Developing a thermal characteristic index for lithology identification using thermal infrared remote sensing data

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Abstract

In remote sensing petrology fields, studies have mainly concentrated on spectroscopy remote sensing research, and methods to identify minerals and rocks are mainly based on the analysis and enhancement of spectral features. Few studies have reported the application of thermodynamics for lithology identification. This paper aims to establish a thermal characteristic index (*TCI*) to explore rock thermal behavior responding to defined environmental systems. The study area is located in the northern Qinghai Province, China, on the northern edge of the Qinghai-Tibet Plateau, where mafic-ultramafic rock, quartz-rich rock, alkali granite rock and carbonate rock are well exposed; the pixel samples of these rocks and vegetation were obtained based on relevant indices and geological maps. The scatter plots of *TCI* indicate that mafic-ultramafic rock and quartz-rich rock can be well extracted from other surface objects when interference from vegetation is lower. On account of the complexity of environmental systems, three periods of *TCI* were used to construct a three-dimensional scatter plot, named the multi-temporal thermal feature space (MTTFS) model. Then, the Bayes discriminant analysis algorithm was applied to the MTTFS model to extract rocks quantitatively. The classification accuracy of mafic-ultramafic rock is more than 75% in both training data and test data, which suggests *TCI* can act as a sensitive indicator to distinguish rocks and the MTTFS model can accurately extract mafic-ultramafic rock from other surface objects. We deduce that the use of thermodynamics is promising in lithology identification when an effective index is constructed and an appropriated model is selected.

Keywords: lithology identification; thermal characteristic index; multi-temporal thermal feature space model.

1. Introduction

With the development of remote sensing science over the past decades, numerous investigations and studies for mineral exploration and lithology mapping have been conducted using remote sensing data from airborne or spaceborne sensors at macroscopic scales. Mineral and rock spectral information from airborne and spaceborne instruments has been meticulously measured by some pioneer researchers (Hunt and Salisbury, 1970; Hunt, 1977; Salisbury and Walter, 1989; Christensen et al., 2000; Cooper et al., 2002; Guha et al., 2012a, 2012b; Pour et al., 2013). Based on the spectral reflectance features from the visible to near-infrared (VNIR) and shortwave infrared (SWIR) wavelengths, many alteration minerals such as carbonates, sulfates, hydroxides and oxides have been well identified and mapped (Abrams et al., 1977; Thompson et al., 1999; Christensen et al., 2000; Gan et al., 2003; Ting et al., 2006). Additionally, quartz, olivine, feldspar, carbonate and silicate minerals show prominent emission features in thermal infrared (TIR) bands due to the fundamental vibrations of Si-O band and C-O band (Lyon, 1965; Hunt, 1977; Christensen et al., 2000), based on which a series of indices have been proposed to identify some specific rocks, such as the carbonate rock index, the sulfuric acid rock index and the mafic-ultramafic rock index (Ninomiya and Fu 2002; Rockwell and Hofstra, 2008a, 2008b; Oztan and Suzen, 2011; Ding et al., 2014). The methods for rock identification mainly focus on the analysis and enhancement of spectral features, including principal component analysis (PCA), spectral angle mapping (SAM), band ratio (BR), false color composite (FCC), matched-filtering, etc. (Honarmand et al., 2012; Yajima and Yamaguchi, 2013; Pournamdari and Hashim, 2014). However, spectral feature analyses still have many limitations in identifying lithology. It has been acknowledged that different objects have similar spectral features, which commonly occurs in nature. Furthermore, a rock type index is generally sensitive to some specific rocks or minerals (Ninomiya and Fu 2002; Rockwell and Hofstra, 2008a, 2008b; Oztan and Suzen, 2011; Ding et al., 2014). Hence, fine-scale recognition of lithology is difficult. Other non-spectroscopic parameters, indicators, methods, information and disciplines should be considered in lithology identification, as has been emphasized in many studies (Saadi et al., 2008; van der Meer et al., 2012; Kuenzer

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and Dech, 2013; Ding et al., 2014).

Material thermal characteristic, one of the important physical properties, represent material heat exchange ability to surroundings, which has very complex relationships with material color, roughness, chemical components, exposure (i.e., aspect and slope), thermal inertia, etc. (Mather, 1988; Kuenzer and Dech, 2013). One of the most important physical parameters of thermal characteristic is surface temperature variation (Kuenzer and Dech, 2013). Thermal inertia, which determines the resistance of a material to temperature change, has been employed by many researchers to map and monitor minerals and rocks over large spatial areas (Kahle et al., 1976; Nasipuri et al., 2005; Ramakrishnan et al., 2013; Sefton-Nash et al., 2012). Thermal inertia mapping can be derived from remotely sensed thermal imagery (i.e., daytime and nighttime images) corresponding to diurnal phases (i.e., heating and cooling processes) of any surfaces. However, for many specific regions, such as the study area in this paper, only a limited amount of nighttime thermal imagery, indispensable for thermal inertia mapping, can be obtained during a satellite's path around the world. Furthermore, diurnal thermal imagery of the same area is difficult to obtain simultaneously. As a result, the application of thermal inertia has been greatly restricted.

Nevertheless, airborne or spaceborne sensors provide a straightforward and consistent way to obtain thermal infrared data, which can be used to derive surface temperature. Temperature, one of the important physical parameters, is required by many fields of study, such as urban heat island effects, climate change and earth observations (Voogt and Oke 2003; Bhang and Park, 2009; Liu and Zhang, 2011; Tomlinson et al., 2011; Li et al., 2013; Krishna and Sharma, 2013). All surface objects, regardless of the land or ocean surface, have specific thermal characteristics in a defined environmental system, resulting in temperature differences. Compared with thermal inertia, which is based on the temporal temperature difference, the surface object temperature difference is actually the material thermal behavior responding to a given environmental system (i.e., atmospheric temperature).

In fact, appropriate and straightforward application of temperature seldom exists in terms of lithological identification. The straightforward application of temperature, however, has been widely implemented for soil moisture retrieval and urban heat effect research, which leads to the proposed temperature-vegetation dryness index by integrating soil temperature with the remotely

sensed normalized difference vegetation index (Price, 1990; Carlson et al., 1994; Sandholt et al., 2002; Chauhan et al., 2003; Garcia et al., 2004; Wang et al., 2006; Stisen et al., 2008; Tiangco et al., 2008). Further, multi-temporal thermal data has been used for the classification of different land cover types (Nemani and Running 1997; B. Bechtel and Daneke 2012). Bechtel (2015) proposed the use of multi-temporal annual land surface temperature (LST) data derived from 1 km MODIS data for lithological classification, which provides a referable idea. In this paper, we explored the direct application of temperature differences of objects for the purpose of lithology identification, based on which a sensitive thermal characteristic index (*TCI*) was established by considering temperature parameters of surface objects and environmental information (e.g., atmospheric temperature), and multiple periods of *TCI* were integrated to construct a multi-temporal thermal feature space model for extracting rocks with stability. This study provides a reference for detecting rocks.

2. Study area and data

2.1 Study area

The study area (Fig. 1) is located between 38°10'E and 38°45'N and between 98°45'E and 99°30'E in the northern Qinghai Province of western China, which lies in the western region of the Chi-lien Mountain Range of the northern Qinghai-Tibet Plateau. The endogenous minerals mainly include chromite, magnetite, lead, zinc, copper, gold, tungsten, molybdenum, etc., whereas the exogenous minerals primarily include gypsum, marble and alluvial gold. The region has an average elevation of approximately 4200 m and has a plateau continental climate. The annual mean temperature is approximately -3.76°C; the coldest month is December, with a mean temperature of -24.3°C, whereas the hottest month is August, with a mean temperature of 14.80°C.

Fig. 1. Location map of the study area.

Two subareas (study area A and study area B) were selected based on field work and remote sensing images at sites where the rocks were relatively well-exposed. Study area A is the main study area, as shown on the compiled lithological map (Fig. 2 (a)). The main lithology of this area includes serpentinite, gabbro, felsic rocks and sandstone, with few carbonate rocks exposed in this region. Serpentinite and gabbro rocks are both the major components of mafic-ultramafic rocks during the Caledonian orogeny and are seldom distributed in lower volcanic groups of Ordovician age. Sandstone is the major type of quartz-rich rock in this area and is mainly distributed in the lower Ordovician sandstone-slate group. The representative felsic rocks are granitoids, which are related to the origin of nonferrous metals, rare metals and radioactive element ore deposits; the main forming minerals of felsic rocks are feldspar and quartz.

Study area B, which was chosen for the purpose of extracting carbonate rocks, contains the Precambrian gneiss group, where the carbonate rocks are especially well-exposed in addition to gneiss, sandstone, slate and quartz-rich rocks (Fig. 2 (b)). The components of these carbonate rocks in this area are mainly marble, dolomite and limestone. Furthermore, intrusive rocks including alkali granite, hornblende alkali granite and porphyritic alkali granite during the Caledonian orogeny are observed; however, these rocks are not well-exposed.

Fig. 2. Generalized lithological maps of (a) study area A, (b) study area B, which are modified after Ding et al. (2015)

2.2 Data collection and processing

Twelve scenes of Landsat 8 data with less cloud over the study area provided by **USGS**

EROS data center (<http://glovis.usgs.gov/>) were acquired from 2013 to 2014. All of the images were obtained at local time of approximately 10:00~10:15 a.m. The atmospheric temperature data corresponding to remote sensing data were acquired from the China Meteorological Data System (<http://data.cma.cn>). All of the data were ranked based on the maximum atmospheric temperature (T_{a_max}) and grouped into three levels, including the low temperature group (Level I), moderate temperature group (Level II) and high temperature group (Level III). The details are shown in Table 1.

Table 1

Landsat 8 data and atmospheric temperature data (ranked to three levels) used in this study.

Data number	Data acquisition date	Landsat 8 data ID	T_a (°C) range of one day	T_a level
G1	2013-12-19	LC81340332013353LGN00	-20.2 ~ -5.7	Level I
G2	2014-01-04	LC81340332014004LGN00	-18.7 ~ -4.0	
G3	2013-11-17	LC81340332013321LGN00	-19.7 ~ -2.4	
G4	2013-12-03	LC81340332013337LGN00	-22.0 ~ -1.0	
G5	2013-11-01	LC81340332013305LGN00	-15.8 ~ -0.4	Level II
G6	2014-10-19	LC81340332014292LGN00	-6.8 ~ 0.3	
G7	2014-04-26	LC81340332014116LGN00	-13.9 ~ 6.8	
G8	2013-09-30	LC81340332013273LGN00	-5.9 ~ 6.2	
G9	2014-05-28	LC81340332014148LGN00	0.4 ~ 8.2	Level III
G10	2013-05-25	LC81340332013145LGN01	-6.2 ~ 13.5	
G11	2014-08-16	LC81340332014228LGN00	2.2 ~ 14.8	
G12	2013-08-13	LC81340332013225LGN00	0 ~ 20.3	

Note: the data number in the first column is ranked based on the maximum atmospheric temperature.

The remote sensing data are Level-1 digital numbers (DN) of the sensor data, which have been systematically radiation-calibrated and geometry-corrected. To achieve the temperature image, the Landsat 8 TIR data (Table 2) need to be pre-processed, including radiation-calibrated, atmospheric correction and temperature derivation. The data preprocessing is detailed as follows:

Table 2

The information of Landsat 8 TIR data used in this study.

TIR bands	Spatial resolution (m)	Wavelength range (μ m)	Central wavelength (μ m)
Band 10	100	10.6~11.19	10.9
Band 11	100	11.50~12.51	12.0

(1) The TIR bands were radiation-calibrated to obtain sensor radiance data using Eq. (1)

$$L_{\lambda} = M_l * Q_{cal} + A_l, \quad (1)$$

where L_λ represents the at-sensor radiance, M_l is band-specific multiplicative rescaling factor, Q_{cal} is the digital number of a given pixel and A_l is the band-specific additive rescaling factor. M_l and A_l are available in the metadata file associated with Landsat 8 image.

(2) To obtain surface radiance data, atmospheric correction was conducted to eliminate the influence of the atmosphere, which is based on the In-Scene Atmospheric Compensation algorithm (ISAC) (Johnson and Young, 1998; Hernandez-Baquero, 2000).

(3) The emissivity normalization algorithm (NEM) (Kealy et al., 1993) was used to retrieve the surface temperature by separating temperature and emissivity. The NEM assumes that the emissivity in a band arrived at a known maximum value ε_{max} (0.96 was set in this paper), then temperature (T_i) for TIR bands is calculated using a gray body whose radiance has the maximum value of ε_{max} . The maximum T_i will be T_{NEM} , then the emissivity is calculated by substituting T_{NEM} into the planck function.

All the procedure of data preprocessing, including radiation-calibrated, atmospheric correction and temperature derivation, was achieved using ENVI 5.2 SP1.

Furthermore, five typical categories of surface objects were discussed in this paper, including mafic-ultramafic rock, quartz-rich rock, alkali granite rock, carbonate rock and vegetation, which are widely distributed in Earth's crust and well-exposed in the study area. In addition, based on the geological maps and relevant indices, a number of training pixels for all of the five types of surface objects were selected to validate the inference in section 3. The number of samples of mafic-ultramafic rock, quartz-rich rock, alkali granite rock, carbonate rock and vegetation are 733, 563, 204, 249 and 611, respectively. The criteria for choosing rock samples is the same as in previous works (Ding et al., 2014, Ding et al., 2015)), which has been described in detail in Ding et al., (2014); thus, we do not discuss the criteria in this paper.

3. Methodology

3.1 Thermal characteristic index

In thermodynamics, the heat from the sun, atmosphere, water and other different sources input to the ground surface can be modeled by a land surface energy balance equation expressed as follows:

$$R_n = G_0 + H_s + \lambda E, \quad (2)$$

where R_n is the net radiation ($W \cdot m^{-2}$), G_0 is the soil heat flux ($W \cdot m^{-2}$), H_s is the sensible heat flux ($W \cdot m^{-2}$), and λE is the latent heat flux ($W \cdot m^{-2}$), which is commonly called evapotranspiration. As described here, R_n consists of three parts; approximately 10~50% R_n turns G_0 into the ground; a part of R_n becomes H_s , resulting in the variation of the ground surface temperature; the rest of R_n transfers to λE through water evapotranspiration transmitted to the air.

All surface objects have specific thermal characteristics in a defined environmental system. To explore the heat exchange ability of surface objects to surroundings, more emphasis was focused on the sensible heat flux. The heat exchange between the atmosphere and surface objects through conduction and convection is quite complex and is related to wind speed, atmospheric temperature, surface properties including color, roughness, thermal inertia and chemical components (Oncley et al., 2007; Zhang, 2012). The sensible heat flux is expressed using the Monin-Obukhov theory:

$$H_s = \rho C_a (T_s - T_a) / r_a, \quad (3)$$

where ρ is the air density ($kg \cdot m^{-3}$), C_a is the specific heat of air ($J \cdot kg^{-1} \cdot ^\circ C^{-1}$) and ρC_a represents the heat capacity of air ($J \cdot m^{-3} \cdot ^\circ C^{-1}$); T_a is the atmospheric temperature ($^\circ C$); T_s is the surface temperature ($^\circ C$); r_a is the aerodynamic resistance depending on wind speed and surface roughness. Since the study area in this paper is not large, we assume the ρ , C_a , and r_a as well as other environmental factors such as snow and ice covered on surface objects is the same. Then the heat exchange between the surface object with the environmental system mainly depends on the temperature difference between T_s and T_a .

At local time of approximately 10:00~10:15 a.m., the remote sensing data were obtained from the Landsat 8 Thermal Infrared Sensors. The difference between an object's temperature (T_s) with the atmospheric temperature corresponding to remote sensing data in 10:00 a.m. of a day (T_{a_c}) is regarded as the net temperature (T_n) of the object. Here we define

$$T_n = T_s - T_{a_c}. \quad (4)$$

The time for T_s is always consistent with T_{a_c} . We assume that temperature effects from ambient conditions are all reflected on atmospheric temperature. Thus, the T_n accounts for environmental effects and the T_n value for different rock types mean their heat exchange ability

to surroundings.

To assess the performance of T_n , we calculated the mean temperature of the surface object samples (T_{s_mean}), and then the mean T_n for objects were deduced as follows:

$$T_{n_mean} = T_{s_mean} - T_{a_c}, \quad (5)$$

where T_{n_mean} is the mean net temperature of surface objects.

The distributions of T_{n_mean} and T_{a_c} in different periods are shown in Fig. 3 which suggests that from G1 to G12, the T_{n_mean} values for mafic-ultramafic rock, quartz-rich rock, alkali granite rock, carbonate rock and vegetation are near the values of 4.62, 9.17, 6.09, 5.91 and 9.44, respectively. Furthermore, the bar plots display similar trends for the five objects, which means the contrast of T_{n_mean} among objects indeed exists and is stable to identify surface objects in different environmental systems. Thus, T_n has the ability of reflecting rocks own heat exchange ability to surroundings so that it can be used as a lithological identification indicator and the ability to ensure the stability of thermal characteristic discrepancy among surface objects in different periods.

Fig. 3. Comparison of the mean net temperature for the five objects with atmospheric temperature in 10:00 a.m. of different periods.

Therefore, T_n should be taken into account to build the thermal characteristic index. Atmospheric temperature has a dynamic change with time, which has a diurnal cycle in a day with the highest temperature occurring at approximately 2:00 p.m., and the lowest temperature occurring at approximately 5:00 a.m. Referring to the construction processing of the

temperature-vegetation dryness index (TVDI) and the normalized differential vegetation index (NDVI), the further normalization was achieved by accumulating the diurnal atmospheric temperature amplitude. Then, the thermal characteristic index (TCI) was developed as follows:

$$TCI = (T_s - T_{a_c}) / (T_{a_{max}} - T_{a_{min}}) \quad (6)$$

Thus, TCI is actually the contrast of **the temperature variation ability of surface object with that of atmosphere**. In short, the TCI , which steadily reflects the thermal behavior of surface objects in response to environmental systems, will be efficient to detect different rock types. The higher the TCI value is, the weaker the resistance to temperature change is; on the contrary, a stronger the resistance to temperature change results in the lower TCI value.

3.2 Multi-temporal thermal feature space model

The environmental system is complex and changeable. Only a time phase TCI to identify rocks may be affected by casual factors and may be unstable. Furthermore, the main rock forming minerals are feldspar, quartz, amphibole, pyroxene, olivine and calcite; the four typical rocks, including mafic-ultramafic rock, quartz-rich rock, alkali granite rock and carbonate rock, are composed of these minerals in different proportions. Thus, the thermal discrepancy among these rocks may be weak under a specific environmental system. In view of this, multiple environment analysis is required.

There are various methods for object classification, of which principle component analysis (PCA), false color composite (FCC), band math, feature space model, etc. (Honarmand et al., 2012; Yajima and Yamaguchi, 2013; Pournamdari and Hashim, 2014) have been widely used in remote sensing petrology. Feature space model is performed through integration analysis of multiple features (Duda et al., 2001) and is suitable in this study. Multi-temporal thermal feature space (MTTFS), which in essence is the multi-temporal TCI space, is performed by the integration analysis of environmental information of multiple time phases. MTTFS will improve the accuracy of rock classification and ensure the stability of TCI .

(1) Construction of the multi-temporal thermal feature space model

In this paper, we selected the TCI from three periods to build a three-dimensional feature space, in which the x-axis, y-axis and z-axis represented TCI from Level I, Level II and Level III, respectively.

(2) Rock discriminant analysis algorithm for the MTTFS model

Linear discriminate analysis (LDA) is a type of supervised algorithm that has been demonstrated as an efficient feature extraction method in the classification and object recognition for its simple calculation and optimal class separability under specific conditions, such as small samples, low data dimensions and few classification categories (Ripley, 1996; Belhumeur et al., 1997; Bian and Zhang, 2000). The Bayes method is one of the typical linear discriminant algorithms, the main principle (Fruhworthschnatter, 1995; Veitch and Vecchio, 2010; Raschke et al., 2013) of which is (i) assuming the sample types are known, prior probability and covariance are calculated and the Bayes discriminant function is established; (ii) prior probability is adjusted by the information provided by the Bayes discriminant function; (iii) the algorithm obtains the probability estimation of a specific sample belonging to some class.

Hence, the Bayes discriminant analysis algorithm is suitable for classifying different objects in the three-dimensional *TCI* feature space in this study. Bayes discriminant function can be expressed as follows:

$$f_{type} = a * TCI_{Level I} + b * TCI_{Level II} + c * TCI_{Level III} + d, \quad (7)$$

where a , b , c and d are constant coefficients; $TCI_{Level I}$, $TCI_{Level II}$ and $TCI_{Level III}$ represent *TCI* in different periods with Level I, Level II and Level III T_a ; f_{type} is the Bayes discriminant functions for study objects fitted by the MTTFS model, namely, $f_{mafic-ultramafic}$, f_{quartz} , $f_{alkali\ granite}$, $f_{carbonate}$ and $f_{vegetation}$, respectively.

The *TCI* value for each sample will be brought into the five Bayes discriminant functions; for example, if the $f_{mafic-ultramafic}$ function has the maximum value, the sample will be classified as a mafic-ultramafic rock. In the same way, if the f_{quartz} , $f_{alkali\ granite}$, $f_{carbonate}$ or $f_{vegetation}$ function values are the maximum, the sample will be classified as quartz-rich rock, alkali granite rock, carbonate rock or vegetation, respectively.

4. Results and discussion

4.1 Analysis of the thermal characteristic index

To assess the effectiveness of *TCI* for detecting rocks, we calculated the *TCI* for each object sample according to Eq. (6); the sample value distributions of *TCI* for the 12 groups data

are shown in the box and whisker plots (Fig. 4). Figure 4 exhibits the following information:

Fig. 4. Statistical characteristics for object samples on the TCI in different periods.

Note, in box and whisker plots of Fig.4, the “□” in the box represents the mean value position, and the whisker range is from the 10% to 90% quantile of the TCI value for object samples.

- (1) Regardless of the period, the TCI values of the five surface objects show discrepancies with each other, indicating that surface objects have specific thermal characteristics in a defined environmental system.
- (2) In Fig. 4 (a), Fig. 4 (b), Fig. 4 (c), Fig. 4 (d), mafic-ultramafic rock has a relatively lower TCI value, whereas quartz-rich rock has a relatively higher TCI value, and the TCI values of alkali granite rock, carbonate rock and vegetation are moderate. This result suggests that mafic-ultramafic rock has a relatively stronger resistance to the atmospheric temperature change, whereas the resistance for quartz-rich rock is lower.
- (3) In Fig. 4 (e), Fig. 4 (f), Fig. 4 (g), Fig. 4 (h) and Fig. 4 (j), mafic-ultramafic rock still have relatively lower TCI values, whereas the vegetation samples have higher TCI values, followed by quartz-rich rock. From Fig. 4 (a) to Fig. 4 (d), the atmospheric temperature is in Level I (0~4°C), under which vegetation is rare and some of the vegetation samples may just

be the bare soil; from Fig. 4 (e) to Fig. 4 (h), the atmospheric temperature is in Level II (7~17°C), and the vegetation is more than in Level I for the gradual warming of the atmospheric temperature. Thus, Fig. 4 illustrates that vegetation has a lower resistance to atmospheric temperature change than rocks.

(4) From Fig. 4 (a) to Fig. 4 (h) as well as Fig. 4 (j), the *TCI* range for the five surface objects is concentrated; the range is similar for each object in different periods. However, the range for vegetation is dispersive in Fig. 4 (i) and Fig. 4 (l); a dispersive range is also observed for alkali granite rock and carbonate rock in Fig. 4 (k). These features may be ascribed to the vegetation effects. When T_a is in Level I and Level II, *TCI* has the capability and stability to detect rocks because the vegetation is sparse. However, when T_a is in Level III, the rock identification is interfered with by the flourishing vegetation.

Table 3

Statistical characteristics of *TCI* values for the five objects in different T_a levels.

T_a Level	Data number	<i>TCI</i> Value				<i>TCI</i> range
		Low	Moderate	Sub-High	High	
Level I	G1	M	A, V	C	Q	Concentrated
	G2	M	A, V	C	Q	Concentrated
	G3	M	A, V	C	Q	Concentrated
	G4	M	A, V	C	Q	Concentrated
Level II	G5	M	A, C	Q	V	Concentrated
	G6	M	A, C	Q	V	Concentrated
	G7	M	A, C	Q	V	Concentrated
	G8	M	A, C	Q	V	Concentrated
Level III	G9	Q	M, V	A	V	Dispersive
	G10	M	A, C	Q	V	Concentrated
	G11	Q, A	M	--	C, V	Dispersive
	G12	C	M, V	A	Q	Dispersive

Note: here, we take M, Q, A, C and V for mafic-ultramafic rock, quartz-rich rock, alkali granite rock, carbonate rock and vegetation, respectively.

To analyze the results intuitively, the overall characteristics of the five objects are detailed in Table 3. The results indicate that mafic-ultramafic rock and quartz-rich rock will be easier identified from other surface objects by using *TCI* when T_a is in Level I (0~4°C). However, when T_a is in Level II (7~17 °C), mafic-ultramafic rock can be identified from other objects, whereas quartz-rich rock cannot be identified due to vegetation interference. Furthermore, when T_a is in Level III (8~13 °C), the *TCI* values of the five objects exhibit differences, however,

they do not exhibit distinct characteristics due to the vegetation interference. In the study area, from April to August, the atmospheric temperature gradually increases; meanwhile, vegetation, which is dispersed in the study area, gradually begins to flourish. The interference from vegetation is inevitable due to its low-to-moderate *TCI* value. Nevertheless, *TCI* acts as a sensitive indicator and has the stability necessary to identify lithology in different environmental backgrounds; mafic-ultramafic rock has distinct thermal characteristics, resulting in class separability, especially under Level I and Level II atmospheric temperatures, with less interference from vegetation.

4.2 Rock identification using the MTTFS model

To construct the MTTFS model, three data sets from Level I, Level II and Level III were needed separately, which has been illuminated in section 3.2. To validate the stability of the MTTFS model, data sets that are similar in terms of month and atmospheric temperature but different in year are used. Based on the above principles, G4, G8 and G12 in 2013 from December, September and August, respectively, were selected as training data sets. G2 (corresponding to G4), G6 (corresponding to G8) and G11 (corresponding to G12) in 2014 from January, October and August, respectively, were selected as test data sets. The information contained in the data sets is detailed in Table 4. The three-dimensional thermal feature space model using *TCI* from the three periods was constructed. To qualitatively analyze the ability of the MTTFS model for lithology identification, a three-dimensional scatter plot using training data was used, as shown in Fig. 5. In this feature space (Fig. 5 (a)), mafic-ultramafic rocks are mainly concentrated on the low-to-middle position, quartz-rich rocks are distributed on the middle-to-high position, and alkali granite rocks and vegetation overlap in the middle position. The distributions for mafic-ultramafic rock and quartz-rich rocks are delineated by ellipses without the interference from alkali granite rock, carbonate rock and vegetation (Fig. 5 (b)). Note that the ellipse is a type of conceptualized expression, which does not mean that the spatial distribution for mafic-ultramafic and quartz rich rocks are elliptical. Compared with *TCI* using only a single data (Fig. 4), the MTTFS displays a better performance in identifying different surface objects, especially mafic-ultramafic rock and quartz rock. Hence, in this feature space, we focus more on mafic-ultramafic rock and quartz-rich rock while taking vegetation interference into consideration.

Table 4

The training and test data sets used in the MTTFS model.

Training data to construct TTFS model				Test data to verification TTFS model			
Data number	Level	Data acquisition date	T_a (°C)	Data number	Level	Data acquisition date	T_a (°C)
G4	Level I	2013-12-03	-22.0 ~ -1.0	G2	Level I	2014-01-04	-18.7 ~ -4.0
G8	Level II	2013-09-30	-5.9 ~ 6.2	G6	Level II	2014-10-19	-6.8 ~ 0.3
G12	Level III	2013-08-13	0.0 ~ 20.3	G11	Level III	2014-08-16	2.2 ~ 14.8

Note: G4, G8 and G12 in 2013 correspond to G2, G6 and G11 in 2014, respectively. All of these data sets were selected based on the proximity in month, atmospheric temperature and the accessibility in different years.

Fig. 5. Conceptual graphs of the MTTFS model for (a) the five objects, (b) the mafic-ultramafic rock and quartz-rich rock with dividing ellipses.

To quantitatively evaluate the performance of the MTTFS model in rock classification, a Bayes linear discriminant analysis algorithm was used to train object samples and then coefficients of object discriminant functions were obtained (Table 5). According to Eq. 7, the object discriminant function in 2013 is expressed as follows:

$$\begin{aligned}
 f_{\text{mafic-ultramafic}} &= -13.747 * TCI_{G4} + 16.772 * TCI_{G8} - 1.162 * TCI_{G12} - 14.089 \\
 f_{\text{quartz}} &= -12.095 * TCI_{G4} + 18.126 * TCI_{G8} + 1.717 * TCI_{G12} - 18.501 \\
 f_{\text{vegetation}} &= -18.529 * TCI_{G4} + 22.649 * TCI_{G8} - 2.461 * TCI_{G12} - 25.200
 \end{aligned} \quad (8)$$

For a specific sample, when $f_{\text{mafic-ultramafic}} > f_{\text{quartz}}$ and $f_{\text{mafic-ultramafic}} > f_{\text{vegetation}}$, the sample will be classified as mafic-ultramafic rock; in the same way, when $f_{\text{quartz}} > f_{\text{mafic-ultramafic}}$ and $f_{\text{quartz}} > f_{\text{vegetation}}$, the sample will be classified as quartz

rich rock; and when $f_{vegetation} > f_{mafic-ultramafic}$ and $f_{vegetation} > f_{quartz}$, the sample will be classified as vegetation.

Table 5

Bayes discriminant function coefficients in the training phase in 2013.

Objects	Bayes discriminant function coefficients			
	G4	G8	G12	(Constant)
Gabbro rock	-13.747	16.772	-1.162	-14.089
Quartz-rich rock	-12.095	18.126	1.717	-18.501
Vegetation	-18.529	22.649	-2.461	-25.200

To assess the performance of the MTTFS model, the confusion matrix as one of the most commonly used methods to evaluate classification results, was applied to the extraction of mafic-ultramafic rock, quartz-rich rock and vegetation. In the confusion matrix, the correctly classified counts or the user accuracy (%) for the three objects are shown in the diagonal positions, and the other data represents the incorrectly classified counts or commission error (%). Table 6 details the performance of the MTTFS model using training data in 2013. To evaluate the stability of the classification results, the MTTFS model was applied to test data, and the results are detailed in Table 7.

Table 6

Confusion matrix of the MTTFS model classification results using test data in 2013.

Objects		Gabbro rock	Quartz-rich rock	Vegetation	Overall
Classified counts	Gabbro rock	563	62	108	733
	Quartz-rich rock	119	433	11	563
	Vegetation	39	127	445	611
Classified percentage (%)	Gabbro rock	76.8	8.5	14.7	100
	Quartz-rich rock	21.1	76.9	2.0	100
	Vegetation	6.4	20.8	72.8	100

Note, the data in the diagonal positions represents the correctly classified counts or the user accuracy (%), whereas the other data represents the incorrectly classified counts to other types or commission error (%).

Table 7

Confusion matrix of the MTTFS model classification results using test data in 2014.

Objects		Gabbro rock	Quartz-rich rock	Vegetation	Overall
Classified counts	Gabbro rock	553	31	149	733
	Quartz rich rock	136	317	110	563
	Vegetation	150	67	394	611
Classified percentage	Gabbro rock	75.4	4.2	20.4	100
	Quartz-rich rock	24.2	56.3	19.5	100

(%)	Vegetation	24.5	11.0	64.5	100
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Note, the data in the diagonal positions means the correctly classified counts or the user accuracy (%), whereas the other data represents the incorrectly classified counts to other types or commission error (%).

For the MTTFS model using training data in 2013, the overall accuracy is 75.6%, and the user accuracy for mafic-ultramafic rock, quartz-rich rock and vegetation is 76.8%, 76.9% and 72.8%, respectively. For mafic-ultramafic rock, 14.7% of samples were incorrectly classified as vegetation, and 8.5% samples were incorrectly classified as quartz-rich rock; for quartz-rich rock, 21.1% samples were classified as mafic-ultramafic rock.

For the MTTFS model using test data in 2014, 66.3% of original cases were correctly classified. Mafic-ultramafic rock, quartz-rich rock and vegetation have a user accuracy of 75.4%, 56.3% and 64.5%, respectively. Similar with using the 2013 data, 20.4% mafic-ultramafic rock samples were incorrectly classified as vegetation; 24.2% of quartz-rich rock samples were incorrectly classified as mafic-ultramafic rock.

In comparing the classification accuracy, regardless of whether training data or test data are used, the user accuracy for identifying mafic-ultramafic rock is greater than 75%. Mafic-ultramafic rock mainly experiences vegetation interference, whereas quartz-rich rock is mainly affected by mafic-ultramafic rock. Nevertheless, the MTTFS model has the capability and stability of identifying mafic-ultramafic and quartz-rich rock by introducing *TCI* as well as the thermal analysis in multiple periods.

4.3. Spatial distribution of mafic-ultramafic rock on Landsat 8 images

Compared with *TCI*, the MTTFS model has better accuracy in identify mafic-ultramafic rock. In this section, we aimed to show the results for extracting mafic-ultramafic rock on Landsat images in study area A. Based on the principle of the Bayes discriminant analysis algorithm, the discriminant function for mafic-ultramafic rocks can be represented as follows:

$$F_{\text{mafic-ultramafic}} = \begin{cases} f_{\text{mafic-ultramafic}} > f_{\text{quartz}} \\ f_{\text{mafic-ultramafic}} > f_{\text{vegetation}} \end{cases} \quad (9)$$

According to Eq. (8), Eq. (9) was further transformed as

$$F_{\text{mafic-ultramafic}} = \begin{cases} -1.652 * TCI_{G4} - 1.354 * TCI_{G8} - 2.879 * TCI_{G12} + 4.412 > 0 \\ 4.782 * TCI_{G4} - 5.877 * TCI_{G8} + 1.0299 * TCI_{G12} + 11.111 > 0 \end{cases} \quad (10)$$

Fig. 6. (a) The results of extracting mafic-ultramafic rocks on Landsat 8 thermal infrared images using *TCI* and the MTTFS model for study area A and (b) with the lithological boundaries derived from Fig. 2 (a).

Then, the map algebraic operation was executed using Eq. (6) and Eq. (10). To visualize the interference from vegetation, the normalized difference vegetation index (NDVI) was calculated using Eq. 11 from Landsat 8 OIL data obtained on August 13, 2013 (Level III). We set the

threshold value for NDVI as 0.1 to visualize the distribution of vegetation pixels.

$$NDVI = (band\ 5 - band\ 4) / (band\ 5 + band\ 4). \quad (11)$$

Figure 6(a) gives the results for extracting mafic-ultramafic rocks, in which the pixels with yellow color are mafic-ultramafic rocks and the pixels with green color are vegetation. To validate the results, the lithological boundaries derived from Fig. 2 (a) were overlapped in Fig. 6(b). The mafic-ultramafic rock pixels are mainly distributed within the lithological boundaries of mafic-ultramafic unite, whereas the remaining pixels mainly display the geologic units of alkali granite and the Mesoproterozoic and Lower Ordovician Sandstone-Slate Group. Alkali granite rock has a moderate thermal sensitivity. The interference from alkali granite rock is ascribed to the moderate thermal sensitivity of alkali granite rock, which has been illustrated in section 4.1. Felsic gneiss has similar rock-forming minerals with alkali granite. Hence, some of the mafic-ultramafic pixels overlap the Mesoproterozoic formation, which is dominated by felsic gneiss. Furthermore, there are a few of alkali granite rocks distributed in the Lower Ordovician Sandstone-Slate Group and Permian, which means some of the pixels in Fig. 6 are not certainly the mafic-ultramafic rocks. The vegetation as shown in Fig. 6 is mainly concentrated on the eastern, which greatly interfere the identification of mafic-ultramafic unit lens in the eastern part. Nevertheless, the MTTFS model shows the capability for extracting mafic-ultramafic rocks from other surface objects.

5. Conclusions

In this paper, based on the heat exchange between surface objects and environmental systems, we established a sensitive thermal characteristic index (*TCI*) using Landsat 8 TIR imagery to explore the ability of direct temperature application to identify lithology. Then, based on *TCI* and thermal information analysis of multiple periods, a multi-temporal thermal feature space (MTTFS) model was built to quantitatively classify rocks. The previous result analysis indicates that the higher the *TCI* value is, the lower the resistance is to environmental temperature change and *TCI* has the capability of extracting mafic-ultramafic rocks in low and moderate environmental temperature when the interference from vegetation is minor. However, the user accuracy for extracting mafic-ultramafic rock is approximately 76%; additional indicators and information need to be taken into consideration in future studies to improve the classification accuracy. Furthermore, to explore whether *TCI* and MTTFS model are effective to other rocks

and larger-scale regions, more studies need to be conducted. Nevertheless, we have proposed a referable method using thermal infrared remote sensing data for lithology identification.

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