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# A review of supervised object-based land-cover image classification

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ABSTRACT

Object-based image classification for land-cover mapping purposes using remote-sensing imagery has attracted significant attention in recent years. Numerous studies conducted over the past decade have investigated a broad array of sensors, feature selection, classifiers, and other factors of interest. However, these research results have not yet been synthesized to provide coherent guidance on the effect of different supervised object-based land-cover classification processes. In this study, we first construct a database with 28 fields using qualitative and quantitative information extracted from 254 experimental cases described in 173 scientific papers. Second, the results of the meta-analysis are reported, including general characteristics of the studies (e.g., the geographic range of relevant institutes, preferred journals) and the relationships between factors of interest (e.g., spatial resolution and study area or optimal segmentation scale, accuracy and number of targeted classes), especially with respect to the classification accuracy of different sensors, segmentation scale, training set size, supervised classifiers, and land-cover types. Third, useful data on supervised object-based image classification are determined from the meta-analysis. For example, we find that supervised object-based classification is currently experiencing rapid advances, while development of the fuzzy technique is limited in the object-based framework. Furthermore, spatial resolution correlates with the optimal segmentation scale and study area, and Random Forest (RF) shows the best performance in object-based classification. The area-based accuracy assessment method can obtain stable classification performance, and indicates a strong correlation between accuracy and training set size, while the accuracy of the point-based method is likely to be unstable due to mixed objects. In addition, the overall accuracy benefits from higher spatial resolution images (e.g., unmanned aerial vehicle) or agricultural sites where it also correlates with the number of targeted classes. More than 95.6% of studies involve an area less than 300 ha, and the spatial resolution of images is predominantly between 0 and 2 m. Furthermore, we identify some methods that may advance supervised object-based image classification. For example, deep learning and type-2 fuzzy techniques may further improve classification accuracy. Lastly, scientists are strongly encouraged to report results of uncertainty studies to further explore the effects of varied factors on supervised object-based image classification.



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## 1. Introduction

In recent years, with advances in remote sensing data acquisition technologies and the increased demand for remote sensing applications, high spatial resolution remote sensing data is steadily becoming more widespread (Belward and Skøien, 2015). This includes satellite (e.g., WorldView, Gaofen, SuperView) and aerial (e.g., unmanned aerial vehicle (UAV)) remote sensing data. The availability and accessibility of vast amounts of high-resolution remote sensing data have created a challenge for remote sensing image classification. As a result, object-based image analysis (OBIA) techniques have emerged to address these issues. The OBIA technique has now replaced the traditional pixel-based method as the new standard method (Blaschke et al., 2014) that will facilitate land-cover classification from high spatial resolution remote sensing imagery. However, it has not yet been quantitatively verified, although consensus appears to have been achieved amongst numerous researchers (Cleve et al., 2008; Myint et al., 2011; Duro et al., 2012a; Tehrany et al., 2014).

Over almost the last twenty years, the remote sensing community has undertaken considerable efforts to promote the use of object-based technology for land-cover mapping (Blaschke and Strobl, 2001; Blaschke et al., 2004; Walker and Blaschke, 2008). The first biennial international conference on OBIA was held in Salzburg, Austria in 2006. It is the most influential international event to date in the OBIA community, and the six conferences have, undoubtedly, considerably promoted the development of OBIA techniques and applications (Hay and Castilla, 2008; Powers et al., 2012; Arvor et al., 2013; Costa et al., 2014; Blaschke et al., 2014). Thanks to the publication of special issues on OBIA in various journals, e.g., the special issue "Geographic Object-Based Image Analysis (GEOBIA)" for journal "Photogrammetric Engineering & Remote Sensing" (Hay and Blaschke, 2010), and the special issue "Advances in Geographic Object-Based Image Analysis (GEOBIA)" for journal "Remote Sensing" (http://www.mdpi.com/journal/remotesensing/special_issues/geobia#editors, 2014), supervised object-based classification techniques have been an integral part of remote sensing research related to land-cover mapping since 2010 (Myint et al., 2011; Dronova et al., 2011; Duro et al., 2012a; Puissant et al., 2014; Ma et al., 2015; Li et al., 2016).

Generally, land-cover mapping is a complicated process with numerous factors influencing the quality of the final product (Khatami et al., 2016). For supervised object-based classification processes, many options must be selected, including image type, segmentation method, accuracy assessment, classification algorithm, training sample sets, input features, and target classes. To deal with these uncertainties, many researchers have devised supervised object-based classification methods that are specifically adapted to individual study areas, which are further compared with existing methods and processes, thereby validating their applicability. However, due to variations between study areas, it is difficult to derive generalized research results. Namely, a certain method may exhibit good classification accuracy and be applicable to a certain study area, yet derive inconsistent results in other study areas. For example, it was already proved that the K-Nearest-Neighbors (K-NN) method generally performed better for land-cover mapping than Decision Tree (DT) and Support Vector Machines (SVM) methods using SPOT 5 images (Tehrany et al., 2014), whereas a superior capability for producing higher classification accuracies using SPOT 5 images in agriculture areas with SVM or Random Forest (RF) methods was demonstrated by Duro et al. (2012a). Therefore, it is important to determine which classification process is the most promising and how various uncertainties affect classification performance. To do this, it is necessary to synthesize the collective knowledge on this topic, as opposed to using individual experience and expertise.

Past review articles have provided useful descriptive summaries and guidelines for the general object-based image analysis technique (Blaschke, 2010; Blaschke et al., 2014), which have focused on the review of more extensive OBIA techniques, including change detection. However, in recent years, supervised classification has shown rapid advances, and thus more and more issues have arisen. Hence, this review presents a summary of the advances in current supervised object-based classification techniques and examines future development prospects. Although the literature on object-based image analysis classification was already reviewed by Dronova (2015), the classification objects of concern only included wetlands. Furthermore, they also reviewed literature on object-based fuzzy rule-based classification, which generated considerable limitations in their research because substantial discrepancies remain between fuzzy rule-based classification and supervised classification.

Meta-analysis techniques provide a unique chance to integrate results from peer-reviewed studies rather than simply describing the results, and therefore allow us to quantitatively or qualitatively assess the patterns and relationships of an effect (e.g., classification performance) due to uncertain factors (e.g., sensor type, classification algorithm, and other variables of interest) (Chirici et al., 2016). In recent years, meta-analysis of remote sensing applications from various perspectives has provided reliable scientific guidance for quantitatively integrating remote sensing research analysis. For example, meta-analysis techniques was employed to examine the rate and magnitude of global urban land expansion (Seto et al., 2011); Numerous studies on supervised pixel-based image classification was synthesized to provide coherent guidance on the relative performance of different classification processes, mainly involving classification algorithms and input data (Khatami et al., 2016); The results of terrestrial aboveground biomass estimation from published studies was summarized to discuss the implications of model errors by sensor type, vegetation type, and plot size (Zolkos et al., 2013).

The main objective of this work is to conduct a meta-analysis of the results of existing studies, in order to (1) document the development and application of supervised object-based land-cover image classification of various factors including sensors, land cover types, targeted classes, supervised classifiers, geographical regions, training sample sizes, segmentation algorithms, accuracy assessment methods, and other uncertain variables; (2) identify and briefly summarize the scientific advances in supervised object-based classification; (3) and provide scientific guidelines for specific readers regarding the use of supervised object-based classification methods for land-cover mapping. Thus, we first describe, in detail, the methods required to perform the meta-analysis, including the data collection process, construction of the database, and the meta-analysis. Then, the results are presented to evaluate the effects with respect to multiple uncertain factors including sensors, land cover types, methodologies, and other variables of interest. Lastly, guidance and important research gaps are presented to improve the supervised classification of object-based land-cover mapping.

## 2. Methods

### 2.1. Data collection

The remote sensing literature reviewed here includes studies applying the supervised object-based image analysis technique to land-cover classification. The systematic literature search was conducted using Scopus databases, which have comprehensively indexed various major international remote sensing journals. Then, Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) were used for study selection (Moher et al., 2009). First, two major categories of keywords were designed to search the relevant literature: OBIA-related keywords (“Object-based image analysis” OR “Object-oriented image analysis” OR “Geographic object-based image analysis” OR “Object-based classification” OR “OBIA” OR “GEOBIA”) and keywords related to land-cover classification (“Classification” OR “Land-cover” OR “Mapping” OR “Land use” OR “Classifier”). By performing the query based on these keywords and using a date of April 15, 2016, 1275 publications were returned using the automated retrieval from Scopus databases, which was further filtered to 783 publications related to Article, Article press, and Review. Following a quick analysis of information related to the 783 publications such as titles or abstracts, 333 publications pertaining to relevant studies on land-cover classification using OBIA techniques were manually selected, of which 193 publications were supervised classification related, and 140 were fuzzy classification related. The following rules were further devised to manually screen out literature and case studies pertaining to supervised object-based image classification.

(1) Extraction of studies on both fuzzy rule-based classification and those on supervised classification, thereby analyzing the level of concern over time.
(2) Elimination of ambiguously stated case studies with only simple descriptions that employ eCognition software for object-based image classification. In these studies, whether the specific classification method is fuzzy rule-based or supervised remains unspecified. Because eCognition software also features the Nearest Neighbor (NN) supervised classifier in addition to the integrated fuzzy rule-based classification method, it is difficult to confirm which method was used.
(3) Exclusion of studies concluding that object-based image classification methods offer no advantage over other classification methods (e.g., pixel-based). For example, research results from Montereale Gavazzi et al. (2016) demonstrate that OBIA exhibits the worst performance with regards to classification accuracies, despite the fact that comparisons are performed against the best classification accuracy in their research.
(4) Elimination of case studies focusing on the extraction of individual classes without covering techniques pertaining to supervised classification, for example, Weed Seedling Detection (Borra-Serrano et al., 2015).
(5) Exclusion of case studies that only briefly mention OBIA and fail to clearly expound the sampling process and the specific classification methods from which classification results were obtained. Furthermore, studies that directly employ various unsupervised object-based classification methods for land-cover identification were also excluded. These studies were also excluded from the meta-analysis process presented in this study, e.g., Ma et al. (2014), Langner et al. (2014), Pereira Júnior et al. (2014), Charoenjit et al. (2015).
(6) Removal of related articles aiming to primarily address change detection without clearly indicating the classification performance of specific supervised classification methods (Walter, 2004).
(7) Elimination of reviews related to OBIA, despite the fact that many reviews significantly furthered OBIA development. These reviews are nonetheless ruled out of meta-analysis, owing to their lack of useful classification data for quantitative analysis. This includes the reviews of Liu et al. (2006), Blaschke (2010), and Blaschke et al. (2014).
(8) When screening or identifying accuracy assessment methods with regards to classification case studies, accuracy assessments using pixels as a statistical unit of accuracy were regarded as area-based assessment, which involves pixel quantity statistics, where the area of each pixel remains constant, e.g., Fernandes et al. (2014).
(9) Classifiers such as CART (Classification and Regression Trees), C4.5, and DT perform image classification by generating binary decision trees in OBIA, which are therefore uniformly categorized as DT classifiers in this study.

Based on above rules, and the careful perusal of 333 publications, 173 related publications that elaborate on the process of supervised object-based classification were selected and used to collect data for meta-analysis.

### 2.2. Data

For the meta-analysis of supervised object-based land-cover image classification, a database with 28 fields was constructed based on the 173 articles related to supervised object-based classification. In addition to general literature identification fields such as Title and Author, this database also contained OBIA-specific information fields, e.g., segmentation method, segmentation scale, classification method, thus enabling the identification of general characteristics of supervised object-based land-cover image classification. Then, qualitative and quantitative information was collected from the literature reviews describing the 254 experiments. Specifically, the resulting matrix, which contained 254 records with 28 fields for the different supervised object-based classification configurations, was used to conduct further meta-analysis and systematic review.

### 2.3. Data analysis

As well as journal and country information, we focused on synthesizing the studies and independently investigating several features of the supervised object-based land-cover image classification process, including: (1) sensors or spatial resolution of images used; (2) segmentation methods or scale; (3) training sample sets; (4) supervised classifiers; and (5) study types or number of classified categories. We extracted and analyzed measures of overall accuracy from the individual case studies. In this study, these measures were calculated into a mean measure and a standard deviation for specific conditions in order to analyze the effect of each individual factor. That is, a specific sensor and a specific supervised classifier were used to evaluate the size of the effect from these various factors. For example, the difference between the mean overall accuracies of different classifiers may be used to assess the effect from classifiers. Coherent guidance on the relative performance of various features of the classification process was also provided to reveal ways of improving classification accuracy by controlling these uncertain factors. For example, the correlation between spatial resolution and study area or segmentation scale was reported, and it was found that the spatial resolution of the image used can determine the characteristics of the study.

To investigate the effect of spatial resolution, spatial resolution was split into 15 groups at intervals of 2 m from 0 to 30 m, thereby collecting statistics on the frequency of image use at different spatial resolutions. Furthermore, sensors were sub-categorized based on their spatial resolution, allowing discrepancies in the frequency of use of different sensors to also be observed.

To assess the effect of training set size on classification accuracy, the assessment methods for classification accuracies reported in the literature were classified into two categories, namely point-based and area-based methods. Thus, the correlation between the size of the training samples and classification accuracies was also assessed.

It is worth noting that, during the analysis of the influence of each uncertainty, some case studies failed to clearly provide information for all fields in Table 1. Hence, in alignment with the specific research objectives, only relevant case studies that clearly expound the corresponding uncertainties were taken into consideration during our statistical analyses. Therefore, the number of experimental case studies that were used for statistical analyses was, in fact, less than 254.

## 3. Results and discussion

### 3.1. General characteristics of studies

Following the in-depth perusal of 173 publications on supervised object-based classification, relevant data was obtained using the methods described in Section 2. The main sources of information were articles published in scientific journals. Statistics reveal that 47 journals published the 173 publications on supervised object-based remote sensing imagery classification. A journal that published only one relevant article was eliminated from the statistics, and the majority of articles were found in 20 journals, detailed below, which together contained 146 articles or approximately

**Table 1**
Checklist of items used when constructing the meta-analysis database for supervised object-based image land-cover classification. 'NA' denotes that no specific methods, type, or data was available for this field.

| ID | Fields | Definition | Type | Categories |
|---|---|---|---|---|
| 1 | Title | Title of the article | Free text | |
| 2 | Authors | Author | Free text | |
| 3 | Year | Year of publication | Free text | |
| 4 | Source title | Journal name | Free text | |
| 5 | Document type | Publication type | Classes | Article; Conference; Book |
| 6 | Citations | No. of citations by other articles | Numeric | |
| 7 | Study type | Type of study | Classes | Application; Theoretical; Comparison; Review |
| 8 | Research institute | Name of research institutes | Free text | |
| 9 | City research institutes | City where the research institutes are located | Free text | |
| 10 | Study country | Country where the study area is located | Free text | |
| 11 | Geographic area | Region (e.g., a province) in country of origin | Free text | |
| 12 | Image resolution | Spatial resolution of imagery | Numeric | |
| 13 | Sensor (Data) type | Sensors | Classes | UAV; SPOT-5; IKONOS; GeoEye-1; Airborne; WorldView-2; Landsat; PolSAR; RapidEye; ASTER; Pléiades; Others |
| 14 | Area | Area of study area | Numeric | |
| 15 | Pre-processing | Whether band transformation is implemented | Classes | Yes; No; NA |
| 16 | Sampling strategy | Method for collecting training sample objects | Classes | Stratified random sampling; simple random sampling; Others; NA |
| 17 | Site type | Type of study area | Classes | Urban; Agriculture; Others, NA |
| 18 | Segmentation method | Segmentation method | Classes | Multi resolution; Others |
| 19 | Feature selection | Whether feature selection is performed | Classes | Feature Space Optimization (FSO); RF; GINI; Relief-F; Correlation-Based Feature Selection (CFS); Others; NA |
| 20 | Classification method | Supervised classification method | Classes | SVM; RF; NN; DT; Others; NA |
| 21 | Accuracy measure | Accuracy assessment index | Classes | OA; Others; NA |
| 22 | Accuracy value | Best accuracy value | Numeric | |
| 23 | Accuracy assessment level | Accuracy assessment methods used | Classes | Point; Area |
| 24 | Confidence interval | Whether confidence level is employed for reliability validation of accuracy assessment | Classes | Yes; No; NA |
| 25 | Samples | Number of samples | Numeric | |
| 26 | Class number | Number of classification classes | Numeric | |
| 27 | Scale | Segmentation scale | Numeric | |
| 28 | Feature calculation | Software for feature calculation and segmentation | Classes | eCognition; ENVI; SPRING; Others; NA |

84% of the identified journal papers. The remaining 27 journals were distributed across a wide range of journals, from computer applications to urban planning, wetlands, wildfires, and forest applications. The top 20 journals for articles related to object-based supervised classification are shown in Fig. 1. Furthermore, the top 5 journals for object-based supervised classification papers were: Remote sensing (25, 14.5%), Remote Sensing of Environment (22, 12.7%), International Journal of Remote Sensing (20, 11.6%), International Journal of Applied Earth Observation and Geoinformation (18, 10.4%), and ISPRS Journal of Photogrammetry and Remote Sensing (11, 6.4%).

The first object-based supervised classification paper identified from the literature search dates back to 2004 (Laliberte et al., 2004). Prior to 2010, object-based supervised classification did not appear to attract much attention, as the number of related publications did not noticeably increase. However, from 2010 onwards, the number of publications on object-based supervised classification began to increase annually until the present. Moreover, the amount is currently accelerating (see Section 3.5). Of the 173 published papers, approximately 61.6% of studies focus on specific applications whereas the remainder focus on methodological issues.

Research institutions with publications pertaining to supervised object-based classification are mainly located in Europe and North America (Fig. 2). All publications come from 34 countries, and the countries with more than 10 publications include, respectively, United States (44), China (19), Canada (15), Germany (13), and Spain (11). In addition, Australia (9), Brazil (6), Netherlands (5),

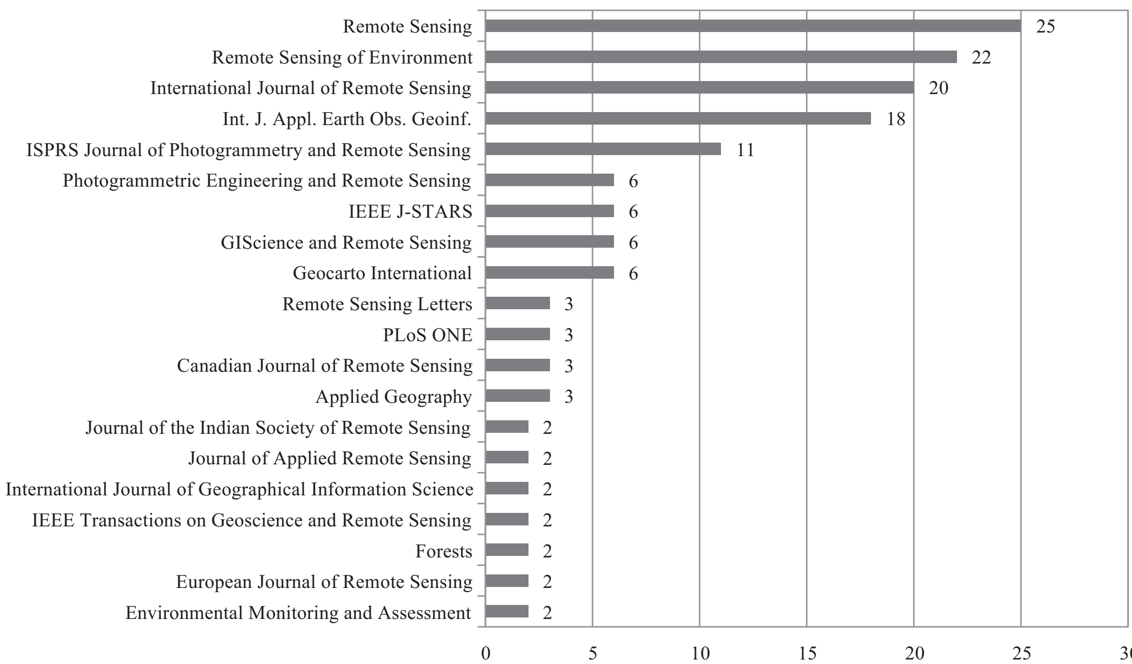
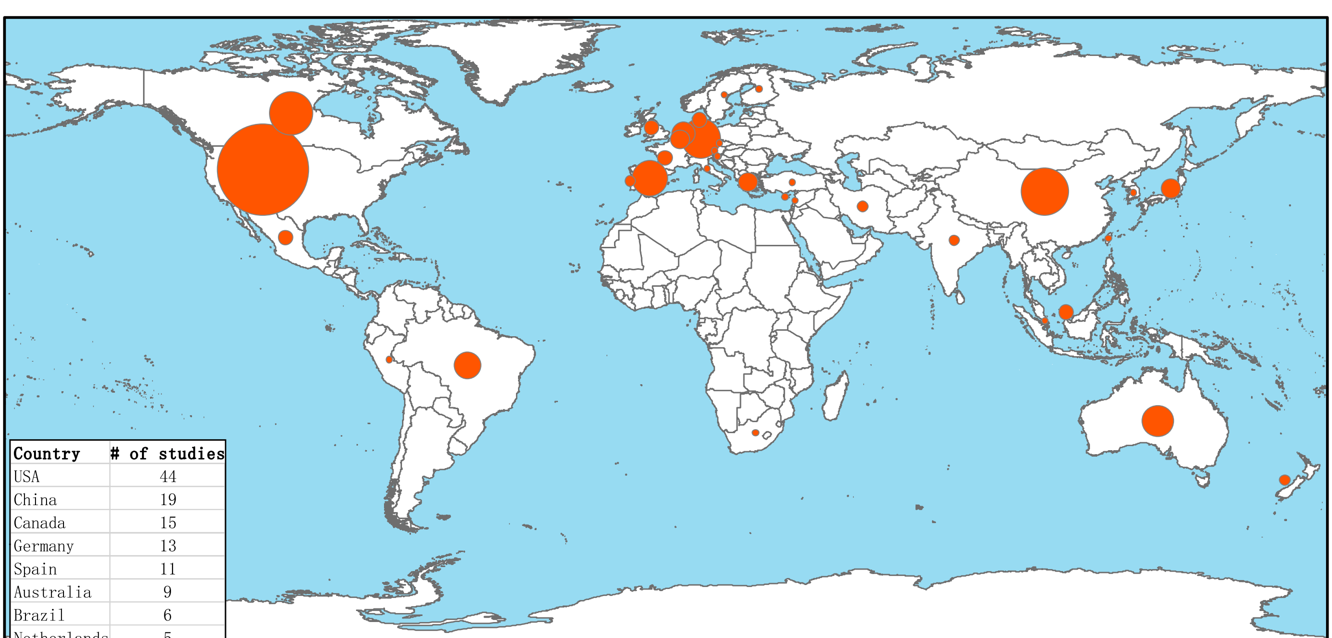



**Fig. 1.** Number of relevant publications per journal.



| Country | # of studies |
|---|---|
| USA | 44 |
| China | 19 |
| Canada | 15 |
| Germany | 13 |
| Spain | 11 |
| Australia | 9 |
| Brazil | 6 |
| Netherlands | 5 |

**Fig. 2.** Distribution of research institutions according to the country reported in the published paper.

Belgium (4), Japan (4), and Greece (4) are also worthy of note, as their number of publications exceeds 3.

High spatial resolution remote-sensing imagery remains undoubtedly the most frequently employed data source amongst those utilized for object-based classification. Furthermore, the number of case studies with a resolution between 0 and 2 m exceeds 90, mainly involving WorldView-2 (WV-2), QuickBird (QB), GeoEye-1, IKONOS, UAV, and Airborne images (Fig. 3). In addition, more than 20 case studies employ SPOT images. In terms of remote sensing imagery with medium resolutions, the data sources for case studies mainly come from satellite remote-sensing images such as ASTER and Landsat TM/ETM+/OLI. Moreover, 17 cases studies adopt ASTER and Landsat OLI remote-sensing images with a resolution of 15 m, and 28 studies employ Landsat TM/ETM+ remote-sensing imagery with a resolution of 30 m.

The spatial resolution of images used determines the scope and size of the study area. Generally, there is a positive correlation between the spatial resolution of images and the size of the study area ($R^2 = 0.22$, $p < 0.001$) (Fig. 4). The area of the remote-sensing images in most studies is less than 300 ha (95.6%). When remote sensing images with a resolution of 15 m are used, the study area drops to between 0 ha and 100 ha. In the case of Landsat images with a resolution of 30 m, the extent of the study area may exceed 100 ha. Moreover, the sparse use of imagery such as MODIS images may result in a vast study area, e.g., study areas exceeding 1000 km$^2$ (Mohler and Goodin, 2012), which are not considered here due to the small number of examples.

Statements regarding training samples are inconsistent among the 254 case studies. Some cases directly use the number of training sample objects, whereas others employ the proportion of

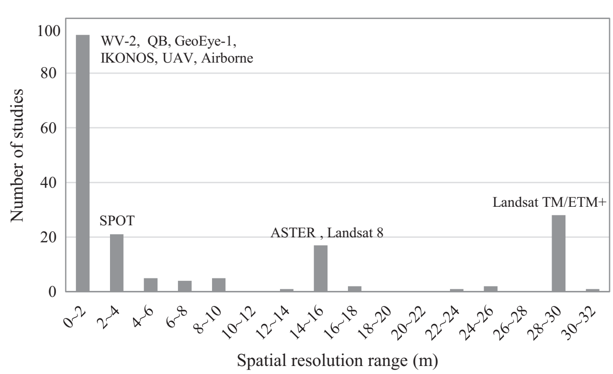



**Fig. 3.** Distribution of image spatial resolution used in the investigated case studies.

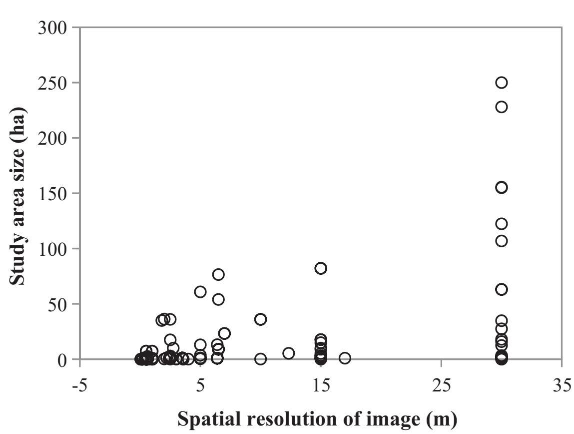



**Fig. 4.** Correlation between resolution and scope of study area ($R^2 = 0.22$, $p < 0.001$).

training samples covered in all classification objects. By normalizing the descriptions regarding the number of training samples, the reported training samples vary from a minimum of 0.098% to a maximum of 80%. 121 case studies clearly delineate accuracy assessment methods, of which 26 studies adopt the area-based method, whereas 95 employ the point-based method.

In addition, feature selection, which is an important classification step that could reduce classification complexity by removing redundant feature information (Ma et al., 2017), still fails to attract adequate attention. Amongst all 254 classification case studies, those that explicitly employ the feature selection method only account for 22%. Moreover, 61% of studies fail to adopt the feature selection method or explicitly state whether the feature selection method is employed. The more frequently used feature selection methods consist of Feature Space Optimization (FSO) (8), DT (7), and Jeffries–Matusita (JM) distance (6), also comprising RF, CART, Correlation-Based Feature Selection (CFS), and Wrapper. In addition, for a small number of studies, manually identified feature combinations are adopted for subsequent classification. For example, feature combinations are manually identified using only spectrum or spectrum + texture (Kim and Yeom, 2014), spectrum + geometry (Maxwell et al., 2015), or spectrum + texture + geometry (Đurić et al., 2014).

### 3.2. Classification performance by sensor type

Regarding supervised object-based image classification sensors, sensor types adopted in less than three case studies were ruled out, e.g., Gaofen-1, Hyperion, Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), PALSAR, National Agriculture Imagery Program (NAIP), and TerraSAR-X, thus, the remaining 12 are predominantly frequently used sensors. Fig. 5 shows the mean classification accuracies of 12 different sensors. It is observed that, except for ASTER and Pléiades images, the mean classification accuracy is generally above 80%. The mean classification accuracy of UAV remains the highest at 86.33%, followed by SPOT-5, QuickBird, and IKONOS, for which the mean classification accuracies are 85.72%, 85.50%, and 85.49%, respectively (see Table 2). Surprisingly, the mean classification accuracy of WorldView-2 only reaches 83.61%; however, its resolution is higher than SPOT-5 and IKONOS. This is likely to result from the extensive use of WorldView-2 in urban study areas. A total of 35 case studies adopting WorldView-2 imagery cover 24 urban area classification cases with a high proportion of up to 68.57%. Due to the complexity of land-cover types in urban study areas, its classification accuracy is typically lower than study areas with other land-cover types (e.g., agriculture areas) (refer to analysis results in Section 3.6.2). In addition, only six experimental case studies employ Pléiades imagery, which all focus on urban study areas (Li et al., 2015a).

### 3.3. Segmentation scale and optimization

In terms of the segmentation software adopted in the 254 case studies, studies on segmentation using eCognition software account for 80.9% and those using ENVI software represent 4.4%. The remaining segmentation software mainly comprises SPRING and ERDAS. To better understand the relationship between segmentation scale and spatial resolution of the remote-sensing imagery, statistics are collected from all studies on multi-resolution segmentation using eCognition software. Furthermore, 92 case studies explicitly delineate the optimized segmentation scale and the image spatial resolution. Analysis of the correlation between scales and resolutions has found that a generally statistically significant correlation ($p < 0.05$) exists between the segmentation scale and the image resolution. In addition, the optimized segmentation scale is typically inversely proportional to the resolution

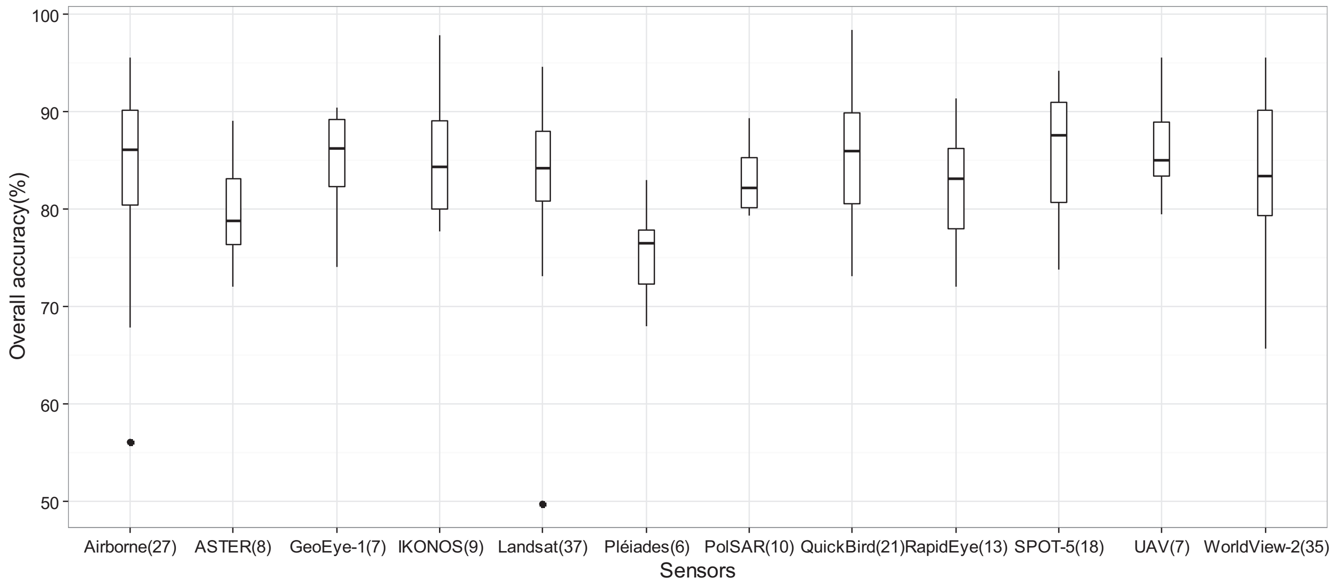



**Fig. 5.** Distribution of overall accuracies for different sensor types.

**Table 2**
Mean overall accuracy for different sensor types.

| Sensors | Mean overall accuracy (%) | Std. (%) |
|---|---|---|
| UAV | 86.33 | 5.25 |
| SPOT-5 | 85.72 | 6.43 |
| QuickBird | 85.50 | 7.40 |
| IKONOS | 85.49 | 7.02 |
| GeoEye-1 | 84.63 | 6.22 |
| Airborne | 84.14 | 9.08 |
| WorldView-2 | 83.61 | 7.72 |
| Landsat | 83.28 | 7.89 |
| PolSAR | 82.93 | 3.51 |
| RapidEye | 82.42 | 5.70 |
| ASTER | 79.49 | 5.45 |
| Pléiades | 75.50 | 5.32 |

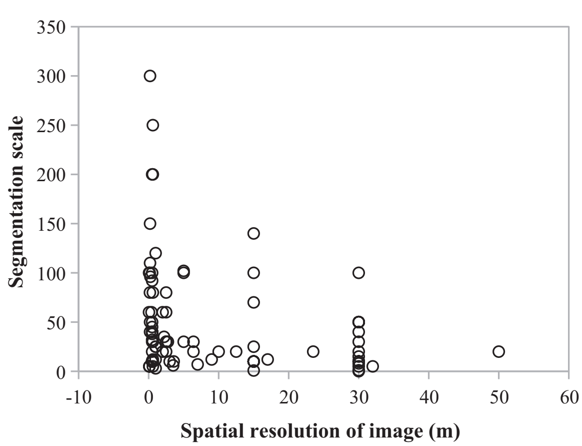



**Fig. 6.** Correlation between spatial resolution and segmentation scale ($R^2 = 0.058$, $p < 0.05$).

(Fig. 6). Generally, the higher the spatial resolution, the smaller the configured optimal segmentation scales. Conversely, the lower the spatial resolution, the greater the configured optimal segmentation scales. However, it can be difficult to determine the optimization scale given the fact that the variability of the scale is affected by other image characteristics, for example, the size of the study area.

For multi-resolution segmentation, numerous studies demonstrate the even greater importance of the scale parameter because it controls the dimension and size of segmented objects, which may directly affect subsequent classification (Smith, 2010; Kim et al., 2011; Myint et al., 2011; Hussain et al., 2013; Drăguţ et al., 2014). The scale issue, therefore, has emerged as a major problem in OBIA, particularly with respect to OBIA studies conducted with multi-scale segmentation methods. It is therefore essential to determine the appropriate segmentation scale and obtain optimized segmentation results (Arbiol et al., 2006). However, in numerous applied studies, land-cover extractions mainly rely on a trial-and-error approach, and segmentation scale parameters are determined based on previous experience (Laliberte and Rango, 2009). This approach is highly inadvisable (Johnson and Xie, 2011); therefore, many researchers have proposed methods to determine optimal segmentation scale parameters (Zhang et al., 2008; Kim et al., 2008; Drăguţ et al., 2010, 2014; Johnson and Xie, 2011; Martha et al., 2011; Drăguţ and Eisank, 2012).

A successful research result on scale optimization is to combine Local Variance (LV) and Rates of Change of LV (ROC-LV) to determine appropriate segmentation scales (Drăguţ et al., 2010), and the corresponding Estimate Scale Parameter (ESP) tool was made public for optimizing scale parameters. However, this method is only capable of processing single-band images. Therefore, they improved this method to enable the simultaneous processing of 30-band images, and developed the improved ESP2 tool, which has been successfully implemented in eCognition software (Drăguţ et al., 2014). Table 3 summarizes some representative segmentation scale optimization methods, which are mainly classified into two categories: supervised and unsupervised. The pros and cons of the above methods are also presented, which can be employed as required on a selective basis. Generally, supervised methods may obtain optimal segmentation results of different land-covers, but manual interpretation of reference objects for different land-covers is required as prior knowledge, such as the Fitting Equation (Ma et al., 2015) and Euclidean Distance 2 (Witharana and Civco, 2014). Unsupervised methods commonly suggest a single optimization scale (i.e., Espindola et al., 2006), or require a difficult threshold (i.e., Johnson and Xie, 2011).

**Table 3**
Representative studies on segmentation scale optimization.

| | Assessment indexes | Methods | Pros and cons | Publication |
|---|---|---|---|---|
| Supervised | Fitting equation | Based on mean area of reference objects, substitute into fitting equation to compute optimized scales for different land-covers | Optimal segmentation results of different land covers may be obtained. Manual interpretation of reference objects for different land covers is required, and the discriminant equation can then be derived | Ma et al. (2015) |
| | Euclidean Distance 2 | Optimize segmentation objects using the ED measure for the reference object and the actual object | Manual interpretation of reference objects for different land-covers is required | Witharana and Civco (2014) |
| Unsupervised | Weighted variance + rate of change (ROC) | Using the variation trend of two indices to determine the candidate optimization scale | Plugins (ESP/ESP2) available that are embedded into eCognition software. Only multiple individual candidate optimization scales may be obtained. ROC bears no specific geometric significance | Drăguţ et al. (2010, 2014) |
| | Normalization (Weighted variance +Moran's I), heterogeneity indexes of neighboring objects | Using normalization heterogeneity indices amongst neighboring objects to determine object merging | Redefine segmentation object to obtain optimal segmentation results for different land covers. Difficult to select merging/decomposition thresholds. Unstable test results with considerable regional limitations | Johnson and Xie (2011) |
| | Weighted variance +Moran's I | Using the variation trend of the two indices to determine optimization scales | Indices have geometric significance, and only a single optimization scale may be obtained | Espindola et al. (2006) |

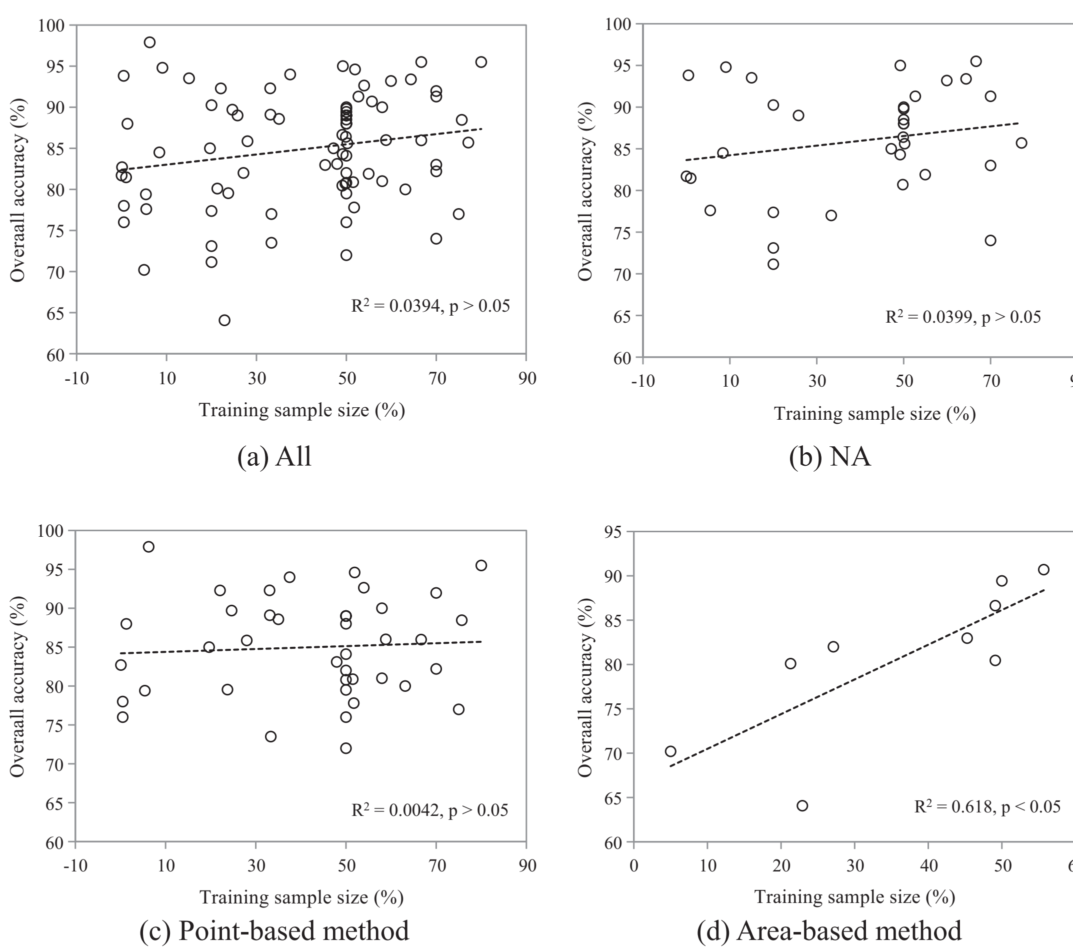



**Fig. 7.** Correlation of classification accuracy and training samples for: (a) all 82 studies that explicitly state the size of training samples; (b) 33 of the 82 case studies that fail to explicitly delineate accuracy assessment methods; (c) 40 of the remaining 49 studies that clearly state the accuracy assessment method and adopt the point-based accuracy assessment method; and (d) the other 9 studies, which employ the area-based accuracy assessment method ($R^2 = 0.618$, $p < 0.05$).

### 3.4. The effect of training set size on accuracy

Fig. 7 presents the statistical analysis of research results that clearly state the number of training samples. The descriptions of training samples in different case studies are inconsistent. For example, the description of some studies use the number of sample objects, whereas other studies employ the proportion of samples. For easy comparison and analyses, training sample proportion is uniformly used here to delineate the size of training samples in supervised classification, namely the proportion of training sample objects and classification objects. In general, with an increase in the size of training samples, the classification accuracy increases accordingly (Fig. 7(a)). Namely, a positive correlation exists between classification accuracy and size of the training sample, which has been consistently shown in many studies (Ma et al., 2015; Li et al., 2016). However, the strength of this positive correlation is very weak. Moreover, with an increase of training samples, classification accuracies exhibit a very limited increase (Fig. 7(a)–(c)), which is illogical. In particular, with respect to the point-based method, the correlation coefficient ($R^2$) for classification accuracy and size of the training samples is only 0.0042. This is likely to result from the considerable uncertainty of the point-based method.

For the case where segmentation objects comprise only homogeneous objects, this method exhibits advantages, and is characterized by fast processing speed and high accuracy; however, when segmentation objects consist of many mixed objects, then the classification accuracy may exhibit a marked fluctuation. This mainly stems from the considerable difficulty in identifying whether mixed objects are correctly classified. Consequently, in the case of the point-based method, classification accuracies exhibit a very limited increase with an increase of training samples. However, in terms of the area-based accuracy assessment method, a strong and significant positive correlation ($R^2 = 0.62$, $p < 0.05$) may be observed between the classification accuracy and the size of the training sample (Fig. 7(d)). This is because the area-based accuracy assessment method is assumed to be more applicable to OBIA, which is capable of clearly defining correctly and incorrectly classified portions among mixed segmentation objects (Whiteside et al., 2014). The statistical analysis presented here proves, from another perspective, the applicability of the area-based method to OBIA accuracy assessment. Unfortunately, many studies still fail to adopt this method for accuracy assessment. Thus, it is suggested that the area-based method is employed more frequently in future OBIA accuracy assessment.

### 3.5. Supervised classification methods

#### 3.5.1. Supervised methods and fuzzy methods

OBIA has been well verified for the classification of high or medium resolution images. In this supervised meta-analysis, we analyzed the distribution of 193 papers published since 2004 for different years. Moreover, our statistics reveal that, since 2003, there have been 140 publications dealing with fuzzy rule-based object-based image classification. Fig. 8 shows the number of studies published each year on fuzzy rule-based classification and supervised classification since 2003. Prior to 2010, the fuzzy rule-based classification technique appears more popular than the supervised classification technique, because of its ability to overcome the uncertainty of classes of segments and the strong transferability of rule sets based on the fuzzy concepts (Walker and Blaschke, 2008; Hofmann et al., 2011; Hofmann, 2016). However, since 2008, the amount of published literature has increased slightly and the object-based image classification technique has received more attention, primarily as a result of the first international conference on OBIA held in 2008 (Hay and Castilla, 2008). Since 2010, the number of studies on supervised object-based classification has increased rapidly, although studies on the fuzzy rule-based classification technique were still increasing during this time. However, in 2015, studies on fuzzy rule-based classification began to decrease. In contrast, research on supervised classification exhibited a more rapid increase (Fig. 8), perhaps because the fuzzy technique had become well known and well documented in the field of OBIA. Conversely, with the in-depth application of supervised classifiers in OBIA, a number of issues regarding supervised classifiers in OBIA began to attract attention (Ma et al., 2015), for example, sample selection (Rougier et al., 2016), feature selection (Laliberte et al., 2012), the supervised classification technique (Li et al., 2016), accuracy assessment (Whiteside et al., 2014), and so forth. Thus, it is considered that supervised object-based remote-sensing image classification techniques may be a key and dominant trend in future OBIA research.

#### 3.5.2. Classification performance by supervised classifiers

Regarding the relationship between supervised classifiers and overall classification accuracies, we collected statistics for all 220 related studies, of which 64 studies adopt the NN classifier, 55 the SVM classifier, 44 the RF classifier, 33 the DT classifier, 14 the Maximum Likelihood Classifier (MLC) classifier, and 10 employ other classifiers. In terms of commonly used supervised classifiers, RF is generally characterized by the highest mean classification accuracy (85.81%), followed by the SVM classifier (85.19%) and the DT classifier (84.15%), whereas those of NN and MLC are relatively lower at 81.58% and 81.55%, respectively (Fig. 9). Despite the fact that training samples or remote-sensing images may vary slightly, the accuracy assessment results of different commonly used classifiers are approximately consistent with most previous research conclusions (Li et al., 2016). Moreover, compared to other factors, classifiers constitute a very important influential factor for supervised classification. The mean classification accuracies of other classifiers are generally higher, which is likely a result of improved classification methods adopted in these studies, including novel methods proposed by researchers, and excellent classification techniques such as the Adaboost and Artificial Neural

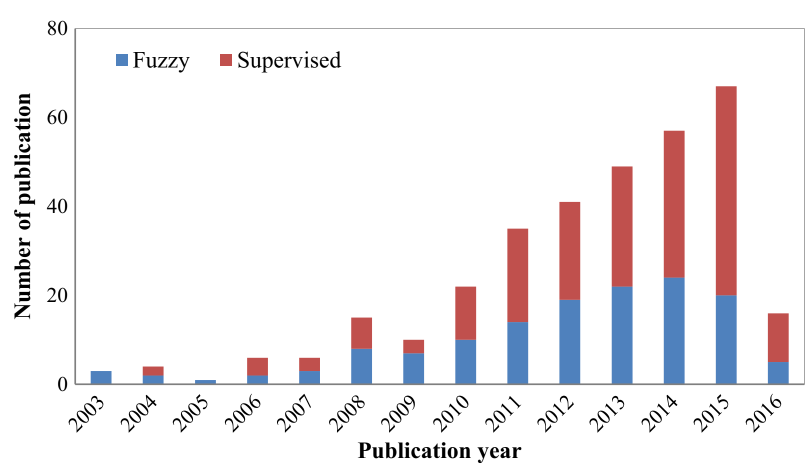



**Fig. 8.** Number of publications per year for object-based land-cover image classification using either fuzzy rule-based or supervised methods.

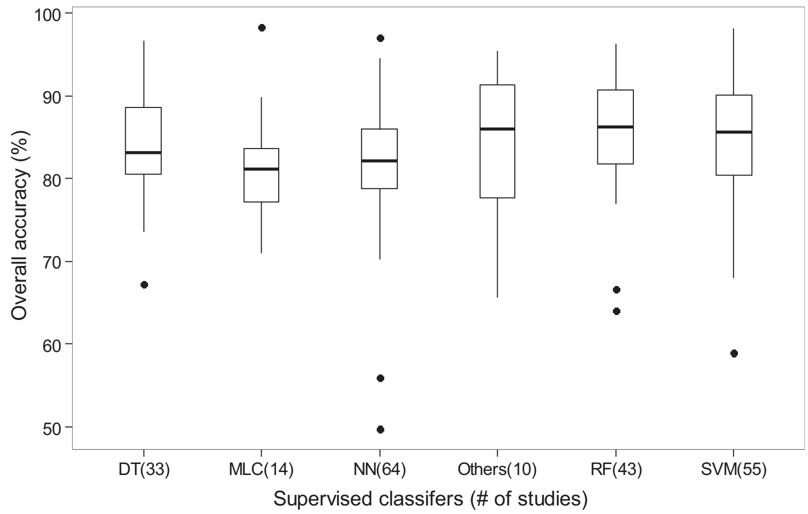



**Fig. 9.** Overall accuracy vs. several supervised classifiers.

Network (ANN) (Zhang, 2015). In addition, some more generic classifiers such as Naive Bayes are also included into the "Others" category; therefore, classification accuracies with other classifiers exhibit considerable fluctuations.

*3.6. Effect of classified types on classification performance*

This section mainly analyzes the relationship between classification accuracies and the number of classes plus major land-cover types of study areas. Research results show that a correlation exists between classification accuracies and the number of classes. Furthermore, the classification accuracy will decrease with an increase in the number of classes. In addition, classification accuracy varies substantially with land-cover type.

*3.6.1. Effect of the number of classes on classification accuracy*

Previous studies have described linear relationships between overall accuracy and targeted classes, and overall accuracy and plot size (Dronova, 2015). However, the statistical results are derived only from studies of OBIA in wetland mapping. In this study, a full review is conducted on OBIA research results for all types of remote-sensing mapping, resulting in 225 case studies that satisfy the conditions, which far exceeds the 61 case studies of Dronova (2015). As for analyzing the effects of the number of classes on

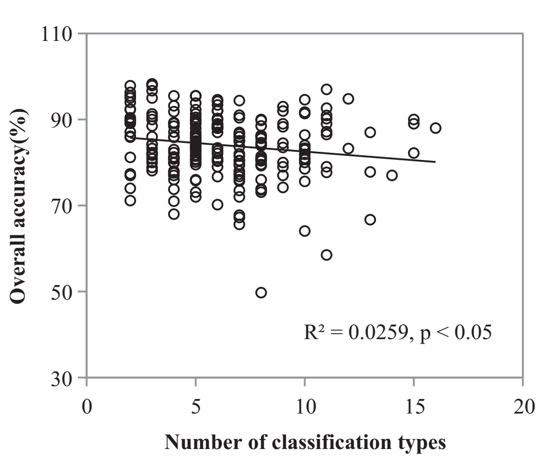



**Fig. 10.** Distribution of classification accuracies with respect to the number of classes in the reviewed papers ($R^2 = 0.0259$, $p < 0.05$).

accuracy, 5 records on classification accuracy values are deleted where the number of classes are equal to or greater than 25, leaving 220 records, the statistics of which are shown in the scatter graph in Fig. 10. Fig. 10 shows the relationship between the number of different classes and classification accuracies, with the number of classes mainly ranging from 2 to 11. In general, our results are consistent with the research conclusion of Dronova (2015); that is, there is a significant and weak negative correlation between the number of classes and classification accuracy, with $p < 0.05$ (Fig. 10). Furthermore, the correlation test of 144 samples also indicates that there is no evident correlation between classification accuracies and the scope of study areas, as the p-value is greater than 0.1.

*3.6.2. Effect of land-cover type on classification accuracy*

The 225 case studies comprise 5 major land-cover types, including agriculture (50 classification accuracies), forest (53 classification accuracies), urban (64 classification accuracies), vegetation (28 classification accuracies), and wetlands (9 classification accuracies). Other land-cover types in this study mainly consist of landslide, coral reef, flood, benthic habitat/seabed mapping, coal mining areas, and aquatic, totaling 20 classification accuracies. Results indicate that the mean overall classification accuracy of agriculture study areas is highest, at 86.04%, followed by that of wetland study areas at 84.46%. Urban, vegetation, and forest study areas are characterized by similar mean classification accuracies of 83.15%, 83.25%, and 82.45%, respectively (Fig. 11). Study areas with a higher level of homogeneity, such as vegetation and forest types, exhibit lower classification accuracies. This is mainly due to the fact that vegetation and forest types were adopted as experimental areas in most earlier studies where NN classifiers are used extensively (Colditz et al., 2006; Yu et al., 2006; Gao, 2008; Mallinis et al., 2008), resulting in generally low classification accuracy. In recent years, however, more theoretical and methodological research has begun to involve the study of agriculture areas (Duro et al., 2012a; Ma et al., 2015; O Connell et al., 2015). Furthermore, excellent machine learning classifiers such as RF and SVM are now applied to the process of object-based image classification (Peña et al., 2014; Qian et al., 2014; Li et al., 2016), thereby enabling higher classification accuracies of agriculture and wetland study areas. However, the complex characteristics of urban land-cover, in contrast to areas such as highly homogeneous agricultural areas, pose intrinsic difficulties for classification (Myint et al., 2011). Therefore, despite a legion of relevant studies (Xu et al.,

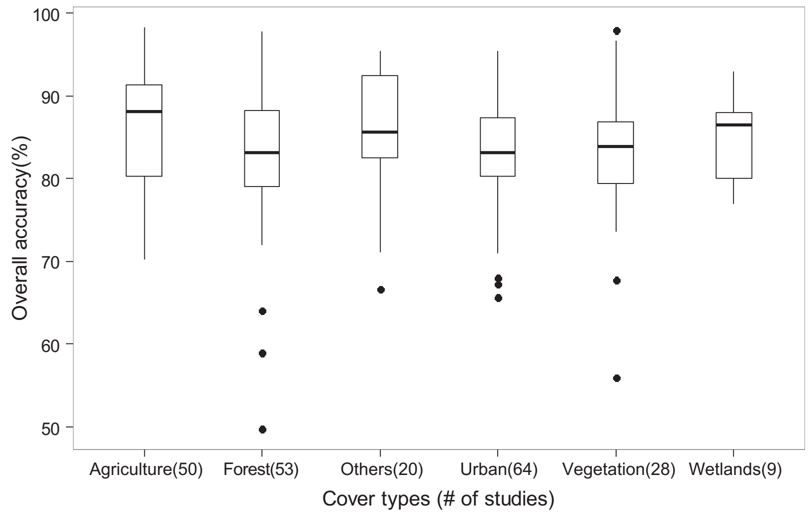



**Fig. 11.** Overall accuracy vs. study area land-cover type.

2010; Aguilar et al., 2013; Du et al., 2015) and the frequent use of advanced classification methods, the classification accuracy for urban study areas remains inferior to that of agriculture study areas.

## 4. Methodological advances: issues and future prospects

Meta-analyses and reviews are useful for documenting the scope, range, geographic distribution, and history of supervised object-based image classification, as well as the interaction effect of the multiple factors on classification accuracy, i.e., spatial resolution, sensors, scale, classes, and methods. In the following sections, an in-depth exploration is carried out with respect to the results of the meta-analyses, a detailed review is conducted of the methods related to key steps in the process of supervised object-based land-cover image classification, and predictions are made regarding the future advances of supervised object-based land-cover image classification.

### *4.1. Development of classification methods*

The results of meta-analyses indicate that supervised classifiers substantially affect the performance of object-based land-cover image classification (see Section 3.5.2). The most frequently cited papers were summarized to find which classifier is given more attention (Table 4), and to extrapolate the significant research results from existing studies on supervised object-based classification. Results show that the most popular classifiers are still the traditional NN and DT classifiers. This mainly results from the extensive use of eCognition software in most supervised object-based classifications, where NN is the only supervised classifier. Moreover, owing to the unique advantage for rule construction featured by eCognition, DT is preferred by many researchers. In addition, since 2011, RF and SVM classifiers have also attracted great attention owing to their excellent classification performance (Duro et al., 2012a; Li et al., 2016).

The application of supervised classifiers in OBIA has attracted widespread attention in recent years. Nevertheless, owing to the effects of various factors such as segmentation scale, that affect which supervised classifier is more applicable to supervised object-based classification, the conclusions from many studies are inconsistent (Maxwell et al., 2015; Li et al., 2016). For example, some studies concluded that the overall classification accuracies of DT were better than those of the K-NN algorithm (Laliberte et al., 2006; Mallinis et al., 2008), while the others suggested that K-NN generally performed better for land-cover mapping (Tehrany et al., 2014). Until recently, by combining a series of uncertainties in OBIA such as segmentation scales, features, and mixed objects, Li et al. (2016) systematically analyzed the performance of various commonly-used supervised classifiers under different conditions, and deemed that, as a whole, RF was the supervised classifier most suitable to OBIA. Moreover, they admitted that the advantages of various classifiers differ under different conditions, for example, the DT and RF classifiers perform better at processing redundant features, while other classifiers benefit more from feature selection (Li et al., 2016).

Deep learning is an excellent classification technique developed in recent years, and therefore has been paid more attention in object-based classification framework (Längkvist et al., 2016; Zhao et al., 2017). It is believed that, in future studies, it will be necessary to introduce it into supervised object-based classification and conduct an in-depth examination on the interactive effects between deep learning and varied factors in OBIA. Thus, it is expected to further promote the development of supervised object-based classification techniques. In addition, type-2 fuzzy techniques may offer another opportunity for object-based image classification, because the development of fuzzy rule-based classification already encounters a bottleneck in the field of object-based

**Table 4**
Supervised classification articles ranked by number of citations normalized by years (as of April 15, 2016).

| Rank | Average number of citations per year | Classifiers used | Publication |
|---|---|---|---|
| 1 | 41 | NN | Myint et al. (2011) |
| 2 | 27 | NN | Yu et al. (2006) |
| 3 | 22 | RF, SVM, DT | Duro et al. (2012a) |
| 4 | 19 | NN | Laliberte et al. (2004) |
| 5 | 18 | DT | Peña-Barragán et al. (2011) |
| 6 | 17 | RF | Stumpf and Kerle (2011) |
| 7 | 15 | DT, NN | Mallinis et al. (2008) |
| 8 | 14 | NN | Wang et al. (2004) |
| 9 | 14 | DT | Ke et al. (2010) |
| 10 | 13 | DT | Qi et al. (2012) |
| 11 | 12 | NN | Yan et al. (2006) |
| 12 | 11 | DT | Laliberte and Rango (2009) |
| 13 | 11 | LDA, DT | Pu and Landry (2012) |
| 14 | 10 | NN | Cleve et al. (2008) |

image classification (Fig. 8). Compared to type-1 fuzzy techniques, type-2 fuzzy techniques, which reveal the depth of uncertainty, are a much softer classifier (Fisher, 2010), and are thus expected to overcome all the effects of the variations inherent in supervised object-based image classification (Li et al., 2016).

### 4.2. Development of sampling methods

Based on the statistics of 254 case studies, only 88 clearly described the sampling methods, of which 45 studies adopted the traditional simple random sampling method, 37 employed the stratified random sampling method, and the other 6 employed other sampling methods, including some new methods. In terms of object-based image classification, the sampling method undoubtedly constitutes a crucial step. Furthermore, the varied sizes of segmentation objects pose sampling difficulties and specificity in the process of object-based classification (Corcoran et al., 2015). However, relevant theoretical research on the sampling process of object-based classification is still insufficient. For example, is remains unknown how the discrepancies will be reflected among training sample objects with different sizes, how the training samples of homogeneous objects better represent corresponding mixed objects with identical classes, and how the mixed objects express corresponding homogeneous objects with identical classes. Subsequently, little attention has been devoted to optimizing sampled training objects (Dronova et al., 2011; Pérez-Ortiz et al., 2016).

Generally, it is considered that mixed objects offer the opportunity to devise novel sampling schemes for supervised object-based image classification. Because mixed objects in object-based classification are the same as mixed pixels in pixel-based classification, numerous sampling schemes have already been devised with respect to this process. The effects of a sampling scheme combining mixed pixels on classification results are assessed (Samat et al., 2015), whereas for supervised object-based image classification, more studies still focus on assessing the effects of training sample size and commonly used sampling methods (Zhen et al., 2013; Ma et al., 2015), thus falling short of designs and studies that exploit advanced sampling schemes.

Therefore, for supervised object-based image classification, we suggest that future studies take advantage of relatively advanced techniques within the existing sampling hierarchy, such as active learning (Tuia et al., 2011; Stumpf et al., 2014; Rougier et al., 2016) and semi-supervised learning (Bioucas-Dias et al., 2013), by combining characteristics of mixed objects, and conduct studies on the optimization of training sample objects. Thus, this would address the problem of reduced classification accuracies due to the small number of coarse-scale sample objects during the sampling process, as well as the discrepancies between mixed and homogeneous objects that were labeled as identical classes. Moreover, the sample training bias would also be addressed, which results from the different sizes of segmentation objects for different land covers within the same scene.

### 4.3. Study of feature selection methods

With the in-depth application of supervised classification in the field of OBIA, feature selection is also gradually attracting attention. Table 5 summarizes the applied studies into feature selection methods in supervised object-based classification. Based on

**Table 5**
Feature selection methods used in OBIA.

| | Methods | Pros and cons | Applications and representative literature |
|---|---|---|---|
| Feature importance assessment methods | RF | Easily adapt to RF classifier, ensuring classification accuracy of the feature selection. Able to generate sorted features | Classification of urban land use (Novack et al., 2011). Classification of land use in agricultural areas in combination with RF classifier (O Connell et al., 2015). Forest habitat type classification (Räsänen et al., 2013) |
| | GINI | Higher feature selection efficiency, able to generate sorted features and classification rules. Easily combined with decision tree classifier | Classification of pasture land-cover types, combining DT classifier (Laliberte and Rango, 2009). GINI index is considered to perform best based on the comparison of multiple feature selection methods (Cánovas-García and Alonso-Sarría, 2015) |
| | SVM/RF-RFE | Generate feature sorting results while achieving best classification accuracy, normally combined with SVM and RF | Landslide detection (Stumpf and Kerle, 2011) and classification of agricultural land-use types (Schultz et al., 2015), combined with RF classifier |
| | Relief-F | Able to generate sorted features; independent of classification model, difficult to determine optimal subsets | Classification of urban land-use, in combination with RF, SVM, and DT classifiers (Novack et al., 2011) |
| | Chi-square | Able to generate sorted features and classification rules | Peña-Barragán et al. (2011) applied Chi-square test index to split the decision tree and achieved agricultural area classification and mapping |
| | Information Gain (IG) | Able to generate sorted features and classification rules, difficult to determine optimal subsets | Vieira et al. (2012) applied IG index to split the decision tree, and achieved sugarcane land-cover classification and mapping; Pérez-Ortiz et al. (2016) applied IG index to screen out top 10 features for weed mapping |
| Feature subset assessment methods | CFS | Directly generate feature subsets, independent of classification model, featuring fast processing speed | Classification of agricultural land-uses in combination with RF classifier (Ma et al., 2015) |
| | Wrapper (RF/SVM) | Easy adaptation to classifiers. Point-based cross-validation is adopted in most cases, susceptible to over-fitting or over-adapting to classifiers. Time consuming. Normally applied in combination with RF and SVM | Classification of agricultural landscape in combination with RF classifier (Duro et al., 2012b); Landslide classification and detection using RF and SVM (Li et al., 2015b) |
| Miscellaneous | JM distance | Able to generate classification distances amongst classes. Generally used for rule-based classification or NN classifier | Rule-based classification of pasture land cover (Kim et al., 2011); JM index is considered to perform best based on the comparison of multiple feature selection methods (Laliberte et al., 2012) |
| | FSO | Integrated in eCognition with easy use. Black-box manipulation, lack of feature importance sorting. Normally used for NN classifier | Mangrove forest classification using NN classifier (Son et al., 2015); Comparison of multiple feature selection methods (Laliberte et al., 2012); Evans et al. (2014) employ it to define optimal feature set for wetland mapping with NN classifier |
| | GA | Black-box manipulation, lack of feature sorting results. Normally used for ANN classifier | Combining neural network for forest mapping (Van Coillie et al., 2007) |

different feature selection results, feature selection methods mainly comprise the feature importance assessment method, the feature subset assessment method, and other selection methods (Ma et al., 2017). The feature importance assessment method may obtain a sorted ranking of importance (e.g., GINI (Laliberte and Rango, 2009; Cánovas-García and Alonso-Sarría, 2015), RF (Novack et al., 2011), Chi-square (Peña-Barragán et al., 2011), and SVM-RFE (Stumpf and Kerle, 2011; Schultz et al., 2015)), whereas the feature subset method can directly attain optimized feature subsets (e.g., Wrapper (Duro et al., 2012b; Li et al., 2015b) and CFS (Ma et al., 2015)), thereby achieving the highest classification accuracy.

Because feature selection may reduce classification complexity or improve classification accuracies, the above studies generally show that feature selection can improve the process of object-based remote sensing image classification. However, not all studies guarantee that feature selection improves classification accuracy, mainly due to uncertainties introduced in the process of object-based imagery classification, e.g., changes of segmentation scales, and the diversity of classifiers. Additionally, studies of other high-dimensional data (e.g., high spectral data) showed that feature selection was characterized by considerable uncertainties in terms of different supervised classification methods (Pal and Foody, 2010; Ma et al., 2015). With respect to the SVM classifier, some studies suggest that SVM is insensitive to the number of data dimensions (Melgani and Bruzzone, 2004; Pal and Mather, 2006), namely the increase or decrease in the number of data dimensions may not affect the classification accuracies of SVM. Conversely, SVM classification accuracy improved was found with the decreased number of dimensions by Weston et al. (2000). Therefore, in the process of SVM-based classification, some uncertainties still exist in feature selection. The same issues exist with the RF classifier, as it has already been applied extensively to object-based remote sensing image classification (Stumpf and Kerle, 2011; Puissant et al., 2014). For example, some studies found that feature selection could improve the performance of the RF classifier for agricultural area mapping (Duro et al., 2012b), while the others proved that the RF classifier is a more stable object-based remote sensing image classification method with or without feature selection (Ma et al., 2015). Hence, in the process of object-based remote sensing imagery classification, due to the diversity of input data or a series of variations introduced during the process of object-based classification (e.g., different classifiers), feature selection requires substantial further research.

Some earlier studies simply stated that the number of employed feature dimensions should be limited to avoid overfitting and a potential decrease in classification accuracy (Leon and Woodroffe, 2011). However, This study in particular shows that, in terms of RF or DT classifiers, an increase in features may not lead to a decrease in object-based classification accuracies (Li et al., 2016). Although the number of features required for different machine learning classifiers to achieve higher and stable accuracy varies slightly (Wieland and Pittore, 2014), previous studies have demonstrated that a higher classification accuracy may be achieved when the number of features is less than 30 (Guan et al., 2013; Ghosh and Joshi, 2014) and, generally, it is not advisable to use too many features in OBIA. This is probably because most features in OBIA belong to secondary derivative features with comparatively high correlation. Therefore, calculating a limited number of features in OBIA not only avoids large computational burdens, but also ensures classification accuracies. However, due to the fact that the performance of different machine learning classifiers varies with different feature selection methods, further exploration should be made into which feature selection method should be used in specific practical applications of OBIA.

### 4.4. Labeling and accuracy assessment

This study also involves a discussion of the labeling of candidate samples during supervised object-based image classification because it is related to whether the correct training samples are obtained. Unfortunately, very few studies have explored this aspect to date. Moreover, the labeling process is not clearly stated in numerous studies on supervised classification, which, we suggest, is essential. Because it was already explicitly demonstrated that accuracy performance benefits more from homogeneous objects (Li et al., 2016), which signifies when the area-based method is used in accuracy assessment, the more homogeneous objects that are selected as training samples or test samples, the higher the classification accuracies. In current studies, the segmentation object will, in most cases, be labeled directly using the class that accounts for a large percentage of the segmentation object (Verbeeck et al., 2012; Ma et al., 2015).

Labels not only influence the sampling process, but are also closely related to the process of accuracy assessment, thereby affecting the assessment of classification accuracy performance. This mainly results from the following two reasons: (1) the actual interpreted image layer objects cannot fully coincide with the segmentation objects and (2) segmentation objects consist of mixed land-cover types. In object-based high-resolution remote-sensing image classification, because the point-based accuracy assessment method (viewing an individual segmentation object as an independent point) remains simple and straightforward, researchers are more inclined to view the object as an individual point, thus the classification of this object is either correct or incorrect (see Section 3.1). However, its classification accuracy increased with increasing scale (Laliberte and Rango, 2009), which is not reasonable over large scales, because an increase in the number of mixed objects may reduce classification accuracy. With advances in OBIA technology, OBIA accuracy assessment methods are emerging as a new research field (Blaschke, 2010; Radoux et al., 2011; Whiteside et al., 2014; Radoux and Bogaert, 2014) as point-based assessment methods gradually exhibit drawbacks (Zhan et al., 2005; Recio et al., 2013; Goodin et al., 2015).

The area-based validation method essentially assesses classification accuracy based on the scope and spatial distribution of segmentation objects (Freire et al., 2014). The main issue is that the unit of accuracy assessment is no longer a regular pixel unit and each object is a geographical object of differing sizes (MacLean and Congalton, 2012). Therefore, researchers had to determine: (1) which unit (point or polygon) should be used to evaluate the classification accuracy (Stehman and Wickham, 2011); and (2) which rule should be used to label the class of object according to the reference layer (Radoux and Bogaert, 2014). Generally, it is considered that accuracy assessment benefits more from a polygon unit. Therefore, a theoretical model based on the area-based accuracy assessment method is proposed by Whiteside et al. (2014), which is, so far, a set of theoretical systems with practical significance for accuracy assessment in OBIA. Subsequently, it is deemed that accuracy assessment studies of object-based classification should first focus on the object labeling issue, because it will not only optimize training sample objects, but also promote the development of accuracy assessment methods.

## 5. Uncertainty in object-based supervised classification

Based on the meta-analysis and review, we summarize the sources of major uncertainties on supervised object-based classification (Fig. 12). Uncertainties in object-based classification mainly stem from the diversity of techniques and methods used in various processing phases, which have already been reviewed in previous

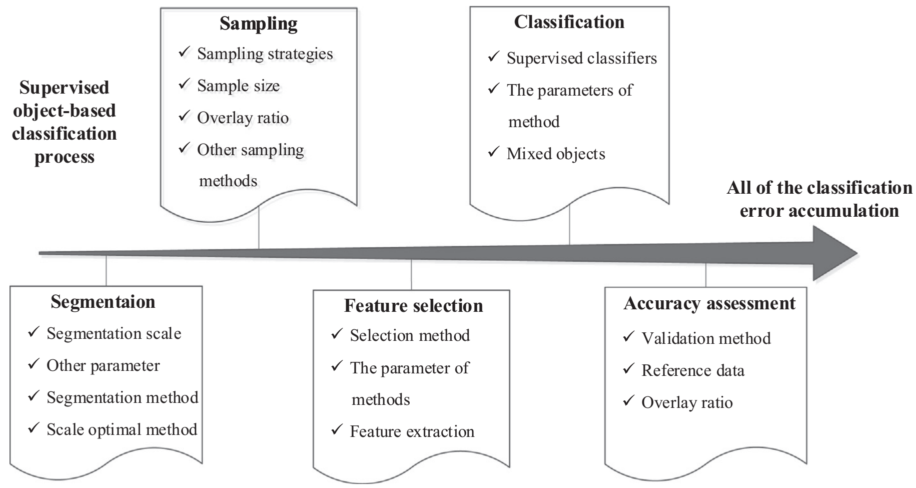



**Fig. 12.** Factors introducing uncertainty into the process of supervised object-based image classification.

sections of this paper (Sections 4.1–4.4). In-depth studies have also been carried out on, for example, the uncertainty of the classification result obtained from a single classifier by Hao et al. (2015) and Li et al. (2016). Therefore, method uncertainties will not be described here; instead, we focus on the effects of uncertainties for parameters involved in various methods and different phases, e.g., spatial scale, segmentation parameters, and data sources.

Scale uncertainties may be classified into the following two categories: firstly, different spatial resolutions leading to uncertainty of classification; secondly, different segmentation scale parameters leading to differing segmentation objects. In terms of different spatial resolutions, Powers et al. (2012) used a re-sampling approach to compare the performance of OBIA classification for images with different spatial resolutions (5, 10, 15, 20, 25, and 30 m) and found that better classification performance can be obtained using a spatial resolution of 10 m. However, based on our statistical analyses of published case studies on supervised classification, studies on OBIA classification are generally more inclined to employ images with high spatial resolutions ranging from 0 to 2 m (Fig. 3). In addition, by means of statistical analyses of classification accuracies for different sensors (Fig. 5), no correlation is observed between better classification accuracies and spatial resolutions in OBIA. Therefore, it remains unknown why this technique applies to images with high spatial resolution, and not to images with low spatial resolution. Hence, related quantitative assessments should be conducted. Furthermore, many studies have been performed on the uncertainties of segmentation scale, and related studies on scale optimization are also detailed in Section 3.3; therefore, they will not be repeated here.

From the perspective of data sources, the effects of various factors related to acquired imagery are encompassed, including sensors (Section 3.2), types of land-cover (Section 3.6.2), and temporal information. Concerning to the uncertainty derived from varied temporal information, the classification accuracies in different seasons or periods exhibit considerable discrepancies because of the changes in phenology (Qi et al., 2015), and therefore multi-temporal datasets enable to decrease classification uncertainty compared to single data sets (Löw et al., 2015).

Most of the above assessment and analyses reflect the uncertainties caused by various factors related to overall classification accuracy. Overall accuracy is highly recommended for assessing uncertainties, because the ultimate goal of OBIA is to obtain better classification accuracies. Furthermore, the concept of uncertainty has been extensively applied to remote-sensing data processing and quality assessment (Foody and Atkinson, 2002; Loosvelt et al., 2012; Olofsson et al., 2013; Löw et al., 2015) because processes such as the acquisition, processing, analysis, and conversion of remote sensing data may all pose certain degrees and types of uncertainties. Consequently, because OBIA remains a newly emerging remote-sensing image processing paradigm (Blaschke and Strobl, 2001; Blaschke et al., 2014), we highly recommend further study on the uncertainties of object-based remote sensing image classification.

## 6. Conclusions

The study was motivated by the popularity of supervised object-based image classification for land-cover mapping. Using information available in 173 scientific publications, a database containing typical fields related to supervised object-based land-cover classification was constructed to serve as a basis for meta-analysis. Subsequently, several conclusions were drawn.

(1) High spatial resolution remote-sensing imagery remains the most frequently used data source for supervised object-based land-cover image classification, and the dominant image resolutions are 0–2 m. Moreover, due to good availability and accessibility, Landsat series remote-sensing images are often employed in supervised object-based classification.
(2) In the studies conducted, the size of most study areas is less than 300 ha (95.6%), which suggests the need for larger study areas in future research, thereby verifying the applicability of the object-based image classification technique over wider areas. Also, a positive correlation exists between the size of study areas and the spatial resolutions used.
(3) With respect to segmentation algorithms, more studies are inclined to adopt the multi-scale segmentation technique. A negative correlation exists between the optimal segmentation scale and the spatial resolution of imagery.
(4) Unsurprisingly, high spatial resolution remote-sensing imagery, such as UAV, is advantageous for obtaining higher overall classification accuracy. However, there are exceptions. For example, Pléiades images are mainly applied to urban areas, which result in anomalously low classification accuracy. Hence, it is necessary to employ more extensive remote-sensing imagery or land-cover types to further verify object-based image classification technique.
(5) A strong positive correlation exists between classification accuracies attained using area-based accuracy assessment methods and the size of training samples, whereas those

obtained using the point-based method are extremely unstable.

(6) The fuzzy rule-based classification technique encounters a bottleneck in object-based classification, whereas supervised object-based classification is experiencing a peak in development. To better address related issues, we strongly encourage scientists using the supervised object-based image classification technique to report results obtained for all the multiple configurations considered during the optimization phase.
(7) RF exhibits the best performance in object-based classification, and has attracted significant attention in recent years, followed by SVM, with MLC performing the worst. Furthermore, NN appears unsuitable for more extensive use in object-based classification. Thus, the use of NN should be reduced, even though it was the most frequently employed classifier for object-based classification.
(8) A negative correlation exists between overall classification accuracy and the number of classes defined.
(9) Regarding the land-cover type of study areas, object-based classification proves more advantageous for land-cover mapping of agriculture study areas. Moreover, it is essential to explore object-based classification methods that are applicable to urban areas.

Although RF and SVM classifiers have also attracted great attention owing to their excellent classification performance, deep learning, which is an excellent classification technique developed in recent years, is still expected to further promote the development of supervised object-based classification techniques. In addition, it seems that rule-based classification already encounters a bottleneck in the field of object-based image classification, and thus type-2 fuzzy techniques are expected to offer another opportunity for object-based image classification.

Mixed objects may offer the opportunity to devise novel sampling schemes for supervised object-based image classification, and therefore future studies should take advantage of relatively advanced techniques within the existing sampling hierarchy, such as active learning and semi-supervised learning, by combining characteristics of mixed objects, and conduct studies on the optimization of training sample objects.

Not all studies can ensure feature selection to improve classification accuracy because of uncertainties introduced in the process of object-based imagery classification (e.g., different classifiers). Hence, feature selection requires substantial further research. Furthermore, it is not advisable to use too many features in OBIA and the number of features should be limited to 30, because most features in OBIA belong to secondary derivative features with comparatively high correlation.

Successfully labeled objects or well-designed labeling rules will not only optimize training sample objects, but also promote the development of accuracy assessment methods. Therefore, we also suggest that accuracy assessment studies of object-based classification should first focus on the object labeling issue.

As mentioned above, the sources of the major uncertainties in supervised object-based classification stem from the diversity of techniques and methods and the variability of parameters (spatial scale, segmentation parameters, and data sources). Due to the lack of such knowledge, we highly recommend further study on the types and effects of uncertainties related to supervised object-based remote sensing image classification.

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