Assessing Heavy Industrial Heat Source Distribution in China Using Real-Time VIIRS Active Fire/Hotspot Data

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Abstract: Rapid urbanization and economic development have led to the development of heavy industry and structural re-equalization in mainland China. This has resulted in scattered and disorderly layouts becoming prominent in the region. Furthermore, economic development has exacerbated pressures on regional resources and the environment and has threatened sustainable and coordinated development in the region. The NASA Land Science Investigator Processing System (Land-SIPS) Visible Infrared Imaging Radiometer (VIIRS) 375-m active fire product (VNP14IMG) was selected from the Fire Information for Resource Management System (FIRMS) to study the spatiotemporal patterns of heavy industry development. Furthermore, we employed an improved adaptive K-means algorithm to realize the spatial segmentation of long-order VNP14IMG and constructed heat source objects. Lastly, we used a threshold recognition model to identify heavy industry objects from normal heat source objects. Results suggest that the method is an accurate and effective way to monitor heat sources generated from heavy industry. Moreover, some conclusions about heavy industrial heat source distribution in mainland China at different scales were obtained. Those can be beneficial for policy-makers and heavy industry regulation.

Keywords: adaptive K-means algorithm; heavy industrial heat sources; time-series; VIIRS active fire product

1. Introduction

Heavy industry is an important component of China’s basic industry and provides technical equipment, power, and raw materials for all sectors of the national economy. In the past few decades, heavy industry has grown rapidly, and a large number of subindustries have emerged. However, in recent years, industry expansion has caused a number of issues, including: haphazard structural expansion, structural reorganization, and disordered layouts. These issues threaten the sustainable and coordinated development of the social economy and also exacerbate regional resource and environmental pressures. Real-time layout maps of heavy industry development are needed to address these concerns [1].

Heat sources are an essential part of production for most heavy industries, such as the flaring of petroleum gas in oil fields and the combustion of fossil fuels in factories (e.g., cement plants, steelworks, etc.) [2]. The thermal anomalies from industrial heat sources can be tracked using satellite remote sensing, which collects consistent and extensive day-and-night data. Satellite images may be
the most effective way to monitor the dynamics of thermal anomalies. Presently, data on thermal anomalies from satellite sensors have been widely used in the detection of global-scale self-ignition fire point data. Some examples of these satellites include: Advanced Very High Resolution Radiometer (NOAA/AVHRR) [3], Along Track Scanning Radiometer (ASTER) [4], FY3-VIRR [5], Landsat 8 [6,7] and the Moderate Resolution Imaging Spectrometer (MODIS). However, there are few studies that have focused on the detection of heavy industrial heat sources. The NPOESS Preparatory Project (NPP) Visible Infrared Imaging Radiometer (VIIRS) is a mature nighttime thermal anomaly product that was successfully applied to volcanic activity [8] and oil and gas exploitation [9]. Liu et al. [2] and Sun et al. [10] used NPP VIIRS Nightfire product data to identify industrial heat sources by combining time–space–temperature information. Schroeder et al. [11] and Giglio et al. [12] applied NPP VIIRS data with a 375-m resolution to daily/nighttime thermal anomaly extraction to make fire point product data more in line with Earth’s true fire point distribution, generating a global scale product. This active fire product provided a greater response for fires in small areas due to its higher spatial resolution and improved nighttime performance. Moreover, the product considered the relative aggregation of hotspots in industrial production. As a result, long-term vector data could be used to cluster and segment heat source objects according to their spatial properties.

These methods can be regarded as data clustering processes that are based on spatial information due to the construction of heat source objects using vector data. We introduced a clustering method that is widely used in pattern recognition, data analysis, and image processing [13] to detect heat source objects. K-means is a simple and effective unsupervised clustering method and is widely used in data clustering. However, there are some drawbacks for the traditional K-means algorithm that require the number of clusters and the cluster center to be preset. Ma et al. [14] used the particle swarm optimization algorithm to initialize the cluster center and solved the random problem of cluster center initialization. Abubaker et al. [15] applied the K-nearest neighbor method to K-means to eliminate noise data. Lei et al. [16] proposed a robust K-means algorithm based on splitting and clustering, which realized the clustering of video data. The VIIRS active fire hotspot product is a long-term vector dataset that is affected by the spatial distribution of natural fire point data (e.g., straw burning, forest fires, urban fires, volcanic eruptions). The fire hotspots for heavy industry heat sources are clustered. However, the number of heavy industries in different regions are all different due to the different distribution of mineral resources and the level of local economic development. So, the key issue for heavy industry heat source discovery and detection is choosing the best method for setting the cluster num for K-means segmentation based on the characteristics of VIIRS active fire hotspots.

The real-time NASA Visible Infrared Imaging Radiometer (Land-SIPS) VIIRS 375-m active fire product (hereafter referred to as VNP14IMG) was introduced to address these issues. The product is based on an improved adaptive K-means algorithm model and was proposed to reveal the spatiotemporal patterns and development of heavy industry in China’s mainland. In this study, VNP14IMG was selected from the Fire Information for Resource Management System (FIRMS). Furthermore, we employed an improved adaptive K-means algorithm to realize the spatial segmentation of long-order VNP14IMG and constructed heat source objects. Lastly, we used a threshold recognition model to delineate heavy industry objects from heat source objects.

The remainder of this article is organized as follows. Section 2 describes the study data, main data processing steps, and methodology. Section 3 presents the experimental results that were obtained from VNP14IMG. Section 4 discusses and assesses the heavy industrial heat source distribution in mainland China. Conclusions are drawn in Section 5 along with recommendations for future research.
The nation became the world’s second-largest economy by nominal GDP and had the largest purchasing power parity (PPP) in 2016. China also has the world’s largest population, reaching over 1.404 billion in 2017. Chinese cities have experienced an unprecedented level of development, with the population shifting from rural to urban areas in recent years [17]. The study area was divided into seven regions according to the natural and socioeconomic situation at the provincial scale [18] (Figure 1).

Though mainland China has made huge achievements over the past years, it faces serious and numerous environmental pollution issues. In January 2013, eastern China experienced a smog outbreak that affected 600 million people and covered 17 provinces, municipalities, and autonomous regions [19]. An “Air Pollution Prevention Plan” was announced by the State Council on 12 September 2013 to improve the quality of the environment [20]. Industrial sources (e.g., heavy coal-burning regions) were a significant source of haze, which prompted the State Environmental Protection Administration to shut down thousands of industries responsible for pollution [21].

![Figure 1. The seven regions in Chinese geography. EC: East China, MC: Middle China, NC: North China, NEC: Northeast China, NWC: Northwest China, SC: South China and SWC: Southwest China.](image_url)

2.2. Data Sources

2.2.1. VIIRS Active Fire/Hotspot Data

In this study, the NASA Land-SIPS VIIRS 375-m active fire product (e.g., VNP14IMG) was selected as observational data to evaluate heavy industrial heat source distribution. Observations were based on the instrument’s 375-m (I-bands) nominal resolution Collection 1 (C1) reprocessed data from the NASA Land-SIPS [22]. However, these channels were not originally designed for active fire detection; thus, the VNP14IMG product was designed using VIIRS 375-m (I) channels. Building on the MOD14/MYD14 algorithm, several modifications were implemented to accommodate the unique characteristics associated with VIIRS 375-m data [11]. Compared to other coarser-resolution (≥1 km) satellite fire detection products, the improved 375-m data provide greater response over fires of relatively small areas as well as improved mapping of large fire perimeters. Consequently, the data are well suited for use in support of fire management (e.g., near real-time alert systems) as well as other science applications requiring improved fire mapping fidelity. The 375-m product complements the
baseline Suomi-NPP/VIIRS 750-m active fire detection and characterization data, which was originally
designed to provide continuity to the existing 1-km Earth Observing System Moderate Resolution
Imaging Spectroradiometer (EOS/MODIS) active fire data record.

The VIIRS instrument was first launched onboard the Suomi National Polar-orbiting Partnership
(S-NPP) satellite in October 2011. VNP14IMG was proposed following the successful application of
375-m data for active fire detection. The first active fires were detected using the VIIRS sensor on
19 January 2012, after the instrument was fully commissioned. It can be freely downloaded from the
FIRMS [23]. Ranging from 19 January 2012 to 31 December 2017, 6,574,250 observed fire hotspots were
used. The spatial density distribution image of the 6,574,250 fire hotspots is provided in Figure 2.

Figure 2. Spatial density distribution of 6,574,250 fire hotspots in China’s mainland regions.

2.2.2. Auxiliary Data

The heavy industrial heat source distribution in mainland China was investigated using real-time
VIIRS active fire/hotspot data based on an improved adaptive K-means algorithm in different
administrative regions. China’s national, provincial, and country boundaries were acquired from the
Global Administrative Areas website. The coordinate reference system for the boundary files was
based on the WGS84 datum. Additionally, high-resolution images from Google Earth were utilized to
support the verification of heavy industrial heat sources.

3. Heavy Industrial Heat Source Detection Model Using Real-Time VIIRS Active Fire/Hotspot
Data Based on an Improved Adaptive K-means Algorithm

3.1. Data Preprocessing

The computational complexity of the heat source object detection model was positively correlated
with the size of the dataset. When the amount of fire hotspots increased, the computational
complexity increased exponentially. Additionally, the spatial distribution area of one heavy industry
area was almost impossible to divide among two or more administrative counties due to China’s
regional development. The long-term time series for VNP14IMG products was divided according
to county-level administrative boundaries. In this study, 6,574,250 fire hotspots were divided into 3366 subhotspots using administrative county boundaries.

3.2. Heat Source Object Detection Model Using Real-Time VIIRS Active Fire/Hotspot Data

Static and persistent industrial heat sources in the VNP14IMG time series were found tightly distributed around their hot centers due to position invariance and temporal consistency. The K-means algorithm was used to cluster fire hotspots based on their spatial location. A heat source object detection model was adopted using real-time VIIRS active fire/hotspot data based on an improved adaptive K-means algorithm. The model contained two steps: the segmentation of long-term time-series fire hotspots and the combination of heat source objects based on their topology association.

3.3. Segmentation of Long-Term Time-Series Fire Hotspots

The traditional K-means algorithm was improved to determine the number of heat source objects based on their distribution. The initial heat source objects were divided until one heat source object satisfied the final segmentation conditions, such as a minimum size and fire point number. We set \( O_{ik} (k = \{1, 2, 3, \ldots, K\} \) as heat source objects. \( K_0 \) represented the number of heat source objects constructed after the i-th small fire point file was clustered. The main process is described as follows:

Step 1: An initial cluster number \( C \) calculation was initialized according to the size of the fire points.
Step 2: The initial heat source objects, \( O_{ik} (k = \{1, 2, 3, \ldots, C\}) \), were clustered based on the K-means clustering algorithm. \( C \) represents the number of heat source objects at the initial time. \( C \) was set to 2 in this paper empirically.
Step 3: \( O_{ik} \) was filtered into \( O_{ik0} (k = \{1, 2, 3, \ldots, C\}) \) using three multiplied by the standard deviation of the fire points’ locations.
Step 4: The fire points number, \( N_{i0} (i = \{1, 2, 3, \ldots, C\}) \), the width, or \( \text{Width}_{i0} (i = \{1, 2, 3, \ldots, C\}) \), and height, \( \text{Height}_{i0} (i = \{1, 2, 3, \ldots, C\}) \), of the circumscribed rectangle in each heat source object \( O_{ik0} \) was calculated.
Step 5: The heat source object, \( O_{ik} \), was split again and returned to Step 2 if the max value (\( \text{Width}_{i0}, \text{Height}_{i0} \)) was greater than the set threshold \( (B_0) \) and if \( N_{i0} \) was greater than the heat source target point threshold \( (N_0) \). If these conditions were not satisfied, then the filtered heat source object \( O_{ik0} \) was set as an independent heat source object. \( B_0 \) was set to 800 m in this paper empirically.

A total of 6,574,250 fire hotspots were segmented into 319,377 heat source objects.

3.3.1. Combination of Heat Source Objects Based on Their Topology Association

An oversegmentation problem was addressed in the segmentation of long-term time-series fire hotspot processing to ensure segmentation accuracy. A combination model was proposed based on their topology association. Two or more heat source objects were merged into one heat source object based on the topological relationships of each circumscribed rectangle. The main process is described as follows:

Step 1: The heat source object \( O_{ik0} \) was copied into \( O_{ik1} \).
Step 2: The nearest heat source object \( O_{il1} \) was calculated for each of the heat source objects \( O_{ik1} \).
Step 3: The intersection ratio of the circumscribed rectangle boundary between object \( O_{ik1} \) and \( O_{il1} \) was calculated. The objects \( O_{ik1} \) and \( O_{il1} \) were merged into a new object \( O_{ik1_{\text{new}}} \) if the intersection ratio was greater than the set threshold \( l_0 \) and max (\( \text{Width}_{ik1}, \text{Height}_{ik1} \), max (\( \text{Width}_{il1}, \text{Height}_{il1} \)) was smaller than threshold \( B_{i1} \). \( l_0 \) was set to 50% in this paper empirically.
Step 4: \( O_{ik1_{\text{new}}} \) was filtered into \( O_{ik1} \) using three multiplied by the standard deviation of the fire point location.
Step 5: Steps 1–4 were repeated until there were no objects left to be merged.

The initial number of heat source objects \( (319,377) \) was then combined into 264,962 heat source objects.
3.4. Heavy Industrial Heat Source Identification

Heavy industrial heat source objects are static and persistent, while biomass fires are usually sparsely distributed. Thus, heavy industrial heat sources can be distinguished from biomass fires and small industrial heat source objects. In this paper, heavy industrial heat source identification was based on a heat source object threshold model. The number of fire hotspots, hotspot density per square kilometer, and the time span from initial to final detection of heat source objects was used to identify heavy industrial heat sources. Correct identification of heat sources required the following conditions:

1. The days between the start of the fire hotspot and final date in one heat source object was greater than 90.
2. The number of fire hotspots in one heat source object was greater than nine.
3. The fire hotspot density per square kilometer in one heat source object was greater than 50.

Some small companies are limited by economic and natural conditions (e.g., oil and gas distribution) and only operate during certain time periods. Hence, the operational period must be considered when distinguishing heavy industrial heat sources from other heat source objects. In this paper, the time period of one heat source object was equal to the working period of the object divided by the max working period for all heat source objects. In addition to the above three conditions, heavy industrial heat sources satisfied the following conditions:

1. The number of fire hotspots in one heat source object divided by its working period must be greater than 30.
2. The fire hotspot density per square kilometer for one heat source object divided by its working period must be greater than 100.

Using the five conditions above, 4143 heavy industrial heat sources were identified from 264,962 heat source objects.

3.5. Quantitative Analysis

The number of working heavy industrial heat sources (NWH) was extracted in the statistical area for different years. Also, the number of fire hotspots in one working heavy industrial heat source area can represent the production scale of one heavy factory. So, the total number of fire hotspots in working heavy industrial heat sources areas (NFHWH) was also calculated in the statistical area for different years. A linear regression method (Jiang) [18] was introduced to represent the changing trends of each statistical area during the study period. It was possible to reveal the spatiotemporal pattern based on changes in trend characteristics for each area. This method could objectively monitor temporal change trends for working heavy industrial heat sources. Furthermore, the method had the advantage of eliminating NWH/NFHWH outliers by fitting time-series NWH/NFHWH values. The calculation formula is stated as follows:

\[ \text{Slope}_{\text{NWH}} = \frac{t \times \sum_{i=1}^{t} i \times \text{NWH}_i - \sum_{i=1}^{t} i \sum_{i=1}^{t} \text{NWH}_i}{t \times \sum_{i=1}^{t} i^2 - (\sum_{i=1}^{t} i)^2} \]  
\[ \text{Slope}_{\text{NFHWH}} = \frac{t \times \sum_{i=1}^{t} i \times \text{NFHWH}_i - \sum_{i=1}^{t} i \sum_{i=1}^{t} \text{NFHWH}_i}{t \times \sum_{i=1}^{t} i^2 - (\sum_{i=1}^{t} i)^2} \]  

where \( \text{NWH}_i \) represents the NWH value in year (i), and \( \text{NFHWH}_i \) is the NFHWH value for the year. The variable \( t \) refers to the time span (\( t = 6 \) years). If \( \text{Slope}_{\text{NWH}} > 0 \), then the slope represents an increase in working heavy industrial heat sources. A higher slope value indicates a more significant increase. If \( \text{Slope}_{\text{NWH}} < 0 \), then the slope represents a decline in working heavy industrial heat sources. A lower slope value indicates a more significant decline. Otherwise, \( \text{Slope}_{\text{NWH}} = 0 \) suggests that the number of working heavy industrial heat sources is stable. This concept is the same for \( \text{Slope}_{\text{NFHWH}} \) and NFHWH.
4. Results

4.1. Heavy Industrial Heat Source Distribution Characteristics at the National Scale

The spatial distribution of 4143 heavy industrial heat sources in China’s seven mainland regions (Figure 3) revealed that heavy industrial heat sources had been mainly focused in North China (NC), East China (EC), and Northwest China (NWC) in the past six years. In Northeast China (NEC) (including Heilongjiang, Jilin, and Liaoning), the heavy industrial heat sources were not as numerous as their fire hotspots (Figure 2). Further investigation revealed that most fire hotspots in NEC were from burning straw, especially in May and October. Additionally, the Tangshan, Ordos, and Wuhai regions formed widespread heavy industrial heat source areas.

Recent changes for working heavy industrial heat sources were compared, and the numbers of NWH (Figure 4a) and NFHWH for different years (Figure 4b) were calculated. The max number of NWH values occurred in 2013 and 2014 but have declined since 2014. This suggests that small- and medium-sized heavy industrial heat sources were limited or shut down due to environmental protection policies. The max number of NFHWH values occurred in 2013 but have since declined. These values were observed to stabilize in 2015. Overall, the scale of production for China’s heavy industry is steadily growing, while NWH values have been decreasing since 2015.

High-resolution images from Google Earth were selected to verify the results of the model. (Figure 5). Figure 5a is an image of oil mining fields in the Taklimakan Desert in Xinjiang, abandoned in March 2015. Figure 5b depicts a chemical production area in Inner Mongolia, including coal, smelting, and calcium carbide chemical plants. Figure 5c depicts an open pit mine field in Inner Mongolia, abandoned in July 2013. A calcium carbonate plant is found in Shanxi (Figure 5d). Figure 5e is a petrochemical plant at Dalian Port. Figure 5f,i,j are cement plants in Tibet, Hainan, and Zhejiang. The steel plant shown in Figure 5G is located at Tangshan.

Figure 3. Spatial distribution of 4143 heavy industrial heat sources in China’s seven mainland regions.
Figure 4. Changes for 4143 heavy industrial heat sources at the national scale. (a) The number of working heavy industrial heat sources (NWH) present in different years. (b) The number of fire hotspots in working heavy industrial heat sources areas (NFHWH) present in different years.

Figure 5. High-resolution imagery used to validate the model.
4.2. Heavy Industrial Heat Source Distribution Characteristics at Regional Scales

NWH and NFHWH in seven regions were calculated to examine changes in working heavy industrial heat sources at the regional scale (Figure 6). The largest number of NWH and NFHWH values were observed in North China (NC), followed by Northwest China (NWC) and East China (EC). Conversely, the smallest value was observed in South China (SC). The number of NWH and NFHWH values in NC accounted for about 30% of the total in the entire mainland. This region consisted of a large industrial zone, including steel industries in Hebei, coal-mines in Shanxi, and open pit mines in Inner Mongolia [24]. NWC values accounted for about 20% of the total value. This was due to the presence of numerous oil and gas fields in Xinjiang [24] and Yulin in Shaanxi. The area also consisted of Shizuishan Shi, which is known as the “city plugged up with coal” in Ningxia [25]. The EC area accounted for the third largest percentage of the total. This is because the region includes five coastal provinces and Shanghai, which all contain numerous metal and coal resources [24].

![Figure 6](image_url)

**Figure 6.** Changes in heavy industrial heat sources at the regional scale. (a) The NWH values for different regions and years. (b) The NFHWH values for different regions and years.

The NC, NWC, and EC areas all had similar trends at the national scale from 2012 to 2017. There was a subsequent increase and decrease in NWH values. The fire hotspots increased and decreased from 2013 onwards and became stabilized in 2015. The NC area had the most significant change in values during the past six years. The number of NWH and NFHWH values reached a maximum in 2013, then NWH sharply declined. The fire hotspots had also rapidly decreased until 2016. This decrease was mainly attributed to the “Air Pollution Prevention Plan” [20] announced by the State Council on 12 September 2013. This action had the effect of controlling smog in most NC, EC, and MC regions. The trends observed in the SC region were different compared to other regions from 2012 to 2017. The number of NWH and NFHWH values all continued to slowly increase over the six-year period.

*Slope NWH* and *Slope NFHWH* values illustrate the changing trends for each statistical area during the past six years (Figure 7). The smallest *Slope NWH* and *Slope NFHWH* values were also present in the NC region (Figure 7a,b). This suggests that NWH and NFHWH declined significantly during the six-year period. The *Slope NWH* values in the EC and NEC regions were also observed to decrease. The NWH values in the SWC and MC regions were observed to be stable, with their
Slope_NWH values being equal to 0. Moreover, the number of working heavy industrial heat sources in the SC region increased slightly and had a Slope_NWH value of 5.0.

Figure 7. Changes in heavy industrial heat sources at the regional scale from 2012 to 2017. (a) The Slope_NWH values for different regions. (b) The Slope_NFHWH values for different regions.

The distribution of Slope_NFHWH values are displayed in Figure 7b. These values reflect the production scale of working heavy industrial heat sources. The Slope_NFHWH value in the SWC region was $-357$. This suggests that NFHWH values had largely decreased, while Slope_NWH values
also slightly declined. The \textit{Slope}\textsubscript{\textit{NFHWH}} values in the NEC, EC, and MC regions also declined. The NFHWH values in the NWC and SC regions increased with \textit{Slope}\textsubscript{\textit{NFHWH}} > 0. The production scale increased in the NWC region, while NWH values decreased. This suggests that China’s western development strategy [26] was effective.

4.3. Heavy Industrial Heat Source Distribution Characteristics at the Provincial Scale

The heavy industrial heat source characteristics for 31 provincial administrative regions in mainland China were analyzed using NWH and NFHWH values. Figure 8a reveals the statistical results of the number of NWH in each province. Five provinces provided the highest figures, including: Xinjiang, Hebei, Shanxi, Inner Mongolia, and Shandong. The lowest four figures corresponded to Tibet, Shanghai, Beijing, and Hainan. Results indicate that the number of fire hotspots in heavy industrial heat sources was related both to the level of heavy industrial development and administrative area size. The largest values were found in Xinjiang, Hebei, Shanxi, Inner Mongolia, and Shandong provinces, which have more heavy industries and wider areas. Moreover, there were many oil and gas fields in Xinjiang and steel industries in Hebei. Shanxi has abundant coal resources, while Inner Mongolia had numerous open pit mines. Gold, antimony, natural sulfur, and gypsum are abundant in Shandong. Most provinces had a similar trend for the 2012-to-2017 period. There was an initial increase in values, followed by a subsequent decrease. Hebei and Shanxi provinces have had the fastest rate of reduction in values since 2013. This decrease was mainly due to the “Air Pollution Prevention Plan” that was announced on 12 September 2013. High reduction rates were also observed in Xinjiang and Shandong. These rates were followed by: Yunnan, Shaanxi, Liaoning, Jiangsu, Sichuan, and Ningxia provinces. Additionally, Guangdong, Hunan, Guangxi, Fujian, Qinghai, and Tibet experienced an upward trend. Tibet has had the fastest growth since 2015. These results show that the heavy industrial economy has risen rapidly in undeveloped provinces, as a result of government investment.

The number of NFHWH values indicates a reduction in the total scale of production for heavy industry in administrative areas (Figure 8b). The largest five numbers of fire hotspots were the same as the number of NWH in Figure 8a. However, their ranks were different. Hebei had the most fire hotspots, followed by Inner Mongolia, Shanxi, Xinjiang, and Shandong provinces. Xinjiang had the largest number of working heavy industrial heat sources but was ranked fourth in NFHWH values, which was equivalent to half of the total values for Hebei. Moreover, the NFHWH values in Hebei accounted for nearly 20% of mainland China. This supports the claim by many scholars that Hebei may be responsible for smog in Beijing and North China [27]. Additionally, the number of NFHWH values in Inner Mongolia has fallen sharply since 2015, with a drop of nearly 70%. This was mainly due to the sluggish nature of the coal industry. Finally, the smallest NFHWH values were found in Tibet, although the province has featured the fastest growth in NWH values since 2015.

The distribution of \textit{Slope}\textsubscript{\textit{NWH}} and \textit{Slope}\textsubscript{\textit{NFHWH}} values were mapped to illustrate the changing trends for each statistical area during the past six years (Figure 9). The smallest \textit{Slope}\textsubscript{\textit{NWH}} values were found in Hebei, followed by Shanxi, Shandong, and Xinjiang. Results suggest that all NWH values declined significantly over the past six years. Moreover, the NWH values for provinces located near Beijing also declined during the same period. The NWH values for Sichuan, Anhui, Hubei, Guangxi, Jiangxi, Hunan, Chongqing, and Guizhou provinces were observed to slightly increase. These provinces had \textit{Slope}\textsubscript{\textit{NWH}} values that ranged between 0 and 1. Additionally, the values in Fujian and Guangdong also increased. These results suggest that the “Central Rise Plan” was successful.

\textit{Slope}\textsubscript{\textit{NFHWH}} values are displayed in Figure 9b. The slope value reflects the production scale of working heavy industrial heat sources. The smallest value was found in Inner Mongolia, which currently has a stagnating coal industry. Most of the provinces in Middle China also had lower values, although NWH values have increased slightly. These provinces included: Sichuan, Anhui, Jiangxi, Hunan, Chongqing, and Guizhou. Additionally, the NFHWH values in Tibet, Guangxi, and Guangdong provinces were observed to increase.
Figure 8. Changes in heavy industrial heat sources at the provincial scale. (a) The number of NWH for different provinces and years. (b) The number of NFHWH for different provinces and years.
Figure 9. Changes in heavy industrial heat sources at the provincial scale from 2012 to 2017. (a) The Slope_NWH values for different provinces. (b) The Slope_NFHWH values for different provinces.

The distribution of heavy industrial heat sources was mapped to examine the heat source characteristics for 31 provincial administrative regions in 2017 (Figure 10). The number of NFHWH values indicates a reduction in the total scale of production for heavy industry in administrative areas in 2017 (Figure 10a). Hebei had the most fire hotspots, followed by Inner Mongolia, Shanxi, Xinjiang,
and Shandong provinces. Further, as a distribution map of NFHWH in 2017, it has similar disciplines to Figure 8a.

The NFHWH values for different provinces (2017) per 10,000 square kilometers are displayed in Figure 10b. The largest three numbers were for Hebei, Shanxi, and Ningxia, followed by Jiangsu, Tianjin, and Shandong. Of note is that Beijing was surrounded by larger NFHWH values per 10,000 square kilometers, such as Hebei, Tianjin, and Shanxi. This may partly explain why the air pollution in Beijing is so serious. However, Xinjiang, with a larger administrative district, had a small value.

Figure 10. Distribution of heavy industrial heat sources at the provincial scale (2017). (a) The NFHWH values for different provinces (2017). (b) The NFHWH values for different provinces (2017) per 10,000 square kilometers.
5. Conclusions

Heavy industry has grown rapidly in the past few decades, and a large number of subindustries have emerged. This has led to haphazard structural re-equalization as well as scattered and disorderly layouts in mainland China. Further, it has exacerbated pressures on regional resources and the environment. The NASA Land-SIPS VIIRS 375-m active fire product (VNP14IMG) can reveal the spatiotemporal patterns of heavy industry development in the study area. So, it was selected from the FIRMS and used in this study. Furthermore, an improved adaptive K-means algorithm was proposed to realize the spatial segmentation of long-order VNP14IMG and constructed heat source objects. Lastly, a threshold recognition model was used to delineate heavy industry objects from normal heat source objects. The results suggest that the model was an accurate and effective means of monitoring heat sources produced by heavy industry. The following conclusions are drawn from this study:

1. Mainland China’s heavy industrial heat sources were mainly focused in North China (NC), East China (EC), and Northwest China (NWC). The Tangshan, Ordos, and Wuhai regions consisted of widespread heavy industrial heat source areas.

2. The total number of working heavy industrial heat sources (NWH) and the number of fire hotspots in working heavy industrial heat sources (NFHWH) values increased from 2012 to 2013. They reached a maximum in 2014 and 2013, respectively, and declined thereafter.

3. The largest NWH and NFHWH values were observed in North China (NC), followed by Northwest China (NWC) and East China (EC), and the NWH and NFHWH values in NC accounted for about 30% of the total in the mainland. The values experienced an initial increase and reached a maximum value in 2013, then sharply declined thereafter.

4. The largest NWH values were located in Xinjiang province, followed by Hebei, Shanxi, Inner Mongolia, and Shandong. Conversely, the largest NFHWH values were found in Hebei, accounting for nearly 20% of the entire mainland. Additionally, Guangdong, Hunan, Guangxi, Fujian, Qinghai, and Tibet provinces revealed an upward trend.

The results suggest that the real-time VIIRS active fire/hotspot data and the improved adaptive K-means algorithm were successful in monitoring heavy industrial economic development. Moreover, this conclusion can be beneficial for policy-makers and heavy industry regulation. Future studies should focus on collecting additional data with longer periods to reveal the development patterns in recent decades. Lastly, we plan on examining the relationship between heavy industrial heat source distribution and economic development, as well as the relationship between heavy industrial heat source distribution and climate change, which are important issues regarding the Kyoto Protocol (1992) [28] and the Paris Agreement (2015) [29].

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References


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