Academic Journal of Science and Technology
ISSN: 2771-3032 | Vol. 4, No. 3, 2022

Research on Remote Sensing Retrieval Method of PM2.5 Based on FY-4A Satellite with Multiple Machine Learning Methods

Wenwei Li[1], Xiaofang Liu[1, *]

[1] School of Computer Science and Engineering, Sichuan University of Science & Engineering, Yibin, 644000, China
[*] Corresponding author: Liu Xiaofang(Email: lxf1969@suse.edu.cn)

Abstract: Satellite remote sensing technology can see the breadth and fineness that humans cannot see, and can see the spatio-temporal changes that humans cannot see. The inversion of PM2.5 based on remote sensing satellite has wide spatial coverage and relatively high spatial and temporal resolution, and the estimation results are reliable and easy to obtain, which can provide the data basis and scientific basis for managing PM2.5 pollution. This paper summarizes 2 aspects from remote sensing information processing technology and PM2.5 concentration estimation model. The development trend of current satellite remote sensing technology is analyzed from the perspective of the principle and development of satellite remote sensing technology, and the basic analytical thinking and analytical steps of current remote sensing information technology processing are described from the starting point of remote sensing information acquisition and processing technology; the advantages, disadvantages and adaptability of different models are pointed out through the comparative analysis of domestic and foreign estimation models of PM2.5 concentration. The study shows that the number of remote sensing satellites in China is increasing year by year, and remote sensing data and estimation models are being used effectively and improved gradually.

Keywords: Satellite remote sensing, PM2.5 inversion, Machine learning, Remote sensing applications.

1. Introduction

With rapid global urbanization and industrialization, anthropogenic emissions of air pollutants remain high, with PM2.5 (fine particles ≤2.5 μm in size) becoming one of the most serious air pollution pollutants. Studies [1-3] have shown that short-term or long-term exposure to PM2.5 can have adverse effects on human health, leading to increased morbidity and mortality from diseases such as chronic obstructive pneumonia, heart disease, and cancer. Relevant data from the World Health Organization (WHO) [4] indicate that approximately 4.2 million and 7 million people die each year from ambient air pollution and particulate air pollution. In China, especially in some high population density and high pollution areas (e.g., Beijing-Tianjin-Hebei region [5] and Yangtze River Delta region [6-7]), PM2.5 pollution is one of the major risk factors for premature mortality in the population [8]. Currently, PM2.5 pollution has become a focal point of concern for the public, researchers and policy makers.

2. Satellite Remote Sensing Technology

Satellite remote sensing is an important technical means to collect data information of the Earth, which has many characteristics such as no national boundary limitation, wide coverage area, periodicity of observation, and objective data [9]. It can see the breadth and fineness that humans cannot see, and can see the spatial and temporal changes that humans cannot see. According to the field of earth observation, it is mainly divided into three major types of land satellites, ocean satellites and meteorological satellites.

From the stages of development of remote sensing technology, we can find a common feature is non-contact remote observation. Therefore, we also often define remote sensing as remote sensing, which is a general reference to all non-contact, long-distance detection. At present, the remote sensing technology we are talking about mainly refers to the application of detection instruments to detect, without contact with the detection target, the electromagnetic wave characteristics of the target from a distance to record, through analysis, to reveal the characteristics of the object properties and its changes in a space detection technology.

Satellite remote sensing takes artificial earth satellite as the remote sensing platform, mainly using radio and radar and other technical means to observe and sense the surface target directly from space. At present, satellite remote sensing technology has been widely used in various fields such as agriculture, forestry, geology, ocean, military and environmental protection. Through the observation of remote sensing satellites, it can obtain a large range of data image information, and its speed of information acquisition and short cycle time are incomparable to manual field measurement and aerial photogrammetry. Moreover, the access to information is less restricted by conditions. In deserts, swamps, high mountains, and water bodies under the ice layer, which are difficult to be reached by human beings, various valuable information can be obtained timely through remote sensing satellites. Fewer foreign remote sensing satellites will be launched in 2020, and the total number of launches of other countries is about one-half of China's launches (13/27). 164 global remote sensing satellites were launched in 2018, 82 in 2019, and 40 in 2020 so far, and the number of global remote sensing satellite launches has declined in the past three years. Combined with the China Remote Sensing Industry Market Foresight and Investment Strategic Planning Analysis Report [10], there are three overall trends: 1) optical imaging satellites account for more than half of the total; 2) near-Earth orbit satellites account for the vast majority; and 3) the number of commercial remote sensing satellites accounts for a rising proportion.

Today, China's satellite development has now gone through more than 40 years, and the number of remote sensing satellites is increasing, showing the "three high" characteristics of high spatial resolution, high spectral resolution and high temporal resolution. And it is also widely used in environmental protection, monitoring, land, planning and other industries.

3. Remote Sensing Data Processing and Information Extraction Techniques

Remote sensing data acquisition and distribution, data processing and information extraction are the two basic steps of satellite remote sensing application. Thanks to the overall progress of China's satellite remote sensing technology and the drive of open source thinking, China has made great progress in remote sensing data processing and information extraction technology, and the technical capability is changing from catching up with the world's advanced technology mainly to independent innovation mainly.

3.1. Quantification of remote sensing data

From the perspective of quantification of remote sensing data, the remote sensing data currently released in China are mainly level 1 relative radiation correction products, which require users to produce their own standard products, making differences in quantitative parameters such as reflectance and temperature in the inversions of different users.

3.2. Remote sensing data information extraction

From the perspective of remote sensing data information extraction, domestic remote sensing information extraction technology has changed from traditional statistical methods to data-driven and artificial intelligence methods, but on the whole, the application of industry a priori knowledge is still insufficient, and the integration of data-driven and knowledge-driven methodologies will be one of the key issues in the industrialization of the technology.

(1) Remote sensing data analysis thinking

Algorithmic thinking is based on the remote sensing data level, using image spectral, texture, shape features, and even DEM or spatial and temporal high-dimensional feature expansion as much as possible, and the process of obtaining remote sensing information using sample learning based on machine learning algorithms [15-16]. The current widely focused deep learning can also be considered as a class of algorithmic thinking. It combines data and algorithms in depth based on deep convolutional neural networks to directly fit the mapping relationship between the image space of remote sensing images and the target object, making the features that need to be designed manually hidden in the linked parameters of the automated fit, without the need to manually display the design of interpretable features [17-18]. A constraint for it to be achieved with high accuracy is that the visual features of the sample images are locally correlated or local feature features do not change with position [19].

Geological thinking is commonly proposed by researchers in the field of geology [16-17,20-21], which makes full use of the existing knowledge and relevant data in the field of geology and simulates the way of thinking of geological experts in interpretation [22-23]. An early representative study was an expert intelligent interpretation system based on high-resolution remote sensing images [24-25]. After that, spatial cognition has received wide attention and importance from the geoscientific community, and the research content mainly focuses on several aspects such as universal laws of spatial cognition, mining of structured geographic information and spatio-temporal reasoning, and some studies on the interface between remote sensing information extraction and geoscientific knowledge have been carried out under the impetus of this. For example, remote sensing-based high-precision vertical band mapping of mountains using topography and existing small-scale vegetation maps [26-29].

(2) Remote sensing data processing

The process of remote sensing data processing is shown in Figure 1.

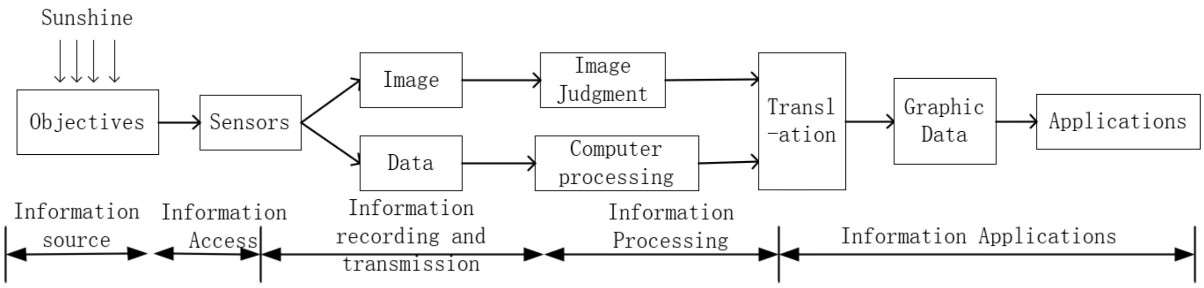

Figure 1. System Architecture

Considering the great potential demand for satellite remote sensing data in China's national economic construction, it is necessary to establish a product and technology system oriented to global standards and specifications based on domestic satellite constellation resources, fully integrate the technical achievements in communication, navigation, network, GIS and other related fields, build high-performance and intelligent practical software tools and platforms, provide broader and deeper business services, and establish sustainable industrial development capability through the gradual development and improvement of market mechanism.

4. PM2.5 Inversion Model

PM2.5 concentration estimation methods are divided into three main categories, and PM2.5 concentration estimation methods are shown in Figure 2. Empirical statistical methods including machine learning, chemical transport model-based methods, and other methods such as semi-empirical formulations. The performance of each method depends on the study area and period as well as the spatial and temporal resolution of the data, and a single method does not always perform best in different applications [30].

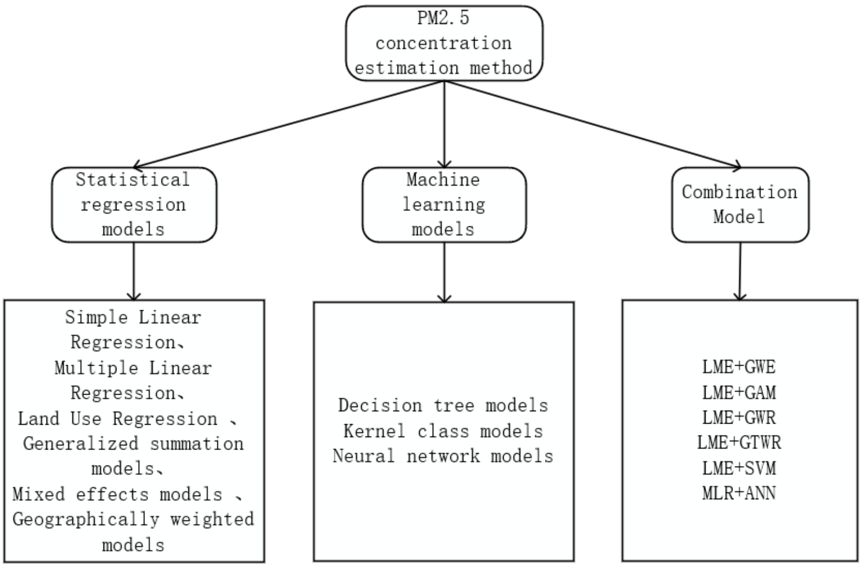

Figure 1. PM2.5 concentration estimation method

4.1. Statistical regression models

Previous studies established linear regression models (SLR) based on the linear relationship between AOD-PM2.5 and obtained better fitting results [31-32]. However, this relationship varies from region to region and time to time due to the effects of emissions and changing meteorological conditions. More meteorological variables (including relative humidity, temperature, wind speed, and planetary boundary layer height, etc.) need to be incorporated, and multiple linear regression models (MLR) can better represent the AOD-PM2.5 relationship [33-34].

Currently, related studies usually use MLR models as a comparison model to other models or combine other models to better estimate PM2.5 concentrations. For example, Li et al [35] developed a generalized regression neural network model (GRNN) to estimate PM2.5 concentrations in China with a CV R2 of 0.82 compared to the MLR model (CV R2 = 0.53); Chelani et al [36] estimated PM2.5 concentrations in five Indian cities by building a combined model of MLR model and MLR residual model, and the combined model outperformed MLR; Ahmad et al [37] developed a new method combining MLR and artificial neural network (ANN) to estimate PM2.5 concentrations in Karachi (a city in Pakistan) for 2015-2017 using AOD, land use and meteorological parameters with R2 range of 0.76 to 0.96. Land use regression model (LUR) was developed using MLR model based on land use related variables that reflect the characteristics of the surrounding environment such as industrial land area, road length, traffic volume and population density [38].

Xu Gang et al [39] selected six types of predictor variables for land use road traffic, population density, industrial pollution sources, elevation, and meteorological variables with PM2.5 to develop a LUR model to simulate the spatial distribution of PM2.5 concentrations in Beijing, Tianjin, and Hebei in 2013 with a CV R2 of 0.78. Li et al [40] established the relationship between seasonal MAIAC AOD and measured ground-level PM2.5 concentrations in Beijing and developed seasonal LUR model, and the results showed that incorporating AOD into the LUR model could improve the performance of the model in spring and provide more reliable results during the test. The above approach neither takes into account the time-varying nature of the predictor variables that shadow the AOD-PM2.5 correlation nor the spatially non-constant nature of the relationship.The linear mixed effects (LME) model proposed by Lee et al [41] in 2011 uses fixed and random slopes and intercepts to calibrate the predictor variables to establish the AOD-PM2.5 relationship (CV R2=0.92). Among them, the random effect reflects the variation of the variable with time or monitoring stations, and the fixed effect is the average effect of AOD on PM2.5, independent of the variation of time and monitoring stations [42]. On this basis, Sun Cheng et al [43] developed an LME model between PM2.5 data and MODIS AOD, meteorological variables, and land use variables with a CV R2 of 0.77. Ma et al [44] proposed a nested LME model, including nested monthly, weekly, and daily specific random effects for the AOD-PM2.5 relationship, to estimate PM2.5 concentrations in the Yangtze River Delta (CV R2= 0.67).Kloog et al [45] proposed a three-stage LME model and verified the feasibility in England (CV R2=0.83).Wang et al [46] constructed a spatio-temporal linear mixed effects (STLME) model based on AHIAOD to estimate the hourly values of PM2.5 concentrations in the Beijing-Tianjin-Hebei region in 2018 (time-dimensional CV R2=0.75, spatial dimension CV R2=0.83). Currently, many studies still use the LME model to estimate PM2.5 concentrations, but often add the AOD complementary model or more models to improve the estimation accuracy.Brunsdon et al [47] based on the assumption that "the regression coefficients are a function of the spatial location of the observation points in the linear regression" and assign spatial weights based on the distance between observation points. Hu et al. [48] introduced AOD into GWR and performed the estimation of PM2.5 concentration in the United States. Later, Ma et al [49] proposed a daily GWR model and confirmed that adding meteorological and land use information to the model could greatly improve the model performance. Based on this, to better capture both spatial and temporal heterogeneity, Bai et al [50] proposed a geo-temporally weighted regression model (GTWR) and confirmed that it has better performance than a single GWR model. To better estimate PM2.5 concentrations in the absence of AOD, He et al [51] developed an improved geographic and time-weighted regression model (iGTWR) that incorporates seasonal features in the data and achieves comparable performance to the standard GTWR model for days with paired PM2.5-AOD samples, and for days without PM2.5-AOD data pairs showed better predictive power. Meanwhile, He et al [52] developed another spatio-temporal regression model for estimating daily PM2.5 concentrations in combination with the interior point algorithm (IPA), which achieved good validation (CV R2 = 0.80). In addition, adding interaction terms (quadratic terms) to the GTWR model can better describe the nonlinear effects [53].

In addition to the models mentioned above, other studies have used generalized summation (GAM) models [54-55], kriging methods [56], or nonlinear regression models. All these PM2.5 estimation models use AOD as the main independent variable, the predictability of the models is limited, their R2 is generally low, and there are differences between regions. However, these models have been gradually optimized or integrated into other models.

4.2. Machine learning models

Machine learning models, with their powerful ability to handle complex nonlinear relationships among various interacting variables and to accommodate growing data sizes and predictor variables [57-58], are widely applied to estimate near-ground PM2.5 concentrations. There are three main types of machine learning models, which are decision tree-type models, kernel-type models, and neural network-type models.

Among the decision tree class models, the more popular models: random forest (RF), gradient boosting decision tree (GBDT), gradient boosting machine (GBM), and extreme gradient boosting (XGB).Wei et al [59] developed a spatio-temporal random forest (STRF) model to estimate daily PM2.5 concentrations at 1 km resolution in China in 2016 and confirmed that it outperformed some statistical regression models (MLR, GWR, and LME+GWR). Currently, studies using RF models and improved models for PM2.5 concentration estimation continue to increase [60,61-63].GBDT shows greater robustness and generalization ability than RF models when dealing with complex variables of interest [57]. In addition, GBM and XGB are representative boosting methods with the advantage of reducing model bias and variance, but both methods suffer from overfitting problems and require adjustment of model parameters [64].

Support vector machines (SVMs) based on machine learning and generalization theory are representative algorithms that use kernel class models. It has better performance compared to other machine learning models [65-66]. In addition, there are studies that optimize SVMs or integrate them into other models. For example, Hou et al [67] developed a continuous super-relaxed support vector regression (SOR-SVR) model to estimate PM2.5 concentrations based on AOD and meteorological parameters with an R2 of 0.87. Yang et al [68] proposed a two-stage statistical model combining LME and SVM to estimate PM2.5 concentrations near the ground in Fuzhou with an R2 of 0.81.

Neural network algorithms have been used for PM2.5 concentration estimation, including artificial neural networks (ANN), deep neural networks (DNN), back propagation neural networks (BPNN), generalized regression neural networks (GRNN), and deep belief networks (DBN). Currently, various typical neural network models have been used to improve the accuracy of PM2.5 estimation by applying structural deformation. For example, Li et al [69] developed a geo-intelligent deep learning (Geoi-DBN) model that incorporates geographic correlation into an intelligent deep learning architecture and performs significantly better than traditional neural networks.Zang et al [70] combined PM10 and PM2.5 and hourly AHIAOD into an improved generalized regression neural network model, the PCA-GRNN model. The R2 reached 0.74 compared to the conventional GRNN model (R2 = 0.67).Chen et al [58] combined AOD, meteorology and other auxiliary variables to develop an adaptive deep neural network (SADNN) model to estimate daily spatially continuous PM2.5 concentrations for 2017-2018 with an R2 of 0.86.

4.3. Combination Model

To reduce the bias associated with individual model estimates, many studies have begun to calibrate the spatio-temporal relationships between PM2.5, AOD, and other auxiliary variables by combining 2 or more models.

The LME+GWR or LME+GAM model in Figure 3-1 is the most commonly used combination approach, where the residuals are modeled with AOD using the second-stage model by considering the residuals between the first-stage model estimation results and the original data. guo et al [71] confirmed that the combined LME+GWR model is superior to the single LME model; Ma et al [72] found that the LME+GAM model is better at estimating daily-scale PM2.5 concentrations with larger errors and performed better at monthly and seasonal levels; Zhang et al [73] used the two combined models for comparison and found that the LME+GWR model outperformed the LME+GAM model. In addition, the TEFR+GWR spatial structure adaptive combination model developed by Yao et al [74] and the IPW+GAMM+KED three-stage combination model developed by Liang et al [75] also achieved the desired effect of estimation. More and more studies improve the accuracy of PM2.5 estimation by adding machine learning models to the combined models, such as MLR+ANN or LME+SVM combined models with CV R2 ranging from 0.8 to 0.9. The addition of machine learning models can effectively improve the accuracy of PM2.5 concentration estimation and better explain the nonlinear relationships between variables that cannot be quantified by statistical regression models. In summary, the combined model has better near-ground PM2.5 concentration estimation capability than the individual models. However, the additional steps may make the analysis process more complicated and the technical details may be more confusing.

4.4. Combination Model

Selection of traditional machine learning models for PN2.5 inversion based on data from Jilin Province in 2018.Where DNN is a 6-layer structure (1024, 512, 256, 128, 128, 64).

Table 1. Algorithm Comparison

Number	RF	LR	CatBoost
MAE	8.38	18.08	11.84
RMSE	15.08	27.38	19.23
R2	0.75	0.17	0.61

The results of the PM2.5 inversion model based on the multi-machine learning method in Jilin Province are shown below.

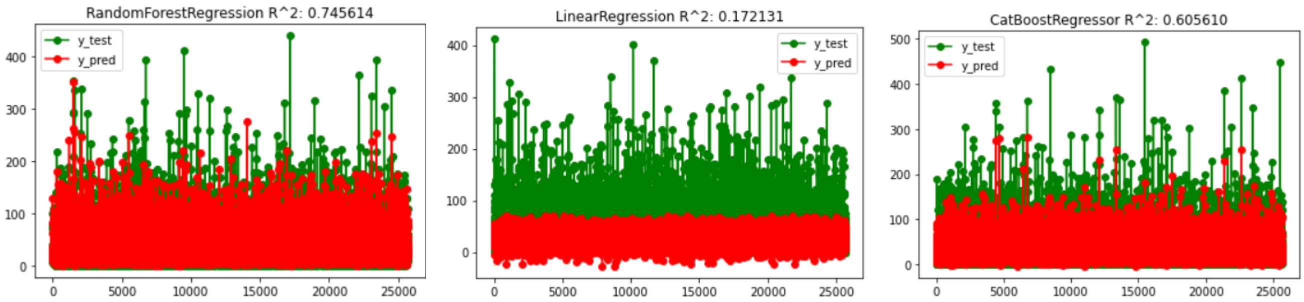

Figure 3. Comparison of multiple machine learning models

5. Conclusion

The manuscript should include a conclusion. In this section, summarize what was described in your paper. Future directions may also be included in this section. Authors are strongly encouraged not to reference multiple figures or tables in the conclusion; these should be referenced in the body of the paper.

References

[1] Lim S S, Vos T, Flaxman A D, et al. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990-2010: a systematic analysis for the global burden of disease study 2010[J]. The Lancet, 2012, 380(9859): 2224-2260.

[2] Cohen A J, Brauer M, Burnett R, et al. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the global burden of diseases study 2015[J]. The Lancet, 2017, 389(10082): 1907-1918.

[3] Gu Y, Wong T W, Law C K, et al. Impacts of sectoral emissions in China and the implications: air quality, public health, crop production,and economic costs[J]. Environmental Research Letters, 2018, 13(8): 084008.

[4] World Health Organization (WHO). Air Pollution. 2021(https://www.who.int/airpollution/en/).

[5] Wang Qing, Zhu Huanhuan, Du Peng, etc Research on health benefit prediction of the "Fourteenth Five Year Plan" and medium and long-term PM2.5 pollution control targets in Beijing, Tianjin, Hebei and surrounding areas [J] Environmental Science Research, 2021, 34 (1): 220-228.

[6] Zhang Yihua Temporal and spatial variation characteristics of PM2.5 regional pollution in Yangtze River Delta [J/OL] Environmental science research: October 15, 2021 https://doi.org/10.13198/j.issn.1001-6929.2021. 09.03.

[7] Wang Xiaoyuan, Jiang Fei, Xu Shengchen, et al Assessment on the Emergency Emission Reduction Effect of Heavy Air Pollution in the Yangtze River Delta Region [J] Environmental Science Research, 2020, 33(4): 783-791.

[8] Wang Qing, Wang Jiaonan, He M Z, et al. A county-level estimate of PM2.5 related chronic m ortality risk in China based on multi-model exposure data[J]. Environment International, 201 8, 110: 105-112.

[9] Zhao Zhongming, Gao Lianru, Chen Dong, et al Development of satellite remote sensing and image processing platform [J] Chinese Journal of Image Graphics, 2019, 24 (12): 13.

[10] Prospective Economist Analysis on the Current Situation and Development Trend of the Global Remote Sensing Satellite Launch Market in 2020 [EB/OL] 2020-05-01.

[11] Jordan M. I, Mitchell T. Machine learning: Trends,perspectives, and prospects[J]. Science, 2015, 349(6245): 255-260.

[12] Lake B M, Salakhutdinov R, Tenenbaum J B. Human-level concept learning through probabilistic program induction[J]. Science, 2015, 350(6266): 1332-1338.

[13] Silver D, Schrittwieser J, Simonyan K, et al. Masteringthe game of Go without human knowledge[J]. Nature, 2017, 550(7676): 354-359.

[14] Silver D, Huang A, Maddison C J, et al. Mastering thegame of Go with deep neural networks and tree search[J]. Nature, 2016, 529(7587): 484- 489.

[15] Jean N, Burke M, Xie M. Combining satellite imageryand machine learning to predict poverty[J]. Science, 2016, 353(6301): 790-794.

[16] Baez-Villanueva O M, Zambrano-Bigiarini M, Beck H, et al. RF-MEP: A novel Random Forest method for merging gridded precipitation products and ground-based measure ments[J]. Remote Sensing of Environment, 2020, 239(111606):1-19.

[17] Zhang L P, Zhang L F, Du B. Deep learning for remotesensing data: A technical tutorial on the state of the art[J]. IEEE Geoscience & Remote Sensing Magazine, 2016, 4(2): 22-40.

[18] Yuan Q Q, Shen H F, Li T W, et al. Deep learning in environmental remote sensing: Achievements and challenges[J]. Remote Sensing of Environment, 2020, 241(111716).

[19] Goodfellow I, Bengio Y, Courville A. Deep learning [M]. Cambridge: The MIT Press, 2016.

[20] Zhou Chenghu, Luo Jiancheng Geoscience Calculation of High Resolution Satellite Remote Sensing Image [M] Beijing Science Press, 2008.

[21] Gong Peng A View on the Application of Remote Sensing Science [J] Journal of Remote Sensing, 2019, 23 (4): 567-569.

[22] Blaschke T. Object based image analysis for remote sensing[J]. ISPRS Journal of Photogrammetry and RemoteSensing, 2010, 65(1): 2-16.

[23] Blaschke T, Hay G J, Kelly M, et al. Geographic objectbased image analysis-towards a new paradigm[J]. ISPRS Journal of Photogrammetry and Remote Sensing, 2014, 87: 180-191.

[24] Zhu A X, Band L E. A knowledge-based approach to dataintegration for soil mapping[J].Canadian Journal of Remote Sensing, 1994, 20(4): 408-418.

[25] Yan Shouyong Theory and method of remote sensing image group interpretation [M] Beijing Ocean Press, 2007.

[26] Yao Y H, Suonan D Z, Zhang J Y. Compilation of 1:50 000 vegetation type map with remote sensing imagesbased on mountain altitudinal belts of Taibai Mountain inthe North-South transitional zone of China[J]. Journal of Geographical Sciences, 2020, 30(2): 267-280.

[27] Rahbek C, Borregaard M K, Colwell R K, et al. Humboldt's enigma: What causes global patterns of mountain biodiversity[J]. Science, 2019, 365(6458): 1108-1113.

[28] Fattorini S, Di B L, Chiarucci A. Recognizing and interpreting vegetational belts: New wine in the old bottles ofa von Humboldt's legacy[J]. Journal of Biogeography, 2019, 46(8): 1643- 1651.

[29] Zhang Baiping, Zhou Chenghu, State Peng Discussion on the information atlas of China's ft vertical belt [J] Journal of Geography, 2003, 58 (2): 163-171.

[30] Ranjan A K,Patra A K,Gorai A K. A review on estimation of particulate matter from satellite- based aerosol optical depth: data, methods, and challenges[J]. Asia-Pacific Journal of Atmosp heric Sciences, 2020, 57(3): 679-699.

[31] Wang Jun, Christopsir S A. Intercomparison between satellite-derived aerosol optical thickne ss and PM2.5 mass:implications for air quality studies[J]. Geophysical Research Letters, 200 3, 30(21): 2095.

[32] Engel-Cox J A, Holloman C H, Coutant B W, et al. Qualitative and quantitative evaluation of MODIS satellite sensor data for regional and urban scale air quality[J]. Atmospheric Environ ment, 2004, 38(16): 2495-2509.

[33] Guptaa P,Christopher S A. Particulate matter air quality assessment using integrated surface, s atellite, and meteorological products:multiple regression approach[J]. Journal of Geophysical Research, 2009, 114: D14205.

[34] Li Xiaotian, Wu Shaohua, Xu Yuyue, et al Simulation of temporal and spatial variation pattern of PM2.5 mass concentration in Jiangsu Province [J] environmental monitoringManagement and Technology, 2017, 29 (2): 16-20.

[35] Li Tongwen, Shen Huanfeng, Zeng Chao, et al. Point-surface fusion of station measurements and satellite observations for mapping PM2.5 distribution in China:methods and assessment [J]. Atmospheric Environment, 2017, 152: 477-489.

[36] Chelani A B. Estimating PM2.5 concentration from satellite derived aerosol optical depth and meteorological variables using a combination model[J]. Atmospheric Pollution Research, 201 9, 10(3): 847-857.

[37] Ahmad M, Alam K, Tariq S, et al. Estimating fine particulate concentration using a combined approach of linear regression and artificial neural network[J]. Atmospheric Environment, 201 9, 219: 117050.

[38] Shin M, Kang Y, Papk S, et al. Estimating ground-level particulate matter concentrations usin g satellite-based data:a review[J]. GIScience & Remote Sensing, 2019, 57(2): 174-189.

[39] Xu Gang, Jiao Limin, Xiao Fengtao, et al The land use regression model simulates the spatial distribution of PM2.5 concentration in Beijing Tianjin Hebei [J]. Drought District Resources and Environment, 2016, 30 (10): 116-120.

[40] Li Runkui, Ma Tianxiao, Xu Qun, et al. Using MAIAC AOD to verify the PM2.5 spatial patte rns of a land use regression model[J]. Environmental Pollution, 2018, 243: 501-509.

[41] Lee H J, Liu Y, Coull B A, et al. A novel calibration approach of MODIS AOD data to predict PM2.5 concentrations[J]. Atmospheric Chemistry and Physics, 2011, 11(15): 7991-8002.

[42] Xu Xinghan, Zhang Chengkun, Liang Yi. Review of satellite-driven statistical models PM2.5 concentration estimation with comprehensive information[J].Atmospheric Environment, 202 1, 256: 118302.

[43] Sun Cheng, Wang Wei, Liu Fangtian, et al Study on temporal and spatial variation model of PM2.5 concentration in Hebei Province based on linear mixed effect model[J]. Environmental Science Research, 2019, 32 (9): 1500-1509.

[44] Ma Zongwei, Liu Yang, Zhao Qiuyue, et al. Satellite-derived high resolution PM2.5 concentr ations in Yangtze River Delta region of China using improved linear mixed effects model[J]. Atmospheric Environment, 2016, 133: 156-164.

[45] Kloog I, Koutrakis P, Coull B A, et al.Assessing temporally and spatially resolved PM2.5 exp osures for epidemiological studies using satellite aerosol optical depth measurements [J]. At mospheric Environment, 2011, 45(35): 6267-6275.

[46] Wang Wei, He Junchen, Miao Zelang, et al. Space-Time Linear Mixed-Effects (STLME) model for mapping hourly fine particulate loadings in the Beijing-Tianjin-Hebei region, China[J].Journal of Cleaner Production, 2021, 292:125993.

[47] Brunsdon C, Fotheringham A S, Charltoam E. Geographically weighted regression: a method for exploring spatial nonstationarity[J]. Geographical Analysis, 1996, 28(4):281-298.

[48] Hu Zhiyong. Spatial analysis of MODIS aerosol optical depth, PM2.5, and chronic coronary heart disease[J]. International Journal of Health Geographics, 2009, 8:27.

[49] Ma Zongwei, Hu Xuefei, Huang Lei, et al. Estimating ground-level PM2.5 in China using sat ellite remote sensing[J]. Environmental Science & Technology, 2014, 48(13): 7436-7444.

[50] Bai Yang, Wu Lixin, Qin Kai, et al.A geographically and temporally weighted regression mod el for ground-level PM2.5 estimation from satellite-derived 500m resolution AOD[J]. Remote Sensing, 2016, 8(3): 262.

[51] He Qingqing, Huang Bo. Satellite-based high-resolution PM2.5 estimation over the Beijing-T ianjin-Hebei region of China using an improved geographically and temporally weighted regr ession model[J]. Environmental Pollution, 2018, 236: 1027-1037.

[52] He Qingqing, Huang Bo. Satellite-based mapping of daily high-resolution ground PM2.5 in C hina via space-time regression modeling[J]. Remote Sensing of Environment, 2018, 206: 72-83.

[53] He Qingqing, Gu Yefu, Zhang Ming. Spatiotemporal trends of PM2.5 concentrations in centra l China from 2003 to 2018 based on MAIAC-derived high-resolution data[J]. Environment In ternational, 2020, 137: 105536.

[54] Liu Yang, Paciorek C J, Koutrakis P. Estimating regional spatial and temporal variability of P M2.5 concentrations using satellite data, meteorology, and land use information[J]. Environm ental Health Perspectives, 2009, 117(6): 886-892.

[55] You Wei, Zang Zengliang, Pan Xiaobin ,et al. Estimating PM2.5 in Xi'an,China using aerosol optical depth:a comparison between the MODIS and MISR retrieval models[J]. Science of th e Total Environment, 2015, 505: 1156-1165.

[56] Beloconi A,Kamarianakis Y,Chrysoulanks N. Estimating urban PM10 and PM2.5 concentrati ons, based onsynergistic MERIS/AATSR aerosol observations,land cover and morphology da ta[J]. Remote Sensing of Environment, 2016, 172: 148-164.

[57] Zhang Tianning, He Weihuan, Zheng Hui, et al. Satellite-based ground PM2.5 estimation usin g a gradient boosting decision tree[J]. Chemosphere, 2021, 268: 128801.

[58] Chen Binjie, You Shixue, Ye Yang, et al. An interpretable self-adaptive deep neural network f or estimating daily spatially-continuous PM2.5 concentrations across China[J]. Science of the Total Environment, 2021, 768: 144724.

[59] Wei Jing, Huang Wei, Li Zhanqing, et al. Estimating 1-km-resolution PM2.5 concentrations a cross China using the space-time random forest approach[J]. Remote Sensing of Environment, 2019, 231:111221.

[60] Jiang Tingting, Chen Bin, Nie Zhen, et al. Estimation of hourly full-coverage PM2.5 concentr ations at 1-km resolution in China using a two-stage random forest model[J]. Atmospheric Re search, 2021, 248: 105146.

[61] Huang Keyong, Xiao Qingyang, Meng Xia, et al. Predicting monthly high-resolution PM2.5 c oncentrations with random forest model in the North China Plain[J]. Environmental Pollution, 2018, 242: 675-683.

[62] Zhao Chen, Wang Qing, Ban Jie, et al.Estimating the daily PM2.5 concentration in the Beijing-Tianjin-Hebei region using a random forest model with a 0.01°*0.01° degrees spatial resolu tion[J]. Environment International, 2020, 134: 105297.

[63] Bai Heming, Zheng Zhi, Zhang Yuanpeng, et al. Comparison of satellite-based PM2.5 estimat ion from aerosol optical depth and top-of-atmosphere reflectance[J]. Aerosol and Air Quality Research, 2021, 21(2): 200257.

[64] Shin M, Kang Y, Park S, et al. Estimating ground-level particulate matter concentrations usin g satellite-based data:a review[J]. GIScience & Remote Sensing, 2019, 57(2): 174-189.

[65] Moazami S, Noori R, Amiri B J, et al. Reliable prediction of carbon monoxide using develop ed support vector machine[J]. Atmospheric Pollution Research, 2016, 7(30): 412-418.

[66] Yeganeh B, Hewson M G, Clifford S, et al. A satellite-based model for estimating PM2.5 con centration in a sparsely populated environment using soft computing techniques[J]. Environm ental Modelling & Software, 2017, 88: 84-92.

[67] Hou Weizhen, Li Zhengqiang, Zhang Yuhuan, et al. Using support vector regression to predict PM10 and PM2.5[J].IOP Conference Series:Earth and Environmental Science, 2014, 17: 012268.

[68] Yang Lijuan, Xu Hanqiu, Jin Zhifan. Estimating ground-level PM2.5 over a coastal region of China using satellite AOD and a combined model[J]. Journal of Cleaner Production, 2019, 227: 472-482.

[69] Li Tongwen, Shen Huanfeng, Yuan Qiangqiang, et al. Estimating ground-level PM2.5 by fusi ng satellite and station observations:a geo-intelligent deep learning approach[J]. Geophysical Research Letters, 2017, 44(23): 11985-11993.

[70] Zang Lin, Mao Feiyue, Guo Jianping, et al. Estimation of spatiotemporal PM10 distributions i n China by combining PM2.5 observations with satellite aerosol optical depth[J]. Science of t he Total Environment, 2019, 658: 1256-1264.

[71] Guo Wei, Zhang Bo, Wei Qiang, et al. Estimating ground-level PM2.5 concentrations using t wo-stage model in Beijing-Tianjin-Hebei,China[J].Atmospheric Pollution Research, 2021, 12: 101154.

[72] Ma Zongwei, Hu Xuefei, Sayera M, et al. Satellite-based spatiotemporal trends in PM2.5 con centrations: China, 2004-2013[J]. Environmental Health Perspectives, 2016, 124(2): 184-192.

[73] Zhang Kainan, De Leeuw G, Yang Zhiqiang, et al. Estimating spatio-temporal variations of P M2.5 concentrations using VIIRS-derived AOD in the Guanzhong Basin, China[J]. Remote S ensing, 2019, 11(22): 2679.

[74] Yao Fei, Wu Jiansheng, Li Weifeng, et al. A spatially structured adaptive two-stage model for retrieving ground-level PM2.5concentrations from VIIRS AOD in China[J]. ISPRS Journal o f Photogrammetry and Remote Sensing, 2019, 151: 263-276.

[75] Liang Fengchao, Xiao Qingyang, Wang Yuejie, et al. MAIAC-based long-term spatiotempora l trends of PM2.5 in Beijing, China[J]. Science of the Total Environment, 2018, 616-617: 158 9-1598.