Remotely Sensed Big Data: Evolution in Model Development for Information Extraction

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Since the 1960s, remote sensing (as an innovative, comprehensive, and interdisciplinary academic area) has been adopted in a wide range of disciplines related to Earth observation, including hydrology, ecology, oceanography, glaciology, geology, military, intelligence, business, economy, and planning [1]–[3]. The constant development of the remote sensing image acquisition technology now allows for the collection of a wide variety of images with different characteristics and resolutions, obtained by remote sensing instruments mounted on spacecraft or aircraft platforms. These images record some type of signal or energy measured from the Earth's surface, which depends on the type of sensor used.

1) Active instruments [2], [3] measure the pulses of artificial energy that scan the surface, such as sound navigation and ranging (SONAR), radio detection and ranging (RADAR), and other related

Digital Object Identifier 10.1109/JPROC.2019.2948454

techniques, such as synthetic aperture radar (SAR) and interferometric SAR (InSAR), or light detection and ranging (LiDAR). These instruments produce the artificial (acoustic or laser) signal themselves and record the reflect responses from the observed surface.
2) Passive instruments [2], [3] record the energy emitted by the observed surface, such as the thermal radiation of the objects and elements contained in the observed area, or the sunlight that these elements absorb and reflect. Optical remote sensing instruments (including multispectral and hyperspectral sensors) measure the reflectance spectrum of the objects and materials contained into a target area, which is determined by their physical and chemical properties. That is, these data collect information describing the ground materials' behavior across the electromagnetic spectrum, capturing the reflected solar radiation in the visible, near-infrared (NIR), and short-wave infrared (SWIR) wavelengths.

Using mathematical models, the recorded information can be interpreted in order to describe terrain characteristics [4], [5]. From the 1960s to 1980s, the analysis of remotely sensed data was mainly accomplished by means of digital signal processing approaches. Applications such as target detection, image classification, and land surface parameter extraction were mainly based on statistical models, applied to optical and microwave data [6]–[8]. The seminal works of Richards [2], Strahler [9], Lee *et al.* [10], and Cressie [11] adopted traditional statistical methods to remote sensing image analysis and modeling. Swain and Davis [12] studied the characteristics of various data acquisition systems and the fundamentals of pattern recognition through statistical models used for information extraction from remotely sensed data. Their works established the foundations in the development of statistical modeling techniques for remote sensing data analysis and defined a "digital signal processing era" in remote sensing technology. Commonly used information extraction models included regression models applied to infrared [13] and hyperspectral data [14], supervised classification techniques based on relatively simple statistics (such as maximum likelihood and decision trees), unsupervised classification (fuzzy clustering) [15]–[17], grayscale stretching and strengthening models (wavelet analysis [18]–[20], fuzzy mathematics [21], [22] and random fields [23], [24]), visual interpretation, and target detection models based on human experience [24]. However, statistical models faced important challenges, such as sample representation and model versatility, because the quality of remote sensing images is highly susceptible to external factors, such as the atmospheric conditions and terrain characteristics.

In the 1990s, remote sensing science and technology entered a "quantitative remote sensing era" that was characterized by the consideration of physical information in remotely sensed data [5]. A landmark event was the fact that the Earth Observing System (EOS) satellite began to provide global quantitative remote sensing products through the moderate resolution imaging spectroradiometer (MODIS), which allowed researchers to develop physical models from these products. By investigating the processes and the consequences of the interactions between remote sensing signals and transmission media and targets, physical models were able to quantitatively invert and calculate target geoscience parameters. Such physical models included radiation transfer models [26]–[29], geometric optical models [30]–[33], hybrid models [34], and process models [35]–[39] developed to characterize plant growth mechanisms, the terrestrial carbon cycle, the nitrogen cycle, or the water cycle. Based on the fundamental physical processes and mechanisms, physical models either provide a dynamic evolution process, with definite analytical equations, or clear physical meaning, with detailed physical quantities [40]. Compared with statistical models, quantitative models could address more diverse applications, thus improving the capability of remote sensing technology when recognizing the essential features of ground objects. However, developing physical models is challenging because these models are usually based on complicated nonlinear equations and require many input parameters and *a priori* knowledge about the observed objects. In order to overcome these issues in practice, some approximations need to be made [28], [29], [32]. In other words, statistical models are easier to derive and might yield higher accuracies than physical models in some case studies, but statistical models are difficult to apply in different regions and contexts due to spatial heterogeneity. Physical models are based on solid physical mechanisms and could address more diverse applications. However, developing physical models is challenging due to complex nonlinear relationships between the electromagnetic signals and objects and the need for many input variables as well as *a priori* knowledge. As a result, hybrid models combining statistical and physical models are widely used, and normally comprise the use of a quantitative remote sensing product or physical model to invert an intermediate parameter, and then adopting statistical models together with other parameters to invert or estimate the target parameters using both microwave [41] and optical [42] remote sensing data.

In recent years, with the rapid development of aerospace technology (from micro/nanosatellites to satellite constellation networks and future intelligent remote sensing satellite systems, from drone to stratospheric airships, and from ground observation stations to wireless systems), the systems used for Earth observation now confirm a full network integrating aerospace and Earth-based instruments. Such integrated network exhibits the potential to provide high-dimensional and high-frequency Earth observation data. The amount of data collected from different imaging modes, bands, resolutions, observation scales, and dimensions, as well as its sources of auxiliary calibration and verification are increasing tremendously [2]. The concept of big data [43] conveys a new scientific discovery and information mining approach, which covers both the data itself and the mining methodologies. Compared with traditional remote sensing information extraction approaches, which mainly adopt statistical and physical models, contemporary remote sensing data information extraction technologies are gradually entering a "remotely sensed big data era," which is characterized by intelligent information extraction. Under this background, remotely sensed data information extraction will face new opportunities and challenges in terms of methods and applications.

I. DEEP LEARNING FOR REMOTELY SENSED BIG DATA EXPLOITATION

Since the beginning of the 2010s, the rapid development of massive, multisource, and heterogeneous data has not only driven the development of data analysis methods and technologies but also changed the way humans use remotely sensed data to understand the world. Traditionally, information extraction models were primarily constructed through experimental and theoretical methods, relying significantly on prior knowledge and experience in the remote sensing area. With the tremendous availability of multisource remotely sensed data, information extraction and knowledge discovery now mainly focus on the data itself rather than on the inherent prior knowledge. These approaches are mainly established by means of deep mining and learning from large amounts of data.

The models driven by a large number of data samples for knowledge discovery and information extraction are commonly referred to as data models. Such models need to be trained by intelligent methods using a large number of samples in order to automatically and intelligently extract relevant information and discover knowledge. This process not only requires high-performance computing architectures but also necessitates new data processing methods. In practice, available high-performance computing architectures can hardly satisfy the processing precision and efficiency of remotely sensed big data [47]. Consequently, intelligent information extraction through machine learning algorithms has gradually become a necessary requirement in the current remotely sensed big data era. Specifically, shallow learning methods (including artificial neural networks and support vector machines) have been widely applied [48]–[52]. However, the sample data size used in shallow learning methods is relatively small, and the number of modeled parameters is quite limited. Hence, the generalization ability of these models is weak, which restricts the universal applications of data models.

Deep learning has been proposed to overcome the above-mentioned issues [53], [54]. As a new field in artificial intelligence, deep learning has achieved breakthroughs in various areas [53], such as image recognition and speech recognition [55]–[58], molecular structure analysis [59], particle physics [60], and gene expression [61]. In 2013, deep learning was listed as the first in the top ten technological breakthroughs [64] because it has surpassed humans in many tasks [54], [62], [63]. Remote sensing images observe terrain features at large scales under complex scenes. Different terrain features have a strong scale effect, prominent spatial position patterns, significantly distinct electromagnetic wave characteristics, and unique geographical environments [62], [65]. Under these intricate factors, the limitations of human prior knowledge and the challenge of massive data processing greatly restrict the application of traditional methods, such as statistical models, physical models, and shallow learning that is based on data models in remote sensing information extraction. Developing fast, efficient, and intelligent approaches to extract information from massive and complex remote sensing data becomes the fundamental task of remote sensing in the data model era. The excellent performance of deep learning in other areas provides an unprecedented opportunity to solve this challenge [66].

Deep learning satisfies the urgent needs in contemporary remote sensing applications by providing a high-level methodological and implementation approach for intelligent information extraction. As a machine learning method based on data representation, it also offers significant advantages over traditional approaches for remote sensing information processing [53].

1) It mainly focuses on features and information extraction from the data itself rather than on expert prior knowledge or manual selection; hence, the dependence of traditional remote sensing information processing methods on prior knowledge can be significantly alleviated [62], [67].
2) The fundamental unit of deep learning is pixel convolution that combines low-level features to form more abstract high-level features; compared with traditional pixel processing methods that cannot capture the abundant semantic information present in the scenes, deep learning is able to extract rich semantic features contained in remotely sensed images [67]–[69].
3) The multilayer structure of deep neural networks is able to extract multiscale image information [70].
4) Deep neural networks provide complex architectures with hundreds of layers and thousands of

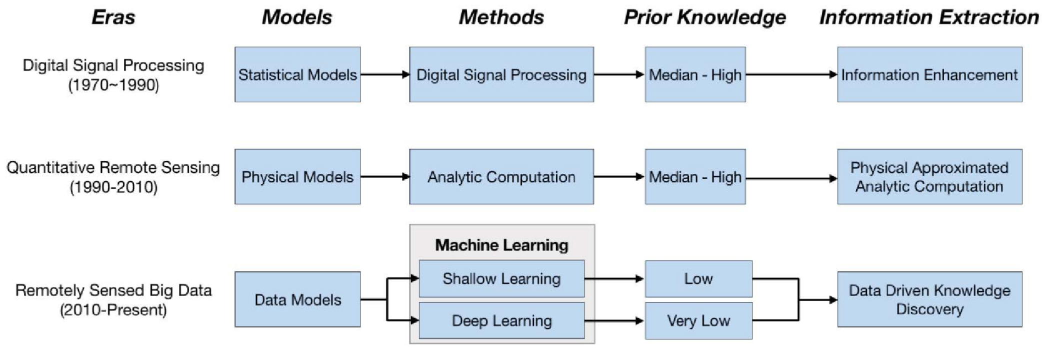

Fig. 1. ***Development periods in remote sensing models for information extraction.***

parameters. Such architectures are able to model the nonlinear relationships between remote sensing data and land surfaces, capturing multidimensional features, and revealing complex terrain characteristics. Hence, data models based on deep learning now play an important role in remote sensing information extraction [71].

Currently, deep-learning approaches are widely applied in many remotely sensed data processing disciplines, including target detection, image classification, and parameter retrieval. For instance, an important requirement for target detection is how to extract effective features from image data with complex backgrounds. In practice, targets of interest can be man-made objects, such as airplanes, vehicles, ships, pipelines, tanks, airports, and buildings, or natural objects with unique spectral characteristics, such as rocks, drug crops, and leaking oil and gas [72]–[75]. The intrinsic features of the target can be easily extracted by deep-learning approaches. The aggregation of low-level features and/or advanced semantic features can significantly improve the feature representation of the target and, thus, improve the accuracy and efficiency of the target detection process [76], [77]. In the context of remote sensing image classification, which is another important remote sensing application, deep learning can not only extract the structural features of high-dimensional spectral data efficiently but also model the characteristics of different types of features, textures, objects, and so on. These complex spatial patterns present in images are usually robust and invariant [68], [78], [79]. In addition, deep learning has been successfully applied in the fields of hyperspectral image classification [68], [79], multisource remote sensing image classification (including SAR and optical data) [80], high-spatial resolution image classification [81], multiscale classification feature learning [70], spectral and spatial information fusion [82], and so on. These methodological approaches are still developing and expanding. In addition, multilayer neural networks can better estimate complex nonlinear functions involving multiple variables. The variable relationships hidden in the data can be autonomously learned, which is well-suited for remote sensing parameter inversion containing complex or unknown processes. Compared with a large number of applications in target recognition and image classification, the applications of deep learning in remote sensing parameter inversion are still in their initial exploration stage [71]. Previous studies attempted to perform fusion of different kinds of data (such as optical, SAR, and LiDAR) to evaluate sea ice density [83], biomass inversion [84], leaf nitrogen concentration estimation [85], sea surface temperature [86], PM2.5 content inversion [87], cloud optical thickness estimation [71], soil water content estimation, and other aspects [88]. Several applications have already achieved encouraging results, while the potential of these applications still needs to be further explored by the remote sensing community.

II. SUMMARY OF DEVELOPMENTS IN REMOTE SENSING MODELS

According to the above-mentioned discussion, Fig. 1 summarizes the developments in the three main development periods in remote sensing models for information extraction (advances in digital signal processing, advances in physical models, and deep learning for remotely sensed data exploitation).

We have investigated the publication trends in the most representative remote sensing journals in order to further analyze the consolidation of models in the most representative development areas, specifically *Remote Sensing of Environment* and the IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING (called the IEEE TRANSACTIONS ON GEOSCIENCE ELECTRONICS from 1963 to 1979). Due to the limited number of articles before the 1980s, we aggregated the publications at yearly intervals. According to the above-mentioned description, the proportion of articles using statistical models, physical models, and data models in the collected journal articles has been calculated for each year. The results of our survey are summarized in Fig. 2.

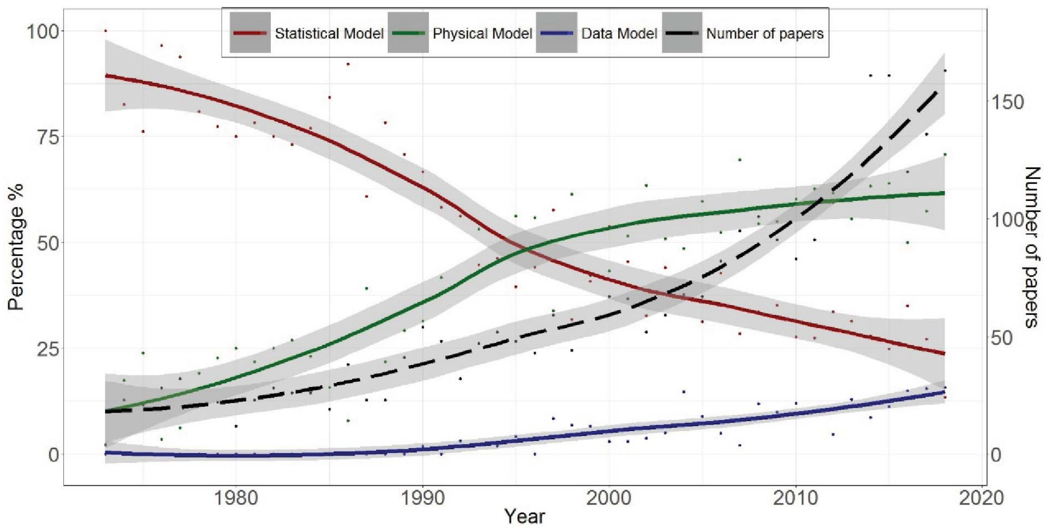

Fig. 2. ***Analysis of the percentage (left axis) and the number of articles (right axis) published since 1973 in two of the main remote sensing journals:*** Remote Sensing of Environment ***and the IEEE Transactions on Geoscience and Remote Sensing. Red, green, and blue lines: the percentage of articles on statistical models, physical models, and data-driven models, respectively. Black line: the total number of articles published in the three aforementioned categories (right axis).***

Overall, Fig. 2 shows that the number of articles published in the areas of remote sensing image processing and applications is increasing through time. The number of articles published in recent years is about ten times more than the number of articles published in the early 1970s. The articles applying statistical models occupied a large proportion for a long time and consisted of more than 50% of the articles until the mid-1990s. However, the number of articles using statistical models has been declining since the end of the 1970s. The trend of articles using the physical model is almost completely opposite. After the 1970s, the total number of articles using physical models shows a steady upward trend. Specifically, the proportion of articles utilizing physical models increased significantly during the mid-1980s to the end of the 1990s, while the number of publications based on statistical models shows the highest decline rate. An intersection of temporal trend lines of publications using statistical and physical models appears in the mid-1990s. This marks an interesting shift from digital signal processing to quantitative remote sensing. The main topics investigated in the area of physical models include atmospheric correction models, bidirectional reflectance distribution function (BDRF)-based physical models, and marine optical models. Research on data-based models emerged in the 1990s and accounts for about 18% of the articles in recent years. The majority of the topics addressed include artificial intelligence algorithms represented by deep learning. Furthermore, there is a clear upward trend in the future.

According to our literature survey in the aforementioned journals, we can anticipate that the proportion of articles on statistical models will decline in the future, while the proportion of articles on physical models will still take a large portion. We can see in Fig. 2 that, from 2012, the growth rate on the number of articles on data model-based remote sensing image analysis and applications both exceeded the growth rate of the articles on physical models. It is expected that scientists around the world will continue to work on the physical mechanisms of the electromagnetic spectrum, surface, and atmosphere to promote the progress of physical models in the future. However, we also anticipate that the development of data models will be significantly accelerated, mainly because of the advances in deep learning for big remotely sensed data analysis, which are convenient to satisfy the application requirements of complex and diverse remote sensing applications. Although the use of data models can overcome the difficulties faced by statistical and physical models, these models cannot be used (in our opinion) independently. Quite opposite, it is important to combine the advantages of these three types of models to leverage their unique capabilities in complex scenarios [89], [90]. To support customized, differentiated, fine quality services for various applications, the boundaries of these three models may become blurred in the future, leading to full integration of the well-differentiated remote sensing models that we have observed in the literature so far.

III. DISCUSSION

Big data are different from traditional data due to their particular characteristics: volume, variety, velocity, and veracity (4Vs). In the context of information extraction from remote sensing data, the challenges of these characteristics are as follows.

1) *Volume:* Different sensors around the world are collecting enormous remote sensing data

continuously every second. Collecting, storing, reading, and further analyzing such amount of remote sensing data are extremely hard.
2) *Velocity:* Due to a large amount of data available, realizing fast or near-real-time remote sensing data processing and information extraction in different applications is very challenging
3) *Veracity:* Although data models developed from deep-learning algorithms could significantly enhance the model accuracy compared to statistical/physical models (with the increase of the training data sets), the remaining challenge is how to learn and validate knowledge derived from data models.
4) *Variety:* The complexity and diversity of remote sensing sensors, context, and applications make it difficult to accurately extract valuable information from data.

In order to address the aforementioned challenges, several research directions have been specifically suggested [43]:
1) building object-oriented remote sensing databases containing detailed *a priori* knowledge;
2) developing deep-learning algorithms able to adopt the characteristics of remote sensing data;
3) implementing remote sensing algorithms on big data processing platforms.

IV. CONCLUSION

This article reviewed and analyzed the development of remote sensing models from the early 1970s until today, with a focus on the current status and future development on deep learning for the analysis of remotely sensed big data. Our literature survey confirms that there have been three main development stages for remote sensing models. Before the 1990s, remote sensing information extraction mainly adopted statistical models, and few studies attempted to employ physical models. After the 1990s, both statistical models and physical models attracted the attention of many researchers and were significantly investigated, while the development of data-driven models was at the very early stage. Recently, there has been a significant decrease in the investigations focused on statistical models. Although physical models were quite dominant in the remote sensing field, data models are now developing rapidly, leading to the beginning of a remotely sensed big data era that is supported by the improvement of Earth observation technology and computing power as well as on the great existing demand for remote sensing applications. Specifically, the data model represented by deep learning has become the most prominent feature of remote sensing information extraction in this era. The following specific guidelines are provided as a result of our review work.

1) Deep-learning models are very promising for remote sensing data interpretation, but, currently, the available number of training samples is limited. In this regard, it is important to create robust models able to function with a very limited number of labeled samples. In this way, it is possible to reduce the cost associated with the acquisition of new data sets with larger amounts of labeled data. This will allow to reduce the training time and the number of labeled samples needed to create robust models.
2) Moreover, new big data processing frameworks are required as a natural solution for the processing of a large amount of remote sensing data. In this regard, both high-performance computing and high-throughput computing alternatives should be further explored, including parallelization on GPUs and distribution/parallelization on clusters with cloud computing-based solutions.
3) Last but not least, low- and high-power consumption architectures also need to be used to adapt current models to onboard exploitation, performing a thorough assessment regarding how deep-learning models can be further optimized. This can significantly relieve ground-segment computation and communication in the data interpretation tasks. ■

Acknowledgment

The authors would like to thank the associate editor and the anonymous reviewers for their outstanding comments and suggestions, which greatly helped them to improve the technical quality and presentation of the manuscript. This work was supported by the Strategic Priority Research Program of the Chinese Academy of Sciences under Grant XDA19080302 and in part by the National Natural Science Foundation of China under Grant 91638201.

REFERENCES

[1] A. Goldberg, B. Stann, and N. Gupta, "Multispectral, hyperspectral, and three-dimensional imaging research at the U.S. Army Research Laboratory," in *Proc. 6th Int. Conf. Int. Fusion*, vol. 1, 2003, pp. 499–506.
[2] J. A. Richards, *Remote Sensing Digital Image Analysis—An Introduction*. Berlin, Germany: Springer, 2012.
[3] B. Zhang, "Current status and future prospects of remote sensing," *Bull. Chin. Acad. Sci.*, vol. 32, no. 7, pp. 774–784, 2017.
[4] R. A. Schowengerdt, *Remote Sensing, Models and Methods for Image Processing*. New York, NY, USA: Academic, 1997.
[5] S. Liang, *Quantitative Remote Sensing of Land Surfaces*. Hoboken, NJ, USA: Wiley, 2004.
[6] R. M. Haralick, F. Caspall, and D. S. Simonett, "Using radar imagery for crop discrimination: A statistical and conditional probability study," *Remote Sens. Environ.*, vol. 1, no. 2, pp. 131–142, 1970.
[7] G. Asrar, "Estimation of total above-ground phytomass production using remotely sensed data," *Remote Sens. Environ.*, vol. 17, no. 3, pp. 211–220, 1985.
[8] F. Baret and G. Guyot, "Potentials and limits of vegetation indices for LAI and APAR assessment," *Remote Sens. Environ.*, vol. 35, nos. 2–3, pp. 161–173, 1991.
[9] A. H. Strahler, "The use of prior probabilities in maximum likelihood classification of remotely sensed data," *Remote Sens. Environ.*, vol. 10, no. 2, pp. 135–163, 1980.
[10] T. Lee, J. A. Richards, and P. H. Swain, "Probabilistic and evidential approaches for multisource data

analysis," *IEEE Trans. Geosci. Remote Sens.*, vol. GE-25, no. 3, pp. 283–293, May 1987.

[11] N. Cressie, *Statistics for Spatial Data*. New York, NY, USA: Wiley, 1993.

[12] P. H. Swain and M. S. Davis, "Remote sensing: The quantitative approach," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-3, no. 6, pp. 713–714, Nov. 1981.

[13] C. J. Tucker, "Red and photographic infrared linear combinations for monitoring vegetation," *Remote Sens. Environ.*, vol. 8, no. 2, pp. 127–150, May 1979.

[14] G. L. Wiegand and A. J. Richardson, "Leaf area, light interception, and yield estimates from spectral components analysis," *Agronomy J.*, vol. 76, no. 4, pp. 543–548, 1984.

[15] M. A. Friedl and C. E. Brodley, "Decision tree classification of land cover from remotely sensed data," *Remote Sens. Environ.*, vol. 61, pp. 399–409, Sep. 1997.

[16] M. Pal and P. M. Mather, "An assessment of the effectiveness of decision tree methods for land cover classification," *Remote Sens. Environ.*, vol. 86, no. 4, pp. 554–565, Aug. 2003.

[17] U. C. Benz, "Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information," *ISPRS J. Photogramm.*, vol. 58, nos. 3–4, pp. 239–258, Jan. 2004.

[18] J. Zhou, D. L. Civco, and J. A. Silander, "A wavelet transform method to merge Landsat TM and SPOT panchromatic data," *Int. J. Remote Sens.*, vol. 19, no. 4, pp. 743–757, 1998.

[19] L. M. Bruce, C. H. Koger, and J. Li, "Dimensionality reduction of hyperspectral data using discrete wavelet transform feature extraction," *IEEE Trans. Geosci. Remote Sens.*, vol. 40, no. 10, pp. 2331–2338, Oct. 2002.

[20] G. L. Galford, J. F. Mustard, J. Melillo, A. Gendrin, C. C. Cerri, and C. E. P. Cerri, "Wavelet analysis of MODIS time series to detect expansion and intensification of row-crop agriculture in Brazil," *Remote Sens. Environ.*, vol. 112, no. 2, pp. 576–587, 2008.

[21] F. Wang, "Fuzzy supervised classification of remote sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 28, no. 2, pp. 194–201, Mar. 1990.

[22] S. Bandyopadhyay, U. Maulik, and A. Mukhopadhyay, "Multiobjective genetic clustering for pixel classification in remote sensing imagery," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 5, pp. 1506–1511, May 2007.

[23] G. R. Cross and A. K. Jain, "Markov random field texture models," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-5, no. 1, pp. 25–39, Jan. 1983.

[24] R. C. Dubes and A. K. Jain, "Random field models in image analysis," *J. Appl. Statist.*, vol. 16, no. 2, pp. 131–164, 1989.

[25] J. P. Watson, "A visual interpretation of a Landsat mosaic of the okavango delta and surrounding area," *Remote Sens. Environ.*, vol. 35, no. 1, pp. 1–9, 1991.

[26] S. Chandrasekhar, *Radiative Transfer*. New York, NY, USA: Dover, 1960.

[27] J. Ross, *The Radiation Regime and Architecture of Plant Stands*. London, U.K.: Springer, 1981.

[28] R. B. Myneni, G. Asrar, and E. T. Kanemasu, "The theory of photon transport in leaf canopy," in *Theory and Application of Optical Remote Sensing*. New York, NY, USA: Wiley, 1987.

[29] G. Asrar, R. B. Myneni, and B. J. Choudhury, "A 3-D RT method for optical remote sensing of vegetation land surface," in *Proc. 5th Int. Colloq. Phys. Meas. Signatures Remote Sens.*, Courchevel, France, 1991, pp. 361–367.

[30] X. LI, "An invertible coniferous canopy reflectance model," M.S. thesis, Dept. Geography, Univ. California, Santa Barbara, CA, USA, 1981.

[31] X. Li and A. H. Strahler, "Geometric-optical modeling of a conifer forest canopy," *IEEE Trans. Geosci. Remote Sens.*, vol. GE-23, no. 5, pp. 705–721, Sep. 1985.

[32] X. Li and A. H. Strahler, "Geometric-optical bidirectional reflectance modeling of the discrete crown vegetation canopy: Effect of crown shape and mutual shadowing," *IEEE Trans. Geosci. Remote Sens.*, vol. 30, no. 2, pp. 276–292, Mar. 1992.

[33] J. M. Chen and S. G. Leblanc, "A four-scale bidirectional reflectance model based on canopy architecture," *IEEE Trans. Geosci. Remote Sens.*, vol. 35, no. 5, pp. 1316–1337, Sep. 1997.

[34] X. Li, A. H. Strahler, and C. Woodcock, "Hybrid geometric optical-radiative transfer approach for modeling albedo and directional reflectance of discontinuous canopies," *IEEE Trans. Geosci. Remote Sens.*, vol. 33, no. 2, pp. 466–480, Mar. 1995.

[35] P. J. Sellers and Y. Mintz, "A simple biosphere model (SIB) for use within general circulation models," *J. Atmos. Sci.*, vol. 43, pp. 505–531, Feb. 1986.

[36] C. S. Potter *et al.*, "Terrestrial ecosystem production: A process model based on global satellite and surface data," *Global Biogeochem. Cycles*, vol. 7, no. 4, pp. 811–841, 1993.

[37] S. D. Prince and S. N. Goward, "Global primary production: A remote sensing approach," *J. Biogeogr.*, vol. 22, pp. 815–835, 1995.

[38] L. Dente, G. Satalino, F. Mattia, and M. Rinaldi, "Assimilation of leaf area index derived from ASAR and MERIS data into CERES-Wheat model to map wheat yield," *Remote Sens. Environ.*, vol. 112, no. 4, pp. 1395–1407, Apr. 2008.

[39] Z. Su *et al.*, "Observation of hydrological processes using remote sensing," *Treatise Water Sci.*, vol. 2, pp. 351–399, 2011.

[40] X. Y. Xu, *Remote Sensing Physics*. Beijing, China: Peking Univ. Press, (in Chinese), 2006.

[41] H. Rahman, M. M. Verstratete, and B. Pinty, "Coupled surface-atmosphere reflectance (CSAR) model: 2. Semiempirical surface model usable with NOAA advanced very high resolution radiometer data," *Geophps. Res.*, vol. 98, no. D11, pp. 20791–20801, 1993.

[42] J. Qi *et al.*, "Leaf area index estimates using remotely sensed data and BRDF models in a semiarid region," *Remote Sens. Environ.*, vol. 73, no. 1, pp. 18–30, 2000.

[43] M. Chi, A. Plaza, J. A. Benediktsson, Z. Sun, J. Shen, and Y. Zhu, "Big data for remote sensing: Challenges and opportunities," *Proc. IEEE*, vol. 104, no. 11, pp. 2207–2219, Nov. 2016.

[44] B. Zhang, "Remotely sensed big data era and intelligent information extraction," *Geomatics Inf. Sci. Wuhan Univ.*, vol. 43, no. 12, pp. 1861–1871, 2018.

[45] G. M. Foody, "Using prior knowledge in artificial neural network classification with a minimal training set," *Int. J. Remote Sens.*, vol. 16, pp. 301–312, 1995.

[46] X. Li, F. Gao, J. Wang, and A. Strahler, "A priori knowledge accumulation and its application to linear BRDF model inversion," *J. Geophys. Res., Atmos.*, vol. 106, no. D11, pp. 11925–11935, 2001.

[47] Y. Ma *et al.*, "Remote sensing big data computing: Challenges and opportunities," *Future Generat. Comput. Syst.*, vol. 51, pp. 47–60, Oct. 2015.

[48] J. A. K. Suykens and J. Vandewalle, "Least squares support vector machine classifiers," *Neural Process. Lett.*, vol. 9, no. 3, pp. 293–300, Jun. 1999.

[49] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *J. Comput. Syst. Sci.*, vol. 55, no. 1, pp. 119–139, Aug. 1997.

[50] D. J. Lary, *Artificial Intelligence in Geoscience and Remote Sensing* (Geoscience and Remote Sensing, New Achievements). Vukovar, Croatia: InTech, 2010.

[51] D. J. Lary, A. H. Alavi, A. H. Gandomi, and A. L. Walker, "Machine learning in geosciences and remote sensing," *Geosci. Frontiers*, vol. 7, no. 1, pp. 3–10, 2016.

[52] P. Liu, K.-K. R. Choo, L. Wang, and F. Huang, "SVM or deep learning? A comparative study on remote sensing image classification," *Soft Comput.*, vol. 21, no. 23, pp. 7053–7065, 2017.

[53] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, May 2015.

[54] J. E. Ball, D. T. Anderson, and C. S. Chan, Sr., "Comprehensive survey of deep learning in remote sensing: Theories, tools, and challenges for the community," *J. Appl. Remote Sens.*, vol. 11, no. 4, p. 042609, Sep. 2017.

[55] A. Krizhevsky, I. Sutskever, and G. Hinton, "Imagenet classification with deep convolutional neural networks," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 25, 2012, pp. 1090–1098.

[56] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proc. Int. Conf. Learn. Represent.*, Apr. 2015, pp. 1–14. [Online]. Available: https://arxiv.org/pdf/1409.1556v6.pdf

[57] G. E. Hinton *et al.*, "Deep neural networks for acoustic modeling in speech recognition," *IEEE Signal Process. Mag.*, vol. 29, no. 6, pp. 82–97, Oct. 2012.

[58] A. M. Badshah, J. Ahmad, N. Rahim, and S. W. Baik, "Speech emotion recognition from spectrograms with deep convolutional neural network," in *Proc. IEEE Int. Conf. Platform Technol. Service*, vol. 17, Feb. 2017, pp. 1–5.

[59] K. T. Butler, D. W. Davies, H. Cartwright, O. Isayev, and A. Walsh, "Machine learning for molecular and materials science," *Nature*, vol. 559, pp. 547–555, Jul. 2018.

[60] R. Alexander *et al.*, "Machine learning at the energy and intensity frontiers of particle physics," *Nature*, vol. 560, pp. 41–48, Aug. 2018.

[61] M. K. K. Leung, H. Y. Xiong, L. J. Lee, and B. J. Frey, "Deep learning of the tissue-regulated splicing code," *Bioinformatics*, vol. 30, no. 12, pp. i121–i129, 2014.

[62] X. X. Zhu *et al.*, "Deep learning in remote sensing: A comprehensive review and list of resources," *IEEE Geosci. Remote Sens. Mag.*, vol. 5, no. 4, pp. 8–36, Dec. 2017.

[63] D. Silver *et al.*, "Mastering the game of go with deep neural networks and tree search," *Nature*, vol. 529, no. 7587, pp. 484–489, 2016.

[64] MIT Technology Review. (2013). *10 Breakthrough Technologies 2013*. [Online]. Available: https://www.technologyreview.com/lists/technologies/2013/

[65] L. Zhang, L. Zhang, and B. Du, "Deep learning for remote sensing data: A technical tutorial on the state of the Art," *IEEE Geosci. Remote Sens. Mag.*, vol. 4, no. 2, pp. 22–40, Jun. 2016.

[66] S. Wang, D. Quan, X. Liang, M. Ning, Y. Guo, and L. Jiao, "A deep learning framework for remote sensing image registration," *ISPRS J. Photogramm.*, vol. 145, pp. 148–164, Nov. 2018, doi: 10.1016/j.isprsjprs.2017.12.012.

[67] G. Cheng, P. Zhou, and J. Han, "Learning rotation-invariant convolutional neural networks for object detection in VHR optical remote sensing images," *IEEE Trans. Geosci. Remote Sens.*, vol. 54, no. 12, pp. 7405–7415, Dec. 2016.

[68] Y. Chen, H. Jiang, C. Li, X. Jia, and P. Ghamisi, "Deep feature extraction and classification of hyperspectral images based on convolutional neural networks," *IEEE Trans. Geosci. Remote Sens.*, vol. 54, no. 10, pp. 6232–6251, Oct. 2016.

[69] L. Mou, P. Ghamisi, and X. X. Zhu, "Deep recurrent neural networks for hyperspectral image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 7, pp. 3639–3655, Jul. 2017.

[70] Q. Liu, R. Hang, H. Song, and Z. Li, "Learning multiscale deep features for high-resolution satellite image scene classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 1, pp. 117–126, Jan. 2017.

[71] R. Okamura, H. Iwabuchi, and K. S. Schmidt, "Retrieval of optical thickness and droplet effective radius of inhomogeneous clouds using deep learning," *Atmos. Meas. Tech.*, vol. 10, pp. 4747–4759, Dec. 2017.

[72] P. Zhang, X. Niu, Y. Dou, and F. Xia, "Airport detection on optical satellite images using deep convolutional neural networks," *IEEE Geosci. Remote Sens. Lett.*, vol. 14, no. 8, pp. 1183–1187, Aug. 2017.

[73] G. Chen, Y. Li, G. Sun, and Y. Zhang, "Application of deep networks to oil spill detection using polarimetric synthetic aperture radar images," *Appl. Sci.*, vol. 7, no. 10, p. 968, 2017.

[74] Y. Xu, L. Wu, Z. Xie, and Z. Chen, "Building

extraction in very high resolution remote sensing imagery using deep learning and guided filters," *Remote Sens.*, vol. 10, p. 144, Jan. 2018.
[75] J. Tang, C. Deng, G.-B. Huang, and B. Zhao, "Compressed-domain ship detection on spaceborne optical image using deep neural network and extreme learning machine," *IEEE Trans. Geosci. Remote Sens.*, vol. 53, no. 3, pp. 1174–1185, Mar. 2014.
[76] Y. S. Cao, X. Niu, and Y. Dou, "Region-based convolutional neural networks for object detection in very high resolution remote sensing images," in *Proc. Int. Conf. Natural Comput., Fuzzy Syst. Knowl. Discovery*, 2016, pp. 548–554.
[77] K. Li, G. Cheng, S. Bu, and X. You, "Rotation-insensitive and context-augmented object detection in remote sensing images," *IEEE Trans. Geosci. Remote.*, vol. 99, no. 4, pp. 2337–2348, Apr. 2017.
[78] E. Maggiori, Y. Tarabalka, G. Charpiat, and P. Alliez, "Convolutional neural networks for large-scale remote-sensing image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 2, pp. 645–657, Feb. 2017.
[79] V. Slavkovikj, S. Verstockt, W. De Neve, S. Van Hoecke, and R. Van de Walle, "Hyperspectral image classification with convolutional neural networks," in *Proc. ACM*, 2015, pp. 1159–1162.
[80] X. Xu, W. Li, Q. Ran, Q. Du, L. Gao, and B. Zhang, "Multisource remote sensing data classification based on convolutional neural network," *IEEE Trans. Geosci. Remote.*, vol. 56, no. 2, pp. 937–949, Feb. 2018.
[81] C. Zhang *et al.*, "A hybrid MLP-CNN classifier for very fine resolution remotely sensed image classification," *J. Photogramm. Remote Sens.*, vol. 140, pp. 133–144, Jun. 2018.
[82] A. B. Hamida, A. Benoit, P. Lambert, and C. B. Amar, "3-D deep learning approach for remote sensing image classification," *IEEE Trans. Geosci. Remote Sens.*, vol. 56, no. 8, pp. 4420–4434, Aug. 2018.
[83] L. Wang, "Sea ice concentration estimation during melt from dual-Pol SAR scenes using deep convolutional neural networks: A case study," *IEEE Trans. Geosci. Remote.*, vol. 54, no. 8, pp. 4524–4533, Aug. 2016.
[84] J. García-Gutiérrez, E. González-Ferreiro, D. Mateos-García, and J. C. Riquelme-Santos, "A preliminary study of the suitability of deep learning to improve LiDAR-derived biomass estimation," in *Proc. Int. Conf. Hybrid Artif. Intell. Syst.*, 2016, pp. 588–596.
[85] X. Yu, H. Lu, and Q. Liu, "Deep-learning-based regression model and hyperspectral imaging for rapid detection of nitrogen concentration in oilseed rape *(Brassica napus L.)* leaf," *Chemometrics Intell. Lab. Syst.*, vol. 172, pp. 188–193, Jan. 2017.
[86] A. Ducournau and R. Fablet, "Deep learning for ocean remote sensing: An application of convolutional neural networks for super-resolution on satellite-derived SST data," in *Proc. IEEE Workshop Pattern Recognit. Remote Sens.*, Dec. 2017, pp. 1–6.
[87] T. Li, H. Shen, Q. Yuan, X. Zhang, and L. Zhang, "Estimating ground-level $PM_{2.5}$ by fusing satellite and station observations: A Geo-intelligent deep learning approach," *Geophys. Res. Lett.*, vol. 44, no. 23, pp. 11985–11993, 2017.
[88] D. Zhang, W. Zhang, W. Huang, Z. Hong, and L. Meng, "Upscaling of surface soil moisture using a deep learning model with VIIRS RDR," *ISPRS Int. J. Geo-Inf.*, vol. 6, no. 6, p. 130, 2017.
[89] S. H. Khan, X. He, F. Porikli, M. Bennamoun, F. Sohel, and R. Togneri, "Learning deep structured network for weakly supervised change detection," 2016, *arXiv:1606.02009*. [Online]. Available: https://arxiv.org/abs/1606.02009
[90] S. H. Khan, X. He, F. Porikli, and M. Bennamoun, "Forest change detection in incomplete satellite images with deep neural networks," *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 9, pp. 5407–5423, Sep. 2017.