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Object-Based Image Analysis: Evolution, History, State of the Art, and Future Vision

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Acronyms and Definitions

API	Application programming interface
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ECHO	Extraction and classification of homogeneous objects
ENVI	Environment for visualizing images
GEOBIA	Geographic object-based image analysis
GIS	Geographic information system
GIScience	Geographic information science
GPL	General public license
GPS	Global positioning system
ISI	Institute for Scientific Information
LiDAR	Light detection and ranging
NGO	Nongovernmental organization
OBIA	Object-based image analysis
OGC	Open Geospatial Consortium
PPGIS	Public participation geographic information system
RGB	Red, green, blue color system
RS	Remote sensing
RSGISLib	Remote sensing and GIS software library
SAGA	System for automated geoscientific analyses
UAS	Unmanned aerial systems
VGI	Volunteered geographic information
WoS	Web of science

14.1 Introduction

Remote sensing, what it is and what it can be used for, is laid out in various chapters of this comprehensive book. We may only state here that remote sensing has a short history—when compared to traditional disciplines such as mathematics or physics. Contrarily, we may state that it has a long history when we compare it to recent Internet-based technology like social media or, closer to our field, the tracking of people and moving objects by means of cell phone signals. Remote sensing has been a domain for specialists for many years and to some degree it still is. Similarly, geographic information system (GIS) has for years been a field where professionals worked on designated workstations while not being fully integrated in standard corporate information technology infrastructures. The latter changed more than a decade ago, while for remote sensing only recently, one may still witness remnants of historical developments of Remote Sensing (RS)-specific hardware and software. The dominant concept in remote sensing has been the pixel, while GIS functionality has always been somehow splintered into the raster and vector domains. Blaschke and Strobl (2001) provocatively raised the question "What's wrong with pixels?"

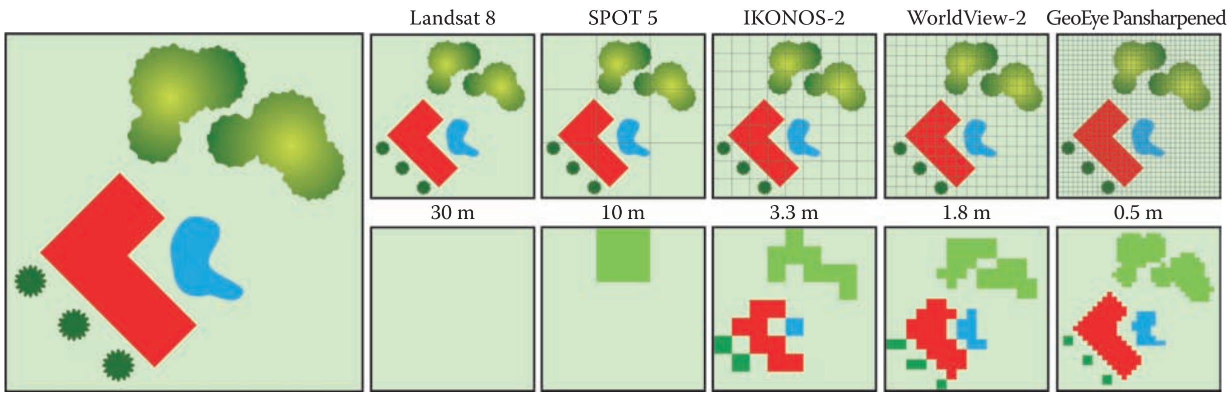

FIgure 14.1 Objects and resolutions: OBIA methods are associated with the notion of high resolution—whereby *high* has always to be seen in context.

having identified an increasing dissatisfaction with pixel-by-pixel image analysis. Although this critique was not new (Cracknell 1998; see also Blaschke and Strobl 2001; Burnett and Blaschke 2003; Blaschke 2010; Blaschke et al. 2014 for a more thorough discussion), these authors described a need for applications *beyond pixels* and for specific methods and methodologies that support this (Figure 14.1).

Over the last years, the number of applications that conceptually aim for objects—still built on the information of the underlying pixels—rose quickly. Blaschke et al. (2014) identified a high number of relevant publications that use—with some degree of fuzziness in their terminology—the concept of object-based image analysis (OBIA). They even claim that this concept and its instantiation to a particular order of scale—the *geographic* as opposed to applications in medical imaging or cell biology—is a new paradigm in remote sensing. For this level of scale and the *geodomain*, this paradigm is then referred to by some scholars as Geographic Object-Based Image Analysis (GEOBIA), while the generic principles—the multiscale segmentation and object handling—may generically be called OBIA. Other sources use the more generic term of OBIA when referring to the geospatial domain also, and Blaschke et al. refer to Kuhn (1962) stating that an inconsistent use of terminology can be expected for a new paradigm. Nevertheless, it is high time to consolidate this terminology and to support a coherent usage of terms and naming conventions—after having agreed upon the concepts and the conception of the overall approach.

This chapter therefore briefly explains OBIA methods as used in the geospatial domain and elsewhere. We will start from the quest to partitioning geospatial data into meaningful image objects and the needs and possibilities to assessing their characteristics through spatial, spectral, and temporal scale. At its most fundamental level, OBIA requires image segmentation, attribution, classification, and the ability to query and link individual objects (aka segments) in space and time. We will elucidate the evolution of this approach, its relatively short history, and its older origins. Instead of a comprehensive state-of-the-art analysis, we refer to the key literature and try to summarize the core concepts for the reader in an understandable way, with a particular emphasis on a common nomenclature, definitions, and reporting procedures. Ultimately, we will ask where this development will lead to in terms of applications, research questions and needs in education, and training and professional workforce development, and we conclude with the main advances and recommendations for future work.

14.2 History of OBIA

14.2.1 Intellectual Roots

14.2.1.1 Conceptual Foundations

The conceptual foundations of OBIA are rooted in the 1960s with predigital aerial photography. The spatial information found in digital imagery that is harnessed in the object-based approach, for example, image texture, contextual information, pixel proximity, and geometric attributes of features, were discussed in the 1960s as possible components to yet possible automation of photo interpretation. In his seminal work on aerial photography and early remote-sensing applications, Colwell (1965) describes the photo interpretation process as the act of examining photographic images for the purpose of identifying objects and judging their significance. He said that photo interpretation involves the observation of the size, shape, shadow, tone, texture, pattern, and location of the features, as well as the significance of the features, based largely on their *interrelationships* or *association* (Colwell 1965). His assessment of the potential for automation of an object recognition process depended on the capacities of a digital scanner and the ability of an algorithm to assess the differences, in photographic tone, between a *blob* and its surroundings (Colwell 1964, 1965). Colwell was an important advisor on the Landsat 1 mission, and his ideas on extraction of meaningful features transferred to his ambitions for the satellite missions (Colwell 1973).

14.4.1.2 Image Segmentation

Image segmentation is the division of an image into different regions, each having certain properties, and it provides the building blocks of OBIA (Blaschke 2010). The desire expressed by Colwell and others in the 1960s to more automatically delineate meaningful features, objects, or *blobs* in his early terminology launched numerous approaches to image segmentation that rapidly advanced in the 1980s. It is widely agreed that the

TABLE 14.1 Overview of Major Groups of Image Segmentation Techniques

	Main Issues	Strengths	Weaknesses
Thresholding and clustering	Threshold values are applied globally (to the whole image) or locally (applied to subregions)	Most thresholding algorithms are computationally simple. Clustering an image or a raster may be intuitive for a given number of clusters	The results depend on the initial set of clusters and user values or thresholds, respectively
Edge detection	Boundaries of object or regions under consideration and edges are assumed to be closely related, since there are often sharp differences in intensity at the region boundaries	Discontinuities are identified across the array of values studied. Particularly suited for internally relatively homogeneous objects such as buildings, roads, or water bodies	Edges identified by edge detection are often disconnected. To segment an object from an image, however, one needs closed region boundaries. Typically problematic in objects with high internal heterogeneity such as forests
Region growing	Starting from the assumption that the neighboring pixels within one region have similar values, a similarity criterion is defined and applied in to neighboring pixels		Selection of the similarity criterion significantly influences the results

segmentation algorithms implemented in the OBIA software of today owe a debt to theoretical and applied work in the 1970s and 1980s that developed and refined numerous methods for image segmentation (Blaschke et al. 2004; Blaschke 2010). Early key papers for the remote-sensing field include Kettig and Landgrebe (1976) who presented experimental results in segmentation of Landsat 1 (ERTS-1) imagery, and McKeown et al. (1989) who developed a knowledge-based system with image segmentation and classification tools designed for semiautomated photo interpretation of aerial photographs. Key reviews are provided in numerous papers (Fu and Mui 1981; Haralick and Shapiro 1985; Pal and Pal 1993). Building on that work, image segmentation techniques implemented today include those focused on thresholding or clustering, edge detection, region extraction, and growing, and some combination of these has been explored since the 1970s (Fu and Mui 1981; Blaschke 2010) (Table 14.1).

14.2.2 Needs and Driving Forces

With a focus on geospatial data, OBIA has particular needs that were not anticipated by its antecedents. The OBIA methods were driven first by the need to more accurately map multiscaled Earth features with high-spatial-resolution imagery such as the tree, the building, and the field. Following that, the spatial dimension of objects (distances, pattern, neighborhoods, and topologies) was mined for classification accuracy (e.g., Guo et al. 2007). Most recently, the OBIA field has been characterized by discussions of object semantics within fixed or emergent ontologies (Arvor et al. 2013; Yue et al. 2013) and by the need for interoperability between OBIA and GIS and spatial modeling frameworks (Harvey and Raskin 2011; Yue et al. 2013). The OBIA approach has evolved from a method of convenience to what has been called a new paradigm in remote sensing and spatial analysis (Blaschke et al. 2014).

14.2.3 GEOBIA Developments

14.2.3.1 Emergence (1999–2003/2004)

The emergence of OBIA has been written about extensively elsewhere (e.g., Blaschke 2010; Blaschke et al. 2014) and had its largest boost from the availability of satellite imagery of increasing spatial resolution such as IKONOS (1–4 m), QuickBird (resolution), and OrbView (resolution) sensors (launched in 1999, 2001, and 2003, respectively) (Blaschke 2010). This ready availability of high-resolution multiband imagery coincided with increasing awareness in the remote-sensing literature that novel methods to extract meaningful and more accurate results were critically needed. The *business-as-usual* pixel-based algorithms were not reliable with imagery exhibiting high local variability and obvious spatial context (Cracknell 1998; Townshend et al. 2000; Blaschke and Strobl 2001).

Importantly, the software package called eCognition from the company Definiens (subsequently called Definiens Earth Sciences) became commercially available from 2000. This event is marked as a milestone in the emergence of a body of work on OBIA, as it was the first commercially available, object-based, image analysis software (Flanders et al. 2003; Benz et al. 2004; Blaschke 2010), and many peer-reviewed papers during this phase relied on the software. The eCognition software is built on to the approach originally known as Fractal Net Evolution (Baatz and Schäpe 2000; Blaschke 2010) that is not easily nor often described in detail in early papers that relied on the software.

Representative papers demonstrating the utility of the newly released software from this time frame include the following. Flanders et al. (2003) evaluated the object-based approach from eCognition software and classified forest clearings and forest structure elements in British Columbia, Canada, using a Landsat-enhanced thematic mapper plus image. They found that forest clearings as well as forest growth stage, water, and urban features were classified with significantly higher accuracy than using a traditional pixel-based method. With slightly different results, Dorren et al. (2003) also compared pixel- and object-based classification of forest stands using Landsat imagery in Austria. They used eCogntion for the object-based approach and found that while the pixel-based method provided slightly better accuracies, the object-based approach was more realistic and better served the needs of local foresters. Benz et al. (2004) used eCognition to update urban maps (buildings, roofs, etc.) from high-resolution (0.5 m) RGB aerial orthoimages in Austria. Theirs was an early and comprehensive examination of

TABLE 14.2 Overview of Early Application Fields

Application	Images	Comparison to Pixel-Based/Findings	Software
Forest clearings and forest structure (Flanders et al. 2003)	Landsat-enhanced thematic mapper plus image	Significantly higher accuracy of OBIA compared to pixel based	eCognition
Forests (Dorren et al. 2003)	Landsat	Pixel-based method provided slightly better accuracies, but the object-based approach was more realistic and better served the needs of local foresters	eCognition
Update urban maps (Benz et al. 2004)	High-resolution (0.5 m) RGB aerial orthoimages	Comprehensive examination of the use of the software. Discussed, for example, the importance of semantic features and uncertainties in representation	eCognition
Shrub cover and rangeland characteristics (Laliberte et al. 2004)	Historic (1937–1996) scanned aerial photos and a contemporary QuickBird satellite image		eCognition
Correlate field-derived forest inventory parameters and image objects (Chubey et al. 2006)	IKONOS-2 imagery	The strongest relationships were found for discrete land-cover types, species composition, and crown closure	eCognition
Vegetation inventory (Yu et al. 2006)	Digital airborne imaging system imagery	The object-based approach outperformed the pixel-based approach	
Map surface coal fires (Yan et al. 2006)	ASTER image (15 m resolution)	The OBIA approach yielded classifications of marked improvement over the pixel-based approach	

the use of the software, and they discussed numerous aspects of the OBIA approach that are still actively discussed today—for example, the importance of semantic features and uncertainties in representation. Laliberte et al. (2004) used a combination of historic (1937–1996) scanned aerial photos and a contemporary QuickBird satellite image to map shrub cover and rangeland characteristics over time. The eCognition was critical in their workflow. Chubey et al. (2006) used eCognition to segment IKONOS-2 imagery and decision tree analysis to correlate field-derived forest inventory parameters and image objects for forests in Alberta, Canada. They found that the strongest relationships were found for discrete land cover types, species composition, and crown closure. While much work focused on the use of eCognition for high-resolution imagery, not all work in this phase did. Many papers explored the method using Landsat imagery (e.g., Dorren et al. 2003) (Table 14.2).

14.2.3.2 Establishment (2005–2010)

14.2.3.2.1 Accuracy

Many papers during this time frame focused on proving the utility of the new approach and provided comparisons between OBIA and pixel-based classifiers (Yan et al. 2006; Cleve et al. 2008; Maxwell 2010). For example, Yu et al. (2006) used high-spatial-resolution digital airborne imaging system imagery and associated topographic data of the Point Reyes National Seashore in California, United States, for a comprehensive and detailed vegetation inventory at the alliance level. The object-based approach outperformed the pixel-based approach. Yan et al. (2006) compared pixel- and object-based classification of an Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) image (15 m resolution) to map surface coal fires and coal piles. The OBIA approach yielded classifications of marked improvement over the pixel-based approach. Similar results were shown using high-resolution aerial imagery for urban features (Cleve et al. 2008), Landsat imagery, and land cover (Maxwell 2010).

14.2.3.2.2 Applications

From 2005 to 2010, there was a wide net cast around OBIA application areas. Table 14.3 provides an overview of the various application areas, which emerged over these years.

Capturing, attributing, and understanding changing landscapes continues to be a primary research area in remote sensing, and the use of OBIA methods for studying and understanding

TABLE 14.3 Development of OBIA Application Fields

Application Area	Examples
Forests	Flanders et al. (2003)
	Dorren et al. (2003)
Individual trees	Guo et al. (2007)
	De Chant et al. (2009)
Forest stands	Radoux and Defourny (2007)
	Gergel et al. (2007)
Parklands	Rocchini et al. (2006)
	Yu et al. (2006)
Rangelands	Laliberte et al. (2007)
Wetlands and other critical habitat	Bock et al. (2005)
Urban areas	Weeks et al. (2007)
	Cleve et al. (2008)
	Durieux et al. (2008)
Land use and land cover	Maxwell (2010)
Public health	Kelly et al. (2011)
Disease vector habitats	Koch et al. (2007)
	Troyo et al. (2009)
Public health infrastructure (e.g., refugee camps)	Lang and Blaschke (2006)
Hazard vulnerability and disaster aftermath	Al-Khudhairy et al. (2005)
	Gusella et al. (2005)

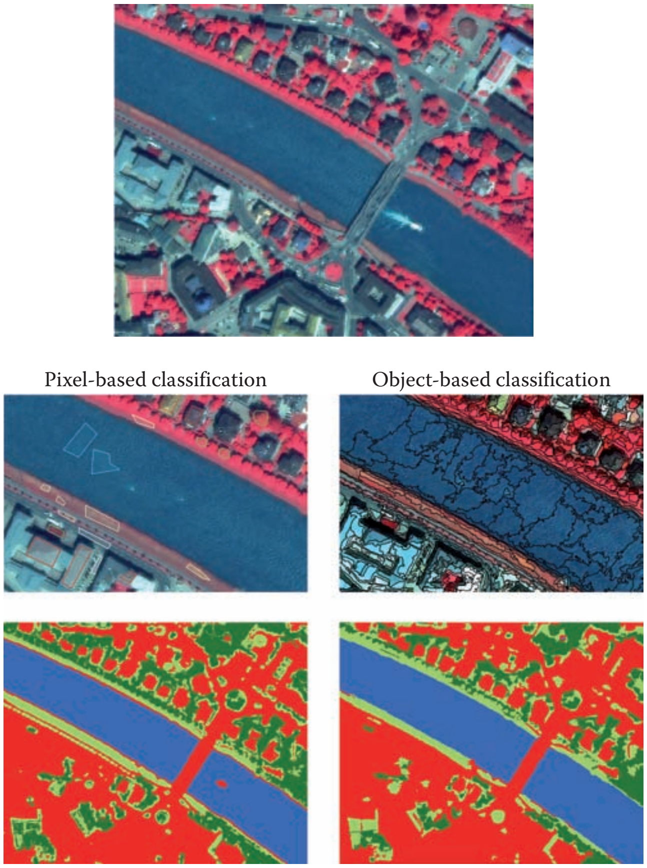

Figure 14.2 Object-based versus pixel-based classification.

change were increasingly popular during this period. In a comprehensive review article, Chen et al. (2012) presented a timely overview of the main issues in remote-sensing change detection and suggested reasons for favoring object-based change detection over pixel-based approaches. They suggested that an object-based approach to change detection allows for multiscale analysis to optimize the delineation of individual landscape features, it reduces spurious changes due to high spectral variability in high-spatial-resolution imagery, and the approach also allows for more meaningful ways to evaluate change (Figure 14.2).

14.2.3.2.3 Data Fusion

Data fusion became increasingly common during this phase. The utility of light detection and ranging (LiDAR) data for capturing height, that could be used in both segmentation and classification, was recognized soon after LiDAR became somewhat operational. Pascual et al. (2008) incorporated LiDAR data to help characterize forest stands and structure using OBIA in a complex Pinus sylvestris–dominated forest in central Spain. Zhou and Troy (2008) used LiDAR with high-resolution digital aerial imagery to analyze and characterize the urban landscape structure of Baltimore at the parcel level. Ebert et al. (2009) used optical, LiDAR, and digital elevation models to estimate social vulnerability indicators through the use of physical characteristics and hazard potential. Tullis et al. (2010) found that certain land covers (e.g., forest and herbaceous cover rather than impervious surface) benefited more from a synergy between LiDAR and optical imagery. Image fusion has also involved multiple spatial and spectral resolutions. For example, Walsh et al. (2008) used both QuickBird and Hyperion hyperspectral imagery to map an invasive plant species in the Galapagos Islands. The fusion of multi- and hyperspectral imagery was beneficial.

14.2.3.2.4 Software

During this time frame, papers evolved from naive and sometimes simplistic use of complicated software (e.g., "we used eCognition to segment and classify our imagery") to more nuanced descriptions of methodology. Editorial boards of journals with higher impact factors (e.g., Remote Sensing of Environment) began demanding more explanation in a method section than the use of a software package. The success of the suite of eCognition/Definiens software packages likely prompted rapid development of alternative software for the OBIA workflow. Berkeley Image Seg (Clinton et al. 2010), Visual Learning Systems' Feature Analyst extension for ArcGIS (Visual Learning Systems 2008), System for Automated Geoscientific Analyses (SAGA) (Böhner et al. 2006), Environment for Visualizing Images (ENVI) Feature Extraction (Hölbling and Neubert 2008), ERDAS IMAGINE's objective module (ERDAS 2009), and IDRISI Taiga's segmentation module (Clark Labs 2009) appeared between 2006 and 2010. Use of additional, external software, particularly for the classification step of the OBIA workflow, became increasingly common. For example, many papers discuss the use of decision trees such as classification and regression trees (CART), usually run externally to a software package such as eCognition, in R (http://www.r-project.org/) or See5 (Quinlan 2013), to classify objects. Yu et al. (2006) used this approach to map vegetation alliances in a California reserve; Laliberte et al. (2007) did so with high-resolution data over rangelands, as did Chubey et al. (2006) for forest inventory mapping. Green and Lopez (2007) used CART to label polygons created in eCognition for benthic habitat in Texas, and Stow et al. (2007) used a similar combined approach to map urban areas in Accra, Ghana. Since then, eCognition has implemented a decision tree algorithm for classification.

Next to the commercial software mentioned, several open-source software products have been developed. While earlier attempts may be considered to be more of an academic, not very user-friendly and not well-documented prototypical software such as GeoAida (Bückner et al. 2001), recent open-source developments aim to compete with commercial software such as eCognition, ERDAS, or ENVI in respect to a modern user-friendly GUI and software documentation. InterIMAGE is an open-source and free-access framework for knowledge-based image classification. It is based on algorithms from GeoAida and provides a capacity for customization and extension tools. Costa et al. (2010) describe the InterIMAGE system as a multiplatform framework, implemented for Linux and Windows operational systems (http://www.lvc.ele.puc-rio.br/projects/interimage/).

A more recent development is the Geographic Data Mining Analyst. It bridges GIS and image-processing functionality and includes algorithms for segmentation, feature extraction, feature selection, classification, landscape metrics, and multitemporal methods for change detection and analysis (Körting et al. 2013).

Bunting et al. (2014) developed the open-source platform RSGISLib for data-processing techniques. Users interact with the software through an XML script, where XML tags and attributes are used to parameterize 300 available commands. The developers claim that command options are easily recognizable to the user because of their logical and descriptive names. Through the XML interface, processing chains and batch processing are supported. More recently, a Python binding has been added to Remote Sensing and GIS Software Library (RSGISLib) allowing individual XML commands to be called as Python functions. The software has been released under a GPL3 (General Public License) license and makes use of a number of other open-source software libraries (e.g., Geospatial Data Abstraction Library (GDAL)/OGR); a user guide and the source code are available at http://www.rsgislib.org.

14.2.3.3 Consolidation (Since Around 2010)

Since around 2010, the field has emerged from its earlier stages and is displaying more maturity. Blaschke et al. (2014) raise the discussion that in some ways, this maturity suggests a label of new *paradigm*. From a workshop on OBIA convened at the 2012 GIScience Conference in Columbus, OH, to discuss key theoretical and applied aspects of the approach emerged several important topics for the next decade: integration with GIS, semantics, accuracy, change, standards, and learning from the past. These themes are born out in the literature. There have also been some important developments on the software front. For example, in 2010, Trimble (a company expert in field and mobile technology and one of the leading manufacturers of research and survey grade GPS systems) purchased Definiens Earth Sciences ("Trimble Acquires Definiens' Earth Sciences Business to Expand its GeoSpatial Portfolio": https://www.trimble.com/news/release.aspx?id=061110a), with expectations that the OBIA workflow would be of particular use to mobile mapping, survey, and urban environment reconnaissance. Additionally, there has been increasing use in the remote-sensing world of unmanned aerial systems (UAS) or drones, which provide small footprint, very high-resolution imagery (cm to meter pixel size). Once geometric and radiometric corrections and mosaicking have been applied, these images are routinely being approached with the OBIA workflow. UAS provide the ability for repeated deployment for acquisition of multispectral imagery at high temporal resolution data at very high-spatial resolution. For example, Laliberte et al. (2011) acquired multispectral imagery using UAS and obtained orthorectified, radiometrically calibrated image mosaics for the purpose of rangeland vegetation classification. They relied heavily on an OBIA approach for classification of rangeland classes and achieved relatively high accuracies. Castro et al. (2013) were able to generate weed maps early in the growing season for maize fields by using an unmanned aerial vehicle and OBIA.

The current global explosion of imagery resources at high-temporal and high-spatial resolution is actively changing all aspects of the geospatial enterprise. The ways in which we acquire, store, serve, and generate information from an increasing supply of imagery across domains necessitate the continued development of streamlined OBIA workflows that render imagery useful through geospatial semantics and shared knowledge (Harvey and Raskin 2011; Blaschke et al. 2014). The time-sensitive decision support tasks found in disaster response, for example, which typically make use of rapidly acquired imagery to find targets, are often facilitated currently by human volunteers or *distributed thinking* (Zook et al. 2010). These tasks in the future might be supported by OBIA workflows. And the accelerated pace of geospatial work that accompanies disaster response is increasingly characteristic of science in general than it has ever been in the past. Decisions that routinely waited for annual, seasonal, or monthly data (e.g., forest loss, peak greenness, soil water deficits) can now be made based on data at finer spatial and temporal resolutions (e.g., Hansen et al. 2014). Doubtlessly, future research within OBIA will focus on transferring imagery quickly into comprehensive and web-enabled geographic knowledge bases to be used for decision making (Table 14.4).

14.3 OBIA: A Short Summary of the State of the Art

This section is kept very short and aims to succinctly summarize the main findings from other state-of-the-art reviews, particularly Blaschke (2010) and Blaschke et al. (2014).

14.3.1 Segmentation Is Part of OBIA but Not Married to It

A common denominator of OBIA applications was, and still is, that they are built on image segmentation (see also Burnett and Blaschke 2003; Benz et al. 2004; Liu et al. 2006; Hay and Castilla 2008; Lang 2008). Image segmentation is not at all new (Haralick and Shapiro 1985; Pal and Pal 1993) but has its roots in industrial image processing and was not used extensively in geospatial applications throughout the 1980s and 1990s (Blaschke et al. 2004).

Interestingly, not only independent from most of the OBIA-related developments described in Blaschke (2010) but also triggered by the advent of high resolution satellite imagery, Aplin et al. (1999) and Aplin and Atkinson (2001) developed an approach to segment image pixels using vector field boundaries and to assign subpixel land cover labels to the pixel segments. Subsequently, hard per-field classification, the assignment of land cover classes to fields (land cover parcels) rather than pixels (Aplin et al. 1999), was achieved by grouping and analyzing all land cover labels for all pixels and pixel segments within each individual field. Their approach was somewhat different in a sense that they aimed to classify predefined objects, namely, fields. These developments coincided later with the *OBIA community* when Paul Aplin and Geoff Smith organized

TABLE 14.4 Summary of Historic Effects and OBIA Developments

External Effects/Triggers	OBIA Developments
1972: Landsat 1 and its multispectral sensor set the standard for civilian remote-sensing applications for the next decades	
Late 1970s: image segmentation techniques are developed and are subsequently being used in image processing but not much in geospatial applications	Kettig and Landgrebe (1976) developed the first hybrid classification approach that included neighborhood aspects
Late 1999 and 2000: advent of the first two civilian 1 m resolution satellites mark a new area of high-resolution spaceborne imaging	1999/2000: commercialization of Definiens company and eCognition software
1998/1999: commercial LiDAR systems available June 2003: Orbview-3 high-resolution digital airborne cameras such as the Ultracam (Leberl and Gruber 2003)	July 2001 first scientific workshop on OBIA methods: FE/GIS'2001: Remote sensing: New sensors—innovative methods, Salzburg, Austria (German language) 2002: first book on OBIA in German language based on the 2001 workshop (Blaschke 2002) 2001–2003: first dozen papers in peer-reviewed journals
2004 onward: more high-resolution satellites, decreasing prices of data, higher accessibility	2005: First OBIA-related book for the fast developing Brazilian market (Blaschke and Kux 2005)
2005: Google Earth raised public awareness about remote-sensing imagery and subsequently increased demand for information products	OBIA workshop at the XII Brazilian remote sensing symposium, June 2005, Goiania, Brazil 2006: first OBIA conference in Salzburg, Austria 2007: OBIA workshop at UC Berkeley 2008: GEOBIA international conference in Calgary, Alberta, Canada 2009: Object-based landscape analysis workshop at the University of Nottingham, United Kingdom 2010: GEOBIA international conference in Ghent, Belgium 2012: GEOBIA international conference in Rio de Janeiro, Brazil 2014: GEOBIA international conference in Thessaloniki, Greece

a symposium on "object-based landscape analysis" in 2009 in Nottingham, United Kingdom, and edited a special issue in *International Journal of Geographical Information Science* (Aplin and Smith 2011).

Although most scientists would associate OBIA with segmentation, recent work has shown that some segmentation steps typically involved in OBIA research do not necessarily play a major role, as sometimes postulated in the earlier development of OBIA. See particularly the discussion of Tiede (2014) who in essence decouples OBIA from image processing and Lang et al. (2010, 2014) and their work on concept-related fiat objects, geons, and on *latent phenomena*.

14.3.2 Classification

Blaschke and Strobl (2001) have posed the question "What's wrong with pixels?" and elucidated some shortcomings of a pure per-pixel approach. This was certainly not the first time to highlight the limitations of treating pixels individually based on multivariate statistics. In fact, Kettig and Landgrebe (1976) developed the first algorithm called Extraction and Classification of Homogeneous Objects (ECHO), which at least partially utilizes contextual information. Based on the short history of OBIA in the section before, we may argue that around the turn of the millennium, the quest for objects reached a new dimension. Particularly for high-resolution image, it seems to make much sense to classify segments—rather than pixels. The segments may or may not correspond exactly to the objects of desire. Burnett and Blaschke (2003) called such segments from initial delimitation steps object candidates. They already offer parameters such as size, shape, relative/absolute location, boundary conditions, and topological relationships, which can be used within the classification process in addition to their associated spectral information.

There is increasing awareness that object-based methods make better use of—often neglected—spatial information implicit within remote-sensing images. Such approaches allow for a tightly coupled or even full integration with both vector- and raster-based GIS. In fact, when studying the early OBIA literature for the geospatial domain, it may be concluded that many applications were driven by the demand for classifications, which incorporate structural and functional aspects.

One good example of a comprehensive review is the paper by Salehi et al. (2012). They conducted recent literature and evaluated performances in urban land cover classifications using high-resolution imagery. They analyzed the classification results for both pixel-based and object-based classifications. In general, object-based classification outperformed pixel-based approaches. These authors reason that the cause for the superiority was the use of spatial measures and that utilizing spatial measures significantly improved the classification performance particularly for impervious land cover types.

14.3.3 Complex *Geo-Intelligence* Tasks

Increasingly, OBIA is used beyond simple image analysis tasks such as image classification and feature extraction from one image or a series of images from the same sensor.

Today, terabytes of data are acquired from space- and airborne platforms, resulting in massive archives with incredible information potential. As Hay and Blaschke (2010) argue, it is only recently that we have begun to mine the spatial wealth of these archives. These authors claim that, in essence, we are data rich but geospatial information poor. In most cases, data/image access is constrained by technological, national, and security barriers, and tools for analyzing, visualizing, comparing, and sharing these data and their extracted information are still in their infancy. In the few years since this publication, *big data* have fully arrived in many sciences, and this debate seems not to be OBIA specific from today's point of view.

Furthermore, policy, legal, and remuneration issues related to who owns (and are responsible for) value-added products resulting from the original data sources, or from products that represent the culmination of many different users input (i.e., citizen sensors), are not well understood and still developing. Thus, myriad opportunities exist for improved geospatial information generation and exploitation.

OBIA has been claimed to be a subdiscipline of GIScience devoted to developing automated methods to partition remote-sensing imagery into meaningful image objects and assessing their characteristics through scale (Hay and Castilla 2008). Its primary objective is the generation of geographic information (in GIS-ready format) from which new geo-intelligence can be obtained. Based on this argument, Hay and Blaschke (2010) have defined geo-intelligence as geospatial content in context.

The final theme is intelligence—referring to geo-intelligence—which denotes the *right* (geographically referenced) *information* (i.e., the content) in the *right situation* so as to satisfy a specific query or queries within user-specified constraints (i.e., the context).

Moreno et al. (2010) describe a geographic object-based vector approach for cellular automata modeling to simulate land-use change that incorporates the concept of a dynamic neighborhood. This represents a very different approach for partitioning a scene, compared to the commonly used OBIA segmentation techniques, while producing a form of temporal geospatial information with a unique heritage and attributes.

Lang (2008) provided a more holistic perspective on an image analysis and the extraction of geospatial information or what he called at this time an upcoming paradigm. He started from a review of requirements from international initiatives like Global Monitoring of Environment and Security (now Copernicus), and he discussed in details the concept of *class modeling*. Also, such methods may need further advancement of the required adaptation of standard methods of accuracy assessment and change detection. He introduced the term *conditioned information*. With this term, he addresses processes that entail the creation of new geographies as a flexible, yet statistically robust and (user-) validated unitization of space.

Lang et al. (2014) developed the concept of geons as a strategy to represent and analyze latent spatial phenomena across different geographical scales (local, national, and regional) incorporating domain-specific expert knowledge. The authors exemplified how geons are generated and explored. So-called composite geons represent functional land-use classes, required for regional-planning purposes. They are created via class modeling to translate interpretation schemes from mapping keys. Integrated geons, on the other hand, address abstract, yet policy-relevant phenomena such as societal vulnerability to hazards. They are delineated by regionalizing continuous geospatial data sets representing relevant indicators in a multidimensional variable space. In fact, the geon approach creates spatially exhaustive sets of units, scalable to the level of policy intervention, homogenous in their domain-specific response, and independent from any predefined boundaries. Despite its validity for decision making and its transferability across scales and application fields, the delineation of geons requires further methodological research to assess their statistical and conceptual robustness.

14.4 Ongoing Developments: Influences of OBIA to Other Fields and Vice Versa

14.4.1 GIScience and Remote Sensing

OBIA arguably has its roots firmly in the field of remote sensing. Developments in remote sensing through the decades of the 2000–2010s—including most importantly the widespread availability of high-resolution imagery globally, but also from LiDAR and novel methods of data fusion—have continued this alliance. However, this early grounding of OBIA in theoretical and practical aspects of remote sensing is recently being enhanced through multiple novel interactions with aspects of the GIScience field, and OBIA is poised to develop further from new trends in GIScience.

Since Goodchild (1992) first coined the term GIScience, suggesting it as a manner of dealing with the issues raised by GIS technology by focusing on the unaddressed theoretical shortcomings of conventional GIS, the contents and borders have constantly shifted, especially in light of recent advances in geospatial technologies, including remote sensing (Blaschke and Merschdorf 2014). In order to deal with the special properties of spatial information in an era of Web 2.0 technologies, the field of GIScience has embraced not only classic geographical knowledge and concepts but also increasingly incorporated approaches from other disciplines such as computer science and cognitive sciences (Blaschke and Merschdorf 2014). In turn, other disciplines have recently discovered the potential of GIScience, utilizing its tools and methodologies to serve their own needs and to drastically advance the knowledge base in their own respective fields. Such is not least the case for remote sensing, which has experienced a drastic shift from purely pixel-based methods of image interpretation to the identification of *objects* in remotely sensed imagery by means of OBIA. Hay and Castilla (2006) propose that OBIA is a subdiscipline of GIScience, combining a "unique focus on remote sensing and GI" (Hay and Castilla 2006:1). In this sense, OBIA may be seen as the first in a string of developments leading to the consolidation of GIS and remote sensing, facilitated through the common denominator of GIScience. This implies that current and ongoing developments in the discipline of GIScience may bare a significant impact on the field of remote sensing. Such developments include but are not limited to volunteered geographic information (VGI), ubiquitous sensing, indoor sensing, and the integration of in situ measurements with classic remote-sensing datasets.

Web 2.0 technologies have had a significant impact on GIScience, as they have enabled the bidirectional and participatory use of the Internet (Blaschke and Merschdorf 2014). These technologies go beyond *GIS-centered* assemblages of hardware, software, and functionalities. Wiki-like collective mapping environments, geovisualization APIs, and geotagging may either be based on GIS or they have common denominators in the digital storage, retrieval, and visualization of information based upon its geographic content (Sheppard 2006).

These developments have led to an influx of spatial content, contributed by individual users or groups of users, which nowadays composes a valuable data source in GIS. Such content has been termed as "volunteered geographic information," by Goodchild (2007), and Atzmanstorfer and Blaschke (2013) claim that its full realm of possibilities, in terms of citizens partaking in planning initiatives, yet remains unknown. VGI is not only limited to online applications such as the provision of geotagged photographs on the photo management service Flickr or geolocated messages on the online messaging portal Twitter but also includes the information collected by wireless sensors on common mobile devices. Due to the proliferation of wireless sensors in all sorts of mobile devices, sensory data collection is no longer constrained to few experts equipped with expensive sensors but rather has shifted more into the lay domain. In GIScience, this notion is referred to as ubiquitous sensing and can be used for monitoring activities and locations of users, or groups of users, in near real time. The near real-time capabilities of ubiquitous sensing can assist decision makers in a variety of applications, such as emergency response, public safety, traffic management, environmental monitoring, or public health (Resch 2013). For example, Sagl et al. (2012) utilize the movements of cell phones between pairs of radio cells—termed as handovers—in order to analyze spatiotemporal urban mobility patterns and demonstrate how mobile phone data can be utilized to analyze patterns of real-world events using the example of a soccer match, while Zook et al. (2010) present how a mash-up of various data sources, including both government data and VGI, significantly contributed to disaster relief in Haiti, following the earthquake in 2010.

While VGI is oftentimes a passive by-product, resulting from the use of Web 2.0 technologies and mobile-computing devices, millions of internet users can nowadays choose to actively utilize GIS methodologies and applications by means of public participation geographic information system (PPGIS). Manifestations of such participation can, for instance, be found in the widespread community of users contributing to virtual globes and maps by superimposing new layers, such as street networks or landmarks, or even in disaster relief efforts such as the recent search for the debris of the missing Malaysian Airline flight MH370, which was assisted by tens of thousands of Internet users, who helped in sifting through the vast magnitude of satellite data recorded during the time frame in question.

The contribution of the general public, be it actively by uploading data to virtual globes or maps or passively by utilizing social media platforms such as Twitter or Flickr, has also fuelled the collection of in situ data, such as photos taken at a certain location and values measured there. Such data are particularly valuable in the era of very high-resolution satellite imagery, as well as the subsequent surge of urban remote-sensing applications, such as the mapping of megacities, the monitoring of fast-expanding settlements in developing countries, or the routine monitoring of informal settlements, conducted either by public administration or by commercial companies, as outlined by Blaschke et al. (2011). Based on an extensive literature review, Blaschke et al. (2011) conclude that the increased availability of high-resolution satellite imagery has resulted in a greater demand for timely urban mapping and monitoring. However, remotely sensed imagery, which provides the basis for urban mapping applications, can only provide the bird's-eye view of a given location, neglecting ground information such as the building facades or interiors. With the advent of widely applied Open Geospatial Consortium (OGC) standards, in situ measurement data recorded at ground locations can be integrated with the remote-sensing imagery, providing a more holistic approach to urban-mapping applications (Blaschke et al. 2011). Blaschke et al. (2011) note that although remote sensing and in situ measurements are currently two separate technologies, the strengths of both can be combined by means of sensor webs and OGC standards, potentially producing new and meaningful information (Blaschke et al. 2011). They conclude that "while available information will always be incomplete, decision makers can be better informed through such technology integration, even if loosely coupled" (Blaschke et al. 2011:1768).

Another trend enabled by the recent advances in mobile technology is the concept of indoor sensing, sometimes referred to as indoor geography (Blaschke and Merschdorf 2014). Naturally, remote-sensing imagery can only provide a planar view of the Earth's surface, including natural features, as well as human infrastructure. While LiDAR technology complements the classic 2D imagery with the added dimension of depth, it still doesn't provide any insight as to the contents of buildings. In this sense, indoor sensing may be a future trend in indoor positioning and mapping, whereby sensor fusion will evolve to support indoor locations, paving the way for geoenabled manufacturing (Blaschke and Merschdorf 2014).

14.4.2 Changing Workplace

In the past, remote sensing and GIS were distinctly separated disciplines, whereby remotely sensed imagery was primarily considered as a data source for GIS (Jensen 1996). However, in light of more recent technical and theoretical advancements, these disciplines have begun to consolidate, not least attributed to the quest for tangible objects. The emergence of OBIA as a subdiscipline of GIScience laid a foundation for the use of shared methodologies, and remote sensing was recognized as "one element of an integrated GIS environment, rather than simply an important data source" (Malczewski 1999:20). The bidirectional nature of the relationship between remote sensing and GIS implies that not only advances in remote sensing technology influence the GIS environment but also vice versa. In this sense, we can witness the impact of recent trends in GIScience, described in Section 14.4.1, on the remote-sensing discipline. Especially, the technological advances brought about by the Web 2.0, such as VGI, ubiquitous sensing, or PPGIS, call for new approaches of data integration, with the primary aim of developing more comprehensive and accurate datasets. Such integration can complement the bird's-eye view perspective offered by remotely sensed imagery, with in situ information, which in turn can more efficiently represent dynamic urban environments (Blaschke et al. 2011). To this end, OGC standards can provide the necessary interface for data integration, as is the case for the Global Earth Observing System of Systems, which seamlessly integrates remotely sensed imagery with in situ measurements.

One particular example of an OBIA application as a substitute for GIS overlay is provided by Tiede (2014). GIS-overlay routines usually build on relatively simple data models. Topology is—if at all—calculated on the fly for very specific tasks only. If, for example, a change comparison is conducted between two or more polygon layers, the result leads mostly to a complete and also very complex from–to class intersection. Additional processing steps need to be performed to arrive at aggregated and meaningful results. To overcome this problem, Tiede (2014) presented an automated geospatial overlay method in a topologically enabled (multiscale) framework. The implementation works with polygon and raster layers and uses a multiscale vector/raster data model developed in the OBIA software eCognition. Advantages are the use of the software inherent topological relationships in an object-by-object comparison, addressing some of the basic concepts of object-oriented data modeling such as classification, generalization, and aggregation. Results can easily be aggregated to a change-detection layer; change dependencies and the definition of different change classes are interactively possible through the use of a class hierarchy and its inheritance (parent–child class relationships). The author demonstrates the flexibility and transferability of change comparison for Corine Land Cover data sets. This is only one example where OBIA and GIS are fully integrated, and although this case may be being an exception so far, one field may jeopardize the other field if the fields are seen isolated.

14.4.3 Who Uses OBIA?

In a recent publication, Blaschke et al. (2014) found an increasing number of publications concerned with OBIA in peer-reviewed journals, special issues, books, and book chapters and concluded that OBIA is a new evolving paradigm in remote sensing and to some degree in GIScience also. However, they also noted that the exact terminology used within these publications is distinctly ambiguous, as is characteristic for an emerging multidisciplinary field (Blaschke et al. 2014). Therefore, we herein aim to review the literature databases of the ISI's (Institute for Scientific Information) Web of Science (WoS), as well as Scopus, in an attempt to quantify who uses OBIA, both in terms of countries of origin and contributing field, and to track its presence in literature over the past years.

A search in the WoS database for the phrases *object-based image analysis* or *object-oriented image analysis*, or *OBIA*, or *geographic object-based image analysis, (GEOBIA)*," contained in the title, abstract, or keywords, returns a total of 451 articles (April 17, 2014). When analyzing which countries the publications primarily come from, we determined that the highest number of publications is contributed by the United States, accounting for 24% of all publications; followed by the People's Republic of China with a 14% contribution; Germany contributing 12%; Austria 8%; Canada 7%; Australia, Brazil, and Netherlands 6%, respectively; and Italy and Spain with 4% each, just to name the top 10 contributing countries. This shows that while the United States is the main contributor, accounting for nearly a quarter of all publications returned in the search, many other smaller countries also make a noteworthy contribution. In particularly remarkable is the 8% contribution made by Austria, which has only a fraction of the population (approx. 8.5 million) compared to most other countries represented within the top 10. Compared to the leading country—United States—Austria has merely 2.7% of the population but has 33% as many publications. Such a comparison becomes even more extreme when made with China, the second largest contributor, whereby Austria has only 0.6% as many inhabitants but accounts for 57% as many publications. This shows that there may be certain research clusters in certain countries, which largely contribute to OBIA/GEOBIA research, rather than all countries contributing relatively to their population (Figure 14.3).

A further analysis consisting of the research areas contributing to OBIA/GEOBIA reveals that the largest contribution is made by remote sensing, accounting for 61% of all publications. The second largest contributor, namely, imaging science, accounts for only 31%, followed by geology with a share of 27%. A full chart of the top 10 contributing fields is depicted in Figure 14.4.

When assessing the publication years, it is notable that the number of publications on the topic of OBIA/GEOBIA has drastically increased over the last 5 years, whereby 22% were written in 2013 alone, as compared to >16% prior to 2008. The first OBIA publication indexed in ISI's WoS database dates back to 1985, preceding the second OBIA publication by 10 years, and at least 20 years prior to a steady incline in the number of publications (Figure 14.5).

When the same search is conducted in the Scopus database (same phrases searched for in title, abstract, and keywords), a total of 586 publications are returned (April 17, 2014). The discrepancy in terms of numbers of publications as compared to the WoS database can be attributed to the fact that Scopus contains a broader range of document types, such as notes, short surveys, and in press articles, while the WoS database only contains peer-reviewed journal articles, conference proceedings, reviews, and editorials, all of which are additionally included in Scopus.

Although including a slightly greater number in overall publications, the trends revealed in the Scopus data are largely in line with those depicted in the WoS data. Some discrepancies were found in terms of research areas, which, however, may largely be down to the different naming conventions utilized by both databases (e.g., the top contributing discipline to OBIA/GEOBIA in the Scopus database is "Earth and Planetary Sciences," with a total of 315 publications or 54%, which corresponds to the largest WoS

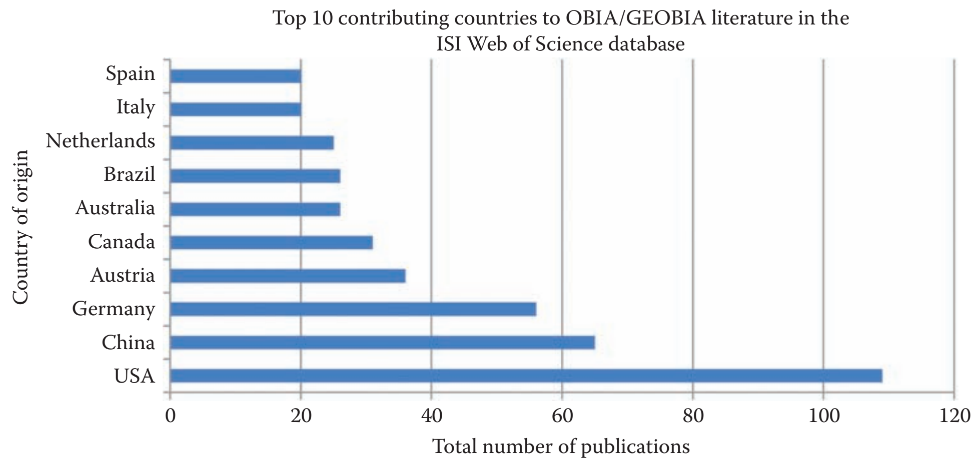

FIGURE 14.3 Top 10 contributing countries to the OBIA/GEOBIA literature in the Web of Science database and their respective contributions.

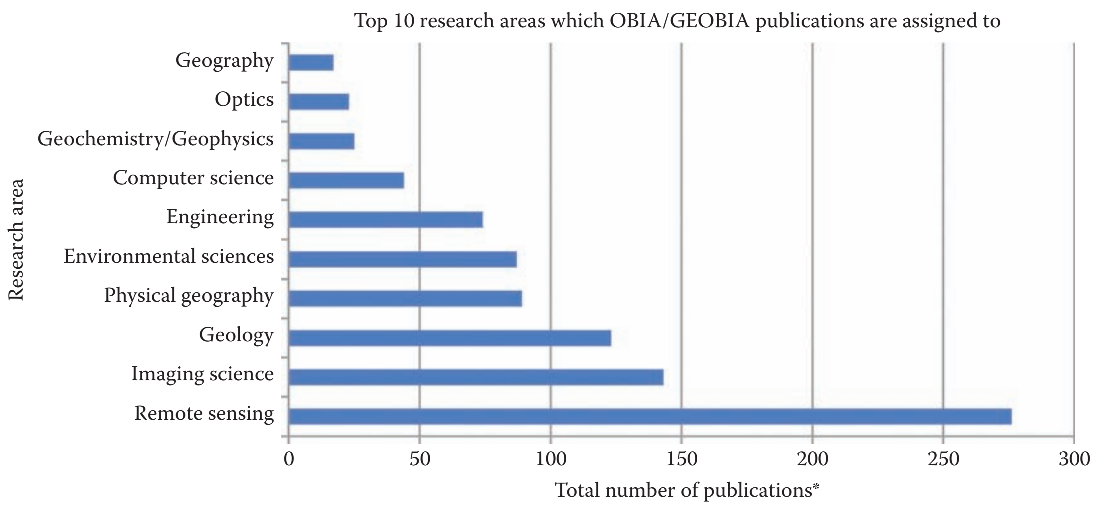

FIGURE 14.4 Main research areas for OBIA/GEOBIA publications in ISI's Web of Science database. *The total numbers add up to more than the total of 451 publications due to the fact that some multidisciplinary publications may have been assigned to more than one research area.

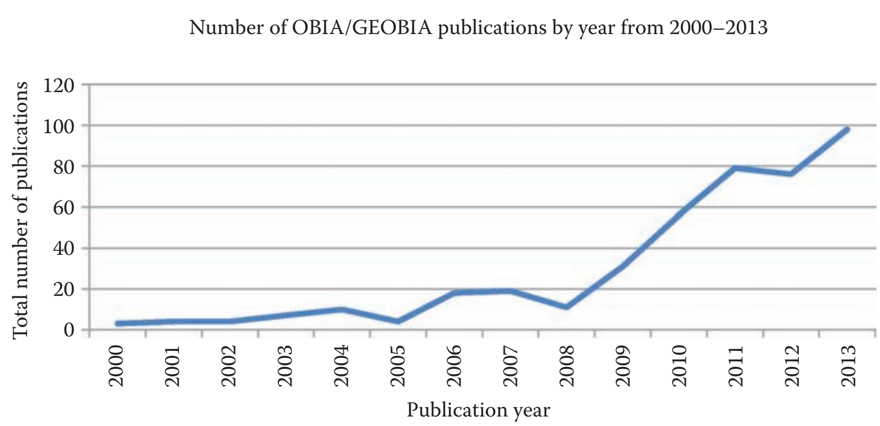

FIGURE 14.5 Number of OBIA/GEOBIA publications by publication year from 2000 to 2014, as indexed in ISI's Web of Knowledge database.

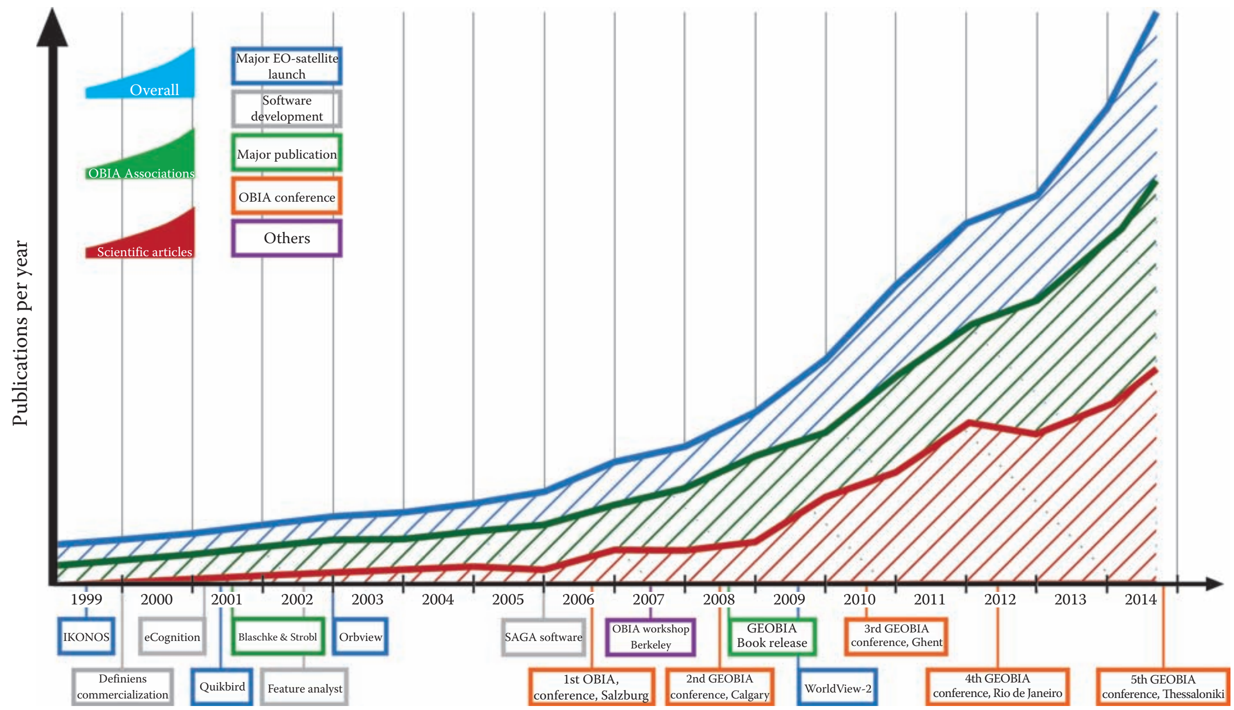

FIgure 14.6 Milestone timeline of OBIA/GEOBIA development from the late 1990s ‘until today.

contributor of “Remote Sensing”). Furthermore, both the publication year timeline and the contributing countries roughly correspond to the results obtained from the analyses of the WoS data.

In conclusion, when analyzing the literature, and some key milestone events and publications, the rise of OBIA/GEOBIA can be clearly traced through the course of the last decade and a half. This is depicted in the timeline shown in Figure 14.6, which exemplifies how both technological and methodological advances gave birth to object-oriented approaches and, according to Blaschke et al. (2014), to a new paradigm in remote sensing although it must be clearly stated that in absolute terms *classic* per-pixel methods are represented way more in publications at the moment.

14.5 Concluding Perspectives

14.5.1 New Paradigm: The Need for a Common Nomenclature and Sound Methodologies

OBIA has certainly arrived at the sciences. While the first years of the development were characterized by a lack of high-quality peer-reviewed scientific publications, the last few years witnessed a sharp increase in such articles. Some of them are remarkably highly cited such as the review paper by Blaschke (2010). Much of the excitement about this new methodology or paradigm has to do with the increasing availability of high-resolution datasets, which can now be used to produce information and, in particular, information on demand or *conditioned information*. Some predict that researchers, policy makers, citizen groups, and private institutions might use information contributed by ordinary people for any number of purposes, including emergency response, mobilizing activist efforts, monitoring environmental change, filling gaps in existing spatial databases, or identifying and addressing needs and problems in urban neighborhoods.

OBIA has developed a rich array of approaches for grappling with the challenges associated with high-resolution data. One remaining task is to standardize terms across methods and methodologies being used. While Blaschke et al. (2014) argue that this is very common for a new paradigm, it is nevertheless troublesome. OBIA needs to urgently harmonize and streamline the terms being used. Otherwise, a widespread recognition from other fields may be hindered.

14.5.2 Toward a Civilian Geo-Intelligence

We do not exactly know how the future will look like. One possible development can best be illustrated by the power and the innovative potential of the *object-by-object change comparison framework* (Tiede 2014) described before. This framework yields flexible, transferable, and highly complex change comparisons that can be visualized or calculated and aggregated to higher level composite objects. Here, the geon concept of Lang et al. (2014) comes into play: as briefly described, it also allows for the creation of more conceptual objects that may represent latent phenomena, which are not directly mappable.

Hay and Blaschke (2010) suggested the term (civilian) geo-intelligence. Since then, the number of technical developments and the number of documented applications, which may support the hypothesis of locational intelligence, have clearly grown. As discussed earlier, Lang (2008) laid some theoretical foundations for the concept of *conditioned information*, and Lang et al. (2014) developed the concept of geons, which may also serve as units to characterize and delimitate latent phenomena.

An area for future research emerges from a wider set of organizational changes within the software industry such as the *software as a service* paradigm. This is a significant development in the organization and deployment of remote-sensing image analysis for the professional and advanced users. It may also open opportunities for nonexpert users in remote sensing in general and for OBIA in particular. Tiede et al. (2012) presented an OBIA geoprocessing service that integrates OBIA methods into a geoprocessing service. This development was—to our best knowledge—the first integration of an eCognition-based OBIA application into an interactive WebGIS geoprocessing environment.

Interestingly, the emergence of OBIA has not been generating a substantial quantity of critical reflection neither about the technology as such nor about the wider scientific and technological implications of this paradigm for various user groups, both geographically and seen along an educational ladder (students–graduates–professionals in private industry and academia).

Another future research area concerns the remote sensing and GIScience practices of nonprofessional actors, not as outsourced operatives for research institutions but as private actors or NGOs following their own agendas. In remote sensing in general, much more than in GIScience, the vast majority of existing literature investigates widely agreed scientific or commercially interesting problems and reflects both the focus of an Anglophone research community looking primarily back in time and a focus primarily on activities in the global North by state actors. Although we did not carry out a severe literature study, we may speculate that OBIA researchers may be a little bit less Anglophone dominated than the general remote-sensing community.

14.5.3 Epistemological and Ontological Challenges

We may claim here for the field of remote sensing that some long-known principles about technological determinism (McLuhan 1964 who basically claimed that humans shape their tools and they in turn shape humans) may become more obvious today because its practical and theoretical implications are now much faster discovered. Nevertheless, the process of the social shaping of technology can be long term, interactive, and sometimes conflict ridden (Rohracher 2003).

Like GIS, which has for some years been decried as *ontologically shallow* and insufficient to the task of comprehending the many epistemological points of difference among users (Schuurman 1999), remote-sensing literature offers very little in regard to its ontological and epistemological foundation. Without doubt, remote-sensing principles have solid foundations in physics. Only through the amalgamation with GIS-principles with OBIA the need for a theoretical, that is, epistemological and ontological, establishment increases. As long as the pixel is more or less the only subject of studies and, more importantly, as long as objects of interest are smaller than or similar in size compared to the pixels, such questions may not be urgent. With the advent of high-resolution imagery, the question "What's wrong with pixels?" (Blaschke and Strobl 2001) is valid to be asked. In fact, concerns about the appropriate use of technology in the application of remote-sensing data suggest that nonexpert users involved in interpretation tasks may gain a relatively sophisticated understanding not just of what the technology can do but of the processes involved in visualizing and disseminating findings via interactive representations and WebGIS.

We refer to Pickles (2004) who contends that the contingent nature of technical outcomes from GIS use is often overlooked, and the exploitation of some groups, particularly those with less access to technology, becomes a real possibility. He also emphasizes how important it is "to study maps in human terms, to unmask their hidden agendas, to describe and account for their social embeddedness and the way they function as microphysics" (Pickles 2004, p. 181).

Lastly, we may call for a relaxation of a potential friction between OBIA and per-pixel approaches. There are dozens, most likely more than a hundred, of scientific papers that compare both methods. Nevertheless, the future may not be dominated by an *either-or* question. Rather, we should be cautious about abandoning too hastily the concepts and terminologies of the *old* paradigm with reference to its dazzling object of cognition in this debate—the pixel. The pixel is a technical construct that may be useful in many cases from a technical, that is, data acquisition, point of view but sometimes also as a cognitional prerogative. In this sense, the aforementioned question "what's wrong with pixels" (Blaschke and Strobl 2001) may appear in a less unfavorable light—for the latter, the pixels.

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