., Kharrat, A., 2015. Spatio-temporal compression of trajectories in road networks. GeoInformatica 9 (1), 117–145.
Qin, R., Grün, A., 2014. 3D change detection at street level using mobile laser scanning point clouds and terrestrial images. ISPRS J. Photogramm. Rem. Sens. 90, 23–35.
Quartulli, M., Olaizola, I., 2013. A review of EO image information mining. ISPRS J. Photogramm. Rem. Sens. 75, 11–28.
Rabe, C., Müller, T., Wedel, A., Franke, U., 2010. Dense, robust and accurate motion field estimation from stereo image sequences in real-time. In: European Conference on Computer Vision, pp. 582–595.
Raguse, K., Heipke, C., 2009. Synchronization of image sequences – a photogrammetric method. Photogramm. Eng. Rem. Sens. 75 (5), 535–546.
Reid, W., Chen, D., Goldfarb, L., Hackmann, H., Lee, Y., Mokhele, K., Ostrom, E., Raivio, K., Rockström, J., Schellnhuber, H., Whyte, A., 2010. Earth system science for global sustainability: grand challenges. Environ. Dev. Sci. 330 (6006), 916–917.
Remondino, F., Fraser, C., 2006. Digital camera calibration methods: considerations and comparisons. In: The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. XXXVI-5, pp. 266–272.
Ren, A.Z., Shi, J.Y., Shi, W.Z., 2007. Integration of fire simulation and structural analysis for safety evaluation of gymnasiums-with a case study of gymnasium for Olympic Games in 2008. Autom. Construct. 16 (3), 277–289.
Ricotta, C., Carranza, M., 2013. Measuring scale-dependent landscape structure with Rao's quadratic diversity. ISPRS Int. J. Geo-Inform. 2 (2), 405–412.
Ripperda, N., 2008. Grammar based facade reconstruction using RJMCMC. Photogrammetrie • Fernerkundung • Geoinform. (2), 83–92
Robinson, N., Regetz, J., Guralnick, R., 2014. EarthEnv-DEM90: a nearly-global, void-free, multi-scale smoothed, 90m digital elevation model from fused ASTER and SRTM data. ISPRS J. Photogramm. Rem. Sens. 87, 57–67.
Roig, G., Boix, X., Ben, Shitrit H., Fua, P., 2011. Conditional random fields for multi-camera object detection. In: International Conference on Computer Vision, pp. 563–570.
Rottensteiner, F., Sohn, G., Gerke, M., Wegner, J., Breitkopf, U., 2014. Results of the ISPRS benchmark on urban object detection and 3D building reconstruction. ISPRS J. Photogramm. Rem. Sens. 93 (7), 256–271.
Ruiz, M., López, F., Páez, A., 2012. Comparison of thematic maps using symbolic entropy. Int. J. Geogr. Inform. Sci. 26 (3), 413–439.
Sandau, R. (Ed.), 2009. Digital Airborne Camera. Springer, Berlin.
Sandau, R., Röser, H.-P., Valenzuela, A. (Eds.), 2011. Small Satellite Missions for Earth Observation – New Developments and Trends. Springer, Berlin.
Schiermeier, M., 2013. Outlook for earth – a special issue on the IPCC. Nature 19 (501/297), 304–305.
Schindler, K., Ess, A., Leibe, B., van Gool, L., 2010. Automatic detection and tracking of pedestrians from a moving stereo rig. ISPRS J. Photogramm. Rem. Sens. 65 (6), 523–537.
Schindler, K., 2012. An overview and comparison of smooth labeling methods for land-cover classification. IEEE Trans. Geosci. Rem. Sens. 50 (11), 4534–4545.
Schmeller, D.S., Julliard, R., Bellingham, P., Böhm, M., Brummitt, N., Chiarucci, A., Couvet, D., Elmendorf, S., Forsyth, D., Moreno, J., Gregory, R., Magnusson, W., Martin, L., McGeoch, M., Mihoub, J.-B., Proenca, V., van Swaay, C., Yahara, T., Belnap, J., 2015. Towards a global terrestrial species monitoring program. J Nat. Conserv. 25, 51–57.
Schubert, J., Moradi, F., Asadi, H., Luotsinen, L., Sjöberg, E., Höfling, P., Linderhed, A., Oskarsson, D., 2015. Simulation-based decision support for evaluating operational plans. Oper. Res. Perspect. 2, 36–56.
See, L., Schepaschenko, D., Lesiv, M., McCallum, I., Fritz, S., Comber, A., Perger, C., Schill, C., Zhao, Y., Maus, V., Athar, M., Albrecht, S., Cipriani, A., Vakolyuk, M., Garcia, A., Rabia, A., Singha, K., Marcarini, A., Kattenborn, T., Hazarika, R., Schepaschenko, M., 2015. Building a hybrid land cover map with crowdsourcing and geographically weighted regression. ISPRS J. Photogramm. Rem. Sens. 103, 48–56.
Sester, M., Arsanjani, J., Klammer, R., Burghardt, D., Haunert, J., 2014. Integrating and generalizing volunteered geographic information. In: Burghardt, Duchene, Mackaness (Eds.), Abstracting Geographic Information in a Data Rich World – Methodologies and Applications of Map Generalisation. Springer, Berlin.
Sester, M., Brenner, C., 2009. A vocabulary for a multiscale process description for fast transmission and continuous visualization of spatial data. Comput. Geosci. 35 (11), 2177–2184.
Sieber, R., Hollenstein, L., Eichenberger, R., 2012. Concepts and techniques of an online 3D atlas–challenges in cartographic 3D geovisualization. Leveraging Applications of Formal Methods, Verification and Validation. Applications and Case Studies, LNCS, vol. 7610. Springer, Berlin, pp. 325–326.
Simón, L., Ramos, F., Avilés, R., Botezan, I., del Valle, Gastaminza F., Cobo, Serrano S., 2014. Open data as universal service, new perspectives in the information profession. Proc. – Soc. Behav. Sci. 147, 126–132.
Spiegel, M., 2007. Improvement of interior and exterior orientation of the three line camera HRSC with a simultaneous adjustment. In: The International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences, vol. XXXVI-3/W49B, pp. 161–166.
Stange, H., Bothe, S., 2013. Reality monitoring. Crisis Prevent. 2 (1), 25–27.
Steiniger, S., Hunter, A., 2013. The 2012 free and open source GIS software map – a guide to facilitate research, development, and adoption. Comput. Environ. Urban Syst. 39, 136–150.
Stettner, R., 2010. Compact 3D flash lidar video cameras and applications. In: Turner, M., Kamerman, G. (Eds.), Proc. SPIE 7684, Laser Radar Technology and Applications, vol. XV, 8p.
Stoter, J., Post, M., van Altena, V., Nijhuis, R., Bruns, B., 2014. Fully automated generalization of a 1:50k map from 1:10k data. Cartogr. Geogr. Inform. Sci. 41 (1), 1–13.
Strecha, C., Pylvänäinen, T., Fua, P., 2010. Dynamic and scalable large scale image reconstruction. In: IEEE Conference on Computer Vision and Pattern Recognition, pp. 358–365.
Sui, D., Elwood, S., Goodchild, M. (Eds.), 2013. Crowdsourcing Geographic Knowledge Volunteered Geographic Knowledge in Theory and Practice. Springer, Berlin.
Suresh, S., 2012. Global challenges need global solutions. Nature (490), 337–338.
Swain, N., Latu, K., Christensen, S., Jones, N., Nelson, J., Ames, D., Williams, G., 2015. A review of open source software solutions for developing water resources web applications. Environ. Modell. Softw. 67, 108–117.
Thrun, S., Burgard, W., Fox, D., 2005. Probabilistic Robotics. The MIT Press, Cambridge, MA.
Ti, P., Li, Z., 2014. Generation of schematic network maps with automated detection and enlargement of congested areas. Int. J. Geogr. Inform. Sci. 28 (3), 521–540.
Tournaire, O., Brédif, M., Boldo, D., Durupt, M., 2010. An efficient stochastic approach for building footprint extraction from digital elevation models. ISPRS J. Photogramm. Rem. Sens. 65 (4), 317–327.
Trinder, J., Fritz, L., 2008. Historical development of ISPRS. In: Li, Z., Chen, J., Baltsavias, M. (Eds.), Advances in Photogrammetry, Remote Sensing and Spatial Information Sciences. Taylor & Francis, London, pp. 3–13.
UN-GGIM, 2013. United Nations Global Geospatial Information Management: Future Trends in Geospatial Information Management – the Five to Ten Year Vision, New York. ISBN: 978-0-319-08792-3.
Vallet, B., Brédif, M., Serra, A., Marcotegui, B., Paparoditis, N., 2015. TerraMobilita/iQmulus Urban point cloud analysis benchmark. Comput. Graph. 49 (6), 126–133.
van de Weghe, N., de Roo, B., Qiang, Y., Versichele, M., Neutens, T., de Maeyer, P., 2014. The continuous spatio-temporal model (CSTM) as an exhaustive framework for multiscale spatio-temporal analysis. Int. J. Geogr. Inform. Sci. 28 (5), 1047–1060.
van Dijk, T., Haunert, J., 2014. Interactive focus maps using least-squares optimization. Int. J. Geogr. Inform. Sci. 28 (10), 2052–2075.
van Gasselt, S., Nass, A., 2011. Planetary mapping – the data model's perspective and GIS framework. Planet. Space Sci. 59, 1231–1242.
Vaz, E., Aversa, J., 2013. A Graph theory approach for geovisualization of land use change: an application to Lisbon. J. Spatial Organ. Dynam. 1 (4), 254–264.
Veenendaal, B., Li, S., Dragićević, S., Brovelli, M., 2014. Analytical geospatial digital earth. Int. J. Digit. Earth 7 (4), 253–255.
Vogel, C., Schindler, K., Roth, S., 2013. Piecewise rigid scene flow. In: International Conference on Computer Vision, pp. 1377–1384.
Vosselman, G., 2009. Advanced point cloud processing. In: Fritsch (Ed.), Photogrammetric Week 2009. Wichmann, Heidelberg, pp. 137–146.
Whitcraft, A., Becker-Reshef, I., Justice, C., 2015. A framework for defining spatially explicit earth observation requirements for a global agricultural monitoring initiative. Rem. Sens. 7, 1461–1481.
Wise, S., 2000. GIS data modelling—lessons from the analysis of DTMs. Int. J. Geogr. Inform. Sci. 14 (4), 313–318.
Wojek, C., Roth, S., Schindler, K., Schiele, B., 2010. Monocular 3D scene modeling and inference: understanding multi-object traffic scenes. In: European Conference on Computer Vision, pp. 467–481.
Xiao, N., Armstrong, M., 2012. Towards a multiobjective view of cartographic design. Cartogr. Geogr. Inform. Sci. 39 (2), 76–87.
Xiong, B., Jancosek, M., Elberink, S.O., Vosselman, G., 2015. Flexible building primitives for 3D building modeling. ISPRS J. Photogramm. Rem. Sens. 101, 275–290.
Yang, C., Xu, Y., Nebert, D., 2014. Redefining the possibility of digital Earth and geosciences with spatial cloud computing. Int. J. Digit. Earth 6 (4), 297–312.

Yang, M., Förstner, W., 2011. A hierarchical conditional random field model for labelling and classifying images of man-made scenes. In: International Conference on Computer Vision Workshops (WS04), pp. 196–203.

Zell, E., Huff, A., Carpenter, A., Friedl, L., 2012. A user-driven approach to determining critical earth observation priorities for societal benefit. IEEE J. Sel. Top. Appl. Earth Observations Rem. Sens. 5 (6), 1594–1602.

Zhang, L., Thiemann, F., Sester, M., 2010. Integration of GPS traces with road map. In: Proceedings of the 2nd International Workshop on Computational Transportation Science, pp. 17–22.

Zhao, P., Foerster, T., Yue, P., 2012. The geoprocessing web. Comput. Geosci. 47, 3–12.

Zhou, Q., Li, Z., 2014. Use of artificial neural networks for selective omission in updating road networks. Cartogra. J. 51 (1), 38–51.

Zhou, X., Chen, J., Zhan, B., Li, Z., Madden, M., Zhao, R., Liu, W., 2013. A Euler number-based topological computation model for land parcel database updating. Int. J. Geogr. Inform. Sci. 27 (10), 1983–2005.

Zhu, X., Bamler, R., 2012. Super-resolution power and robustness of compressive sensing for spectral estimation with application to spaceborne tomographic SAR. IEEE Trans. Geosci. Rem. Sens. 50 (1), 247–258.

Zia, M.Z., Stark, M., Schiele, B., Schindler, K., 2013. Detailed 3D representation for object recognition and modeling. IEEE Trans. Pattern Recogn. Mach. Intell. 35 (11), 2608–2623.

Zink, M., Bachmann, M., Bräutigam, B., Fritz, T., Hajnsek, I., Krieger, G., Moreira, A., Wessel, B., 2014. TanDEM-X: the new global DEM takes shape. IEEE Geosci. Rem. Sens. Mag. 2 (2), 8–23.