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10-Year NDVI Dataset Development in 361 Cities of China (250-m, 1990–2020)

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Abstract: Vegetation cover is an important indicator used to measure the quality of the ecological environment and human settlements. However, there is still a lack of long-term NDVI datasets within urban areas. Based on Terre-MODIS NDVI and GIMMS NDVI product data, we used deep learning superresolution algorithms to produce 250-m resolution NDVI datasets for China in 1990, 2000, 2010 and 2020. Then, by superimposing the administrative scope and urban physical area in various periods, we extracted the average value of NDVI in different urban boundaries and obtained a statistical dataset of the average NDVI value of China's ten years and 361 cities (250-m, 1990–2020). This dataset indicates an initially decreasing and subsequently increasing trend of NDVI for both all of China and the urban physical areas from 1990 to 2020, yet the NDVI trend has significant spatial heterogeneity. The dataset can support urban ecological and environmental governance, urban green space planning and construction, ecological and environmental policy formulation and government performance assessment, as well as ecosystem evolution research driven by urbanization and climate change. The dataset is archived in .tif and .xlsx formats with a spatial resolution of 250 m and consists of 5 files with data size of 6.51 GB (compressed into 5 files, 1.83 GB).

Keywords: vegetation cover; urbanization; NDVI; urban physical area; deep learning, China

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Dataset Availability Statement:

The dataset supporting this paper was published and is accessible through the *Digital Journal of Global Change Data Repository* at: https://doi.org/10.3974/geodb.2023.04.06.V1 or https://cstr.escience.org.cn/CSTR:20146.11.2023.04.06.V1.

1 Introduction

Vegetation represents an essential element of ecosystems; accordingly, its coverage serves as a key indicator in the examination of broad-scale environmental shifts, informing assessments of

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[2] Liu, H. M., Zhou, T. Y., Gou, P. NDVI dataset of China and average in 361 cities (250-m, 1990–2020) [J/DB/OL]. *Digital Journal of Global Change Data Repository*, 2023. https://doi.org/10.3974/10.3974/geodb.2023.04.06.V1. https://cstr.escience.org.cn/CSTR:20146.11.2023.04.06.V1.

both ecological conditions and habitation livability[1]. Rapid urbanization in China has greatly affected vegetation cover[2], which in turn acts on the urban environment[3], exacerbating the urban heat island effect[4], adversely influencing air pollutant dispersion[5], weakening regional carbon sink capacity[6], and negatively affecting the health and well-being of urban residents[7]. Adequate and equal access to urban green space for all citizens is an important component of the United Nations 2030 Sustainable Development Goal 11[8].

The normalized differential vegetation index (NDVI) is one of the primary indicators reflecting changes in vegetation coverage. GIMMS NDVI and MODIS NDVI product data are the most commonly used NDVI datasets and have been widely applied at regional and global scales[9, 10]. MODIS data are regarded as a continuation of GIMMS data[11], but there are large gaps in spatial resolution and different temporal coverage between them, which limit our proper assessment and understanding of NDVI changes throughout the urbanization process. The existing NDVI datasets are mainly raster data or data within city administrative boundaries, with most time series being after 2000[12, 13], and there is a lack of high-resolution NDVI datasets with long time series inside of the urban physical area.

This paper collects Terre-MODIS NDVI and GIMMS NDVI product data for multiple years, takes the MODIS data with a spatial resolution of 250 m as the benchmark, uses the deep learning superresolution algorithm to spatially downscale the GIMMS dataset to extend the temporal coverage of NDVI under high resolution, and obtains the 250-m resolution NDVI dataset in China for 1990, 2000, 2010 and 2020. Then, this paper examines the Global Urban Boundary (GUB) dataset to determine the physical geographical space of cities in different periods, extracts the NDVI values in the urban physical areas, and calculates the average NDVI values within both the administrative and physical boundaries of 361 cities in China for 1990, 2000, 2010 and 2020. The dataset can provide basic data support for urban ecological and environmental governance, urban green space planning and construction, ecological and environmental policy formulation and government performance assessment, as well as for research in the field of urbanization and the ecological environment.

2 Metadata of the Dataset

The metadata of the NDVI dataset of China and average in 361 cities (250-m, 1990–2020) are summarized in Table 1[14]. The metadata include the dataset full name, short name, authors, year of the dataset, temporal resolution, spatial resolution, data format, data size, data files, data publisher, and data sharing policy.

3 Methods

3.1 Data Sources

The GIMMS NDVI dataset used in this study comes from the third generation of NDVI product data provided by the National Centers for Environmental Information, with a spatial resolution of 1/12 degree (approximately 8-km) and covering the periods 1989–1991 and 2000–2013. The Terre-MODIS NDVI product data come from the MODIS vegetation index product developed by the NASA MODIS land science team according to the unified

Table 1 Metadata summary of the NDVI dataset of China and average in 361 cities (250-m, 1990–2020)

Items	Description
Dataset full name	NDVI dataset of China and average in 361 cities (250-m, 1990–2020)
Dataset short name	ChinaCitiesNDVI_1990_2020
Authors	Liu, H. M. R-7364-2018, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, liuhm@igsnrr.ac.cn Zhou, T. Y., Research Centra of Big Data Technology, Nanhu Laboratory, zhoutianyu@nanhulab.ac.cn Gou, P., Research Centra of Big Data Technology, Nanhu Laboratory, goupeng@nanhulab.ac.cn
Geographical region	China
Year	1990, 2000, 2010, 2020
Temporal resolution	Year
Spatial resolution	250 m
Data format	.tif, .xlsx
Data size	6.51 GB
Data files	1990, 2000, 2010, 2020 China 250-m NDVI annual mean value data 1990, 2000, 2010, 2020 annual mean value data of NDVI at the administrative and physical areas of Chinese cities
Foundations	National Natural Science Foundation of China (42171210); Ministry of Education of P. R. China (22JJD790015)
Data publisher	Global Change Research Data Publishing & Repository, http://www.geodoi.ac.cn
Address	No. 11A, Datun Road, Chaoyang District, Beijing 100101, China
Data sharing policy	***Data*** from the Global Change Research Data Publishing & Repository includes metadata, datasets (in the *Digital Journal of Global Change Data Repository*), and publications (in the *Journal of Global Change Data & Discovery*). ***Data*** sharing policy includes: (1) ***Data*** are openly available and can be free downloaded via the Internet; (2) End users are encouraged to use ***Data*** subject to citation; (3) Users, who are by definition also value-added service providers, are welcome to redistribute ***Data*** subject to written permission from the GCdataPR Editorial Office and the issuance of a ***Data*** redistribution license; and (4) If ***Data*** are used to compile new datasets, the 'ten per cent principal' should be followed such that ***Data*** records utilized should not surpass 10% of the new dataset contents, while sources should be clearly noted in suitable places in the new dataset[15]
Communication and searchable system	DOI, CSTR, Crossref, DCI, CSCD, CNKI, SciEngine, WDS/ISC, GEOSS

algorithm. This study uses the MOD13Q1 dataset, which is synthesized over 16 days at 250-m resolution, and the MOD13A2 dataset, which is synthesized over 16 days at 1-km resolution, both spanning the period 2000–2020. Furthermore, this paper also selects Landsat 5-year NDVI, Aqua MODIS NDVI and NOAA CDR AVHRR NDVI datasets as cross-validation data. The urban administrative division shapefile data in this study come from the National Geomatics Center of China for 2019. They include all prefecture-level administrative units in China, as well as counties directly under the central government in some provinces. The urban physical areas for 1990–2020 are derived from the Global Urban Boundary (GUB) dataset[16]. The dataset combines macroscale kernel density analysis and microscale neighbourhood expansion algorithms for the morphological treatment of urban outer edge areas, capturing the boundaries of all cities and neighbouring settlements with an area of more than 1 km^2 globally. The urban physical areas of this dataset comprise not only impervious surfaces but also other related land types, such as green areas and water bodies within the city. Figure 1 shows the changes in the urban boundaries of Beijing in this dataset as an example.

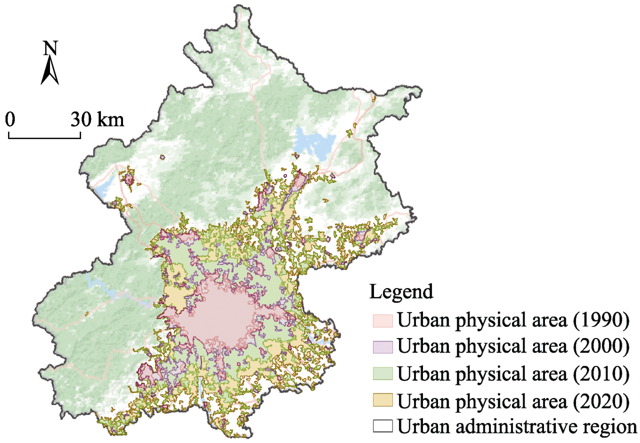

Figure 1 Map of Beijing's administrative area and urban physical areas

3.2 Data Preprocessing

The MODIS NDVI data are regarded as a continuation of the GIMMS NDVI data, and a number of studies have shown that the results of the two data have a strong consistency under certain conversion relationships. This paper uses Fensholt's conversion formula (Equation 1)[11] to convert the GIMMS NDVI data value domain to be consistent with the MODIS NDVI. The formula is based on the regression coefficients derived from the linear regression trend analysis of monthly observations of GIMMS NDVI and MODIS NDVI for the period 2000–2010. Model fitting with regional characteristics was carried out for China, Canada, and Australia, and the results of its long time series have a certain regional representativeness[11].

$$\text{GIMMS NDVI}=1.39\times\text{MODIS NDVI}-0.09 \tag{1}$$

To further verify the applicability of the conversion formula across China, this paper selected five cities located in different regions, Wuhan, Chengdu, Kunming, Hangzhou, and Shenyang, to calculate the root mean square error (RMSE) of 2010 MODIS data after conversion with GIMMS data to reflect the applicability of the formula in the central, western, southern, eastern, and northeastern regions of China. The results are shown in Table 2. The average RMSE between MODIS NDVI and GIMMS NDVI after the conversion is 0.024, with Wuhan having the highest RMSE at 0.034. Therefore, this paper concludes that the formula has good applicability within the Chinese context.

Table 2 The root mean square error (RMSE) between the converted MODIS NDVI and GIMMS NDVI in five cities in China

City	Wuhan	Chengdu	Kunming	Hangzhou	Shenyang	*Average*
RMSE	0.034	0.019	0.033	0.029	0.006	0.024

To weaken the potential influence of the vegetation indices in a single year that may be affected by factors such as changes in meteorological conditions and extreme meteorological hazards, although this dataset focuses on four time points (1990, 2000, 2010, 2020), each time point actually fused 3 years of NDVI data (1989–1991, 2000–2002, 2009–2011 and

2019–2021) to reduce the influence of external factors. To generate the Chinese GIMMS NDVI dataset (1990) and MODIS NDVI dataset (2000, 2010, 2020), the GIMMS NDVI data and MODIS NDVI data (250-m) were preprocessed through Google Earth Engine (GEE) with subset extraction, image mosaic, data cropping, pixel fusion, projection conversion, and calculating the average value of NDVI in each time period to represent the average state of vegetation growth in the corresponding period. In addition, to provide training samples for subsequent superresolution models, this study adopts the same data preprocessing steps on the GEE platform to process the interannual-scale NDVI data (2000–2020) for GIMMS NDVI, MODIS NDVI (1-km) and MODIS NDVI (250-m).

3.3 Image Superresolution Deep Learning Algorithm

This study is based on local-global combined networks (LGC-Net), an image superresolution deep learning algorithm[17] proposed by Lei, to perform second-order superresolution image reconstruction on the GIMMS NDVI dataset using 1-km and 250-m MODSI NDVI datasets. This method enables GIMMS NDVI to be resampled to a higher spatial resolution without losing the original vegetation index features. In the first stage, we trained GIMMS NDVI (2000–2010) with 1-km MODIS NDVI data (2000–2010) to develop the 8-km to 1-km superresolution model training procedure and then reconstructed GIMMS NDVI data at 1-km resolution. In the second stage, the reconstructed 1-km GIMMS NDVI images are trained with 250-m MODIS NDVI data to complete the 1-km to 250-m superresolution model training procedure. Then, we compare the generated results with the original GIMMS NDVI results for errors to further optimize the accuracy of the superresolution model. Finally, the 1990 GIMMS NDVI data with completed data preprocessing were input into this second-order superresolution model to reconstruct the 1990 GIMMS NDVI data at 250-m resolution. The algorithm principle of LGC-Net is shown in Figure 2. (1) To obtain the representation of the main features of the different layers using multilayer convolution. (2) In the local-global information combination part, a multifork structure is realized by cascading the results of different layers. (3) Finally, a higher resolution reconstruction of the image is performed in the reconstruction section.

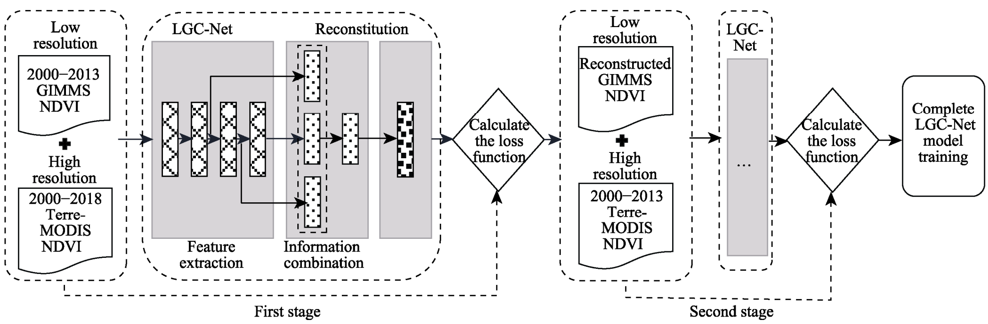

Figure 2 Flowchart of LGC-Net image superresolution deep learning algorithm

3.4 Methods

The main development process of this dataset is shown in Figure 3. First, following the steps of data preprocessing in the previous section, we preprocessed the data for the 2000–2013

GIMMS NDVI dataset and the 2000–2013 Terre-MODIS dataset (1-km and 250-m, respectively) and input these data as training sets into the LGC-Net deep learning model for training to obtain the image superresolution model. Then, we input the preprocessed low-resolution 1990 GIMMS NDVI dataset into the model and perform two-stage image reconstruction to produce the reconstructed 250-m resolution GIMMS NDVI dataset. We collated, aligned and unified coordinate projections of the reconstructed GIMMS and MODIS NDVI datasets and performed data accuracy validation to generate 250-m NDVI datasets for all of China in 1990, 2000, 2010, and 2020. Finally, we spatially overlaid the national prefecture-level administrative region and the national GUB shapefile data with the NDVI dataset to crop and extract all the pixel points within urban administrative and physical areas and calculated their NDVI mean values to obtain the urban 250-m resolution vegetation cover dataset in China (1990–2020).

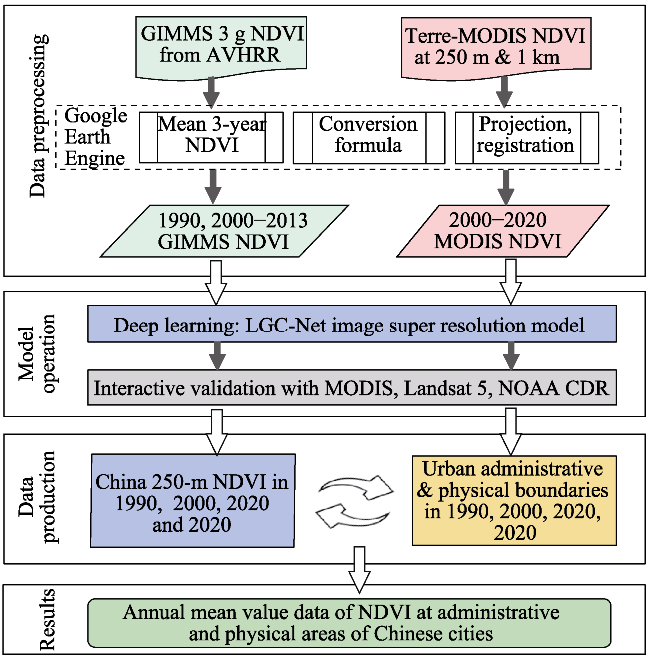

Figure 3 Methodology flowchart of dataset develpoment

4 Data Results and Validation

4.1 Data Composition

The composition, data size, data format and nomenclature of the NDVI dataset of China and the average in 361 cities (250-m, 1990–2020) are shown in Table 3, which mainly includes 4 raster data and 2 statistical table data.

4.2 Data Results

4.2.1 Spatial and Temporal Variation in NDVI in China from 1990 to 2020

Figure 4 shows the distribution of NDVI in China at 250-m resolution from 1990 to 2020. Excluding the impact of water bodies, the average values of the China-wide NDVI in 1990, 2000, 2010 and 2020 are 0.316, 0.299, 0.287 and 0.297, respectively, showing a trend of first decreasing and then increasing. In other words, the overall national greenness of China showed a falling tendency from 1990 to 2010, but it had improved significantly in the last 10 years.

Table 3 Data list of the NDVI Dataset of China and Average in 361 Cities (250-m, 1990–2020)

Data	Corresponding files	Data size	Data format
1990, 2000, 2010, 2020 China 250-m NDVI annual mean value data	China_1990_2020_NDVI	6.51 GB	.tif
1990, 2000, 2010, 2020 annual mean value data of NDVI at administrative and physical areas of Chinese cities	ChinaCities_1990_2020_NDVI	81 KB	.xlsx

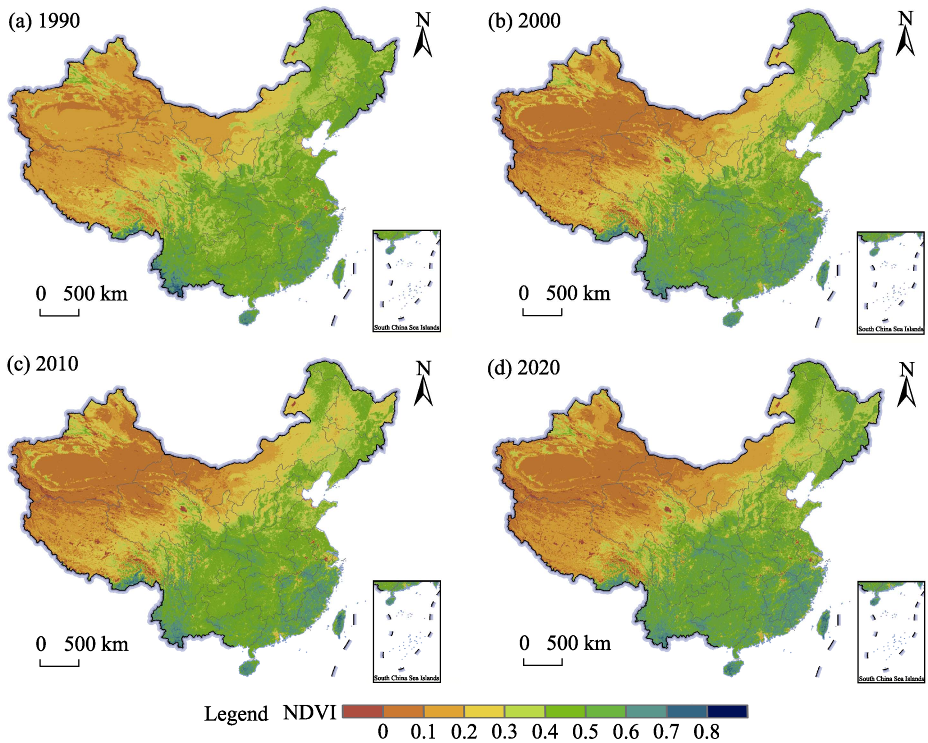

Figure 4 Maps of Spatial and temporal patterns of NDVI in China during 1990–2020

From the perspective of the spatial pattern, the spatial distribution pattern of the vegetation index in China was relatively stable from 1990 to 2020. Due to natural geographical conditions and climatic factors, the NDVI values generally show a progressive decline from the southeast coast to the northwest inland areas. High value areas (NDVI>0.6) are mainly distributed in the hilly and coastal areas of southeastern China, as well as on the Yunnan-Guizhou Plateau in the south. Median value areas (0.6>NDVI>0.3) are mainly found in the North China Plain in eastern China, the Sichuan Basin in the west, and parts of northeast China. Low value areas (NDVI<0.3) are mainly distributed in the Qinghai-Tibet Plateau and Tarim Basin in the west and the Inner Mongolia Plateau in the north. Comparing Figure 4a and Figure 4d, it can be found that from 1990 to 2020, the vegetation greenness is generally enhanced in most of the southern regions and the Loess Plateau area, while the vegetation greenness decreases significantly in the densely populated urban areas, including the Yangtze River Delta, Beijing-Tianjin-Hebei, Pearl River Delta, and Shandong Peninsula urban agglomeration. Other areas with obvious reductions in vegetation greenness are mainly distributed in the western regions.

4.2.2 Spatiotemporal Changes in NDVI within the Urban Administrative and Physical Areas from 1990 to 2020

Figure 5 illustrates the spatial and temporal changes in NDVI within the urban administrative and physical areas for 361 cities in China from 1990 to 2020. The spatiotemporal distribution and trends of NDVI within the administrative areas are generally consistent with the raster scale features discussed above, although NDVI inside urban physical areas does not entirely match the raster scale pattern. For example, in the Yangtze River Delta, the Pearl River Delta, and several cities in the middle reaches of the Yangtze River urban agglomeration, while the average NDVI value in the administrative area is relatively high, the NDVI value in the urban physical area is comparatively low; in Xinjiang, Hotan and Kunyu have relatively low NDVI values within the administrative area, but the urban physical entity-wide NDVI values are fairly high. With the exception of some oasis-type cities in the northwest, the NDVI values of the urban administrative areas are higher than those of the urban physical areas. The national urban physical wide NDVI average values in 1990, 2000, 2010 and 2020 are 0.321, 0.278, 0.264 and 0.290, respectively, indicating a considerable rise in urban greenness across the country in the last decade.

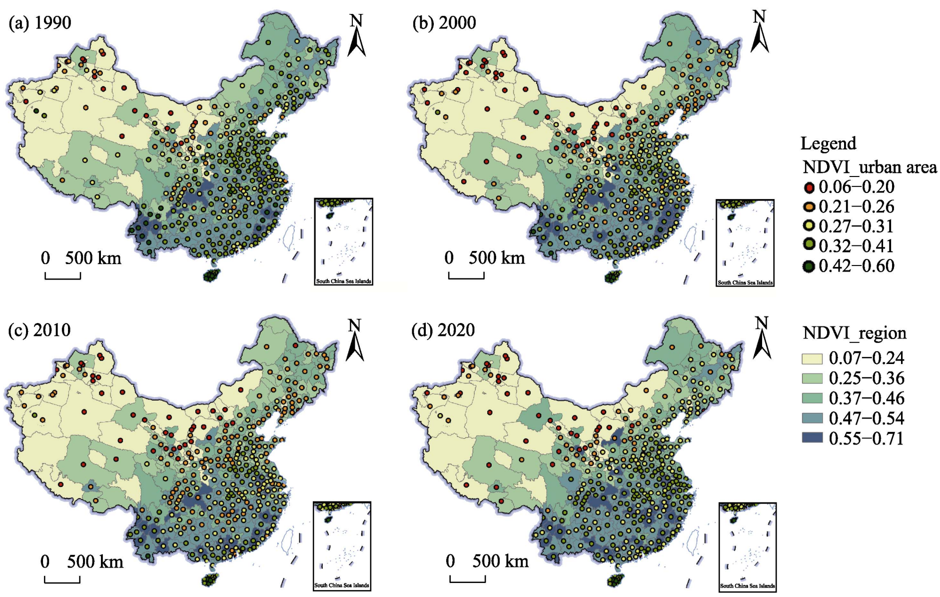

Figure 5 Maps of Spatial and temporal changes in NDVI in the urban administrative and physical areas during 1990–2020

4.3 Data Validation

Since NDVI values lack direct evidence from ground station monitoring, we unified data from various NDVI products into the same spatial resolution and projection coordinate system. We then examined the correlation between this dataset and other data products generated by deep learning models to verify the spatial and temporal reliability of this dataset. In this paper, we take Beijing as the validation area, with a size of approximately 16,392.99 km^2, corresponding to 343,967 pixels at 250-m resolution. The 250-m NDVI dataset (2010) generated in this study was pixel-by-pixel compared with three data products, Aqua-MODIS NDVI, Landsat 5 NDVI, and NOAA NDVI, and the correlation coefficient, R^2, and root mean square error (RMSE) were calculated. From the results in Figure 6, the 250-m NDVI data results have a strong correlation with other NDVI product data, and the correlation coefficients are 0.991,4, 0.842,5, and 0.790,3, respectively. Overall, the accuracy of the 250-m NDVI dataset produced in this paper is positive, and the data results have an acceptable level of reliability.

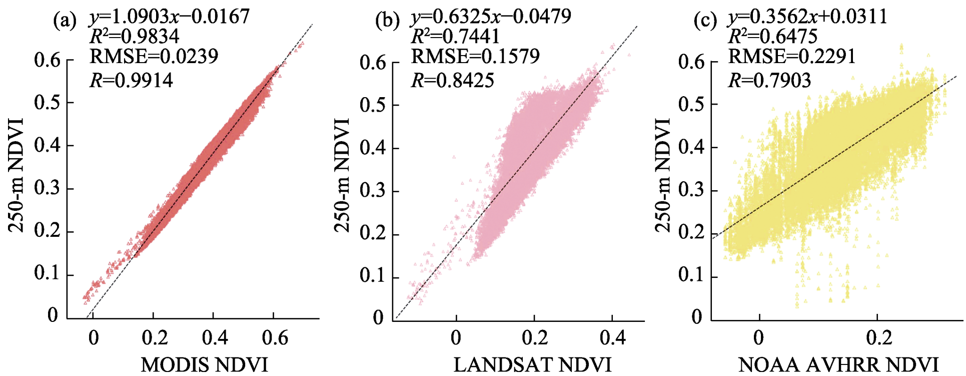

Figure 6 Cross-validation results of model-fitted NDVI with other NDVI product data: (a) Aqua-MODIS, (b) NDVI Landsat 5 NDVI, and (c) NOAA NDVI

5 Discussion and Conclusion

In this research, we produced a 250-m resolution NDVI dataset for Chinese cities from 1990 to 2020 based on long time series GIMMS NDVI data and medium-high spatial and temporal resolution Terre/MODIS NDVI data, combined with the GUB urban boundary dataset, used the Google Earth Engine platform and Python, and adopted an image superresolution algorithm and cross-validation method. Compared with the existing NDVI product data, this dataset extends the observation time of the original medium- and high-resolution NDVI from 20 years to 30 years and calculates the NDVI at the urban physical entity area by overlaying the urban entity boundary data. The reason why we choose the annual mean value of NDVI rather than the annual maximum value of NDVI is that the annual mean value can better reflect the annual contribution of vegetation to human well-being and is more suitable for applications in the direction of human-nature coupling studies, overall evaluation of urban ecological environment, environmental effects of urbanization, and urban ecological governance.

The results show that the NDVI has a decreasing and subsequently increasing tendency from 1990 to 2020 for both all of China and at the urban scale, but there is obvious heterogeneity between regions. Although urbanization has transformed a large number of vegetation-covered areas around cities into impervious surfaces, the NDVI within urban physical areas has shown a significant increase in the last decade. These results indicate that ecological improvement measures and restoration projects such as urban green space construction, returning farmland to forests, afforestation, and nature reserve construction have achieved remarkable results, and urbanization is having more positive impacts on vegetation. This dataset can offer fundamental information for further revealing the mechanism by which vegetation cover in China responds to climate change, human activity, and other drivers over a longer time period. It can also offer data support to guide government departments in evaluating regional ecological and environmental quality, formulating ecological protection policies, and promoting regional sustainable development.

Author Contributions

Liu, H. M. designed the overall dataset development, wrote the data paper and performed data visualization; Zhou, T. Y. collected and processed the data, designed the deep learning model and algorithm, and wrote the data paper; and Gou, P. performed the data validation.

Conflicts of Interest

The authors declare no conflicts of interest.

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