Evaluation of environmental recovery and vulnerability in the Mohe area by using mathematical modeling and remote sensing techniques

Xinyue Che1,*,a†, Ke Diao2,b, † and Kangzhe Zhou3,*, c†

1 College of Letter and Science, University of California Santa Barbara, Goleta, California, 93117, The United States
2 School of Ecosystem and Forest Sciences, University of Melbourne, Melbourne, Victoria, 3010, Australia
3 Environmental Engineering, Rensselaer Polytechnic Institute, Troy, New York, 12180, The United States
†These authors contributed equally.

Abstract. In the Greater Khingan Range, wildfires in forests were frequent and severe. The wildfire in the Greater Khingan Range in 1987 was one of the severest wildfires in human history, and the study is primarily based on this natural disaster. Mohe is a representative region in the Greater Khingan Range field related to wildfire cases. Many indicators affect the relationship between wildfire and forests, such as topography, climate change, and human behaviors. This paper used remote sensing techniques, the AHP model, and the entropy model to study the environmental fragility of forests in the region of Mohe. Present paper used NDVI images from 1987, 1992, 1997, 2002 to detect the vegetation coverage change in this area and found out its potential problems that need to be paid attention to. NDVI images in the paper showed that the vegetation coverage in the region of Mohe was generally low. Therefore, the results indicated that it is necessary to make prevention and conservation in the region of Mohe. By collecting dem images and data from fire yearbooks within these years, the paper summarized seven indicators: vegetation coverage, number of fires, area of damaged forest, number of injured people, slope, altitude, and temperature. Then the paper used the AHP model to calculate the ratio of each indicator affecting wildfire and scored on indicators to observe the quality of the environment under different indicators. AHP tables in the paper showed that the influence of slope and altitude were weak on a wildfire in this region because their scores were constant. Forest quality in 1987 was relatively low, and the trend dramatically increased after this year; however, it decreased again from 1997 to 2002. Besides the AHP model, the paper also provided an entropy model by using the same parameters. Compared to the AHP model, the entropy model was more objective. Although its scores were all higher than the AHP model, the trends of the two models were similar.

1 Introduction

In the ecosystem, forests play a significant role, connecting much wildlife in the world. It was the essential habitat for most tropical species. There was rich biodiversity, and forests in neotropical areas became a breeding site for these species, such as swamps and streams. Also, the tropical forest was the only habitat for these species to live in because of unique vertical stratification [1]. Besides tropical forests, in other areas, the forest also provides shelters and food for wild animals. However, because of human behavior and weather disasters, wildfires happen frequently. Millions of thousands of forests were burned, and wildlife lost protections forever. Consequently, protecting forests is urgent and imperative.

Wildfires are prevalent among vegetation zones globally, such as grasslands and forests [2]. Management of wildfires is urgent because it produces severe adverse effects on the ecosystem. Wildfires generate different categories of pollutants, including CO, SO2, PM10, PM2.5, TSP, NOx, O3, and human health will be affected [3]. PM10 particles in the air with a diameter less or equal to 10 μm, while PM2.5 particles are particles in the air with a diameter less or equal to 2.5 μm. The PM10 level in the air, the most frequently studied index, typically rises up to 1.2 to 10 times the normal condition due to wildfire [3]. Multiple studies have shown that respiratory diseases are directly correlated with wildfire smoke, especially in northern China, where PM2.5 contributes to hazardous pollutants to citizens' respiratory health. Asthma and bronchitis are common respiratory morbidity for inhalation of microparticles as well as chronic heart diseases. There is a significant drop in newborn babies' body weight associated with maternal exposure [4].

Moreover, wildfire is a potential threat to human life and properties because wildfire prediction is not precise [2]. However, wildfire activities have increased during the recent decades and will continue to enlarge in numbers in...
the future. Factors that are tightly correlated with the enhancement in the number of wildfires include sequelae of fire suppression, human residence, natural climate variability, and anthropogenic climate change.

There were many studies based on the fire regime in northeastern China. Some researchers focus on post-fire recovery using NBR techniques to create graphs presenting different extent of fires on the recovery speed of varying forest species [6]. Some studies focused on spatial analyses of fire scars using a remote sensing database [9]. Some studies used The Vegetation Tracker algorithm to detect the relationship between tree changes and different variables based on the small sensing technique [10]. Some researchers paid attention to conditions of wildfire severity related to diverse forests and found out that beetles in California could affect wildfire as well [11]. Some scientists also evaluate after the wildfire in California, developing "green forest" by focusing on different land resilience corresponding to wildfire and other forest types with the suitable land type [12]. However, they mainly focused on the accidents after massive wildfires and based on a single technique or database to do research, lacking various processes and data methods to make analyses.

As a result, this paper would mainly focus on the regions of Mohe in the province of Heilongjiang province. It possesses noticeable vegetation change without depending on specific wildfire cases. The analysis will be based upon various data methods that combine the analytic hierarchy model and entropy evaluation with remote sensing technique. Three categories of analytical tools were involved in the study: the logical hierarchy model, remote sensing technique, and entropy modeling. The rational hierarchy model was used to analyze complex data from cases using math calculation. The present paper would calculate the extent of three terrain indicators, vegetation coverage, number of fires, area of damaged forest, and number of injured people. Then, compared to present which hand affects the wildfire, remote sensing would detect and monitor the characteristics of a site by measuring its emitted radiation on the satellite. This paper would use classification and raster analysis functions in remote sensing techniques to detect the extent of wildfire corresponding to different years of vegetation coverage, slope and altitude. The entropy model is related to probability and uncertainty. It was a measurement index to estimate the complication of the whole system by calculating the entropy formula. This paper would create an entropy model to detect the environmental vulnerability of this region. The result would better help us understand the relationship between wildfire and the forest. By calculating math models and providing graphs, researchers could be more familiar with detailed factors destroying forests in wildfire and making targeted conservation quickly. The primary purpose of this paper was to create a pre-assessment before possible wildfire happened, not focusing on the analysis of damages of a forest after disasters.

2.Methods

2.1 Data source

This article has collected data from 1987 to 2002 to build the APH (Analytic Hierarchy Process) model. Fire histories, climate conditions, geographical conditions, socio-economic conditions, and forest resource conditions were collected and analyzed for the APH model.

The general fire data, including the number of fires, the leading cause, severity, etc., are from China forestry and grassland statistical yearbooks, which can be found on cknii.net. The annual temperature and precipitation data are from the National meteorological information center under China meteorological data service center [20]. Local Administrative District Map in Environmental Systems Research Institute (ESRI) files mapping roads, and boundaries are downloaded from AMAP Inside (https://lbs.amap.com/) and Locaspace [21]. Data Cloud of CAS are the primary source of the local population and road distribution data, including education rate in towns and villages [22]. STRM (Shuttle Radar Topography Mission) data has been downloaded from Landsat5 and Digital Elevation Model (DEM) in Earthexplorer webpage contributed by the cooperation of NASA(National Aeronautics and Space Administration) and Ministry of Natural Resources of the People’s Republic of China [23]. NDVI method analyzes the vegetation index, classification, water bodies, vegetation, hilly areas, scrub area, open area, an agricultural area, thick forest, thin forest by utilizing the remote sensing data technique that involves different bands [13]. In this study, the Equation of NDVI that is applied in our research is as follows:

\[
\text{NDVI} = \frac{(\text{Band5} - \text{Band4})}{(\text{Band5} + \text{Band4})}
\]

Where: Band 4 Visible green (0.5 to 0.6 µm) — powered off due to high current in August 1995; Band 4 Near-Infrared (0.76 - 0.90 µm) 30 m; Band 5 Visible red (0.6 to 0.7 µm); Band 5 Near-Infrared (1.55 - 1.75 µm) 30 m.

To be more specific, under the GIS data analysis, to acquire the attribute data of general fire locations, vegetation classes and terrain factors were being extracted from STRM for model build[14]. QGIS software was used as the primary processing tool for acquiring NDVI data. They built virtual rasters with STRM layers each year under the band combination of 5-4-3, NIR (near-infrared), red, and green. These bands’ bandwidth was 0.85-0.88, 0.64-0.67, and 0.53-0.59 µm with a resolution of 30m. Referencing data from Hou and using Semi-Automatic Classification Plugin installed in QGIS, vegetation classification was set to collect data under different vegetation types, including coniferous forest, mixed forest, broadleaf forest, and shrub [15]. With the support of Mou and his colleague, DEM files were the primary provider for terrain factors and geographical conditions, which were altitude, slope, and aspects. Files about high-density areas and roads were also processed in QGIS to acquire human activities data, such as distances of a forest fire from residential areas and roads, using overlay analysis theory and buffer analysis methods [16].
Since the financial situation should also be under consideration for synthetically modified forest fires, frequency, per capita GDP in Chinayearbook.com was collected to find a relationship with education rate. The population's education rate and GDP have a high positive connection from the same data source, where population quality is high in high per capita GDP areas. Thus, per capita GDP is considered as qualified data to measure the education rate [14].

2.2 AHP modeling

Separating a complicated problem or decision, the AHP could provide detailed hierarchy aspects. It could evaluate ranks and values in all standards and substitutes within certain levels while comparing each other and providing results from the conclusions. It was originated by Dr. Thomas L. Saaty in the University of Pittsburgh, America, as a decision-making tool [17]. AHP is one of the most common methods to forecast forest fire since many factors trigger forest fire, and all triggers do not affect each other.

Unlike complex model building and decision-making, AHP can be specified into four aspects: problem modeling, weight valuation, weights aggregation, and sensitivity analysis.

Structure the problem initially to understand Heilongjiang’s forest fire causes, which can be divided into the goal, criteria, and alternatives three parts. To be more specific, it lists all possible alternatives and all criteria under a clearly illustrated goal. Then problems need to be clarified, as well as the set of sub-problems. Such as drier summer with accumulated leaf litter and dry fuels might cause a forest fire. According to DEM files, criteria for solution evaluation should be revealed during breaking problems into sub-problems. Such as breaking forest type into boreal forest, mixed forest, broadleaf forest, and shrub or breaking slope. To be more specific, five classes including 0-5, >5-20, >20-30, >30-40, and >40. Under this situation, the main objective (modeling chances of forest fire), criteria that cause (temperature, surface feature, topographic feature, and human activities), and alternatives ( alarming for a forest fire or not, the severity of the predicted fire, predicted financial budget and predicted damaged public and private resources)

After the hierarchy has been initiated, judgments and pairwise comparisons would be made to agree on making decisions. Draw on each other’s importance, and preference in relation, criteria in this pairwise comparison would be evaluated and rank. According to Wang’s research, the AHP scale generally ranks from 1 to 5, where 1 means "equal importance" and 5 shows "absolute importance" [14]. The rankings should be documented in a table of values where each column and row should be presenting the same headings. According to Pan’s research and consulting of certain experts, the rank was set in the discussion in this article [18].

In pairwise comparisons, it represents the relative importance of element i to element j, which means the relative importance of element j to segment i. The relative importance of factor i to element k, must meet the condition of to make the evaluation results have complete consistency. The consistency test is to evaluate the coordination between each sub-problem’s importance. Also, preventing the contradiction that elements might be more important than each other.

After finishing the comparison matrices, priorities calculation is the following step. After that,

The following step in the AHP modeling is normalizing the comparisons. Once the equation is ready with weighted criteria, alternatives can be evaluated to gain the most suitable solution that matches forest management needs. Finally, the weight of the forest fire risk factor, the goal of the model, can be obtained by converting the ranking result.

2.3 Entropy

Set within 4 different years, the entropy method is one of the objective weight methods that set these indexes' weight depending on data's dispersion degree[19]. The larger the information entropy of an index is, the less its variation degree is. If an index could provide a more significant amount of information, this index's greater corresponding weight could be. Keeping most of the original data collection, the entropy weight method was accepted as a relatively simple method. The steps as follows:

With positive and negative indicators illustrated previously, the indicator data Zij would be standardized to obtain new data represented by Z′ij. Then the positive indicator was showing higher the better and negative hands showing the opposite.

Then, the percentage of the index value of the i-th item under the j-th index should be calculated as follow:

\[ P_{ij} = \frac{Z_{ij}'}{\sum_{i=1}^{n} Z_{ij}'} \]  

(2)

After that, the information entropy calculation, using the following formula for the j-th index information entropy

\[ e_j = -\frac{\sum_{i=1}^{n} P_{ij} \cdot \ln P_{ij}}{\ln n} \]  

(3)

One notice is when Pij=0, lnPij=0

After all these calculations, the weight could be obtained. Then the equation for j-th index weight is shown as follows:

\[ w_{j}^{ent} = \frac{1 - e_j}{\sum_{i=1}^{n} \left(1 - e_j\right)} \]  

(4)

3 Results and Discussion

NDVI image is a valuable tool for determining the environmental vegetation coverage rate of Mohe. Figure 1 shows the NDVI images in the years 1987, 1992, 1997, 2002. Places with higher vegetation coverage rates are yellow. In contrast, the color purple shows the areas with a low vegetation coverage rate. It can be inferred from the figures that in the year 1987, the vegetation coverage rate...
is still relatively high. However, in the year of 1992, the vegetation coverage rate dropped dramatically. And it recovered slowly from 1997 to 2002. At last, the vegetation coverage rate became relatively high.

Altitude is an essential component while analyzing the environmental quality of Mohe. The contour lines are drawn as red lines, and the labels are marked in Figure 2. A height higher than 897 meters is shown as yellow, and an altitude that is lower than 646 meters is shown as purple. Generally, two elliptical areas in Mohe are high latitudes that possess a latitude higher than 646 meters. Meanwhile, the leeway in other regions is relatively lower.

The slope is a factor that will affect the growth of vegetation in distinctive areas. Figure 3.2 shows the slope in Mohe. In this figure, yellow represents places with a greater slope than 89.9976 degrees, while purple represents a place with a slope lower than 89.9925 degrees. It can be deduced that generally, the slope of Mohe is high due to its mountainous structure.

AHP modeling was constructed to determine the ratio of components that are the most significant for the scoring of the environment each year, which can be used to further calculate the domain’s vulnerability. It can be inferred from the table that vegetation coverage and the number of injured people every year are more important than factors. They were followed by the area of damaged forest. At the same time, the number of fires and temperature are relatively less critical. The least important factors are slope and altitude, which hardly ever changed since 1987. After the utilization of programming, the ratios of each element are obtained. The CI value calculated is 0.0204, and the CR value is 0.015, which are both well below 0.1. This indicates that the model is valid.
Table 1 AHP of different elements of Mohe in 1987, 1992, 1997, 2002[T4]

| Parameters                  | Vegetation coverage rate | Number of fires | Area of damaged forest | Number of injured people | Slope | Altitude | Temperature | Ratio |
|-----------------------------|--------------------------|-----------------|------------------------|--------------------------|-------|----------|-------------|-------|
| Vegetation coverage         | 1                        | 3               | 2                      | 1                        | 5     | 5        | 3           | 0.2712|
| Number of fires             | 1/3                      | 1               | 1/3                    | 1/3                      | 3     | 3        | 1           | 0.1021|
| Area of damaged forest      | 1/2                      | 3               | 1                      | 1/2                      | 3     | 3        | 2           | 0.1676|
| Number of injured people    | 1                        | 3               | 2                      | 1                        | 5     | 5        | 3           | 0.2712|
| slope                       | 1/5                      | 1/3             | 1/3                    | 1/5                      | 1     | 1        | 1/2         | 0.0482|
| altitude                    | 1/5                      | 1/3             | 1/3                    | 1/5                      | 1     | 1        | 1/2         | 0.0482|
| Temperature                 | 1/3                      | 1               | 1/2                    | 1/3                      | 2     | 2        | 1           | 0.0915|

A score range of 1 to 5 was utilized to demonstrate the quality of the environment. In this range, a score of 1 represents terrible quality. Contradictorily, a score of 5 represents excellent quality while 3 represents medium quality. Table 3.2 shows the score and the sum of each element from 1987 to 2002. Because of severe wildfire in 1987, scores of specific indicators in 1987 were deficient, but after 1987, each score in different hands increased slightly. In the Greater Khingan Range area, slope and altitude are unchangeable within these years. Because of its terrain, the hill is relatively low, but it is good for the forest to grow. After the massive wildfire in 1987, the number of fires and injured people decreased in a large amount in the next few years. Comprehensively, the sum of scores shows an increasing trend. The sum increased dramatically from the year 1987 to 1992. Similarly, the sum increased by a relatively high amount from 1992 to 1997 whereas the sum decreased from 1997 to 2002.

Table 2 Scores of elements in the year 1987, 1992, 1997, 2002 by using the AHP model

| Parameters                  | Ratio | 1987 | 1992 | 1997 | 2002 |
|-----------------------------|-------|------|------|------|------|
| Vegetation coverage         | 0.2712| 2.5  | 2.2  | 2.7  | 3.1  |
| Number of fires             | 0.1021| 1.8  | 2.6  | 2.8  | 2.8  |
| Area of damaged forest      | 0.1676| 1    | 4    | 5    | 3    |
| Number of injured people    | 0.2712| 1    | 4    | 5    | 4    |
| slope                       | 0.0482| 2.5  | 2.5  | 2.5  | 2.5  |
| altitude                    | 0.0482| 3    | 3    | 3    | 3    |
| Temperature                 | 0.0915| 1.5  | 1.7  | 1.8  | 2.0  |
| Sum                         | 1     | 1.70293 | 3.03795 | 3.64192 | 3.1623 |

Based on the data in AHP modeling, a trend was constructed to predict environmental vulnerability in the future. It can be inferred from the figure that the score of the environment is generally increasing. However, as the $R^2$ value is only 0.5994, the figure can only be used as a reference rather than a definite representation.

The AHP modeling is a subjective model that is used for evaluating vulnerability. To make the results more persuasive, a more objective model, the Entropy model, was used to obtain the ratio of each element's importance. Multiple data were used to calculate the proportion of each component. The calculated percentages are listed in Table 4.4. As for the results, all of them are relatively higher than the results obtained in the AHP model to some extent. Nonetheless, the general trend that is shown in the table is similar for the two models.
Table 3 Scores of elements in the year 1987, 1992, 1997, 2002 by using the Entropy model

| Parameters               | Ratio | 1987 | 1992 | 1997 | 2002 |
|--------------------------|-------|------|------|------|------|
| Vegetation coverage      | 0.2079| 2.5  | 2.2  | 2.7  | 3.1  |
| Number of fires          | 0.1668| 1.8  | 2.6  | 2.8  | 2.8  |
| Area of damaged forest   | 0.169 | 1    | 4    | 5    | 3    |
| Number of injured people | 0.1983| 1    | 4    | 5    | 4    |
| slope                    | 0.1432| 2.5  | 2.5  | 2.5  | 2.5  |
| altitude                 | 0.1534| 3    | 3    | 3    | 3    |
| Temperature              | 0.1283| 1.5  | 1.7  | 1.8  | 2    |
| Sum                      | 1     | 2.19794 | 3.39657 | 3.91491 | 3.48653 |

The trend is calculated by using the data in the Entropy model. Overall, it shows an increasing yearly trend. However, as the $R^2$ value is merely 0.5911, which is smaller than the value from the AHP model, the figure can only be used as a reference rather than a definite representation.

4 Conclusion

This article used correlation analysis and geographic information system analysis to analyze the influencing factors of general forest fires in Mohe, Greater Khingan Range. Then it uses the AHP method to divide the weight of each influencing factor to study the impact factors of general forest fires in Mohe. As well as using the entropy method to measure the index to estimate the system’s complexity. Data were collected from 1987 to 2002 from the China yearbook, Landsat 5 satellite, and USGS. To build the APH model and to use the entropy method, data was extracted from NDVI and dem files using QGIS. In APH modeling, the table presented that vegetation coverage and the number of injured people every year are more important than the area of damaged forest. While the less critical factor was the number of fires and temperature, slope and altitude were considered as the least important factors. The CI value calculated is 0.0204, and the CR value is 0.015, which are both well below 0.1 to testify the model was valid. AS for the entropy method, it showed an increasing yearly trend. All of them are relatively higher than the results obtained in the AHP model.

Nonetheless, the general trend that is shown in the table is similar for the two models. It is believed that these two models were capable of contributing to forest fire prevention and prediction. To reduce damage caused by forest fire to the local’s health and property, these methods might prove to be valuable and efficient.

Reference

1. Paulson D. (2006) The Importance of Forests to Neotropical Dragonflies. In: Adolfo Cordero R. (Eds.), Pensoft Publishers, Sofia-Moscow. pp. 79-101.
2. Abatzoglou John T., & Williams A. Park. (2016). Impact of anthropogenic climate change on wildfire across western US forests. Proceedings of the National Academy of Sciences of the United States of America, 113(42), 11770–11775.
3. Brigitte Leblon, Laura Bourgeau-Chavez and Jesús San-Miguel-Ayanz (August 1st 2012). Use of Remote Sensing in Wildfire Management, Sustainable Development - Authoritative and Leading Edge Content for Environmental Management, Sime Curkovic, IntechOpen, DOI: 10.5772/45829. Available from:https://www.intechopen.com/books/sustainable-development-authoritative-and-leading-edge-content-for-environmental-management/use-of-remote-sensing-in-wildfire-management
4. Liu, J. C. (1), Uhl, S. A. (1), Bravo, M. A. (1), Bell, M. L. (1), & Pereira, G. (2). (n.d.). A systematic review of the physical health impacts from non-occupational exposure to wildfire smoke. Environmental Research, 136, 120–132. https://doi.org/10.1016/j.envres.2014.10.015
5. Abdo M, Ward I, O'Dell K, Ford B, Pierce JR, Fischer EV, Crooks JL. Impact of Wildfire Smoke on Adverse Pregnancy Outcomes in Colorado, 2007-2015. Int J Environ Res Public Health. 2019 Oct 2;16(19):3720. doi: 10.3390/ijerph16193720. PMID: 31581673; PMCID: PMC6801422.
6. Gandhi, G. M., Parthiban, S., Thummalu, N., & Christy, A. (2015). Ndvi: Vegetation Change Detection Using Remote Sensing and Gis - A Case Study of Vellore District. In Procedia Computer
7. Bright B C, Hudak A T, Kennedy R E, Braaten J D and Khalyani A H. (2019) Examining post-fire vegetation recovery with Landsat time series analysis in three western North American forest types. SpringerOpen. Fire Ecology 15, Article number: 8

8. Paulson D. (2006) The Importance of Forests to Neotropical Dragonflies. In: Adolfo Cordero R. (Eds.), Pensoft Publishers, Sofia-Moscow. pp. 79-101.

9. Abbreviations. (2019) What does FOREST stand for. https://www.abbreviations.com/Forest

10. Tian X R, Ru L, Wang M Y, Zhao F J, and Chen L G. (2013) The fire danger and the fire regime for the Daxin’anling region for 1987-2010. Science Direct. Procedia Engineering 62 1023-1031.

11. Qiu J, Wang H, Shen W, Zhang Y, Su H and Li M. Quantifying Forest Fire and Post-Fire Vegetation Recovery in the Daxin’anling Area of Northeastern China Using Landsat Time-Series Data and Machine Learning. Remote Sens. 2021, 13, 792.

12. Rebecca, B. W, Hugh D. S. (2021) Recent bark beetle outbreaks influence wildfire severity in mixed-conifer forests of the Sierra Nevada, California, USA. Volume 31, Issue 3.

13. Scott L S, Brandon M C, Christopher J F, Mark A F, Chad M H, Eric E K, Malcolm P N, Hugh S, Rebecca B W. (2018) Drought, Tree Mortality, and Wildfire in Forests Adapted to Frequent Fire. BioScience, Volume 68, Issue 2.

14. Gandhi, G.M., Parthiban, S. (2015) Ndvi: Vegetation Change Detection Using Remote Sensing and Gis – A Case Study of Vellore District. Procedia Computer Science., p. 1199-1210.

15. Wang, J., Niu, S. (2012) Research on the spatial distribution of forest fires in Sichuan province. Guangdong Agricultural Sciences., 39(17): p. 233-236.

16. Hou, Junfeng. (2017) Study on occurrence regularity and risk assessment of forest fire in Yuchun Forest Region, Master's, Beijing Forestry University.

17. Huaiyi, M. (2018) Change Detection and Spatial Analysis of Forest Vegetation Based on DEM. Geospatial Information., 16(07): p. 96-100+11.

18. Saaty, T.L. (2004) Decision making — the Analytic Hierarchy and Network Processes (AHP/ANP). Journal of Systems Science and Systems Engineering., 13(001): p. 1-35.

19. Pan, J., Ma, N.(2010) An Appraisal Method of Forest Fires Prevention Ability Based on AHP. The Fourth Annual in China Disaster Prevention Association Risk Analysis Professional Committee. The Province of Ji lin, City of Chang Chun in China.

20. Zhang, P., (2020) Research on Weighted Model of Air Defense Weapon-Target Assignment Based on AHP and Entropy Method.IEEE., p. 802-809.

21. Information from https://data.cma.cn/.

22. Information from http://www.locaspace.cn/.

23. Information from http://www.csdb.cn/.

24. Information from https://earthexplorer.usgs.gov/.