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RESEARCH ARTICLE

Integration of satellite remote sensing data in underground coal fire detection: A case study of the Fukang region, Xinjiang, China

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Abstract Xinjiang in China is one of the areas worst affected by coal fires. Coal fires cannot only waste a large amount of natural resources and cause serious economic losses, but they also cause huge damage to the atmosphere, the soil, the surrounding geology, and the environment. Therefore, there is an urgent need to effectively explore remote sensing based detection of coal fires for timely understanding of their latest development trend. In this study, in order to investigate the distribution of coal fires in an accurate and reliable manner, we exploited both Landsat-8 optical data and Sentinel-1A synthetic aperture radar (SAR) images, using the generalized single-channel algorithm and the InSAR time-series analysis approach, respectively, for coal fire detection in the southern part of the Fukang region of Xinjiang, China. The generalized single-channel algorithm was used for land surface temperature information extraction. Meanwhile, the time-series InSAR analysis technology was employed for estimating the surface micro deformation information, which was then used for building a band-pass filter. The suspected coal fire locations could then be established by a band-pass filtering operation on the obtained surface temperature map. Finally, the locations of the suspected coal fires were validated by the use of field survey data. The results indicate that the integration of thermal infrared remote sensing and radar interferometry technologies is an efficient investigation approach for coal fire detection in a large-scale region, which would provide the necessary spatial information support for the survey and control of coal fires.

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1 Introduction

The term “coal fire” refers to the burning of an outcrop or underground coal seam, which can be caused by both human and natural factors (Li, 2015). Coal fires not only waste large amounts of coal resources, but also produces large amounts of toxic and harmful gas (including CO, CO_2, SO_2, CH_4, and H_2S), as well as a lot of dust. This causes air pollution, and may even be aggravating the greenhouse effect around the world (Ji, 2012b; Song and Kuenzer, 2015). Coal combustion also changes soil properties, which in turn affects plant growth. What is worse, a large amount of surface vegetation is often destroyed in coal fires, which can be followed by flood and soil loss, desertification, biological degradation, and ecological unbalance (Zhang et al., 2014). Coal fires also disturb the surrounding rock stress equilibrium, and can cause surface subsidence, collapse, and ground fissures, as well as posing a threat to local infrastructure and the safety of residents’ lives and properties (Wang et al., 2015; Kuenzer and Stracher, 2012). It is therefore of great practical significance to monitor and control underground coal fires, for the protection of natural resources and the ecological environment.

Since the 1960s, remote sensing technology has been used to monitor and analyze coal fires. Remote sensing technology can realize the monitoring of dynamic large-scale continuous coal fires and provide essential spatial information support for fire-fighting efforts (Li et al., 2016; Song and Kuenzer, 2014, 2017). In 1964, Slavecki (1964) was the first to use a thermal infrared camera to monitor an underground coal fire. Subsequently, Jiang et al. (2011b, 2011c) proposed a method of monitoring underground coal fires by the use of nighttime thermal infrared remote sensing data. Wu (2001) adopted the density segmentation method to process single-band thermal infrared images, and extracted the thermal anomaly areas in remote sensing images. Deng et al. (2001) and Zhang et al. (1997, 2003, 2004) extracted the surface thermal anomaly information from multiple thermal infrared remote sensing time-series images, obtaining remarkable results. Mishra et al. (2011) applied the radiation transfer equation method for the inversion of land surface temperature detected through the use of Landsat-7 ETM + data for the monitoring of a coal fire in Jharia, India. Li et al. (2017) used the signal-window algorithm, two Landsat-5 images obtained in 2008 and 2011, and two Landsat-8 images obtained in 2013 and 2015 to assess the conditions before and after the implementation of fire-fighting activities in the Wuda coalfield of Inner Mongolia, China. However, due to the differences in both the inversion algorithms and the environment in coal fire areas, a uniform standard for the remote sensing based monitoring of coal fires has not been developed (Ji et al., 2012a). Although thermal infrared remote sensing can be used to extract the high-temperature anomaly areas, extensive visual interpretation or field reconnaissance is also needed to confirm the locations of the coal fires (Zhang et al., 2018).

In recent years, with the occurrence of coal fires deeper underground, coal fires are becoming more and more hidden. In addition, the difficulty of controlling residual coal fires has increased, and the reburning of controlled areas has also occurred (Deng et al., 2016). Furthermore, the use of a single coal fire detection method often cannot meet the actual needs, and thus an integrated satellite remote sensing method has been proposed for coal seam fire detection, using surface thermal anomalies, spectral characteristics, as well as land subsidence information (Voigt et al., 2004). Interferometric synthetic aperture radar (InSAR) is an efficient method for earth surface deformation observation, and it can work day and night under all weather conditions, with high temporal and spatial resolutions, covering a large-scale region (Liu, 2016). A long time series of radar remote sensing data can be used to accurately obtain the surface deformation and development laws of a research area (Jiang et al., 2011a). In 1989, for the first time, Gabriel et al. (1989) applied InSAR technology to monitor surface deformation. InSAR technology has since developed rapidly, and has been widely used in the monitoring of various deformation types, especially mining subsidence, oil field subsidence (Fitra and James, 2012; Filatov et al., 2013; Yang et al., 2015), fracture zones caused by volcanos and earthquakes (Agustan, 2010; Samsonov, 2010; Samsonov and Oreye, 2012), urban surface deformation (Lagios et al., 2011; Wang, 2014; Zhu et al., 2014), and landslide deformation (Colesanti et al., 2003; Allievi et al., 2003). InSAR time-series data (including both permanent scatterer interferometric synthetic aperture radar (PS-InSAR) and small baseline subset interferometric synthetic aperture radar (SBAS-InSAR)) can allow high-accuracy measurement of small surface deformation. Such data can also be used to detect the small surface subsidence associated with coal fires, allowing us to extract the possible locations of coal fires (Tao et al., 2012, Jiang et al. 2011a).

In this study, under these circumstances, we explored the use of Landsat-8 data with the generalized single-channel algorithm, as well as Sentinel-1A radar satellite imagery with the InSAR time-series analysis approach. The surface temperature and the corresponding deformation information could thus be obtained for the study region of the southern part of the Fukang region of Xinjiang, China. By combining the respective advantages of optical and SAR images, to make up for their respective deficiencies and improve the reliability of the suspected coal fire detection, a band-pass filter was used with the remote sensing results to extract the possible locations of coal fires. Finally, the remote sensing based coal fire location results were analyzed and verified with the use of field data. In summary, the proposed approach allows accurate and reliable coal fire detection with multi-source remote sensing imagery.

2 Study area and data sets

2.1 Overview of the research region

The research region is located in the west of the Fukang mining area of Xinjiang (88°E–88°12′E and 44°02′N–44°6.7′N), with a total area of about 135 km^2. It lies between the Tianshan Mountains (Bogda Mountain) and the southern margin of the Junggar Basin. The area is mainly covered with sparse vegetation. The terrain is complex and gradually descends from south to north. This area is in the hinterland of Eurasia, and is characterized by a semi-arid to arid continental climate with hot and dry summers and cold and dry winters (Zhou et al., 2005). The coal reserves are abundant, with the main types of coal being gas coal and long-flame coal. These coals form good coking coal, and are also suitable for blending and steam coal. The coal in the mining area is of low coal metamorphism, high volatile matter, and low–medium ash content. The non-cohesive coal seams are loose and easily weathered into powder. When the temperature rises, spontaneous combustion of the coal seams can occur. Moreover, the Mesozoic Jurassic strata are widely exposed in the mining area. The many folds and faults in the strata result in the coal seams coming into contact with the air, which in turn results in multiple coal fire zones. There are numerous coalmines in the research region, including the No. 1 to No. 10 mines, as shown in Fig. 1. These mining

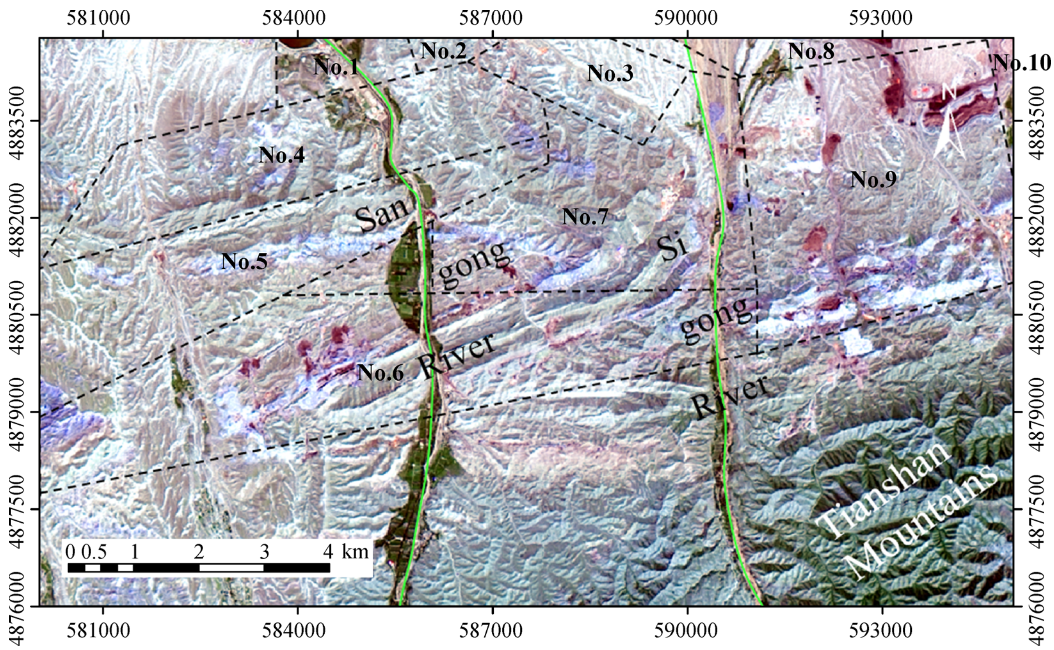

Fig. 1 True-color image of Landsat-8 bands 4, 3, and 2 in the research region.

activities are also an important cause of coal fires. The coal-seam fires in the area have a great destructive effect on the local ecological and geological environment, and also pose a threat to human safety and property (Zhang, 2014; Zeng and Zhang, 2012).

2.2 Data sources

The Landsat-8 imagery was archived from 2013 when the satellite was launched. The spatial resolution of the Thermal Infrared Sensor (TIRS) carried by the satellite is 100 m. It is one of the most advanced thermal infrared sensors, and provides an excellent remote sensing imagery source for coal fire detection. Several Landsat-8 optical satellite images were acquired, including both TIRS data and OLI (Operational Land Imager) data, as listed in Table 1. The images acquired between 2015 and 2017 with low cloud cover were used to obtain the land surface temperature information for the research region. The auxiliary data for the estimation of atmospheric moisture content were obtained from NASA's official website. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) global digital elevation model (GDEM) V2 elevation data with a spatial resolution of 30 m were applied for the terrain radiation correction. And 38 Sentinel-1 IW Mode single look complex (SLC) images with relative orbit 41 and VV polarization selected between 2015 and 2017 were used for the surface deformation estimation by InSAR time-series analysis (Table 2). In addition, the Shuttle Radar Topography Mission (SRTM) DEM data with a resolution of 90 m were used as the external auxiliary data for the topographic phase compensation in the SAR interferometry.

3 Methods

In this study, we first used the generalized single-channel algorithm for land surface temperature inversion to obtain the spatial distribution of the surface temperature in the research region. At the same time, InSAR time-series analysis technology was applied to analyze the surface deformation information. The band-pass filter was then built and used to eliminate or weaken the surface temperature anomalies not caused by coal fires. Thus, the possible locations of coal fires were extracted. Figure 2 shows the technical procedure of coal fire detection.

Table 1 Landsat-8 OLI and TIRS data acquired between 2015 and 2017

No.	Data acquired	No.	Data acquired	No.	Data acquired
1	2015-03-20	4	2016-06-26	7	2017-06-13
2	2015-09-12	5	2016-07-12	8	2017-08-16
3	2015-10-30	6	2016-07-28		

Table 2 Sentinel-1A SAR SLC data acquired between 2015 and 2017

No.	Data acquired	No.	Data acquired	No.	Data acquired
1	2015-01-24	14	2016-01-07	27	2017-01-25
2	2015-02-17	15	2016-01-31	28	2017-02-06
3	2015-03-01	16	2016-02-24	29	2017-03-14
4	2015-03-25	17	2016-03-19	30	2017-04-19
5	2015-04-18	18	2016-04-12	31	2017-05-25
6	2015-05-12	**19**	**2016-05-06**	32	2017-06-30
7	2015-06-29	20	2016-05-30	33	2017-07-24
8	2017-07-23	21	2016-07-17	34	2017-08-29
9	2015-08-16	22	2016-08-10	35	2017-09-22
10	2015-09-09	23	2016-09-27	36	2017-10-28
11	2015-10-03	24	2016-10-21	37	2017-11-21
12	2015-11-20	25	2016-11-14	38	2017-12-15
13	2015-12-14	26	2016-12-08		

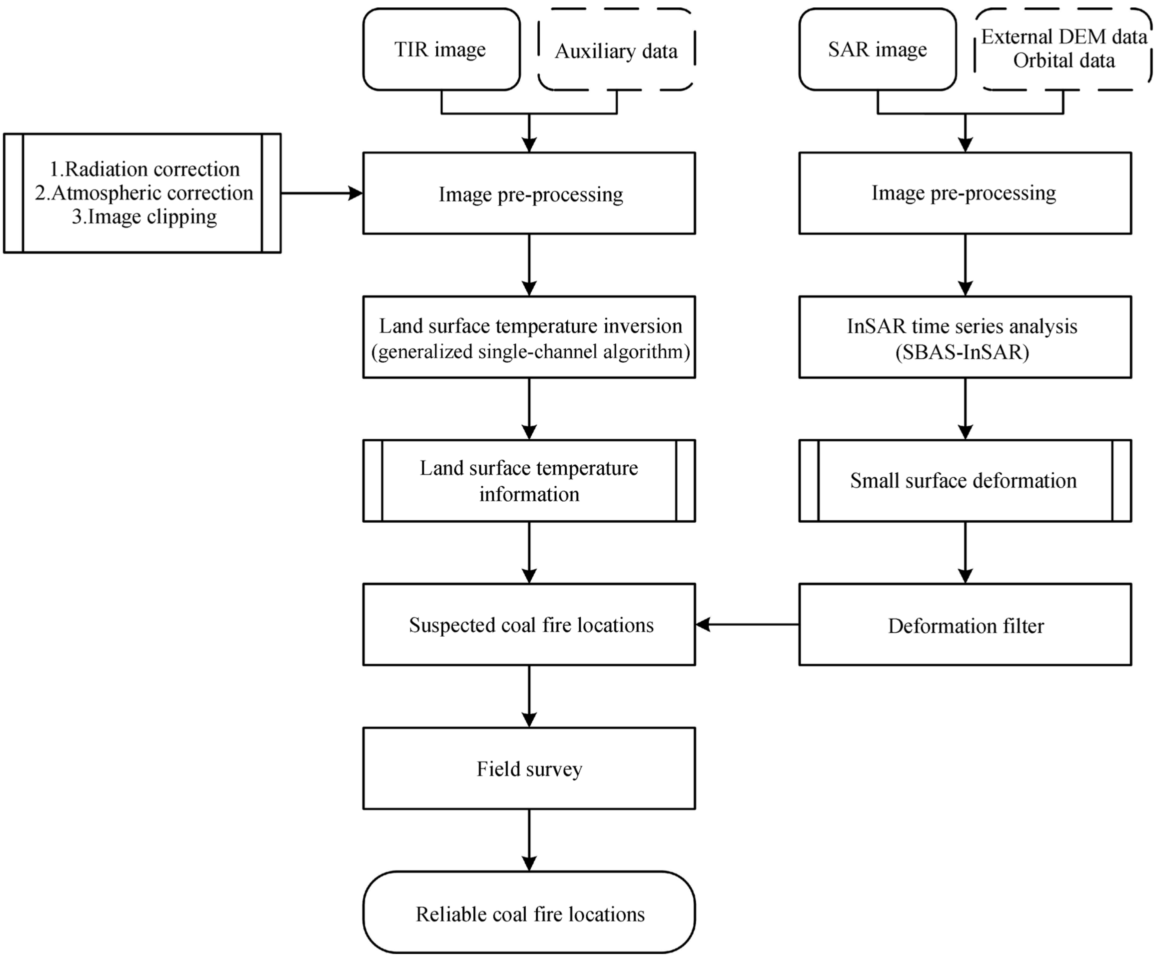

Fig. 2 The technical procedure of coal fire detection.

3.1 Surface temperature inversion

For the Landsat-8 generalized single-channel algorithm, the land surface temperature inversion algorithm considers the influence of both surface emissivity and atmospheric radiation, and is suitable for areas with relatively low atmospheric water vapor content (Ji et al., 2012a). The preprocessing of the original data was first conducted, including radiation calibration and atmospheric correction. The normalized difference vegetation index (NDVI) was then calculated. The surface emissivity was obtained by the $\mathrm{NDVI}^{\mathrm{TEM}}$ method (Qin et al., 2004). The radiation correction of the terrain was carried out by combining the DEM data and using the SCS + C model proposed by Soenen et al. (2005). Then, based on the atmospheric transmittance calculated from the NASA website and the relationship between the atmospheric transmittance and atmospheric moisture content from the 1976 US Standard Atmosphere, the atmospheric moisture content w ($\mathrm{g \cdot cm^{-2}}$) in the research region was obtained. According to the generalized single-channel algorithm developed by Jiménez-Muñoz et al. (2014), the inversion of the land surface temperature was then performed based on the thermal infrared images.

The inversion formula is as follows:

$$T_S = \gamma\left[\frac{1}{\varepsilon_{\mathrm{surface}}}(\psi_1 L_i + \psi_2) + \psi_3\right] + \delta, \tag{1}$$

where γ and δ are the correlation coefficients of Planck's equation, which can be calculated by the spaceborne radiance L_i and the spaceborne brightness temperature T_i. ψ_1, ψ_2, and ψ_3 are three atmospheric parameters, which can be obtained from the atmospheric water vapor content. The formula for this is as follows:

$$\psi_i = c_{i1} \times w^2 + c_{i2} \times w + c_{i3}, \tag{2}$$

where c_{ij} is the coefficient, which can be found by referring to Table 3.

The land surface temperature inversion was carried out on eight images respectively from 2015, 2016, and 2017 to obtain each image's high-temperature anomalies. The research area is relatively small, so the sunlight and atmospheric conditions were basically the same over the whole area. The land surface temperature information obtained from the thermal infrared remote sensing images was then used for a statistical analysis. The mean μ and variance σ of the land surface temperature were used to extract the pixels with values larger than μ + σ as high-temperature anomaly areas (Qiu et al., 2012). The stable surface high-temperature anomaly areas were extracted to reduce the effects of accidental errors. Based on the characteristic of the continuous high temperature of the temperature signals in the temporal dimension in the coal fire areas, we expanded the pixels corresponding to the temperature information in the eight images in the temporal dimension and analyzed their statistical characteristics, such as the mean and variance, as shown in Fig. 3. The characteristics of coal fire change and

Table 3 Coefficient calculation table for the atmospheric parameters in Landsat-8 TIRS band 1 (Wang, 2017)

TIRS band	c_{ij}	$j = 1$	$j = 2$	$j = 3$
Landsat-8 TIRS 1	$i = 1$	0.040 19	0.029 16	1.015 23
	$i = 2$	−0.383 33	−1.502 49	0.203 24
	$i = 3$	0.009 18	1.360 72	−0.275 14

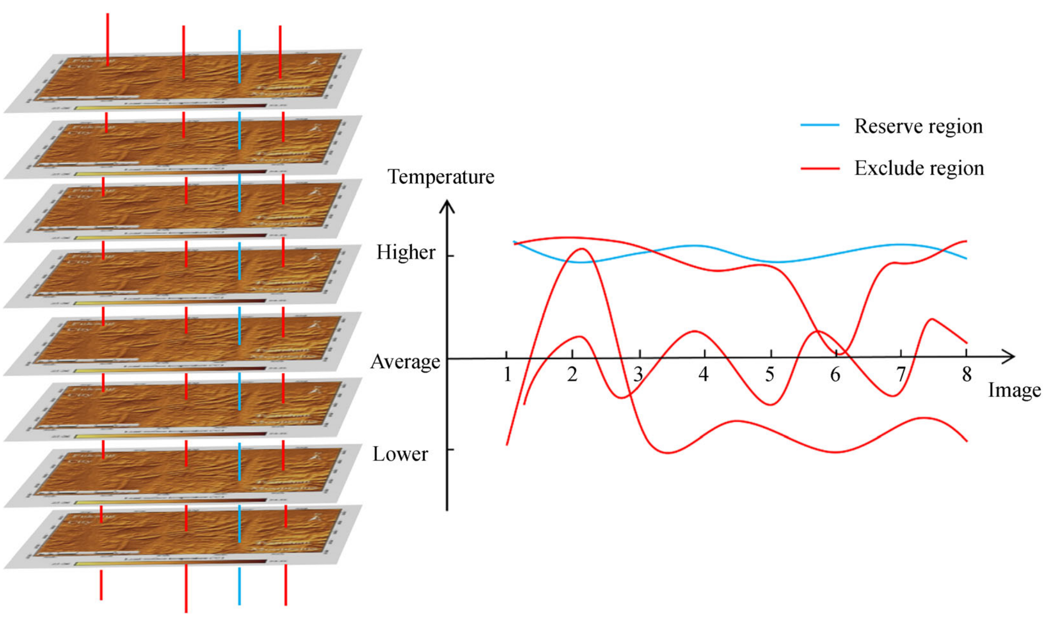

Fig. 3 Schematic diagram of the time-series processing of the land surface temperature information.

development mean that the coal-fire-induced surface high-temperature anomaly was continuous over a certain period of time. Therefore, the high-temperature anomaly areas where both the mean values and variances could meet the conditions were kept, as shown by the blue line in Fig. 3. Other areas which were more affected by errors were eliminated, as shown by the red line in Fig. 3. In addition, according to the coal fire development and combustion characteristics, the coal fire areas are generally not isolated points, so a convolution operation was carried out for the obtained high temperature anomalies, to exclude the sporadic areas. Figure 4 shows the final land surface high-temperature anomaly areas.

3.2 Surface deformation monitoring

Compared with the conventional InSAR technology, the time-series analysis of InSAR can solve the problem of space-time decorrelation and atmospheric delay, to a certain extent. With a high monitoring accuracy, the time-series analysis of InSAR can meet the requirements of the possible small surface subsidence caused by coal-seam combustion (Zhou et al., 2017). The combination of multi-source remote sensing data for coal fire detection can be achieved by using the time-series analysis of InSAR and thermal infrared remote sensing technology for the analysis of surface deformation and temperature information in the suspected coal fire areas. The multiple main image SBAS time-series analysis method proposed by Berardino et al. (2002) was applied in this study to extract the surface deformation in the research region. Compared with the traditional single main image time-series analysis approach, this method can overcome the adverse effects of temporal decorrelation, to some extent, and can select more high-coherence points on the surface. The basic idea of this method is to first group the SAR images into several sets of interferometric pairs, based on the short baseline principle. The least-squares method is then used to obtain each baseline set's surface deformation sequence. Finally, singular value decomposition (SVD) is applied to calculate the multiple small baseline sets, to obtain the average deformation rate of the high-coherence points (Liang, 2014).

The interference was established for the image obtained by the arbitrary interferogram j between t_A and t_B ($t_B > t_A$). The interferometric phases of pixels in azimuth coordinate x and range coordinate r can be expressed as the product of the average rate of phase v_j and the time period between the two time epochs. The phase value of the jth interferogram can then be expressed as follows:

$$\Sigma_{k=t_{A}j+1}^{t_{Bj}}(t_k - t_{k-1})v_k = \delta\varphi_j, \tag{3}$$

where $j\in(1,2,...,M)$, and $\varphi(x,r)$ refers to the phase value of the SAR image at time t.

$$v_j = \frac{\varphi_j - \varphi_{j-1}}{t_j - t_{j-1}}. \tag{4}$$

This can be represented as a matrix, as follows:

$$\boldsymbol{B}v = \delta\varphi. \tag{5}$$

The SVD method is used to calculate matrix $\boldsymbol{B}$, and the

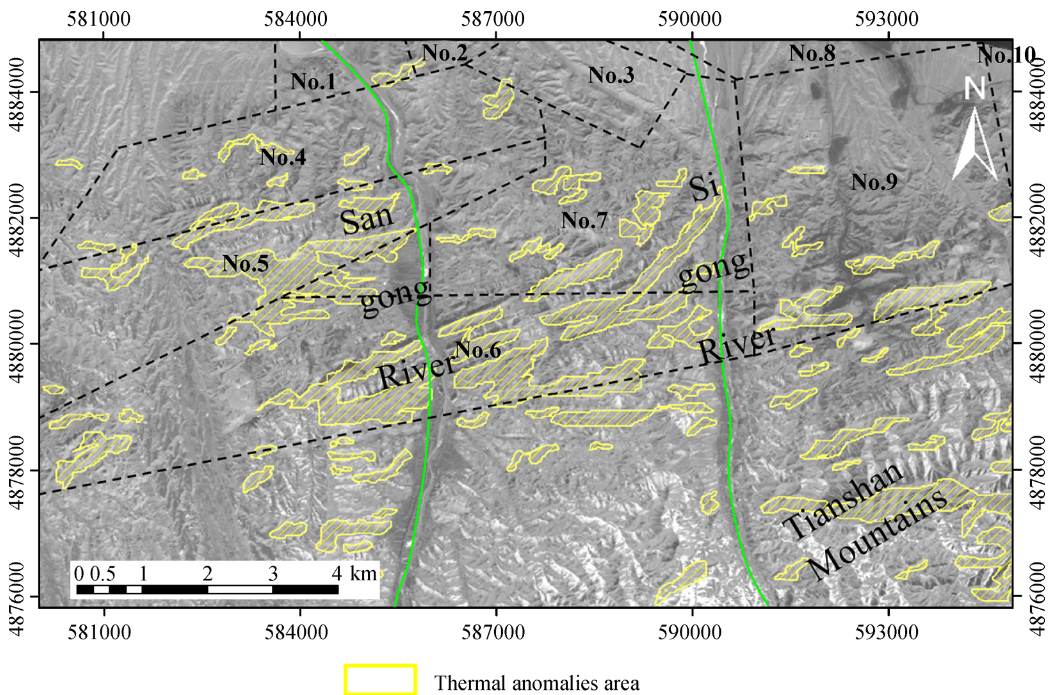

Fig. 4 Schematic diagram of the land surface temperature anomaly areas in the research region.

minimum norm solution of the rate can be obtained.

The original data were first preprocessed. All images were registered to the main images on May 6, 2016. According to the short baseline principle, the differences of each image and the three front and back adjacent images were calculated. A total of 108 small baseline differential interferometric pairs were generated, as shown in Fig. 5. The GACOS atmospheric interference phase correction data and the space-time filtering method were then adopted to weaken the atmospheric effects (Yu et al., 2017, 2018a, 2018b) and obtain the surface deformation information in the research region, as shown in Fig. 5. It can be seen that the north-west part of the region experienced relatively low overall deformation, while the north-central region experienced obvious surface subsidence.

3.3 The detection of suspected coal fire areas

Underground coal combustion results in an increase of land surface temperature, so the land surface temperature can be used as an important basis for coal fire detection. Generally speaking, a high-temperature anomaly threshold is set, and the high-temperature anomaly areas are taken as the possible areas of coal fires. However, some materials with low heat capacities (such as sandstone) may lead to high land surface temperatures that are unrelated to coal fires. Such areas can interfere with the coal fire detection and induce misjudgment. Therefore, the detection of coal fire areas based on a single remote sensing data source is often severely restricted. To implement an accurate remote sensing based survey of a coal fire area, it is imperative to jointly apply multi-source remote sensing data.

Underground coal combustion does not only cause high surface temperature, but it can also change the volume and mechanical properties of the surrounding rocks and trigger collapse, ground fissures, and other geological disasters. The coal fires are in the form of high-temperature anomalies in the thermal infrared images and surface deformation in the time-series interferometric signals. To reduce the influence of errors, the band-pass filter was built with the subsidence rate threshold of 5 mm/year, which was experimentally given according to the mean and standard deviation of the subsidence rate of the study region. Thus, the thermal signals in areas where the surface subsidence rate was higher than the threshold could pass the band-pass filter, while the thermal signals in areas without surface subsidence or with relatively low subsidence rates could not pass the band-pass filter. To improve the accuracy and reliability of coal fire detection, the band-pass filtering was performed on the land surface temperature to exclude some non-coal-fire-related high-temperature anomaly areas. Thus the remaining high-temperature anomaly areas could be considered as the final suspected locations of coal fires. Figure 6 shows the general process flowchart of extracting the suspected coal fire locations by the band-pass filtering method.

4 Results and analysis

There are usually some signs of underground coal combustion on the surface, such as ground fissures, smoke, and even open fires. The aforementioned coal fire detection results were verified based on the coal fire locations detected by field survey over the last five years by the Xinjiang Coalfield Fire Fighting Bureau. As shown in Fig. 7, the areas delineated by the red lines are the suspected coal fire areas, and the green triangles refer to the coal fire locations identified by field survey.

As shown in Fig. 7, seven coal fire locations with

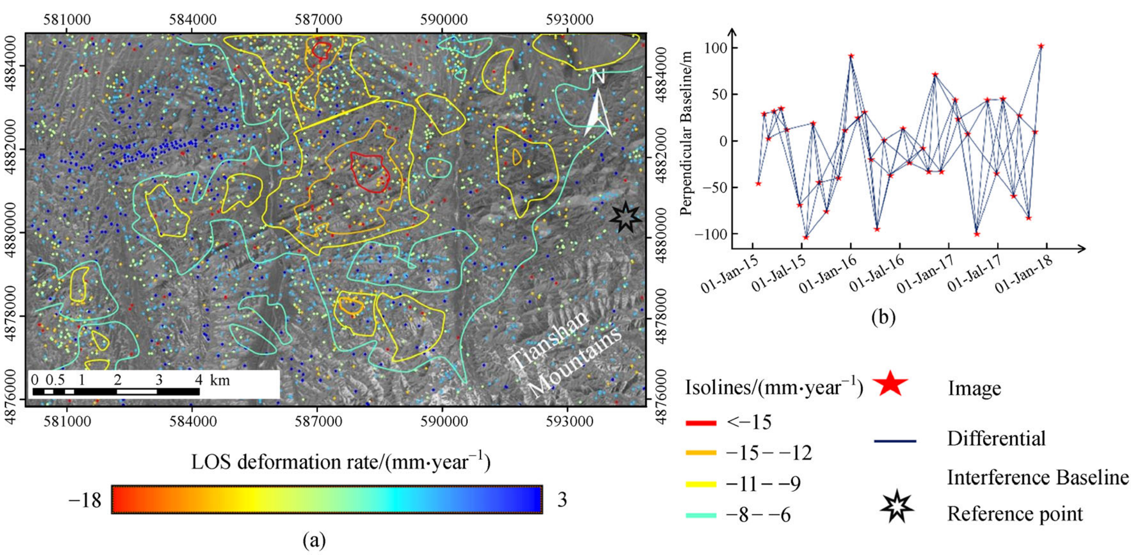

Fig. 5 The rate of surface deformation in the research region (a), and the SBAS-InSAR spatio-temporal baselines (b).

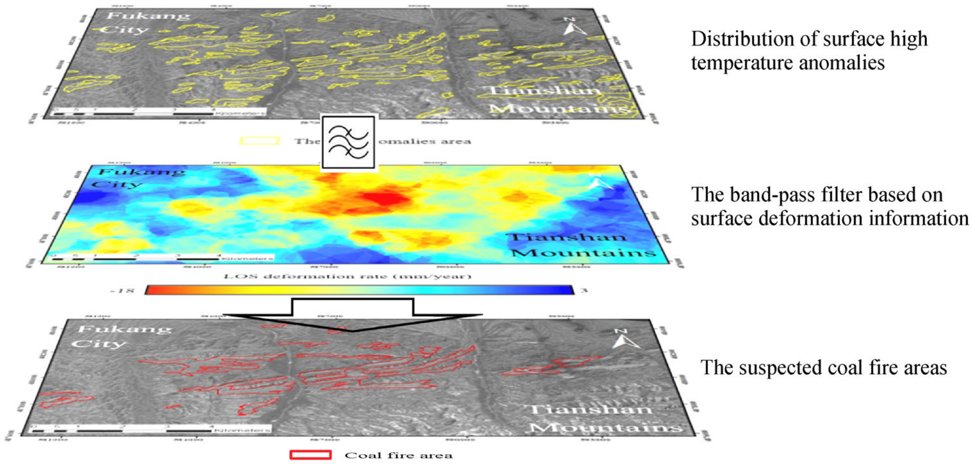

Fig. 6 Schematic diagram of the extraction of suspected coal fire locations by a spatial filter.

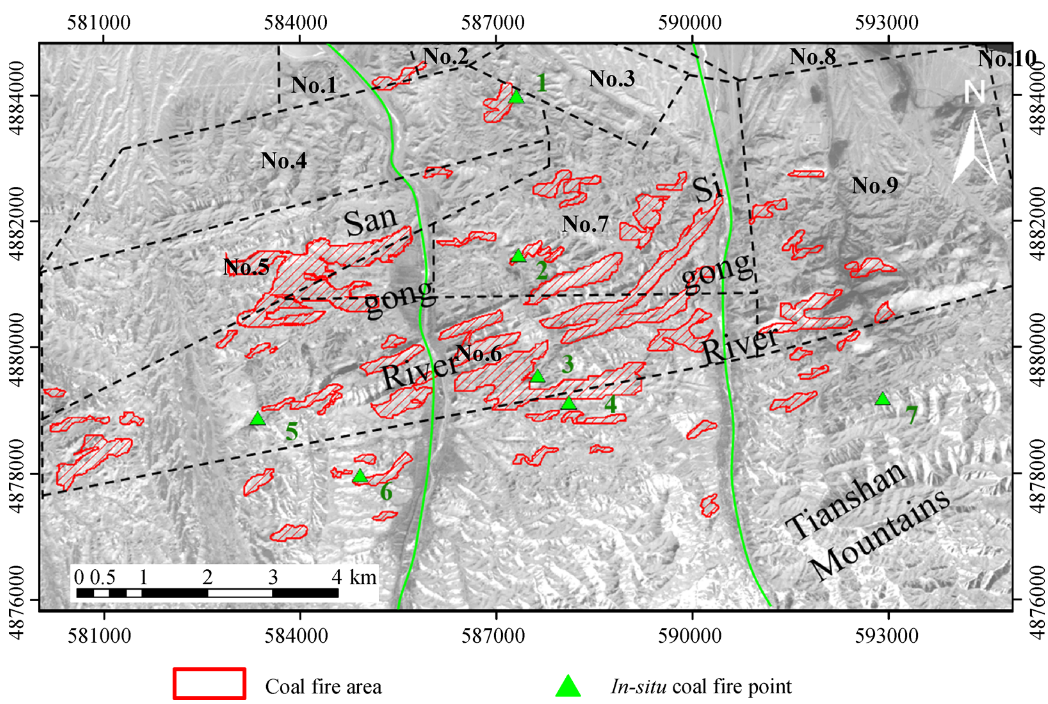

Fig. 7 Overlay sketch of the suspected coal fire areas in the research region and the coal fire locations identified by field survey.

obvious signs were identified by field survey in the research region, which are labeled as green triangles No. 1 to No. 7. Among them, the No. 1 to No. 6 coal fire locations are in or near the suspected coal fire areas. Only the No. 7 coal fire location, which is relatively far from the mine boundary, is also far from a suspected coal fire area. In fact, the No. 7 coal fire location is neither near a high temperature anomaly area nor a subsidence concentration area. Because the field data were recorded over the past five years, and the monitoring results of this paper only cover the period between 2015 and 2017, it was likely that the No. 7 location had an earlier combustion time and that the coal fire was extinguished before 2015. In addition, some locations are near but not in the delineated coal fire areas. This is because the smoke generated by coal fire combustion is transmitted to the surface along rock fractures or mine roadways, and the coal fire locations detected by field survey may not lie right above the combustion areas. For some coal fires deep below the surface of the Earth, geophysical prospecting methods should be combined to obtain a comprehensive judgment.

Figure 7 also shows that the extracted suspected coal fire areas are larger than the areas identified by field investigation. There are two reasons for this. First, a coal fire might occur deep underground, so that no clear signs can be found on the surface, and no coal fire is identified by field survey. Secondly, remote sensing technology suffers from various types of noise, which could lead to errors in the judgment of coal fire areas.

To further analyze the characteristics of the coal fire areas, a horizontal profile line with a length of 4 km was drawn near each coal fire location, showing the land surface temperature and surface deformation information. Figure 8 shows the profile information of the No. 1, No. 2, No. 6, and No. 7 coal fire locations. The red vertical dotted line refers to the *in situ* coal fire point's position, while the green and blue vertical dotted lines refer to 1 km east and west of the coal fire locations. As can be seen in the sub-figures, the land surface temperature was relatively high near the No. 1, No. 2, and No. 6 points, accompanied by relatively high surface subsidence rates. This also indicates that the thermal infrared and InSAR technologies combine well, and can provide a reasonable physical basis for coal fire detection. On the other hand, the land surface temperature was relatively low near the No. 7 coal fire location, and the surface deformation was also low, so it was not delineated as a coal fire area. The profile maps visually indicate that the joint detection method has a certain practicality, and the extracted coal fire areas are of a relatively high accuracy and reliability.

5 Conclusions

In this study, the combination of thermal infrared remote sensing and InSAR technologies was employed to carry out preliminary detection of the suspected coal fire locations in the Fukang region of Xinjiang, China. The verification was conducted using field survey data, and the results indicated that the multi-source remote sensing imagery based integrated method can present us with a low-cost, high-efficiency, safe, and dynamic coal fire detection approach for a large-scale area. The proposed approach could contribute to the general investigation of suspected coal fires and provide the necessary spatial information support and theoretical guidance for fire-fighting work.

Underground coal combustion does not only result in high-temperature anomalies, but it can also induce surface deformation. The surface high-temperature anomaly information can be obtained through inversion by thermal infrared remote sensing technology. At the same time, the InSAR time-series analysis technology can be employed to obtain the surface deformation. A band-pass filter can then

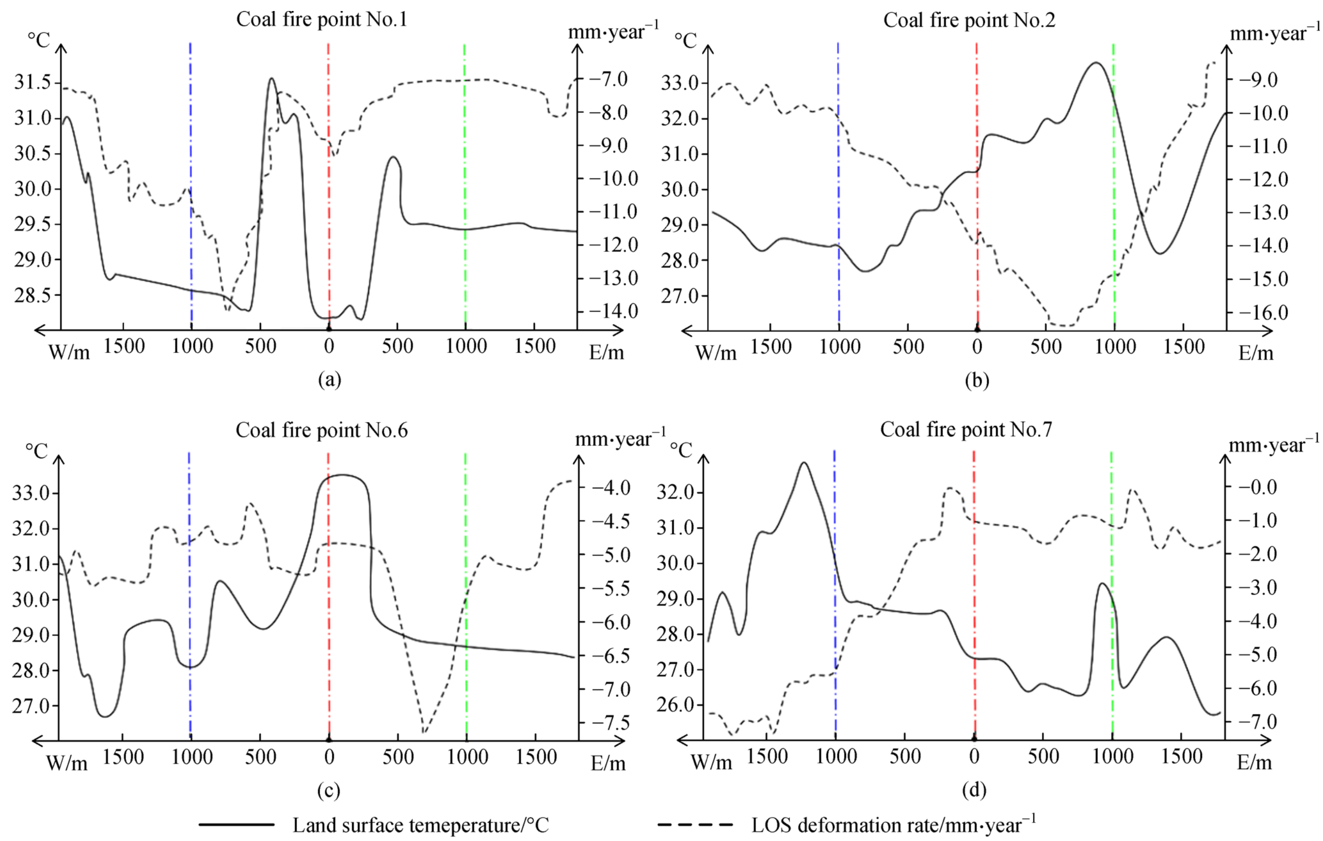

Fig. 8 Profile information of the surface temperature and subsidence at typical coal fire locations: (a), (b), (c), (d) represent the profile information of the No. 1, No. 2, No. 6, and No. 7 coal fire locations, respectively.

be built according to the surface deformation information. On this basis, the band-pass filtering of the land surface temperature information can eliminate some non-coal-fire-related surface temperature anomalies. What is more, long time-series images can help to eliminate the influence of accidental factors and enhance the accuracy of the surface physical information in coal fire areas. The various types of physical information can be integrated by means of the filtering, thus contributing to accurate and reliable coal fire detection.

The spatio-temporal evolution of underground coal fire occurrence and development has complexity and may indeed be hidden, so the accurate delineation of coal fires needs to fully consider temperature, humidity, deformation, and geology. Furthermore, the evolution of coal fires is closely related to human activities. Therefore, the spatial distribution information of roadways and goafs in mining engineering are also of interest. Considering the limitations of remote sensing technology, detection error will still exist in this method. The threshold setting for the high-temperature anomalies and surface subsidence as well as the establishment of multi-source information joint detection model is also worthy of further investigation. With the increasing availability of remote sensing imagery and the continuous improvement of multi-sensor models for joint analysis, the integration of multi-source remote sensing based coal fire detection will provide a much more effective approach for coal-seam fire investigation and control.

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References

Agustan (2010). Ground deformation detection based on ALOS-PALSAR data utilizing DInSAR technique in Indonesia. Dissertation for the Doctoral Degree. Nagoya: Nagoya University

Allievi J, Ambrosi C, Ceriani M, Ceriani M, Colesanti C, Crosta G B, Ferretti A, Fossati D (2003). Monitoring slow mass movements with the permanent scatterers technique. IEEE International Geoscience and Remote Sensing Symposium, Toulouse, France

Berardino P, Fornaro G, Lanari R, Sansosti E (2002). A new algorithm for surface deformation monitoring based on small baseline differential SAR interferograms. IEEE Trans Geosci Remote Sens, 40(11): 2375–2383

Colesanti C, Ferretti A, Novali F, Prati C, Rocca F (2003). SAR monitoring of progressive and seasonal ground deformation using the permanent scatterers technique. IEEE Trans Geosci Remote Sens, 41 (7): 1685–1701

Deng J, Li B, Wang K, Wang C P (2016). Research status and outlook on prevention and control technology of coal fire disaster in China. Coal Science and Technology, 44(10):1–7 + 101 (in Chinese)

Deng W, Wan Y Q, Zhao R C (2001). Detecting coal fires with a neural network to reduce the effect of solar radiation on landsat thematic mapper thermal infrared images. Int J Remote Sens, 22(6): 933–944

Filatov A, Evtyushkin A, Bryksin V (2013). Some results of long term geodynamic monitoring of oil and gas fields and power engineering infrastructure using ENVISAT and ALOS SAR data. Asia-Pacific Conference on Synthetic Aperture Radar (APSAR), Tsukuba, Japan: 181–184

Fitra I, James D (2012). Applications of DInSAR for measuring mine-induced subsidence and constraining ground deformation model. GeoCongres, Oakland, California, United States

Gabriel A K, Goldstein R M, Zebker H A (1989). Mapping small elevation changes over large areas: differential radar interferometry. J Geophys Res-Sol Ea, 94 (B7): 9183–9191

Ji H L, Tashpolat T, Cai Z Y, Shi Q D, Wei J, Xia J (2012a). The inversion and verification of land surface temperature for coal fire areas based on TM data. Remote Sens for Land and Resources, (04): 101–106 (in Chinese)

Ji H L (2012b). Application of multi-scale thermal infrared remote sensing data in coalfield fire area information extraction. Dissertation for the Master's Degree. Urumchi: Xinjiang University (in Chinese)

Jiang L M, Lin H, Ma J W, Kong B, Wang Y (2011a). Potential of small-baseline SAR interferometry for monitoring land subsidence related to underground coal fires: Wuda (Northern China) case study. Remote Sens Environ, 115(2): 257–268

Jiang W G, Wu J J, Gu L, Yang B, Chen Q, Liu X C (2011b). Monitoring method of underground coal fire based on night thermal infrared remote sensing technology. Spectrosc Spect Anal, 31(2): 357–361 (in Chinese)

Jiang W G, Zhu X H, Wu J J, Gu L, Ma G B, Liu X C (2011c). Retrieval and analysis of coal fire temperature in Wuda Coalfield, Inner Mongolia, China. Chin Geogr Sci, 21(2): 159–166

Jiménez-Muñoz J C, Sobrino J A, Skokovic D, Mattar C, Cristobal J (2014). Land surface temperature retrieval methods from Landsat-8 thermal infrared sensor data. IEEE Geosci Remote Sens Lett, 11(10): 1840–1843

Kuenzer C, Stracher G B (2012). Geomorphology of coal seam fires. Geomorphology, 138(1): 209–222

Lagios E, Sakkas V, Novali F, Fumagalli A, Del Conte S (2011). Ground deformation studies in Cephallonia island (Western Greece) based on DGPS & PS interferometry. IEEE International Geoscience and Remote Sensing Symposium (IGARSS), Vancouver, BC

Li F, Liang H D, Zhao X P, Bai J W, Cui Y K (2017). Remote sensing monitoring and assessment of fire-fighting effects in Wuda coal field, Inner Mongolia. Remote Sens for Land and Resources, 29(3): 217–223 (in Chinese)

Li J (2015). Research of information extraction in the hazard area of coal spontaneous combustion based on remote sensing. China Mining Magazine, 24(06): 138–141 + 146 (in Chinese)

Li R R, Ben Z Q, Li P, Qin W Q (2016). Study on the method of coal fire monitoring based on Landsat-8 data. Journal of China Coal Society, 41(7): 1735–1740 (in Chinese)

Liang T (2014). Monitoring the surface deformation of mining area based on short-baseset InSAR technology. Bulletin of Surveying and Mapping, (S2):82–84 (in Chinese)

Liu Y L (2016). Land subsidence monitoring and correlation analysis with ground fluid exploitation using time series In SAR technique over the Yellow River delta (China). Institute of Oceanology, Chinese Academy of Sciences (in Chinese)

Mishra R K, Bahuguna P P, Singh V K (2011). Detection of coal mine fire in Jharia Coal Field using Landsat-7 ETM + data. Int J Coal Geol, 86(1): 73–78

Qin Z H, Li W J, Xu B, Chen Z X, Liu J (2004). The estimation of land surface emissivity for Landsat TM6. Remote Sens for Land and Resources, (3): 28–32, 36, 41 (in Chinese)

Qiu C J, Wang J, Liu L C, Bi F C (2012). Remote sensing technology applied to fire disaster monitoring and measuring of Wuda Coalfield. Coal Engineering, (08):130–133 (in Chinese)

Samsonov S (2010). Topographic correction for ALOS PALSAR interferometry. IEEE Trans Geosci Remote Sens, 48(7): 3020–3027

Samsonov S, Oreye N D (2012). Multidimensional time-series analysis of ground deformation from multiple InSAR data sets applied to Virunga Volcanic Province. Geophys J Int, 191(3): 1095–1108

Slavecki R J (1964). Detection and location of subsurface coal fires. Proceeding of thirds symposium on remote sensing of environment. University of Michinggan: 537–549

Soenen S A, Peddle D R, Coburn C A (2005). SCS + C: A modified sun-canopy-sensor topographic correction in forested terrain. IEEE Trans Geosci Remote Sens, 43(9): 2148–2159

Song Z Y, Kuenzer C (2014). Coal fires in China over the last decade: a comprehensive review. Int J Coal Geol, 133: 72–99

Song Z Y, Kuenzer C (2017). Spectral reflectance (400–2500 nm) properties of coals, adjacent sediments, metamorphic and pyrometamorphic rocks in coal-fire areas: a case study of Wuda coalfield and its surrounding areas, northern China. Int J Coal Geol, 171: 142–152

Song Z Y, Kuenzer C, Zhu H Q, Zhang Z, Jia Y R, Sun Y L, Zhang J Z (2015). Analysis of coal fire dynamics in the Wuda syncline impacted by fire-fighting activities based on *in-situ* observations and Landsat-8 remote sensing data. Int J Coal Geol, 141–142: 91–102

Tao L, Zhang H, Wang C, Tang Y X (2012). A Review on new multi-baseline DInSAR methods for surface deformation monitoring. Remote Sens Techno and App, 27(6): 805–811 (in Chinese)

Voigt S, Tetzlaff A, Zhang J, Künzer C, Zhukov B, Strunz G, Oertel D, Roth A, van Dijk P, Mehl H (2004). Integrating satellite remote sensing techniques for detection and analysis of uncontrolled coal seam fires in North China. Int J Coal Geol, 59(1–2): 121–136

Wang M M (2017). Methodology development for retrieving land surface temperature and near surface air temperature based on thermal infrared Remote Sensing. Institute of Remote Sensing and Digital Earth (in Chinese)

Wang Q (2014). A Study of Ground Deformation over Taiyuan City Using PS-InSAR Technique. Bulletin of Surveying and Mapping, (5):71–75 (in Chinese)

Wang Y J, Tian F, Huang Y, Wang J, Wei C J (2015). Monitoring coal fires in Datong coalfield using multi-source remote sensing data. Trans Nonferrous Met Soc China, 25(10): 3421–3428

Wu D W (2001). Remote sensing prospecting information extraction method and application research in Qinghai Mangya Area. China University of Geosciences (in Chinese)

Yang J K, Chen B Q, Deng K Z, He Q, Zhao W Y (2015). Monitoring and prediction of mining subsidence based on D-InSAR and probability integral method. Metal Mine, 44(4): 195–200 (in Chinese)

Yu C, Li Z, Penna N T (2018a). Interferometric synthetic aperture radar atmospheric correction using a GPS-based iterative tropospheric decomposition model. Remote Sens Environ, 204: 109–121

Yu C, Li Z, Penna N T, Crippa P (2018b). Generic atmospheric correction model for Interferometric Synthetic Aperture Radar observations. J Geophys Res-Sol Ea, 123(10): 9202–9222

Yu C, Penna N T, Li Z (2017). Generation of real-time mode high-resolution water vapor fields from GPS observations. J Geophys Res Atmos, 122(3): 2008–2025

Zeng Q Y, Zhang L S (2012). Discussion on drilling technology in coal seam burning area of Fukang Area in Xinjiang. Guangdong Sci and Techno, 21(07): 139–146 (in Chinese)

Zhang Q S (2014). Fire detection technology of coal spontaneous combustion scope location based on compound mining depth coal seam. Coal Techno, 33(07): 270–271 (in Chinese)

Zhang X, Van Genderen J V, Guan H Y, Kroonenberg S (2003). Spatial analysis of thermal anomalies from airborne multi-spectral data. Int J Remote Sens, 24(19): 3727–3742

Zhang X, Van Genderen J V, Kroonenberg S B (1997). A method to evaluate the capability of Landsat-5 TM band 6 data for sub-pixel coal fire detection. Int J Remote Sens, 18(15): 3279–3288

Zhang X, Zhang J, Kuenzer C, Voigt S, Wagner W (2004). Capability evaluation of 3–5 μm and 8–12.5 μm airborne thermal data for underground coal fire detection. Int J Remote Sens, 25(17): 3047–3058

Zhang X Q, Zhang Y, Yu M D, Li X F, Wang T, Hu S R (2014). Damages and challenge for governing of coalfield fires in Xinjiang. China Min Mag, 23(S2): 93–95 (in Chinese)

Zhang Z M, Jing L M, Liu L, Wang H S (2018). Detecting the underground coal fire by using landsat thermal infrared imagery: Taking Wuda Coalfield as an example. Bulletin of Surveying and Mapping, (03): 93–97 (in Chinese)

Zhou H Y, Wang Y J, Yan S Y, Liu X X (2017). Land subsidence monitoring and analyzing of Cangzhou Area Sentinel-1A/B based time series InSAR. Bulletin of Surveying and Mapping, (07):89–93 (in Chinese)

Zhou J B, Zeng X J, Fan T (2005). Geological characteristics of the coal resource zone at Bukang, Xinjiang. Xinjiang Geology, (02):146–151 (in Chinese)

Zhu C G, Fan H D, Deng K Z (2014). Inversion of subsidence based on temporal InSAR Method in Tanggu Area. Geomatics and Information Science of Wuhan University, 39(2): 248–252 (in Chinese)

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