Geospatial Big Data: New Paradigm of Remote Sensing Applications

Xingdong Deng, Penghua Liu, Xiaoping Liu, Ruoyu Wang, Yuanying Zhang, Jialv He, and Yao Yao

Abstract—**The rapid development of information technology and location techniques not only leads to an increasing growth of massive geospatial big data but also raises the attention of using these data to complement with remote sensing images. Many efforts have been made to utilize geospatial big data to identify human activity patterns and carry out urban and environmental researches, integrating with remote sensing images. Nonetheless, there are still many issues, including the representativeness and locality of geospatial big data, as well as the fusion methods, remain to be further explored. In this article, we first reviewed the innovation and proceedings of data mining and analyzing techniques, as well as remote sensing applications driven by geospatial big data. Besides, two popular concepts, namely, "Social Sensing" and "Urban Computing," were briefly introduced. Then, we highlighted the role of geospatial big data in mining human activity dynamics and socioeconomic characteristics, and the feasibility of combining with remote sensing data for various studies. Lastly, we presented some empirical case studies on the confluence of remote sensing and geospatial big data in land use extraction, environmental and disaster monitoring, as well as socioeconomic dynamics sensing. The provided examples and discussion demonstrated the high efficiency and complementarity of the integration of remote sensing and geospatial big data, which benefits decision making from multiple perspectives and scales.**

Index Terms—**Geospatial big data, integration, remote sensing.**

I. Introduction

REMOTE sensing and Geographical Information System (GIS) have always been providing powerful information for many applications, such as land use mapping [1], change detection [2], and disaster monitoring [3]. As the main data source of earth observation [4], remote sensing images with different spatial [5], temporal [6], and spectral [7] resolutions, collected by optical cameras or LiDAR sensors carried on airborne or satellite platforms [8], [9] play a significant role in the monitoring of the surface and atmospheric environment. However, many problems of utilizing remote sensing images for earth observation and monitoring have not been solved for a long time. On the one hand, due to the long orbit revisiting time of remote sensing satellites, remote sensing images can hardly be applied for continuous and real-time monitoring such as disaster monitoring [10]. On the other hand, remote sensing is powerful in terms of describing and presenting natural and physical geographical characteristics but is almost unable to capture patterns of socioeconomic environments such as patterns of human activities or socioeconomic connectivity among cities [11].

During the recent decades, the rapid development of information technology has led to the explosive growth of data originating from various sensors, driving us into the era of big data [12]. Big data with geographic location information and originating from sensors such as smartphones and handheld Global Positioning System (GPS) devices, have already invaded into our daily life and show great potential in practical applications such as disaster response and environmental monitoring [13]. Owing to the development of new technologies such as smartphones and wireless networks, people can now post and share information with geographical coordinates, such as check-in, photos, and shopping comments, with others through the internet anytime and anywhere [14], which breaks the barrier of face-to-face communication and creates a new form of human activity interaction [15], [16]. In the context of the rapid growth of social media and big data, massive geo-tagged big data are generated due to these spontaneous sharing behaviors and provide possible solutions to explore and reveal patterns of unobservable phenomenon such as human activity dynamics [17]. For example, a large amount of GPS trajectory data, as well as pickup and drop-off location information with timestamp are produced automatically when taking taxis [18]. By analyzing the temporal characteristics of pickup and drop-off activities within geographic units, we can not only identify the urban functions but also figure out the job-housing functional patterns much more accurately than by traditional remote sensing images [19], [20], and the intracity and intercity spatial interaction can be further explored [21].

As discussed, the real-time positioning and sharing of data generated by human activity interaction which are collected by ground equipment provide new possibilities for solving

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the above problems in the context of geospatial big data [22]. Thus, the geospatial big data we mentioned here do not include remote sensing images collected by satellite or unmanned aerial vehicles which may be regarded as traditional geospatial data. As a matter of fact, many studies have integrated remote sensing and geospatial big data mentioned above to solve various problems [3], [23]. For example, in [24], Shi *et al.* combined microblogging data and nighttime light remote sensing to reveal the pattern of human activities and light pollution. In their study, two types of big data originating from social media and remote sensing were coupled to complement each other, which provide a new approach to understand and discover spatiotemporal patterns [25]. It was suggested that data from remote sensing and social media both contain multisensor, multiresolution, and multitemporal information, but remote sensing data reflect more dynamic change of natural elements while social media reflects more human activities [11]. Therefore, the emergence of geospatial big data brings an opportunity to make up for remote sensing images in excavating human activities at a fine scale [26].

However, the vast amount of data brings both opportunities and challenges [27]. The growth of disordered and mixed data makes higher demands for acquisition, storing, managing, processing, visualizing, and verifying [13]. For example, geo-computing [28], spatiotemporal data mining [29], parallel computing [30] methods and techniques are required to discover knowledge from geospatial big data. Besides, how to properly integrate remote sensing images and geospatial big data is still worth to be further studied. Specifically, some studies integrate remote sensing and geospatial big data at the feature level [31], while others fuse at the decision-making level [32].

Many previous studies did not consider the integration of remote sensing and geospatial big data, which may lead to biased or unelaborated description of geographic environment. Thus, in recent years, more and more studies have been carried out to integrate them together, but few articles systematically review and summarize the applications and development trend of the integration of remote sensing and geospatial big data. In this article, we attempted to provide an overview of the integration of remote sensing and geospatial big data in improving application performance. The rest of the contents of this article are organized as follows. Section II described the innovation brought by the emergence of geospatial big data. At the same time, we introduced the proceedings of data mining and analysis techniques driven by geospatial big data and gave an overview of applications of geospatial big data in GIS and remote sensing. Besides, we presented two popular concepts including "Social Sensing" and "Urban Computing" in urban studies of geospatial big data. In Section III, the integration of remote sensing and geospatial big data were first discussed. We have focused on analyzing the complementarities of these different types of data in terms of temporal characteristics, spatial heterogeneity, and geographical representativeness, and then discussed the feasibility and necessity of data fusion. To support the discussion, we have categorized and discussed some application examples of integrating remote sensing and geospatial big data to highlight the outstanding performance in improving environmental studies. Section IV concludes the article.

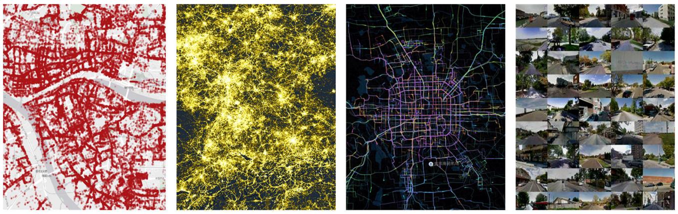
II. Proceedings of Geospatial Big Data

In this section, we introduced the improvements and progress brought about by geospatial big data in remote sensing and urban applications. In this case, from the generation of geospatial big data, we discussed the paradigm shift of data mining and analysis methods driven by geospatial big data, as well as new think on research. We listed some current research examples on the environment and cities based on geospatial big data and introduced two popular and new concepts, that is, "Social Sensing" and "Urban Computing," which were proposed in the context of the increasing popularity of geospatial big data in spatial analysis studies.

A. *Progress in Geospatial Big Data Technologies*

The past two decades has witnessed the fast development of information technology, which not only brought massive big data but also drove the innovation of related disciplines [33]. The emergence of big data attached with spatial location information, that is, geospatial big data, brings us new opportunities to understand the urban environment in an unprecedented way [34]. Benefited from the popularization of sensor devices with GPS, we can collect, share, and analyze hundreds of billions user behavior data with location information every day, which makes the possibility to promote the development of novel concept and analytic skills of spatial analysis technologies [35]. Considered as "sensors," people can help capture human mobility–related information and enrich geographic data in the aspect of socioeconomic attributes [13].

With the rapid advancement of Location Based Service (LBS), the Information Service and Application Provider (ISAP) can easily get access to the locations of users or mobile phones and provide related services from anywhere at any time if authorized [36]. For instance, based on the location of users shared through the internet, the ISAP can recommend hotels, cinemas, libraries, and gas stations within 1 km for users. It is such LBS mode that promotes the generation of endless user behavior data with spatial location and time information [37]. Another major source of geospatial big data is the Volunteered Geographical Information (VGI) [38], or a similar form, that is, the crowdsourcing geographical information [39]. As its name suggests, VGI is the geographical data provided voluntarily by individuals [38]. To be more detail, VGI refers to geographical data uploaded via the internet by citizens, who acts like active sensors in remote sensing [11]. In this way, only an internet-enabled device is needed to allow users all around the world to contribute to the construction of data and information, which greatly reduces the cost of data manufacturing and speeds up the time of data collection and update [39], [40]. For example, Flickr offers online services for storing and sharing digital photos with geographic locations based on social network. OpenStreetMap (OSM) allows for the editing and updating of basic geographic information, making it more convenient to collect and update the map information with users' native experience and knowledge [41]. Ubiquitous sensors make the acquisition and utilization of geospatial data more convenient, thus generating various kinds of formats of geospatial big data [13].



(a) (b) (c) (d)

Fig. 1. Examples of geospatial big data. (a) POIs distribution in Guangzhou, China. (b) GPS positioning points in Germany. (c) Bus trajectories in Beijing, China. (d) Street view images in Shenzhen, China.

While the volume of data has increased dramatically, the computing power and data storage performance of hardware and software have also been greatly improved and evolved. Traditional computing infrastructures are no longer suitable to handle such an enormous volume of complex data with diverse data formats like texts, images, videos, so it puts forward new requirements for the processing, management, and storage of massive data that grow day by day [42]. High-performance computing architectures, most notably cloud computing platforms, are characterized by excellent parallel computing capability and large-scale scalability and flexibility in big data processing through virtualization applications, automated deployment, and distributed computing [43]. Big data storage techniques, such as distributed storage systems [44] and NoSQL [45], provide more flexible, high-performance and parallelizable storage solutions for massive redundant and complex data storage, and make full use of hardware resources by adopting distributed and clustered methods. Moreover, big data have caused a paradigm shift to data-driven researches [46]. That is to say, traditional rule-based or conventional statistical methods may not be able to rapidly and efficiently mine hidden rules from data with unpredictable size and noise, therefore more advanced data mining and processing techniques are further required [17]. Especially in recent years, with the development of the graphics processing unit, deep neural network, that is, deep learning, has been highlighted in mining massive data such as text, image, and voice [47]. On the other hand, deep learning algorithms are also promoted by the emergence of big data due to the characteristic of data-driven.

B. Progress in Geospatial Big Data Applications

At present, the emergence of various spatial–temporal big data, such as the GPS trajectories of taxis, mobile phone signals, check-in data of social media, smart card records of urban public transport facilities, points-of-interests (POI), and geo-tagged photos in Fig. 1, provides many different observation and perception methods for urban environmental researches and urban policymakers.

For example, Yao *et al.* [48] abstracted POIs and traffic analysis zones (TAZ) into words and documents in the field of natural language processing, respectively. The Word2Vec model [49] was employed to represent POIs with vectors and thus TAZs are quantitatively characterized for land use classification. In [50], the authors constructed a synthesized vector of mobile phone activity to sense urban land use patterns by using a semisupervised clustering method. In the literature of Tu *et al.* [51], a new approach was proposed to identify urban functions by integrating mobile phone signals and check-in data. Based on timing distribution characteristics of mobile phone data, in-home and working activities were recognized and the remaining uncertain activities were annotated by the hidden Markov model with the knowledge mined from social media check-in data.

In addition to pattern recognition of land use, geospatial big data are gradually found to play an increasing role in mining patterns of socioeconomic factors such as human mobility. For instance, Noulas *et al.* [52] used online LBS data named Foursquare to study urban mobility patterns of residents in several central cities all over the world by analyzing Foursquare users' sharing behaviors. Liu *et al.* [53] adopted check-in data set collected from a location-based social network service provider and gravity model to identify patterns of interurban trip. As for studies related to urban spatial structure, Li *et al.* [54] proposed a framework for identifying and evaluating Live-Work-Play centers using available POIs which can be regarded as a proxy for identifying urban functions. The results successfully identified urban subcenter for 23 cities in 2009 and 35 Chinese cities in 2014. Gao *et al.* [16] successfully used mobile phone data to find the spatial clustering structures and interaction patterns of communities.

Compared to POI and mobile phone positioning data, Street View (SV) images [see Fig. 1(d)] depict urban street landscape in the format of images rather than texts, thus are getting more and more popular in various urban studies [55], especially for assessing urban built environment including urban walking index evaluation [55], urban street green quantity evaluation [56], [57], and urban land use classification [58]. For instance, Long and Liu [57] proposed an automatic method using Tencent online SV service to determine how green streets are in most Chinese cities. Also, SV images can also be applied to assess residents' subjective feelings to urban space [59], [60]. For example, Zhang *et al.* [61] employed a fully convolutional network to conduct semantic segmentation of SV images, and obtained synthesized features by extracting the pixel proportion of various segmented objects. They trained a classifier using synthesized features and proved that the landscape features presented by SV images can well reflect human perceptions of the city.

C. Social Sensing and Urban Computing

As mentioned above, the spatiotemporal characteristics of human activities become observable and measurable, which leads the widespread usage of geospatial big data in social studies, especially urban studies. In the context of the availability of applying geospatial big data to mine the human activity dynamics and socioeconomic characteristics within the city, two new concepts, that is, "Social Sensing" and "Urban Computing," are proposed, providing new methodologies and systems for urban sensing. The two concepts, proposed by Liu *et al.* [11] and Zheng *et al.* [62], [63], respectively, have attracted significant interests in urban sensing.

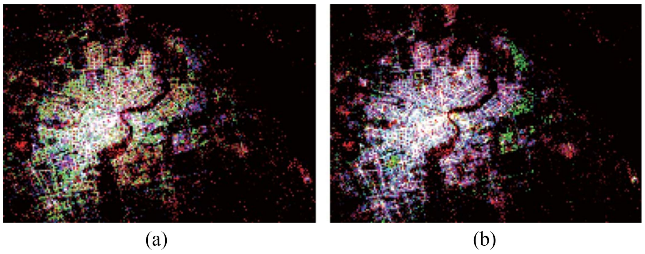


Fig. 2. False color composition of three social sensing data source during different times: (a) 8:00 A.M.–9:00 A.M.; (b) 8:00 P.M.–9:00 P.M. in [11].

Social sensing refers to a kind of geospatial big data, which provides an observation platform for human behaviors, highlighting the concept of "crowd sensing" [64]. Regarded as a complement of remote sensing, social sensing data are intended to detect economic dynamics of human beings such as human mobility, travel behaviors, urban communities, and urban land use patterns [65]. For example, Fig. 2 presents two false color composite images at 8:00 A.M.–9:00 A.M. and 8:00 P.M.–9:00 P.M., respectively. The red, green, and blue channels are characterized and rendered by check-ins, pickups, and drop-offs, respectively. Spatiotemporal characteristics of human behaviors can be easily identified from the false color composite images. In addition to spatiotemporal behavior mining, social sensing provides a new approach and perspective to explore the interaction between human and environment and can applied to address the problem of inferring land use from land cover information [11], [66].

Urban computing aims to mine knowledge from massive and heterogeneous data generated by diverse sources and apply these powerful information to tackle the major problems that cities are faced with [62], [67]. It has an interdisciplinary field that combines computing science with transportation, ecology, and sociology to help us understand the nature of urban phenomena patterns. As presented in Fig. 3, compared to social sensing mentioned above, urban computing pays more attention to integrating basic geographic data, traffic data, mobile signaling data, social media big data, environmental monitoring data, and other data into the urban sensing system for service provision and problem-solving [62].

III. Integration of Remote Sensing and Geospatial Big Data

In this section, we focused on the superiority of the integration of remote sensing and geospatial big data. We first analyzed the bottlenecks in researches using traditional remote sensing images and methods, demonstrating the necessity and feasibility of the integration of remote sensing and geospatial big data. To this end, we categorized some typical case studies that use the combination of multisource geospatial big data and remote sensing data, in order to clarify the general fusion framework in current works.

A. *Remote Sensing and Spatial Big Data Fusion*

Due to ever-advancing technologies, remote sensing is experiencing unprecedented development in recent years, driven by sensor advances and an ever-increasing information infrastructure [9]. As one of the main tasks of remote sensing, the interpretation, and extraction of surface information is the basis and prerequisite for the investigation, detection, monitoring, and analysis of resources, environment, disasters, and cities [68]. In recent years, identifying land use and land cover information on the surface from High Spatial Resolution (HSR) and hyperspectral remote sensing images by using advanced and forefront algorithms has always been a popular research topic in remote sensing [69]–[74].

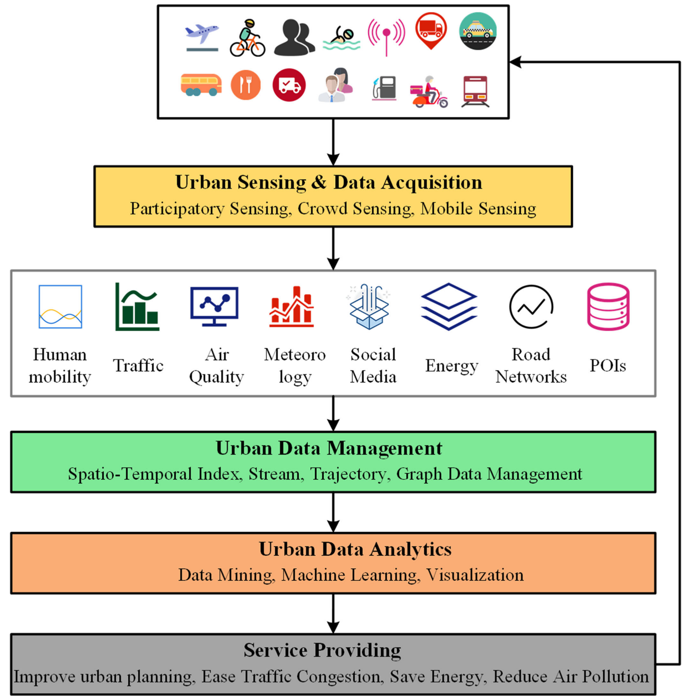


Fig. 3. General framework of urban computing (adapted from [62]).

Basically, according to the spatial analyzing units, studies of land use are conducted with three types, among which the pixel and object units are commonly introduced to evaluate land cover, while scenes are usually used to infer urban functional zones and extract urban land use patterns [75], [76]. Several studies utilized the object-oriented classification models to accurately mine urban land use patterns by using the physical features (such as spectral, shape, and texture features) of ground objects [77]. Whereas, these models mainly focus on mining the low-level semantic land cover information of ground, so that the models of object-oriented classification generally ignore the spatial distribution of ground elements and semantic features, which causes the so-called "Semantic Gap" [76], [78]. Being mindful of these problems, some recent studies adopt scene classification method by using the bag-of-words modeling methods and integrating the physical features of ground by the probabilistic topic models to increase identification accuracy of urban land use with the high-level semantic information [79], [80]. For example, Zhang and Du [81] used the linear Dirichlet mixture model to integrate the HSR images and road data to explore the proportion of land use in per land parcel. Huang *et al.* [82] proposed an ensemble SVM method with the integration of the multisource geospatial data (including grid population, grid GDP, nightlight time data, etc.) to map the regional-scale urban area. Nevertheless, the features of remote sensing images can only stand for the natural-physical properties of ground, whereas land use of zonal types often relate to the human socioeconomic activities, which are very difficult to be acquired from HSR images [75], [76].

From the above discussion, it can be seen that only the land cover information (such as forest land, grassland, built-up area) can be effectively extracted from the spectral information of remote sensing images, while the land use information (such as residential land, commercial land, and industrial land) cannot be distinguished due to its complexity and the similarity of physical properties [31]. The surface physical information obtained from remote sensing images can be used to accurately distinguish among different land cover information, but the identification ability of complex functional zones in urban areas is poor. Fortunately, the emergence of geospatial big data provides a new observation data source for precisely mining urban land use patterns. Similar to remote sensing data sets, current geospatial big data abstract people into sensors and thus can capture human activities better and are more sensitive to our dynamic socioeconomic environments [11]. Besides, it is suggested that the land use information extracted from geospatial big data is more reliable than those obtained from remotely sensed data [83].

Even so, there are still some inevitable questions waiting to be considered and solved. To be first, according to the research conducted by Jendryke *et al*. [84], there is quite high coherence between social media big data and urban built-up environment, that is, most big data representing human activities mainly distribute in the urban built-up areas. By the way, the intensity of human activities varies among different types of urban functional areas. Then the question arises, that is, geospatial big data perform poor in representing and measuring the human activity characteristics in rural areas with low population and activity density [11]. Second, knowledge mined and learned from massive spatial big data in a certain research area is difficult to migrate to other areas, and different time periods, as well as special events, have a great impact on the spatial and temporal patterns of human activities [11]. Third, geospatial big data are massive, disordered, and heterogeneous and can only represent the activity characteristics of a certain group of people but rather all, which makes it very difficult for knowledge mining and effective integration with other source of data [85].

Therefore, we believe that the coupling of remote sensing and geospatial big data can greatly improve the recognition performance of land use patterns and thus assist other applications from multiple perspectives and scales. Specifically, on the one hand, the detailed characterization of human behaviors of geospatial big data provides representative indicators with finer spatiotemporal scales [86] and thus can make up for the shortcomings of remote sensing in complex urban functions identification and real-time continuous dynamic monitoring. On the other hand, remote sensing images own a wide-field view and comprehensive observations [9], presenting a more general understanding in areas that geospatial big data do not significantly work. Practically, many studies have combined remote sensing images and geospatial big data together for urban functional area identification, housing price mapping, disaster warning, etc.

B. Examples

This section introduced some successful cases of integrating remote sensing and geospatial big data in a variety of applications. These examples enable us to generalize and summarize the general perceptions and methodologies used to integrate these different but fairly complementary data and to foresee their future trends. In general, we classify these examples into three categories, namely, land use and land cover extraction, environmental and disaster monitoring, and socioeconomic dynamics sensing.

1) Land Use and Land Cover Extraction: As mentioned in previous sections, land use and land cover have always been an essential issue in remote sensing and GIS. There has long been an endure trend in the exploitation of geospatial big data and remote sensing data for land use and land cover extraction [87], [88]. To our knowledge, the integration of remote sensing and geospatial big data in land use and land cover identification can be summarized in the following two ways: feature fusion and decision fusion. Examples are given below.

Feature fusion for land use and land cover classification is commonly and frequently used. In these methods, features are extracted from multisource geospatial big data, and then data fusion is achieved through an integration of feature concatenating. For example, Hu *et al.* [89] proposed a parcel-based urban land use classification framework by fusing Landsat remote sensing images and POIs. In their study, land parcel units were segmented by trimmed OSM roads and labeled by adopting a similarity assessment based on the features extracted from remote sensing images and POIs. In addition to considering remote sensing images and POI features, Zhang *et al.* [90] also integrated the density of Weibo (a social media software like Facebook) posts to further improve the accuracy of classification. Their method shows significant performance in identifying open space and residential space since Weibo posts contain more individual details.

Fig. 4 presents the urban scene land use classification flowchart by fusing multisource geospatial big data in [31] proposed by Liu *et al.* They combined the spectral, texture, GIST features of high-resolution remote sensing images, POI categorical features, as well as spatiotemporal characteristics of real-time Tencent user density (RTUD) data for land use scene classification. Latent Dirichlet Allocation (LDA) topic model was applied to extract latent high-level semantic information that can represent land use patterns from the low-level features of multisource data. After the above feature engineering, an SVM classifier was adopted to accurately identify land use patterns. Instead of simply concatenating low-level features of multisource big data, high-level semantic features of these heterogeneous data were extracted, respectively, and integrated in the high-level semantic space. In the study of Zhang *et al.* [91], 13 parcel features, including building characteristics derived from LiDAR data set, normalized difference vegetation index (NDVI)

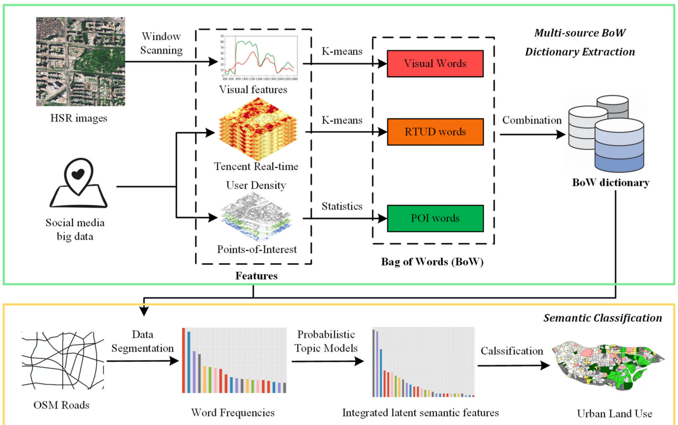


Fig. 4. Urban scene land use classification flowchart by fusing multisource geospatial big data in [31].

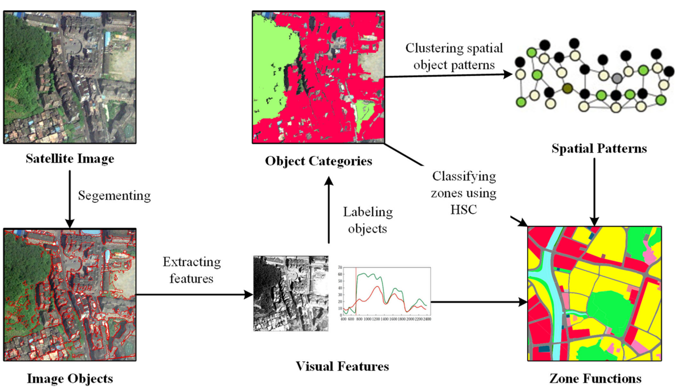


Fig. 5. Procedure of functional-zone classification by using HSC in [82].

extracted from High-Resolution Ortho (HRO) images, and text information detected from Google Street View (GSV) images, are chosen as input variables in a random forest classifier for land use classification. The results indicated that the introduction of GSV images has a positive effect on improving the overall classification accuracy. Besides, the feature importance analysis revealed that the main factors influencing land use classification are the features derived from LiDAR and HRO images. Features extracted from GSV images were not significant but played an important role in improving the classification accuracy of commercial and residential mixed building parcels.

As shown in Fig. 5, Zhang *et al.* [87] proposed a novel method, that is, hierarchical semantic cognition, and integrated four semantic layers, that is, visual features, object categories, spatial object patterns, and zone functions, as well as their hierarchical relations, for land use classification, which outperforms traditional methods like SVM and LDA. A great innovation is that a hierarchical structure instead of roughly stacking feature vectors was put forward to characterize function zones, which might be a potential and expectable trend in future studies.

Decision fusion refers to the comprehensive analysis and determination of results derived from multisource big data in the final stage of land use classification. For instance, Jia *et al.*

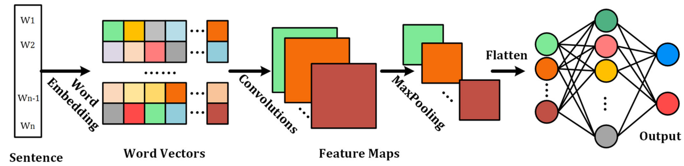


Fig. 6. The structure of the CNN architecture for Weibo message classification in [26].

[32] obtained land cover map and initial land use map, respectively, based on remote sensing images and real-time population positioning data. After implementing preliminary results, comprehensive land use interpretation was conducted to generate the final land use map based on rule-based decision fusion methods.

2) Environmental and Disaster Monitoring: In addition to fundamental geographic features such as land use and land cover, geospatial big data and remote sensing data can be well integrated to map and forecast natural disasters such as floods and typhoons [3], [92], which are rather important for researchers and policymakers.

For example, Wang *et al.* [93] developed a method for detecting and predicting weather-driven natural hazards (such as floods, hurricanes, and other severe weather) by integrating remote sensing and social media data. Their method presented a novel solution to address the inherent limitations and showed valuable capability when large areas were affected. Rosser *et al.* [94] proposed a rapid flood inundation mapping framework by using social media, remote sensing, and topographic data. In their study, geo-tagged photos with keywords of "flood" were retrieved from Flickr to preliminarily determine the cumulative viewshed. The Landsat 8 remote sensing images were used for water detection and DTM was used for aiding flood monitoring. After that, the above-mentioned data were fused and the results showed that the combination of these data sources together enables effective and rapid generation of floodwater inundation mapping at the pixel level. This is a good example to illustrate that real-time and reliable ground observation can be achieved by combing social media big data with complementary remote sensing data set, which is of great significance for real-time monitoring and early warning of disasters.

In the experiment of Li *et al.* [26], social media data were collected to assist in timely emergency monitoring and response. In their work, Weibo messages related to rainfall were acquired and input into a Convolutional Neural Network (CNN) architecture. The structure of the proposed CNN classifier was illustrated in Fig. 6. For each of these Weibo messages, all the segmented words were first embedded into distributed encoding vectors, then the sequences were feed into a CNN architecture to train a discriminating model. The trained model performed well in distinguishing whether a Weibo message was related to heavy rainfall events. By doing so, real-time extreme weather and natural disasters information can be obtained for monitoring, which can further help for decisive and rational response.

3) Socioeconomic Dynamics Sensing: Due to the human activity attributes of geospatial big data, they can be well used to monitor social and economic dynamics [11], which can make

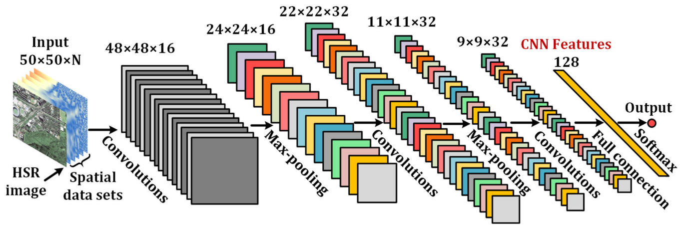


Fig. 7. The proposed UMCNN network used to fuse multisource data sets in [91].

up for the deficiency that remote sensing images can only observe the physical characteristics of the land surface [31], [95]. Socioeconomic factors, such as poverty and house price, can now be quantitatively estimated by adopting remote sensing and geospatial techniques. In fact, there have been studies that identify poverty in the developing world from HSR satellite imagery using deep learning techniques [95]. However, geospatial big data provide more representative information and more timely response compared with remote sensing data sets.

For example, an interesting case study of fine-grained house price mapping in Shenzhen, China was presented in [96]. A total of 4331 sets of valid residence price data in ten districts were obtained from the internet. In addition to the HSR remote sensing image, the POI density images of the study area were obtained by kernel density estimation, and the traffic advantage images were obtained by distance analysis of OSM road network. As previously described, these images produced based on geospatial big data can act as remote sensing images collected through crowd sensors. As illustrated in Fig. 7, taking advantage of HSR remote sensing images and geospatial big data, the authors integrated them together and inputted them to a deep neural network, that is, UMCNN, for training to extract deep features. After multiple times of feature combination, the results suggested that the introduction of geospatial big data can improve the mapping accuracy and robustness effectively. In addition, this research also emitted messages that deep learning models make it possible for continuous mapping of discretely distributed urban environmental elements.

More often, geospatial big data and remote sensing data sets are combined or verified with each other to dig out invisible patterns. In the research of [97], the visible infrared imaging radiometer suite (VIIRS) nighttime light data and human dynamics were used to analyze the nationwide depopulation in urban areas during the Chinese New Year. This study explored the correlation between nighttime light data and social media human mobility data and indicated that the geospatial big data show great potential in observing socioeconomic dynamics at fine-grained timescales.

TABLE I
EXAMPLES OF INTEGRATING REMOTE SENSING AND GEOSPATIAL BIG DATA

Category	Reference	Data Sources	Data fusion strategy
Land use and land cover extraction	[85]	HSR image, POIs, OSM roads	NDVI, NDBI derived from HSR images were combined with POI density.
	[90]	HSR image, POIs, OSM roads, Weibo check-in	Spectral and texture attributes, and landscape metrics derived from HSR images, as well as density of POI and Weibo posts, were combined.
	[31]	HSR image, POIs, OSM roads, RTUD	High-level semantic features, extracted from HSR image features, that is, spectral, texture, SIFT and GIST, POIs and RTUD through topic models, were integrated.
	[91]	LiDAR, HRO image, GSV images	Integration of multiple features, including building area, NDVI, and text length detected from GSV.
	[87]	HSR image, POIs	Four hierarchical semantic feature space, that is, visual features, object category, spatial pattern, zone function, were considered for land use classification by HSC.
	[32]	HSR image, real-time population positioning data	Decision fusion rules were used for determining land use based on initial land use and land cover maps, which were generated from HSR image and population positioning data, respectively.
Environmental and disaster monitoring	[93]	Landsat 8 image, Twitter	Remote sensing information and social media information were integrated after the homogenization process.
	[94]	Flickr photos, Landsat 8 images, DTM	Cumulative viewshed derived from Flickr and DTM was fused with water index extracted from Landsat images to improve the mapping accuracy of flood.
	[26]	Weibo message	Text-format messages were used to train a heavy rainfall events-related classification model to complement the remote sensing data.
Socioeconomic dynamics sensing	[96]	Online housing price data, POIs, OSM roads, HSR remote sensing image,	POI density images and HSR images were composited and used to train a UMCNN model for house price estimation.
	[97]	real-time population positioning data, VIIRS night-light time data	The correlation of the brightness of night-time light data and social media positioning data were built.

C. Example Summary

Table I summarizes some cases mentioned in this article that integrate remote sensing images and spatial big data to improve application and service capacity. It is not difficult to find the current researches pay more attention to extracting features from static geo-tagged point-like data and combining them with features extracted from remote sensing images. In fact, there are still many different types of geospatial big data, especially dynamic or more expressive data, such as trajectory data, crowd profiles, which can be further explored in remote sensing applications. In addition to data sources, fusion strategy might be improved by transforming the linear combination of features into hierarchical structures. Moreover, popular deep learning technologies such as CNN, recurrent neural network, and generative adversarial network, according to the characteristics and application scenarios of the algorithm itself, may play a role in the integration of remote sensing images and geospatial big data for environmental monitoring, evaluation, and prediction [98].

IV. Limitation and Future Research

Although the integration of remote sensing and geospatial big data has great potential for overcoming the limitation of each single source of data, it may also create new problems. For example, remote sensing data and spatial big data usually have different spatial and temporal resolutions, so the process of data fusion is usually time-consuming and it is hard to ensure that the results are both satisfactory in spatial and temporal resolutions. Also, due to the difference in data structure, remote sensing data and geospatial big data are also different in data magnitudes. Geospatial big data are usually much larger than remote sensing data, so it is also hard to collect and preserve it. Last, remote sensing data have wider cover ranges than geospatial big data since the latter usually concentrates in areas of intense human activities. Thus, the range of data fusion can only cover the area where both data ranges overlap.

Despite the limitation, the fusion of remote sensing and geospatial big data still has great potential. For instance, data fusion can help us have a better understanding of the interaction between human activities and natural elements, so how to make the best of the advantages of each data is worth to being further studied. Also, most of the existing studies simply fuse both data and ignore some potential difference, so how to fuse both data when they are in great difference also needs more attention.

V. Conclusion

In this article, we focused on the progress of remote sensing and geospatial big data and the potential that they can fuse with each other to provide more information. We first provided an overview of the research and technological innovation brought by the explosive growth of geospatial big data. Two popular concepts, "social sensing" and "urban computing" were introduced to highlight the important role of social media big data in the study of urban sensing. After that, based on their respective strengths and weaknesses, we analyzed the feasibility and application trends of the integration of remote sensing and geospatial big data. Finally, some examples of combining remote sensing and geospatial big data to solve practical problems including land use and land cover extraction, environmental and disaster monitoring, and socioeconomic dynamics sensing were reviewed, demonstrating the effectiveness of introducing geospatial big data into remote sensing applications.

As location-based human activity information becomes more pervasive, refined, and accessible, geospatial big data will play an irreplaceably significant role in various aspects integrating with remote sensing. Remote sensing information will be organically coupled with citizen sensing knowledge to provide efficient decision-making support from multiple perspectives and scales, driving the remote sensing applications to a new paradigm shift. However, many pieces of research mainly focus on the concatenation of multiple features and many issues remain to be explored, such as the representativeness and locality of geospatial big data. Moreover, the way of multisource geo big data fusion requires further exploration and validation. We believe that data sources, fusion strategies, as well as analytical approaches will get dramatic improvements with the development of emerging technologies and the popularity of interdisciplinarity. More expressive and dynamic geospatial big data such as trajectory flow and user profiles, as well as more advanced and automated algorithms especially deep learning techniques, will be employed in the hierarchical integration of remote sensing and geospatial big data.

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