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REVIEW ARTICLE

Meta-discoveries from a synthesis of satellite-based land-cover mapping research

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Since the launch of the first land-observation satellite (Landsat-1) in 1972, land-cover mapping has accumulated a wide range of knowledge in the peer-reviewed literature. However, this knowledge has never been comprehensively analysed for new discoveries. Here, we developed the first spatialized database of scientific literature in English about land-cover mapping. Using this database, we tried to identify the spatial temporal patterns and spatial hotspots of land-cover mapping research around the world. Among other findings, we observed (1) a significant mismatch between hotspot areas of land-cover mapping and areas that are either hard to map or rich in biodiversity; (2) mapping frequency is positively related to economic conditions; (3) there is no obvious temporal trend showing improvement in mapping accuracy; (4) images with more spectral bands or a combination of data types resulted in increased mapping accuracies; (5) accuracy differences due to algorithm differences are not as large as those due to various types of data used; and (6) the complexity of a classification system decreases its mapping accuracy. We recommend that one way to improve our understanding of the challenges, advances, and applications of previous land-cover mapping is for journals to require area-based information at the time of manuscript submission. In addition, building a standard protocol for systematic assessment of land-cover mapping efforts at the global scale through international collaboration is badly needed.

1. Introduction

Land-cover information is fundamental in a large number of fields of natural science, ranging from climate and hydrological modelling to biogeochemical cycling studies,

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environmental protection, biodiversity conservation, and resource management. Since the advent of satellite remote sensing, land-cover mapping has become one of the most widely studied applications (Tucker, Townshend, and Goff 1985; Running 2008; Yang et al. 2013). Over a period of four decades since the launch of the first land-observation satellite, the Earth Resource Technology Satellite (later changed to Landsat-1), in 1972, substantial advances in sensor technologies have been made. The Landsat series of satellites have acquired nearly 4.5 million scenes of imagery over land (the latest satellite in this series is Landsat-8, which was launched on 11 February 2013 and started acquiring images on 18 March 2013). In addition, hundreds of satellites have been launched to observe land dynamics (Belward and Skøien 2014). The spatial resolution of sensors on board these satellites has increased by a factor of more than 100, from 80 m of the Landsat-1 to 0.41 m of the GeoEye-1 (Orbview-5) satellites. The spectral sampling frequency has increased nearly 100-fold from a few spectral bands to a few hundred. Despite this rapid advancement in hardware, the pace of information extraction from the extremely large volumes of data acquired from these satellites seems to be slow. For example, although the world has been imaged hundreds of times at 30 m resolution or finer, global land-cover maps are primarily created from data acquired from weather satellites that provide daily global coverage from polar orbits (Arino et al. 2008; Loveland et al. 2000; DeFries et al. 2000; Hansen et al. 2000; Bartholomé and Belward 2005; Friedl et al. 2002, 2010; Bontemps et al. 2010; Tateishi et al. 2011), with only a handful of recent exceptions (Gong et al. 2013; Yu, Wang et al. 2013; Yu, Wang, and Gong 2013; Townshend et al. 2012; Sexton et al. 2013; Hansen et al. 2013).

Although a large number of algorithms have been developed by thousands of researchers to map land cover from satellite imagery, some reviews claim that there has been almost no improvement in the accuracy of land-cover and land-use mapping following the introduction of these new algorithms (Hand 2006; Wilkinson 2005). Earlier reviews, which focused mainly on other methods (Lu and Weng 2007; Franklin and Wulder 2002) or examination of the relationships among image classification and its influencing factors (Hand 2006; Wilkinson 2005), did not pay attention to the spatial aspect (study locations). Spatial scientometrics (which uses the address information in publications to locate sites where knowledge has been created) has attracted considerable attention in the recent past (Frenken, Hardeman, and Hoekman 2009; Leydesdorff and Persson 2010; Chen 2010; Bornmann and Waltman 2011; Zhuang et al. 2013). Most of these studies, however, used only authors' affiliation addresses and not the actual locations of study areas as spatial tags. Elsevier recently released a new product, Geofacets (http://www.info.geofacets.com/), to support the search for geological maps and contents from Elsevier's Earth sciences journals. However, currently, geology is the only subject spatialized in Geofacets. A wide range of location-related publications (e.g. land cover) are not included. In this article, we developed the first spatialized literature database on land-cover-mapping research in the world using remotely sensed data, from 6771 research articles published before 2013. The database contains unique records including map location, classification system, type of data used, year of data acquisition, type of classification method, and map accuracy, in addition to information conventionally found in a literature database. This database allows us to access new knowledge because of the spatialization of literature that assembles a large number of land-cover mapping works in their correct geographic locations. Besides, this database also provides us with new evidence to answer questions on the relationship between classification accuracy and many influencing factors. Land-cover mapping accuracy can be affected by many factors ranging from the types of mapping area, types of data, data processing, mapping methods, classification system (which is a constraint to cross-comparison), and methods of accuracy assessment (Li et al. 2014). A complete exploration of those factors is beyond the scope of this article.

2. Methods

2.1. Data collection

A literature search was performed in the ISI Web of Knowledge (http://apps.isiknowledge.com/). Remote-sensing land-cover mapping was searched by listing a number of keywords: 'remote sensing', 'land cover', 'mapping', and 'classification'. After some preliminary testing, we used the following combined query: 'Topic = ("land cover" and "mapping") *or* Topic = ("land cover" and "classification") *or* Topic = ("remote sensing" and "classification") Timespan = All Years. Databases = SCI-EXPANDED, SSCI'. This search included land-cover mapping activities with airborne data and field surveys, but these occupied only a small percentage (<4%). It should be noted that we only included works reported in the form of peer-reviewed papers, published in English, and searchable in the ISI Web of Science. Thus, other mapping projects (completed or ongoing) are not included in our analysis.

The following information (if present) was extracted from each paper (Table 1): (1) corresponding author (email address); (2) research domain; (3) place name of the study area; (4) latitudes and longitudes of the study area; (5) boundary of the study area or bounding rectangle of the study area if the exact boundary was not available; (6) types of remote-sensing data used; (7) other data sets used; (8) years of data sets for mapping; (9) classification algorithm used; (10) classification system; (11) whether a resultant map was presented; (12) whether sample locations are presented; (13) classification accuracy; (14) how the accuracy is evaluated; (15) whether an existing global land-cover product was evaluated in this article; and (16) websites further documenting work presented in the paper. Although somewhat generic, these themes capture an overview of the information (e.g. locations, accuracies, classification systems) required for the present analysis.

Table 1. Literature note table.

ID	Content	Format
1	Corresponding author (email)	Author (author's email)
2	Research domain	Review, Method, Method comparison, change (application domain)
3	Study area – place name	Place name 1, place name 2, …
4	Study area – latit./long.	(Longitude, latitude)
5	Remote-sensing data set	Data set 1, data set 2, …
6	Other data sets	Data set 1, data set 2, …
7	Year for mapping data sets	
8	Classification approach	Supervised, unsupervised, maximum likelihood, neural network, support vector machine, …
9	Classification system	Classification system, author's own
10	Result map?	{Y, N}
11	Sample location?	{Y, N}
12	Accuracy	
13	How was accuracy evaluated?	Expert, confusion matrix, kappa, roc, …
14	Evaluation on current global products?	{Y, N }
15	Websites	Website1, website2, …

2.2. *Location information extraction*

Literature spatialization is the key step in our analysis. It refers to the process of taking non-coordinate-based geographical identifiers (e.g. place name), and finding associated geographic coordinates (latitude and longitude). However, the task of matching place names with locations is problematic due to insufficient descriptions and a large degree of ambiguity (Leidner 2007). Therefore, in this study, the 'place name' was manually processed to reduce variability in different literature. We found that different levels of place names had been used for a study area in different papers, ranging from those of continents to counties, from administrative names to geographical units. Many place names were prefixed by the adjective of the locality (e.g. west, northeastern), and many could not be matched to the names in the GeoNames geographical database (http://www.geonames.org), currently containing over 10 million geographical names. According to our comparison between the latitude and longitude of certain place names after matching and the latitude and longitude extracted from original papers, about 96% of place names were matched to their correct locations.

3. Results and discussion

3.1. *Spatial temporal distribution of land-cover mapping literature*

There is great diversity in the areas of study, purposes of mapping, classification system design, types of data used, methods of mapping, and accuracy assessment. Out of the 6771 papers reviewed, 2172 contain place names detailed at country level or finer (studies on continental and global levels are excluded) (Figure 1), while 1783 papers contain boundary description of study areas (including regional to global level) (Figure 2). The bounding box (latitudes and longitudes) of a study area or exact boundaries were extracted. Accuracy measures based on confusion matrices are most popular, but only 1585 papers report overall accuracy. Over 82% (1315) of the 1585 papers report accuracy values greater than 80%, in contrast to global mapping efforts whose overall accuracies were all below 80%.

Figure 1 shows several intensively mapped regions around the world: North America, Europe, eastern/southern/Southeast Asia, and certain regions in South America (e.g. the Amazon area) and Africa (e.g. the Niger River region, eastern Africa, the Sahara). Mapping activities in China are mostly post-2005 (circles). Land-cover-mapping research has increased exponentially, with most papers published in the twenty-first century (87.9%). Possible reasons for this are (1) this is the period in which the cost of imagery started to fall or became free, and (2) more nations were then launching Earth observation satellites. Basically, data became more affordable and plentiful.

The number of publications by country is uneven (Figure 1). The USA, China, and India are the only three countries with more than one hundred publications, while a few (e.g. Angola, Oman, North Korea) have 0. The Chinese Academy of Sciences (CAS), the National Aeronautics and Space Administration (NASA), and the University of Maryland are the top three in regard to number of publications. However, in terms of number of citations, NASA, the University of Maryland, and Boston University are the top three. Clearly the USA has the most scientific influence in land-cover-mapping research. Economic conditions (10-year average GDP, 2000–2010) (The World Bank (http://data.worldbank.org/), 2011) can explain approximately 74% of the variation in the number of publications from different countries (Figure 1). However, considering the reality that many mapping works are not carried by local personnel but by international projects (e.g.

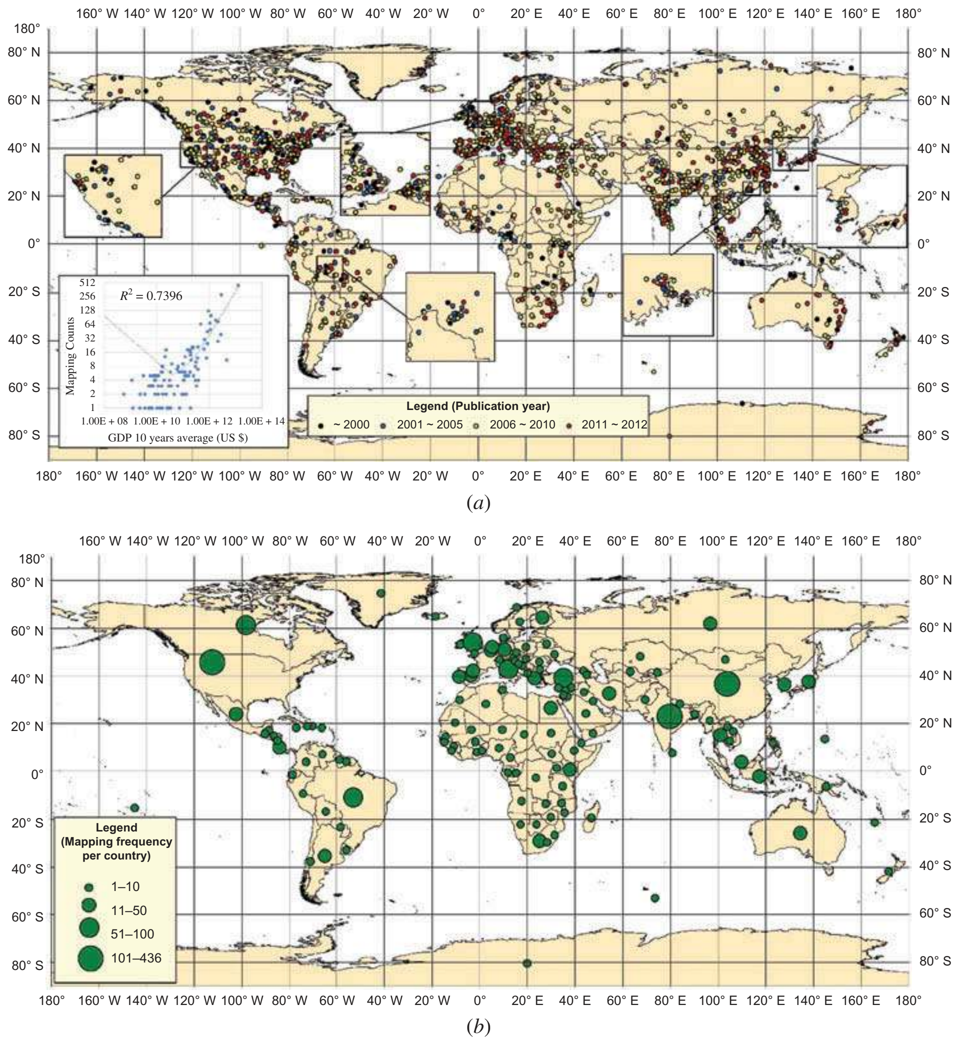


Figure 1. Land-cover-mapping research around the world. (*a*) Central location of study areas and (*b*) mapping frequency by country.

European and US researchers led much of the mapping work in Africa), the location of both the mapping and the founding organizations need to be involved for further exploration.

The mapped areas with explicit location information were overlaid to display the number of times that each area had been mapped (Figure 2). The USA and China are the two countries that contain areas mapped the greatest number of times. China, South India, most of North America, central South America, central Africa, South Africa, the UK, and the Alps region in Europe have all been mapped more than 17 times (light green, orange, and red shading in Figure 2). High-mapping density areas (red shading in Figure 2) in the world include: Pearl River Delta (China); North China (including Beijing, Tianjin, Hebei, Songneng Plain, Inner Mongolia, North Xinjiang); the USA (Wisconsin, New York, Washington, DC, Maryland, Indianapolis (Indiana), Atlanta (Georgia), Chicago (Illinois)), Rondonia (Brazil), and Heredia (Costa Rica).

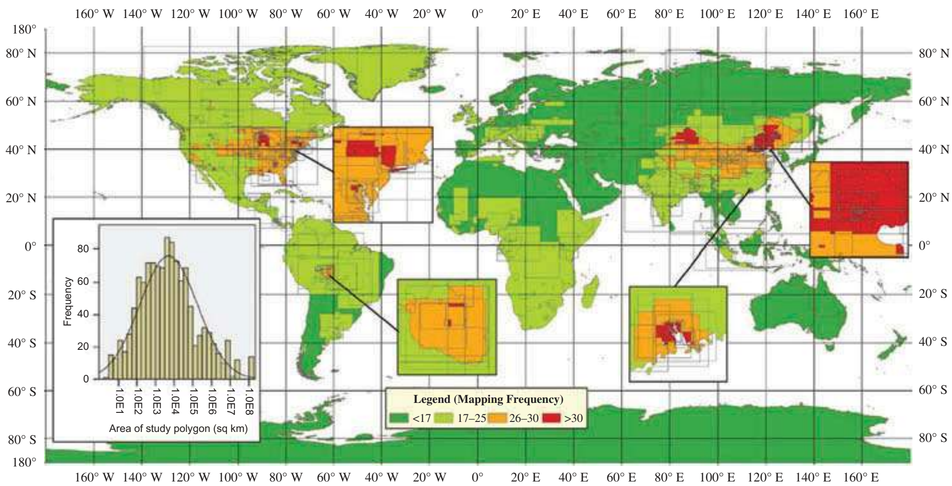


Figure 2. Hotspot areas of land-cover mapping research. Concrete information on areas of study was used to create this map based on 1783 papers that contain sufficient information on the area of study. A histogram of study area size shows that most studies are at a regional scale (100–100,000 km^2).

Some hotspot areas of land-cover mapping are related to areas of major environmental concern. These include rapid urbanization (e.g. Pearl River delta, Beijing, Washington, DC, New York, Atlanta), deforestation in the tropical Amazon, forest fires in western USA, and land degradation in northern China. However, there are significant gaps. There is substantial mismatch (compare Figures 2 and 3) between land-cover-mapping hotspot areas and the world's hotspot areas of biodiversity, such as eastern Africa, Madagascar, northwestern and southwestern South America, New Zealand, and tropical Asia (Meyer et al. 2000; Hoffmann et al. 2010).

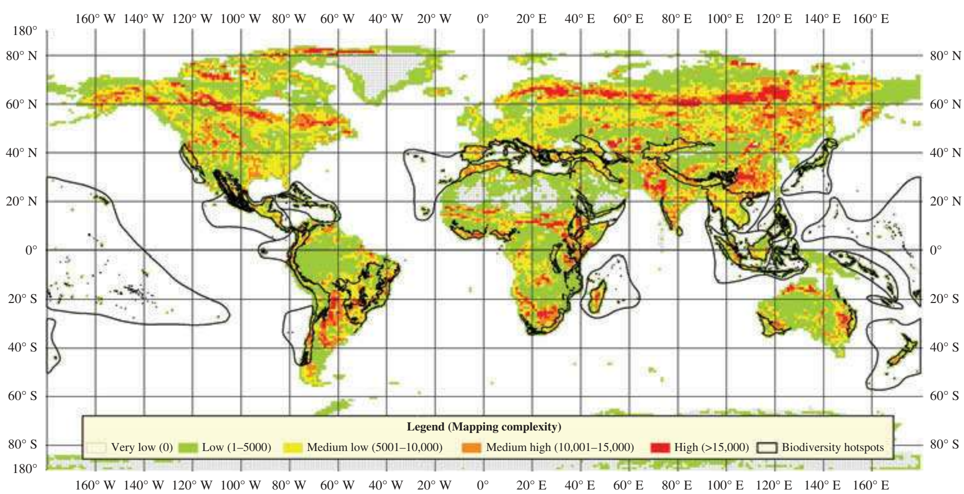


Figure 3. Biodiversity hotspots and the distribution of mapping complexity around the world.

In addition, the Earth's most difficult-to-map areas have not been frequently mapped (compare Figures 2 and 3). These are heterogeneous areas with mixed forests, shrubs, grasslands, and farmlands (Herold et al. 2008). We defined land-cover complexity as an indicator of the degree of mapping difficulty for a particular location. This complexity is measured by the numbers of unreasonably changing pixels (in one 0.5° grid) interannually using MODIS Land Cover data sets for the period 2001–2009 (Liang and Gong 2010, Figure 3). More unreasonable changes (red and yellow shading in Figure 3) indicate greater land-cover complexity for a location, which indirectly implies greater mapping difficulty.

In general, land-cover mapping over a large spatial scale (globally or nationally) can readily benefit from this kind of spatialized database in a variety of ways: (1) using environmental settings as described in peer-reviewed journals over local study areas to include expert knowledge from distant researchers; (2) supporting the validation land-cover products over large areas with local mapping practices that usually involve remotely sensed images with finer spatial resolution; and (3) providing technical guidance on the selection of classification approaches and data sources for a particular area in land-cover mapping efforts over large areas.

3.2. Accuracy-related issues

Although this database allows us to examine the relationship between many factors (see Table 1) and accuracy, a comprehensive and strict analysis of factors influencing land-cover mapping can only be done with all factors systematically compared via broadly based experiments. For example, when two different mapping methods are applied to two different locations, even with the same type of data and land-cover classification scheme, it is hard to obtain definite conclusions on which is better as substantial parameter adjustment may be required on each algorithm. A previous study (Wilkinson 2005) explored many accuracy-related aspects, such as publication year, number of classes, number of features, pixel resolution, experimental area, and also the accuracy trend for neural network and non-neural classification methods. Our analysis provides new evidence for many of the observations made by Wilkinson (2005), such as (1) there is no significant trend of classification accuracy in regard to publication year (the regression line is almost flat, see 4(*a*)); and (2) there is no significant relationship between classification accuracy and study area size (see Figure 4(*b*).

Furthermore, we carried out a more detailed analysis on three selected influential factors (i.e. remote-sensing data set, classification method, and classification system) in relation to accuracy. Sample size, which is critical to accuracy comparison, was not considered in this study due to the fact that very few publications present such information (for exceptions, see Li et al. 2014).

3.2.1. Remote-sensing data sets

The trends of accuracy in regard to publication year for different resolution categories of remote-sensing data sets (high-resolution group: ≤10 m; medium-resolution group: 10–100 m; low-resolution group: >100 m) are all similar (regression line is almost flat) (Figure 5). Generally, this result confirms that no obvious (slightly increasing trend) accuracy improvement in land-cover mapping had been attained by the end of 2012, irrespective of what spatial resolution data sets were used. Most studies used optical images. Unconventional data sets (i.e. hyperspectral – SAR and lidar) were investigated

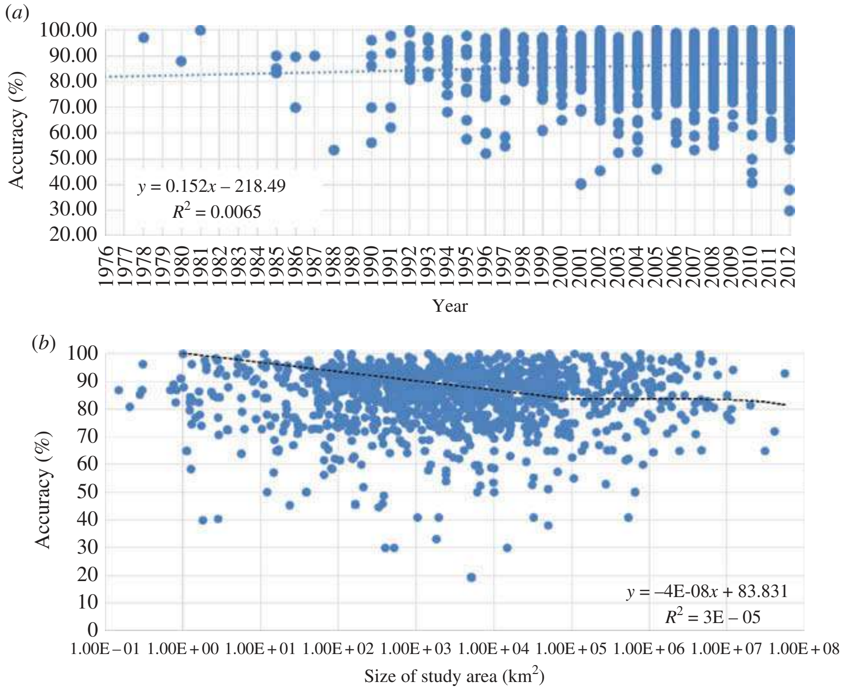


Figure 4. Relationship between accuracy and publication year (*a*) and size of study area (*b*).

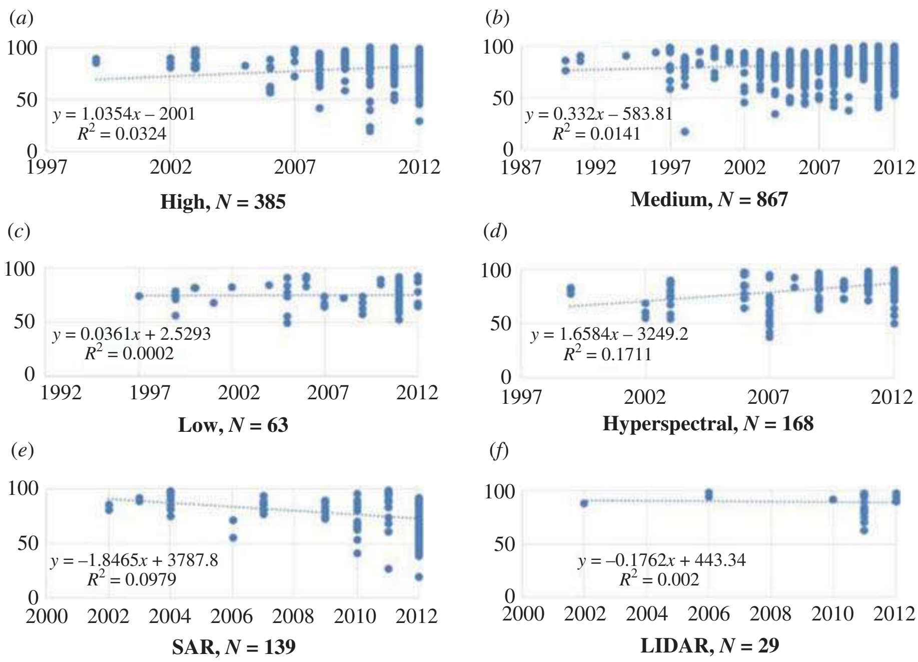


Figure 5. Classification accuracy in relation to date of publication for six subgroup experiments, including three optical medium-spectral resolution groups: (*a*) high-spatial resolution subgroup (≤10 m), (*b*) medium-spatial resolution subgroup (10–100 m), (*c*) low-spatial resolution subgroup (>100 m), (*d*) hyperspectral subgroup, (*e*) SAR subgroup, and (*f*) lidar subgroup.

separately. There is an increasing trend in regard to accuracy for experiments using hyperspectral images. Hyperspectral data are preferred in many applications (e.g. lithological mapping, water environment monitoring, precision agriculture) requiring enhanced capability in discriminating/identifying objects with more spectral sampling from the electromagnetic spectrum. Progress in processing and analysis techniques for hyperspectral data sets is a potential reason for improvement in mapping accuracy. Another reason may be the fact that most hyperspectral applications cover relatively small study areas where more intensive interpretation and analysis can be made. The number of experiments involving SAR and lidar data has increased over time, especially since 2010, but there is a slightly decreasing trend in accuracy in regard to the use of SAR or lidar data. It is not necessarily true that accuracy deteriorates. Having reviewed papers published over hotspot areas, we found that few researchers focused consistently on one area in regard to improving mapping accuracies. The decreasing trend for SAR and lidar data might have been caused by researchers focusing on either difficult-to-map locations or different application domains. Some recent papers compared the effectiveness of combining different types of remote-sensing data sets (e.g. optical and SAR). It is not surprising that those experiments using solely SAR result in lower accuracies than those using either optical images or a combination of optical and SAR images, because SAR images have a much lower signal-to-noise ratio (SNR) than optical images. In regard to lidar, the sample size is too small (sample size $N = 29$) to reach a firm conclusion.

Among all remote-sensing data sets used in land-cover mapping, more than 40% of the 1651 classification experiments used Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data (22 and 18%, respectively). No other data sets were used more than two hundred times (Figure 6). Large differences exist among the various types of remotely sensed data. Lidar, Landsat MSS, IRS, and Landsat TM data resulted in higher accuracy than the average for the 1651 experiments (81.56%), while MODIS, SAR, and IKONOS resulted in lower than average accuracy. In general, images with more spectral bands or a combination of data from different sensors resulted in increased mapping accuracies. Finer-spatial resolution images did not show a clear trend of accuracy improvement. However, it is worth emphasizing that land-cover studies are affected by many factors other than data type itself (e.g. data quality and processing methods, sample quality, validation design, level of land cover detail, and landscape complexity. Hence, a single-factor analysis (such as data set in this case) may not reveal the full characteristics of different data sets used in land-cover mapping, but serves as a reference for future experiments. The same caution applies also to subsequent analyses.

3.2.2. Classification methods

Out of the 1651 classification experiments, the conventional maximum-likelihood classifier (MLC), widely implemented in commercial image-processing software packages, is the most frequently used method (accounting for 32.34% of use) (Figure 7). Comparison of the claimed accuracy of various classification methods used more than 10 times shows that the ensemble method is reported to have the highest accuracy. Ensemble (using multiple classifiers to obtain better prediction than any single classifier), artificial neural network (ANN), and support vector machine (SVM) are the only three methods shown to be better than the average accuracy of the 1651 experiments (81.56%). Meanwhile, K-means and MLC are the only two methods shown to be lower than the average accuracy. The differences among various algorithms are not as large as those among various types of data used.

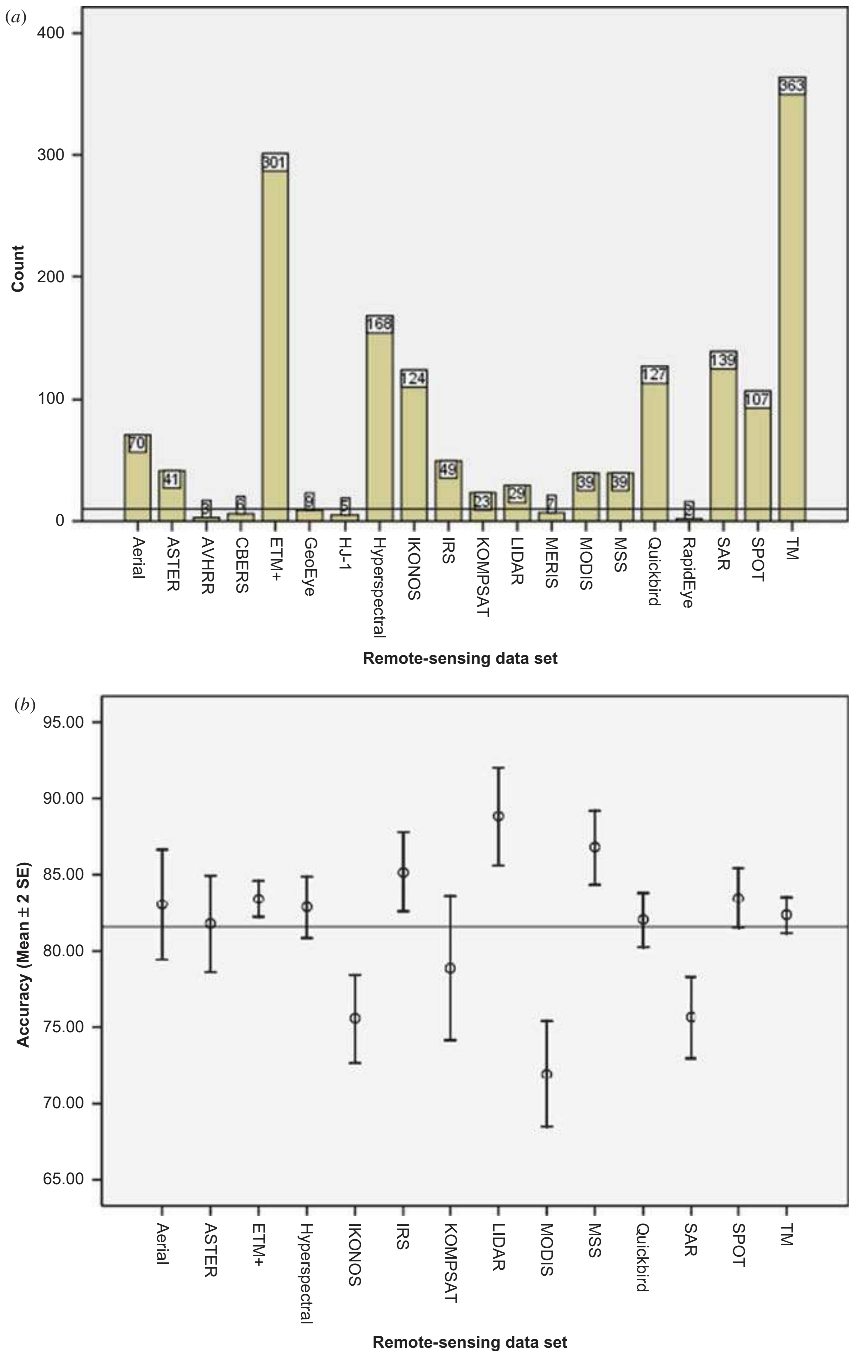


Figure 6. Frequency and accuracy of remotely sensed data types in land-cover mapping. (*a*) Frequency of data types used in experiments (N = 1651); (*b*) classification accuracy in relation to data type (N = 1619; types with <10 experiments are excluded).

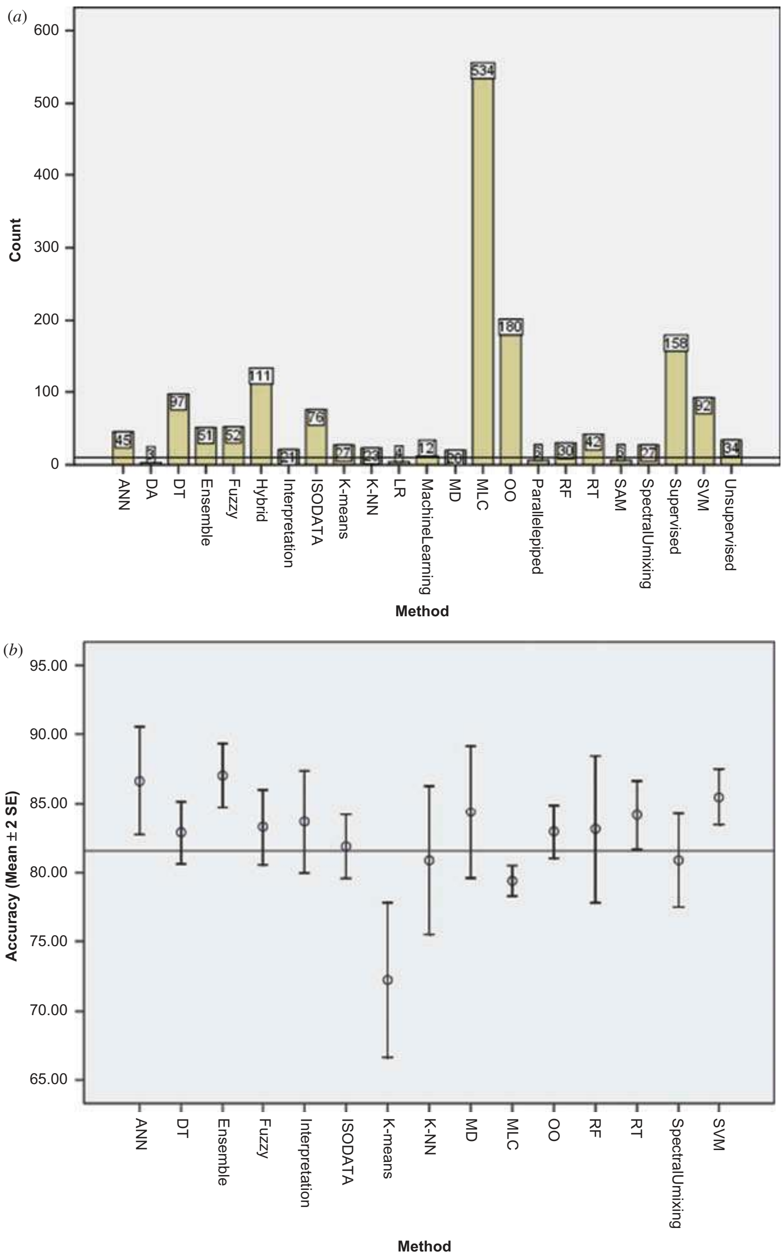


Figure 7. Frequency and accuracy of classification methods in land-cover mapping. (*a*) Frequency of classification methods used in experiments (N = 1651); (*b*) classification accuracy *versus* classification method (N = 1317; <10 experiments and general-type methods (i.e. supervised, unsupervised, machine learning, hybrid) are excluded). ANN: Artificial Neural Network, DA: Discriminant Analysis, DT: Decision Tree, Ensemble: Ensemble classifiers (i.e. AdaBoost, Bagging), Hybrid: unsupervised and supervised hybrid classifiers (e.g. the most common examples are ISODATA and MLC hybrid), Machine Learning: advanced machine learning (i.e. Active Learning, Particle Swarm Optimization), ISODATA: Iterative Self-organizing Data Analysis Techniques Algorithm, K-NN: K-Nearest Neighbour, MD: Minimum Distance, MLC: Maximum Likelihood Classifier, OO: Object Based, RF: Radom Forest, RT: Regression Tree, SAM: Spectral Angle Mapping, SVM: Support Vector Machine.

Since more advanced algorithms are not as widely implemented as traditional ones in conventional remote-sensing image-processing software packages, MLC (which is widely implemented in software and also used as a baseline algorithm for comparison) is the dominant algorithm in terms of use frequency, even at present. Therefore, further software development and training in advanced algorithm implementation and application are needed.

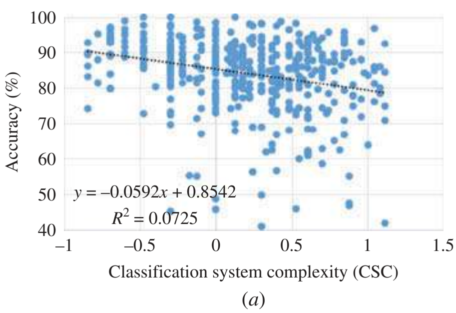
3.2.3. Classification system

It is often postulated that classification accuracy decreases with more complex classification systems of land type, partly due to an increasing portion of mixed pixels. The number of classes is not an indicator of the complexity of a classification system. For example, a classification system using four classes – urban, forest land, water, barren land (all Anderson Level I types, see Anderson et al. 1976 for details) – is no more complex (hard to classify) than a classification system for separating the three cropland classes of wheat, corn, and grassland (all Anderson Level II types). The difference in level of classes in a classification system needs to be considered, and we designed a complexity index for this:

$$\mathrm{CSC} = \log((N2 + 1)(N1 + 1)), \tag{1}$$

where CSC is the complexity index and $N1$ and $N2$ indicate the number of Level I and II classes, respectively. The addition of 1 to both $N1$ and $N2$ is for calculation convenience. The log operation is used to stretch the distribution of the scattered data points. A higher CSC denotes greater complexity.

To support CSC calculation, we cross-walked the classification legend used in each individual paper to the Anderson classification system. Figure 8 shows the relationship between accuracy and CSC for (a) all experiments and (b) experiments using only 30 m data sets. Experiments with the same spatial resolution (30 m in this case) show a more marked reducing trend than the general trend (Figure 8). This result partly supports the postulation that greater complexity in a classification system leads to lower accuracy in classification.



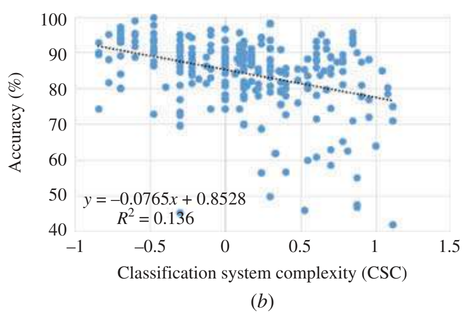


Figure 8. Relationship between accuracy and classification system complexity for (*a*) all experiments ($N = 443$) and (*b*) experiments using only 30 m RS data ($N = 256$).

4. Conclusions and recommendations

In this study we developed the first spatialized database of scientific literature in English to cover land-cover mapping. The interim form of this database is available online at: http://data.ess.tsinghua.edu.cn. Our efforts to extract the location of the study areas from those papers demonstrate that precise and explicit provision of location information in published land-cover mapping research has considerable value. Only after spatialization can we find the mismatches between hotspot areas of land-cover mapping and areas that are difficult to map, or between land-cover hotspots and areas of greater concern in applications such as biodiversity conservation, environmental protection, and agricultural land monitoring. We believe this is only the beginning for analysis of spatialized research. Providing spatially explicit information about study areas and allowing it to be readily included in a map database could bring major benefits to the entire research community in dealing with geographical data. Towards achieving this goal, we recommend that complete geographical information on study areas be provided when submitting any area-based research for publication. Thus, standard submission protocols should be developed and endorsed by publishers. Besides, new software tools that can efficiently (or automatically) extract event-based spatio-temporal information from digital media and convert such information into databases should be developed.

We also analysed several aspects (e.g. data source, classifier, classification system) related to the accuracy of land-cover mapping. However, it should be noted that the notion of accuracy in land-cover mapping is still a problematic issue, since the definitions of class can never be made sufficiently precise to ensure replicability. More broadly, there exist uncertainties in classification systems, quality of data, quality of samples, and flexibility of parameter setting in algorithms. Hence, as a quality parameter, uncertainty should also be evaluated and included in standard submission protocols.

Since the world is so diverse and local knowledge is needed for validation purposes, such an assessment should be done through international collaboration. While some progress has been made in pooling international validation samples through crowdsourcing (Fritz et al. 2009), an international network of algorithm developers, regional scientists, and data suppliers is needed. A key component of this network is the building of a database of typical image samples over representative land-cover areas that can be updated and ground-truthed in timely fashion following certain standards. New algorithms should be evaluated over the entire image-sample database. Providers of all kinds of remotely sensed data covering all selected representative sites and developers of all advanced algorithms should be encouraged to join forces in such an effort.

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References

Anderson, J. R., E. E. Hardy, J. T. Roach, and R. E. Witmer. 1976. “A Land Use and Land Cover Classification System for Use with Remote Sensor Data.” USGS Governmental Report 964. Washington, DC: United States Government Printing Office.

Arino, O., P. Bicheron, F. Achard, J. Latham, R. Witt, and J. L. Weber. 2008. “GLOBCOVER the Most Detailed Portrait of Earth.” *ESA Bulletin-European Space Agency* 136: 24–31.

Bartholomé, E., and A. S. Belward. 2005. “GLC2000: A New Approach to Global Land Cover Mapping from Earth Observation Data.” *International Journal of Remote Sensing* 26: 1959–1977. doi:10.1080/01431160412331291297.

Belward, A., and J. Skøien. 2014. “Who Launched What, When and Why; Trends in Global Land-Cover Observation Capacity from Civilian Earth Observation Satellites.” *ISPRS Journal of Photogrammetry and Remote Sensing*, in press. doi:10.1016/j.isprsjprs.2014.03.009.

Bontemps, S., P. Defourny, E. Van Bogaert, and O. Arino. 2010. “GLOBCOVER 2009 Products Description and Validation Report.” https://globcover.s3.amazonaws.com/LandCover2009/GLOBCOVER2009_Validation_Report_1.0.pdf

Bornmann, L., and L. Waltman. 2011. “The Detection of “Hot Regions” in the Geography of Science – A Visualization Approach by Using Density Maps.” *Journal of Informetrics* 5: 547–553. doi:10.1016/j.joi.2011.04.006.

Chen, C. 2010. “Information Visualization.” *Wiley Interdisciplinary Reviews: Computational Statistics* 2: 387–403. doi:10.1002/wics.89.

DeFries, R. S., M. C. Hansen, J. R. G. Townshend, A. C. Janetos, and T. R. Loveland. 2000. “A New Global 1-km Dataset of Percentage Tree Cover Derived from Remote Sensing.” *Global Change Biology* 6: 247–254. doi:10.1046/j.1365-2486.2000.00296.x.

Franklin, S. E., and M. A. Wulder. 2002. “Remote Sensing Methods in Medium Spatial Resolution Satellite Data Land Cover Classification of Large Areas.” *Progress in Physical Geography* 26: 173–205. doi:10.1191/0309133302pp332ra.

Frenken, K., S. Hardeman, and J. Hoekman. 2009. “Spatial Scientometrics: Towards a Cumulative Research Program.” *Journal of Informetrics* 3: 222–232. doi:10.1016/j.joi.2009.03.005.

Friedl, M. A., D. K. McIver, J. C. F. Hodges, X. Y. Zhang, D. Muchoney, A. H. Strahler, C. E. Woodcock, S. Gopal, A. Schneider, A. Cooper, A. Baccini, F. Gao, and C. Schaaf. 2002. “Global Land Cover Mapping from MODIS: Algorithms and Early Results.” *Remote Sensing of Environment* 83: 287–302. doi:10.1016/S0034-4257(02)00078-0.

Friedl, M. A., D. Sulla-Menashe, B. Tan, A. Schneider, N. Ramankutty, A. Sibley, and X. Huang. 2010. “MODIS Collection 5 Global Land Cover: Algorithm Refinements and Characterization of New Datasets.” *Remote Sensing of Environment* 114: 168–182. doi:10.1016/j.rse.2009.08.016.

Fritz, S., I. McCallum, C. Schill, C. Perger, R. Grillmayer, F. Achard,F. Kraxner, and M. Obersteiner. 2009. “Geo-Wiki.org: The Use of Crowdsourcing to Improve Global Land Cover.” *Remote Sensing* 1: 345–354. doi:10.3390/rs1030345.

Gong, P., J. Wang, L. Yu, Y. C. Zhao, Y. Y. Zhao, L. Liang, Z. G. Niu, X. M. Huang, H. H. Fu, S. Liu, C. C. Li, X. Y. Li, W. Fu, C. Liu, Y. Xu, X. Wang, Q. Cheng, L. Hu, W. Yao, H. Zhang, P. Zhu, Z. Zhao, H. Y. Zhang, Y. M. Zheng, L. Ji, Y. W. Zhang, H. Chen, A. Yan, J. Guo, L. Yu, L. Wang, X. Liu, T. T. Shi, M. H. Zhu, Y. L. Chen, G. W. Yang, P. Tang, B. Xu, C. Giri, N. Clinton, Z. L. Zhu, J. Chen, and J. Chen. 2013. “Finer Resolution Observation and Monitoring of Global Land Cover: First Mapping Results with Landsat TM and ETM+ Data.” *International Journal of Remote Sensing* 34: 2607–2654.

Hand, D. J. 2006. “Classifier Technology and the Illusion of Progress.” *Statistical Science* 21: 1–14. doi:10.1214/088342306000000060.

Hansen, M. C., P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. 2013. “High-Resolution Global Maps of 21st-Century Forest Cover Change.” *Science* 342 (6160): 850–853. doi:10.1126/science.1244693.

Hansen, M. C., R. S. Defries, J. R. G. Townshend, and R. Sohlberg. 2000. “Global Land Cover Classification at 1 km Spatial Resolution Using a Classification Tree Approach.” *International Journal of Remote Sensing* 21: 1331–1364. doi:10.1080/014311600210209.

Herold, M., P. Mayaux, C. E. Woodcock, A. Baccini, and C. Schmullius. 2008. “Some Challenges in Global Land Cover Mapping: An Assessment of Agreement and Accuracy in Existing 1 km Datasets.” *Remote Sensing of Environment* 112: 2538–2556. doi:10.1016/j.rse.2007.11.013.

Hoffmann, M., C. Hilton-Taylor, A. Angulo, M. Bohm, T. M. Brooks, S. M. Butchart, K. E. Carpenter, J. Chanson, B. Collen, N. A. Cox, W. R. T. Darwall, N. K. Dulvy, L. R. Harrison, V. Katariya, C. M. Pollock, S. Quader, N. I. Richman, A. S. L. Rodrigues, M. F. Tognelli, J.-C. Vié, J. M. Aguiar, D. J. Allen, G. R. Allen, G. Amori, N. B. Ananjeva, F. Andreone, P. Andrew, A. L. A. Ortiz, J. E. M. Baillie, R. Baldi, B. D. Bell, S. D. Biju, J. P. Bird, P. Black-Decima, J. J. Blanc, F. Bolaños, W. Bolivar-G., I. J. Burfield, J. A. Burton, D. R. Capper, F. Castro, G. Catullo, R. D. Cavanagh, A. Channing, N. L. Chao, A. M. Chenery, F. Chiozza, V. Clausnitzer, N. J. Collar, L.C. Collett, B. B. Collette, C. F. C. Fernandez, M. T. Craig, M. J. Crosby, N. Cumberlidge, A. Cuttelod, A. E. Derocher, A. C. Diesmos, J. S. Donaldson, J. W. Duckworth, G. Dutson, S. K. Dutta, R. H. Emslie, A. Farjon, S. Fowler, J. Freyhof, D. L. Garshelis, J. Gerlach, D. J. Gower, T. D. Grant, G. A. Hammerson, R. B. Harris, L. R. Heaney, S. B. Hedges, J.-M. Hero, B. Hughes, S. A. Hussain, J. I. Monteza, R. F. Inger, N. Ishii, D. T. Iskandar, R. K. B. Jenkins, Y. Kaneko, M. Kottelat, K. M. Kovacs, S. L. Kuzmin, E. La Marca, J. F. Lamoreux, M. W. N. Lau, E.O. Lavilla, K. Leus, R. L. Lewison, G. Lichtenstein, S. R. Livingstone, V. Lukoschek, D. P. Mallon, P. J. K. McGowan, A. McIvor, P. D. Moehlman, S. Molur, A. M. Alonso, J. A. Musick, K. Nowell, R. A. Nussbaum, W. Olech, N. L. Orlov, T. J. Papenfuss, G. Parra-Olea, W. F. Perrin, B. A. Polidoro, M. Pourkazemi, P. A. Racey, J. S. Ragle, M. Ram, G. Rathbun, R. P. Reynolds, A. G. J. Rhodin, S. J. Richards, L. O. Rodríguez, S. R. Ron, C. Rondinini, A. B. Rylands, Y. Sadovy de Mitcheson, J. C. Sanciangco, K. L. Sanders, G. Santos-Barrera, J. Schipper, C. Self-Sullivan, Y. Shi, A. Shoemaker, F. T. Short, C. Sillero-Zubiri, D. L. Silvano, K. G. Smith, A. T. Smith, J. Snoeks, A. J. Stattersfield, A. J. Symes, A. B. Taber, B. K. Talukdar, H. J. Temple, R. Timmins, J. A. Tobias, K. Tsytsulina, D. Tweddle, C. Ubeda, S. V. Valenti, P. Paul van Dijk, L. M. Veiga, A. Veloso, D. C. Wege, M. Wilkinson, E. A. Williamson, F. Xie, B. E. Young, H. R. Akçakaya, L. Bennun, T. M. Blackburn, L. Boitani, H. T. Dublin, G. A. B. da Fonseca, C. Gascon, T. E. Lacher, G. M. Mace, S. A. Mainka, J. A. McNeely, R. A. Mittermeier, G. M. Reid, J. P. Rodriguez, A. A. Rosenberg, M. J. Samways, J. Smart, B. A. Stein, and S. N. Stuart. 2010. "The Impact of Conservation on the Status of the World's Vertebrates." *Science* 330: 1503–1509.

Leidner, J. L. 2007. "Toponym Resolution in Text: Annotation, Evaluation and Applications of Spatial Grounding of Place Names." PhD thesis, University of Edinburgh..

Leydesdorff, L., and O. Persson. 2010. "Mapping the Geography of Science: Distribution Patterns and Networks of Relations among Cities and Institutes." *Journal of the American Society for Information Science and Technology* 61: 1622–1634.

Li, C. C., J. Wang, L. Wang, L. Y. Hu, and P. Gong. 2014. "Comparison of Classification Algorithms and Training Sample Sizes in Urban Land Classification with Landsat Thematic Mapper Imagery." *Remote Sensing* 6 (2): 964–983. doi:10.3390/rs6020964.

Liang, L., and P. Gong. 2010. "An Assessment of MODIS Collection 5 Global Land Cover Product for Biological Conservation Studies." *Geoinformatics* 2010: 1–6.

Loveland, T. R., B. C. Reed, J. F. Brown, D. O. Ohlen, Z. Zhu, L. Yang, and J. W. Merchant. 2000. "Development of a Global Land Cover Characteristics Database and IGBP Discover from 1 km AVHRR Data." *International Journal of Remote Sensing* 21: 1303–1330. doi:10.1080/014311600210191.

Lu, D., and Q. Weng. 2007. "A Survey of Image Classification Methods and Techniques for Improving Classification Performance." *International Journal of Remote Sensing* 28: 823–870. doi:10.1080/01431160600746456.

Myers, N.,R. A. Mittermeier, C. G. Mittermeier, G. A. B. da Fonseca, and J. Kent. 2000. "Biodiversity Hotspots for Conservation Priorities." *Nature* 403: 853–858. doi:10.1038/35002501.

Running, S. W. 2008. "CLIMATE CHANGE: Ecosystem Disturbance, Carbon, and CLIMATE." *Science* 321: 652–653. doi:10.1126/science.1159607.

Sexton, J. O., X. P. Song, M. Feng, P. Noojipady, A. Anand, C. Huang, D.-H. Kim, K. M. Collins, S. Channan, C. DiMiceli, and J. R. Townshend. 2013. "Global, 30-m Resolution Continuous Fields of Tree Cover: Landsat-Based Rescaling of MODIS Vegetation Continuous Fields with Lidar-Based Estimates of Error." *International Journal of Digital Earth* 6 (5): 427–448. doi:10.1080/17538947.2013.786146.

Tateishi, R., B. Uriyangqai, H. Al-Bilbisi, M. A. Ghar, J. Tsend-Ayush, T. Kobayashi, A. Kasimu, N. T. Hoan, A. Shalaby, B. Alsaaideh, T. Enkhzaya, G. Gegentana, and H. P. Sato. 2011.

"Production of Global Land Cover Data – GLCNMO." *International Journal of Digital Earth* 4: 22–49. doi:10.1080/17538941003777521.

Townshend, J. R., J. G. Masek, C. Q. Huang, E. F. Vermote, F. Gao, S. Channan, J. O. Sexton, M. Feng, R. Narasimhan, D. Kim, K. Song, D. X. Song, X. P. Song, P. Noojipady, B. Tan, M. C. Hansen, M. X. Li, and R. E. Wolfe. 2012. "Global Characterization and Monitoring of Forest Cover Using Landsat Data: Opportunities and Challenges." *International Journal of Digital Earth* 5: 373–397. doi:10.1080/17538947.2012.713190.

Tucker, C. J., J. R. Townshend, and T. E. Goff. 1985. "African Land-Cover Classification Using Satellite Data." *Science* 227: 369–375. doi:10.1126/science.227.4685.369.

Wilkinson, G. G. 2005. "Results and Implications of a Study of Fifteen Years of Satellite Image Classification Experiments." *IEEE Transactions on Geoscience and Remote Sensing* 43: 433–440. doi:10.1109/TGRS.2004.837325.

Yang, J., P. Gong, R. Fu, M. H. Zhang, J. M. Chen, S. L. Liang, B. Xu, J. C. Shi, and R. Dickinson. 2013. "The Role of Satellite Remote Sensing in Climate Change Studies." *Nature Climate Change* 3: 875–883. doi:10.1038/nclimate1908.

Yu, L., J. Wang, N. Clinton, Q. Xin, L. Zhong, Y. Chen, and P. Gong. 2013. "FROM-GC: 30m Global Cropland Extent Derived through Multi-Source Data Integration." *International Journal of Digital Earth* 6 (6): 521–533. doi:10.1080/17538947.2013.822574.

Yu, L., J. Wang, and P. Gong. 2013. "Improving 30 m Global Land-Cover Map FROM-GLC with Time Series MODIS and Auxiliary Data Sets: A Segmentation-Based Approach." *International Journal of Remote Sensing* 34: 5851–5867. doi:10.1080/01431161.2013.798055.

Zhuang, Y. H., X. J. Liu, T. Nguyen, Q. Q. He, and S. Hong. 2013. "Global Remote Sensing Research Trends during 1991–2010: A Bibliometric Analysis." *Scientometrics* 96: 203–219. doi:10.1007/s11192-012-0918-z.