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Spectral determinants of biological soil crusts in the Gurbantungut Desert

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ABSTRACT

As thick crustal layers form on dryland surfaces, they affect the spectral information that is originally dominated by sand or rock. The spectral characteristics of organic matter replace the mineral elements as prominent features. In this case, the growth patterns and spectral characteristics of biological soil crusts (BSCs) can be observed. Satellite spectral data have been used for BSC spatial information extraction. However, the dynamic changes in BSCs can affect the spectra. Two aspects are involved here: moisture change and BSC growth. When these changes are superimposed with BSC succession, they lead to an increase in spectral complexity. This study explored three BSC types, including algal crust, lichen and moss, and discussed their spectra. By selecting BSC samples at different succession states and by combining coverage and simulated precipitation, the response of the spectra to BSC coverage and the spectral characteristics of BSCs under dry and wet conditions were measured and analysed. In addition, the spectral index variations caused by coverage and moisture of three types of BSCs were discussed, where the spectral indices include the normalized difference vegetation index (NDVI), brightness index (BI), crust index (CI), and biological soil crust index (BSCI). The results showed that the succession, moisture and growth of BSCs were the main factors affecting their spectra. BSC types can be distinguished in a particular climatic context to determine the degree of BSC succession. Precipitation in the monitoring areas needs to be considered to avoid the effects of dry and wet BSC variations on remote sensing monitoring. The coverage of different types of BSCs in mixed pixels can be determined by multiple indices. The results of this study will provide a basis for monitoring BSCs using satellite spectral information to guide regional ecological management.

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1. Introduction

The sensitivity of dryland ecosystems to variations in temperature and precipitation makes them vulnerable to damage due to changes in climatic conditions. In response to global climate change, dryland ecosystems may lose some of their

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ecological functions, and this risk is currently attracting increasing attention from researchers. Biological soil crusts (BSCs) are the characteristic pioneer organisms in arid and semi-arid areas and are composed mainly of fungi, green algae, cyanobacteria, lichens, mosses and other organisms. They interact with soil particles to form crust-like organisms on the surface of soil or rock, with a thin thickness (Lan et al. 2017). The formation of BSCs is generally divided into five stages: sand, physical crust, algal crust, lichen and moss (Zhou et al. 2020). Their growth, development and succession are influenced by soil, moisture, climate, and anthropogenic factors.

The physical properties of BSCs, such as colour, biomass and physicochemical properties, change with the different stages of the BSC because of their unique physiological structure and function. BSCs are highly adaptable to the environment and play important ecological roles, such as soil nutrient enrichment and nitrogen fixation (Wang et al. 2017; Ngosong et al. 2020). Algal crust is the most primitive succession stage organism and can secrete filamentous material to maintain its physical shape and change the physicochemical properties of the soil (Li et al. 2012). Although it only accounts for a small proportion of the soil profile, it is located on the soil surface. Its secreted filaments act to fix the soil and change many ecological functions of the soil, such as evaporation and infiltration (Karnieli et al. 1999). Lichen is an important representative species for the transformation of flow sands into fixed sands in arid areas and usually grows in areas with high amounts of soil nutrients (Bates et al. 2010). Moss is the final succession stage of BSCs; it has more chlorophyll and a greater photosynthetic capacity than algal crusts and lichens, at levels more similar to those of vascular plants (Jia et al. 2014). Compared to algal crusts and lichens, mosses can effectively fix the soil and provide the foundation for vegetation growth due to their large biomass. As the biological community evolves from the early to the middle or late succession stages, the interaction between BSCs and soil is enhanced, and the flow sands are transformed into semi-fixed and fixed dunes (Lan et al. 2015).

BSCs affect ecosystem processes in arid and semi-arid areas and potentially impact global biology and climate (Williams et al. 2016; Bowker 2007). When monitoring dryland phenology, ecohydrological effects and productivity or studying dryland degradation at large scales, it is necessary to consider the effects of BSCs to avoid an erroneous assessment of dryland ecosystems. Moreover, BSC spatial information can reveal the evolutionary trend of the ecological environment in arid and semi-arid areas and its response pattern to global change (Potter and Weigand 2018). For example, Chen et al. (2023) showed that monitoring BSCs can map precipitation in deserts without weather stations. Therefore, monitoring their spatial and temporal distribution has important scientific significance for the assessment and restoration of drylands and allows humans to further resist potential natural risks (Chen et al. 2018; Williams et al. 2016; Ochoa-Hueso et al. 2011). However, due to the limited research in large-scale drylands, we lack data on the basic components of dryland ecosystems, especially on the distribution and composition of microbial communities, which are important for assessing the ecological role of biomes and the health of ecosystems. Many studies have been conducted on the physical and chemical properties of BSCs at the site scale (Lan et al. 2017). However, there is a mismatch between the studies at the site scale and the regional scale. Studies of the properties of BSCs conducted on the site scale tend to be refined and specific, whereas large-scale studies tend to be sketchy and fail to address differences among BSCs.

Remote sensing is an important and effective tool for mapping BSCs. The advantage of remote sensing is that monitoring BSCs using spectroscopy does not disturb or destroy BSCs (Young and Reed 2017; Rodríguez-Caballero et al. 2017). Multidimensional remote sensing imagery has been used for BSC monitoring and ecological assessment (Havrilla et al. 2020; He et al. 2021; Rieser et al. 2021). When using hyperspectral or multispectral satellite imagery, such as MODIS or Landsat-8 imagery, the spectral variations in BSCs affect the analysis of dryland ecosystems (Galvão et al. 2013; Cao et al. 2018; Fensholt et al. 2009). On the other hand, previous studies have mainly focused on a certain stage of BSC succession (Fang, Yu, and Qi 2015; Chen et al. 2020). For example, mosses with high biomass are more attractive to researchers than other types of BSCs. Continuous analysis of spectral variations throughout the developmental period of the BSC is lacking. To date, most of the BSC classification studies have focused on supervised classification and machine learning methods that rely on large numbers of samples (Rodríguez-Caballero, Escribano, and Cantón 2014; Théau, Peddle, and Duguay 2005; Yu et al. 2022). For example, Chen et al. (2019) used indices and machine learning to map the BSC coverage of the Mu Us Sandy Land. Although these methods can be used to classify different types of BSCs, they still do not explain the essence of the spectral differences.

Algal crust, lichen and moss are three types of BSCs in different stages of succession with great differences in multiple features, such as biomass, colour, thickness, density, and carbon and nitrogen content, resulting in different spectra and different impacts on soil properties and regional ecosystem processes. Thus, the degree of BSC succession has important ecological significance (Chen et al. 2019; Lehnert et al. 2018), but it can only be determined if accurate spectral identification of BSC types can be achieved. The growth and moisture of BSCs are important factors affecting their spectra (Román et al. 2021; Xiao and Bowker 2020). BSC growth is constantly dynamically changing and has an important relationship with natural and social drivers. In addition, BSC growth leads to changes in biomass. Rodríguez-Caballero et al. (2017) have shown that the biomass of BSCs is closely related to spectral variations. Thus, growth increases the complexity of the spectra in BSC areas. The degree of BSC growth can be quantified by the coverage. On the other hand, BSCs in arid areas are mainly sensitive to changes in moisture which can have a large impact on BSCs because moisture changes their physical structure (Rodríguez-Caballero, Knerr, and Weber 2015). For example, after BSCs are wetted by dew and rain, they rapidly form chlorophyll, causing photosynthesis to be enhanced and their colour to change rapidly, while the leaf surface stretches, both of which have an impact on the spectral response (Rieser et al. 2021). However, due to BSC succession, there are differences in the effect of moisture on different types of BSCs. For example, the physiological adaptation of late successional organisms such as moss to moisture is more pronounced than that of algal crust. Therefore, the spectral response of each BSC type to moisture should be studied separately. Succession, growth and moisture add complexity to the spectra of BSC areas, making it very difficult to study BSCs using remote sensing. Therefore, the influence of these factors mentioned above on the spectra must be clarified before applying remote sensing. However, there has been a lack of systematic analysis and research in this area.

Hyperspectral information can capture the subtle spectral variations of BSCs during the phenological cycle. The index developed from hyperspectral data has achieved good results (Weber et al. 2008). However, hyperspectral data have many limitations, such as high processing costs and small cover areas. In contrast, multispectral sensors have the advantage of accurately mapping BSCs at the ecosystem scale. However, many BSC spectral studies have not used multispectral sensors to obtain multispectral information on BSCs (Fang, Yu, and Qi 2015; Rodríguez-Caballero, Knerr, and Weber 2015). On the other hand, the vegetation index and biocrust index were widely used to calculate BSC ecological parameters. For example, Rodríguez-Caballero et al. (2022) calculated NDVI values of BSCs to analyse changes in BSCs and predict future changes using hyperspectral data and Landsat satellites. In addition, as the most important parameter of terrestrial ecosystems, the vegetation index is widely used to monitor regional and global ecological environments. Therefore, determining the relationship between BSCs and the vegetation index is important. In previous studies, the biocrust index and brightness index have often been used to identify BSC succession (Beaugendre et al. 2017; Román et al. 2019). Indices that can map BSC-dominated areas and distinguish between plant litter, sand and bare soil include the biological soil crust index (BSCI) and crust index (CI) (Chen et al. 2005; Karnieli 1997). However, it is not clear how variations in coverage and moisture affect the indices of different types of BSCs. Clarifying this effect will help to assess the impact of BSC changes on the accuracy of monitoring.

In this study, we accurately measured the spectral variations of BSCs for different coverage and moisture conditions using a spectrometer and an unmanned aerial vehicle (UAV) to complete a systematic elaboration of the spectral variations of different types of BSCs. The objectives of this study were as follows: (1) to analyse the spectra of different types of BSCs under dry and wet conditions and different BSC coverages by using a spectrometer and a multispectral UAV; (2) to study the effect of the combination of moisture and succession on the spectral indices; and (3) to explore the relationship between the combination of coverage and succession and the spectral indices.

2. Materials and methods

2.1. Study area

The Gurbantunggut Desert is located in the Junggar Basin of Xinjiang, China (Figure 1). Desert dunes mostly extend in a north–south direction, with lengths ranging from a few to tens of kilometres. There is little change in the morphology of the landscape in the north–south direction. There is an even seasonal distribution of precipitation and a certain amount of rainfall in winter and spring, which allows short-lived and short-lived-like plants to develop. BSCs are well developed on the surface of the desert, and the BSC coverage is approximately 30% (Wang et al. 2022). They grow mainly by spring snowmelt, temporary precipitation and dew, enter a dormant state during dry and rainless seasons, and maintain strong physiological activity during the freeze–thaw period. Among all BSC types, lichens and mosses are dominant, while algal crusts account for a small proportion.

2.2. Field spectral data

From 21 September 2020, to 6 November 2020, a spectrometer (spectra vista corporation, SVC) was used to measure the spectra of vegetation, litter, sand, algal crust, lichen and moss under clear sky conditions. No rainfall occurred a week before the

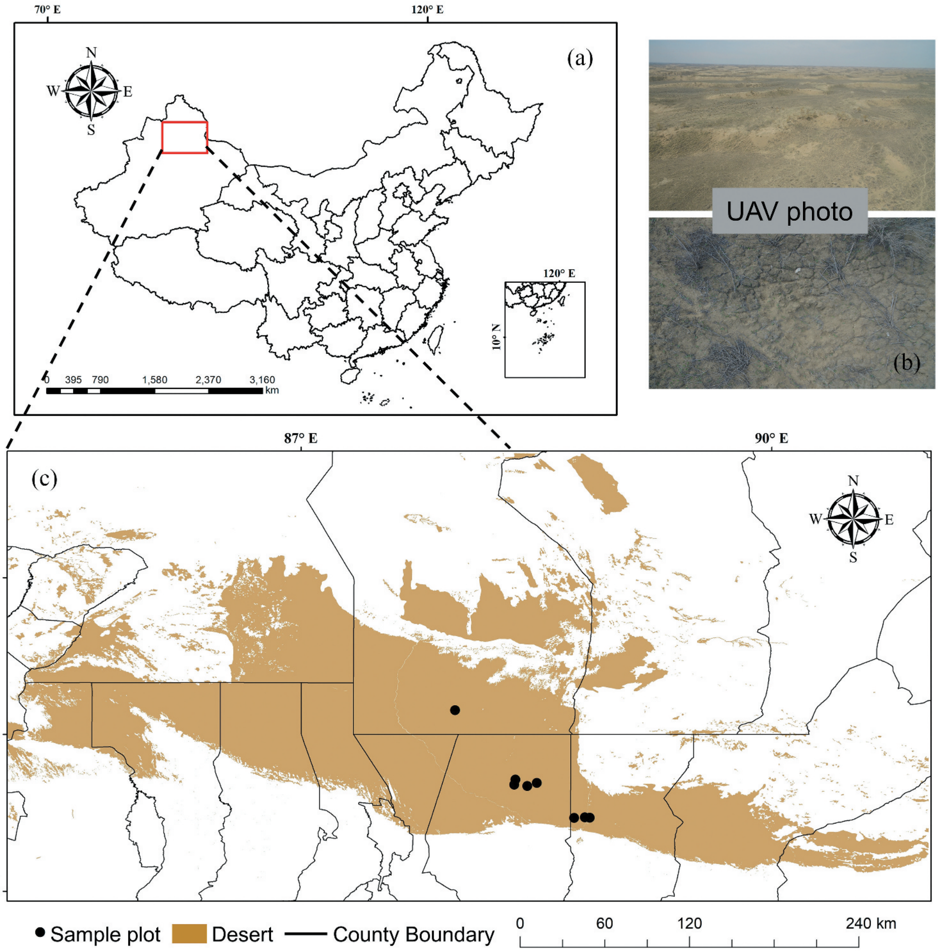

Figure 1. (a) Geographical location map of the Gurbantunggut Desert, northern China, (b) field photos derived from UAV, and (c) the distribution of the Gurbantunggut Desert based on the ChinaCover (Wu et al. 2017).

measurement, and the land surface was in a dry state. The wavelength range of the spectrometer was 350–2,500 nm, and the measurement time was local time 11:00–15:00. During field measurement, the height of the spectrometer from the ground was 83 cm, and the measurement range was within a circular area with a diameter of 37 cm. We calibrated the spectrometer using a white panel before starting the measurement. Each measurement was repeated 5 times, and the average value was taken as the final value of each measurement. The spectra of dry BSCs and other surface components were first measured. Then, clean water was sprayed on the surface, and the spectra of wet BSCs were measured. We also measured the spectra of BSCs with different coverages. A photograph of the BSC area was taken using a digital camera before each spectral measurement, and the spectral measurement area was obtained after masking using ENVI 5.3 (Figure 2). The object–based supervised classification was implemented to calculate the BSC coverage based on eCognition. The segmentation

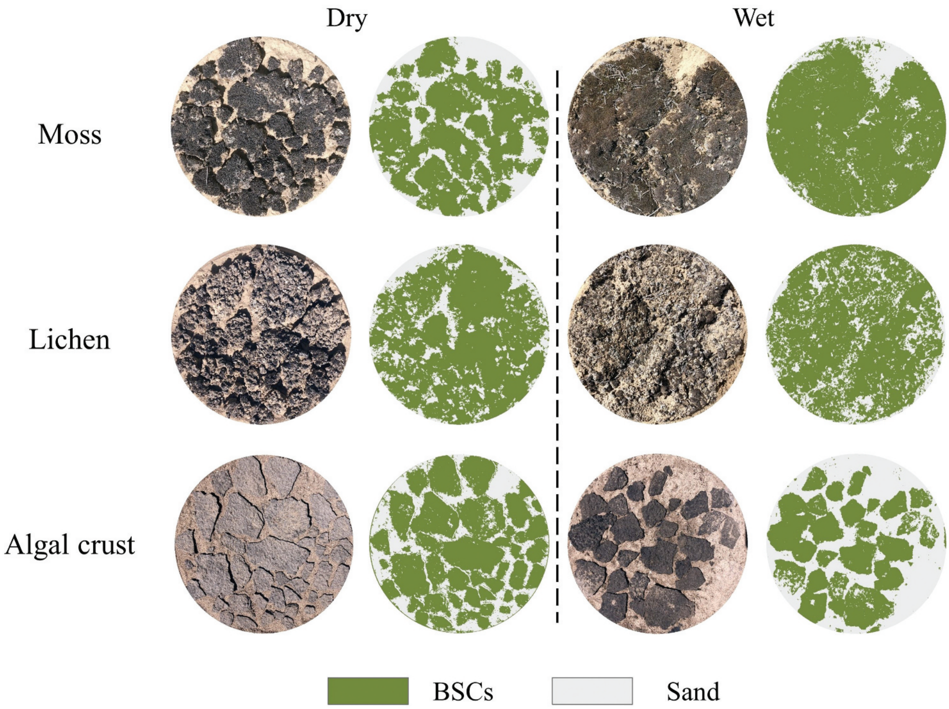

Figure 2. Classification of photos for different types of BSCs under dry and wet conditions.

Table 1. Statistics on the number of BSC samples.

BSCs	Number	
	Dry	Wet
Moss	43	21
Lichen	41	14
Algal crust	34	16

scale was set to 10, and the classification method was nearest neighbour classification. By selecting two types of samples, which are named BSC samples and non-BSC samples, 30 sample objects (groups of pixels) were selected for each type. In addition, three features were selected to construct the feature space, including the mean, brightness and standard deviation. The classification results are shown in Figure 2. The BSC coverage and corresponding spectral results were taken as a sample. A total of 64 moss samples, 55 lichen samples and 50 algal crust samples were collected, and the number statistics of the BSC samples under dry and wet conditions are shown in Table 1.

2.3. Unmanned aerial vehicle data

In September 2020, a DJI Phantom 4 multispectral unmanned aerial vehicle (UAV) equipped with a 5-channel multispectral camera was used to obtain images of different

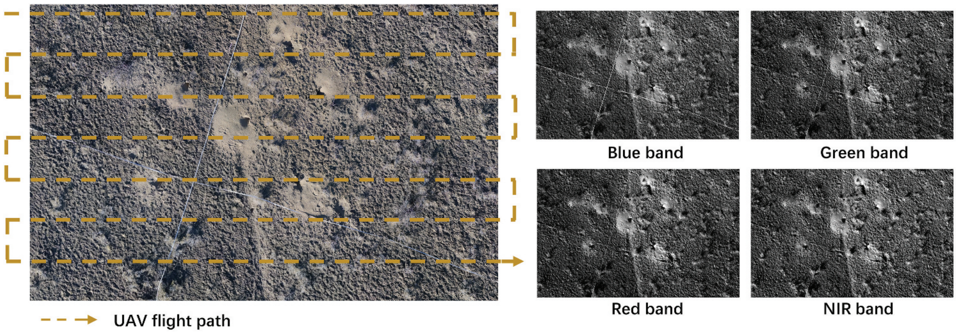

Figure 3. Schematic of the UAV flight path and orthophotos of different bands obtained by the multispectral UAV.

types of BSCs in the Gurbantunggut Desert. BSCs were in a naturally dry state in eight randomly selected sample plots (Figure 1). The selected shooting time was sunny and windless, and the UAV flight altitude was set to 5 m. Thirty-six sample images derived from the UAV were obtained, and the UAV images included blue, green, red and NIR bands (Figure 3). The band parameters of the UAV are shown in Table 2. Based on the real-time kinematic data of the UAV, DJI Terra and ENVI 5.3 were used for image data reading, radiometric correction, image mosaicing and fusion, format conversion and geometric correction. Compared with satellite sensors, the data acquired by UAVs were not affected by the atmosphere. The light intensity sensor of a UAV can compensate for the illumination of the image and eliminate the interference of ambient light on the data to achieve high-precision radiometric correction of the image.

To study the spectral characteristics of wet BSCs, after measuring the dry BSCs, the BSC samples were uniformly sprayed with clean water to simulate the BSC reflectance characteristics after precipitation, and the spectral data in the wide band were measured after wetting. Multispectral images of different types of BSCs under dry and wet conditions were taken using a UAV. Then, we arbitrarily selected the region of interest (ROI) of different surface component types on the multispectral images by using visual interpretation. The selection principle was to select the homogeneous areas with appropriate areas and a certain distance from the boundary for each component type. The samples covered several areas with different brightness ranges, including low, medium and high brightness areas. We selected 102 moss ROIs, 38 lichen ROIs, 104 algal crust ROIs, 16 vegetation ROIs and 15 sand ROIs and took the average spectral reflectance of all pixels in an ROI as the reflectance of the sample. Finally, we calculated the average values of samples of the same category in four bands and the NDVI, BI, CI and BSCI values of each sample based on ArcGIS 10.1.

Table 2. The wavelength range of UAV bands.

Band	Wavelength (nm)
Blue	450±16
Green	560±16
Red	650±16
NIR	840±26

2.4. Index calculation

The NDVI, BI, CI and BSCI, which are common BSC monitoring indices, were used to study the effect of moisture, succession and growth on the indices (Rouse et al. 1974; Escadafal and Bacha 1996; Karnieli 1997; Chen et al. 2005). These indices were defined by the following formula.

$$NDVI = \frac{R_{\mathrm{NIR}} - R_{\mathrm{Red}}}{R_{\mathrm{NIR}} + R_{\mathrm{Red}}} \tag{1}$$

$$BI = \sqrt{{R_{\mathrm{Green}}}^2 + {R_{\mathrm{Red}}}^2 + {R_{\mathrm{NIR}}}^2} \tag{2}$$

$$CI = 1 - \frac{R_{\mathrm{Red}} - R_{\mathrm{Blue}}}{R_{\mathrm{Red}} + R_{\mathrm{Blue}}} \tag{3}$$

$$BSCI = \frac{1 - L \times |R_{Red} - R_{Green}|}{R^{\mathrm{mean}}_{\mathrm{GRNIR}}} \tag{4}$$

where R_{Blue}, R_{Green}, R_{Red} and R_{NIR} represent the reflectances of the blue, green, red and NIR bands, respectively. In Equation 4, L and $R^{\mathrm{mean}}_{\mathrm{GRNIR}}$ represent the coefficient and the average value of the green, red and NIR bands, respectively.

In this study, the indices were calculated using the images of different bands from the multispectral UAV. The spectrometer has high spectral resolution; thus, we took the reflectance of the central wavelength of different bands to calculate the index. The reflectances at wavelengths of 467 nm, 560 nm, 671 nm, and 864 nm, representing the blue, green, red and NIR bands, respectively, were used to calculate the measured spectral index values of different surface components.

3. Results

3.1. Spectral analysis of surface components

As shown in Figure 4, due to the absorption of photosynthetic pigments in the vegetation, the reflectance of the vegetation in the visible (VIS) bands was 0.05 to 0.2. Sand shows no obvious characteristics in the VIS to NIR bands. The reflectance of litter increases monotonically in the VIS wavelengths, which is mainly caused by lignin. The spectra of different types of BSCs under dry conditions are very similar to those of sand, but they also have some commonalities with vegetation spectra. In terms of appearance, the algal crust is thin and light in colour, the lichen is rough with a large number of folds, and the moss has the appearance of a large number of tiny leaf clusters. In the VIS to NIR bands, the reflectance of the BSCs in early succession is generally higher than that of BSCs in late succession, showing spectral features similar to those of sand, and the spectrum of late successional BSCs is similar to that of vegetation. The reflectance of wet lichens and algal crusts is significantly lower than that of dry BSCs. The wet BSCs have a common absorption characteristic at 680 nm, and this phenomenon becomes more pronounced when the development of the BSC is higher. The spectral reflectance of wet moss shows a typical spectrum similar to that of vegetation. Red light is absorbed by the BSCs even when the

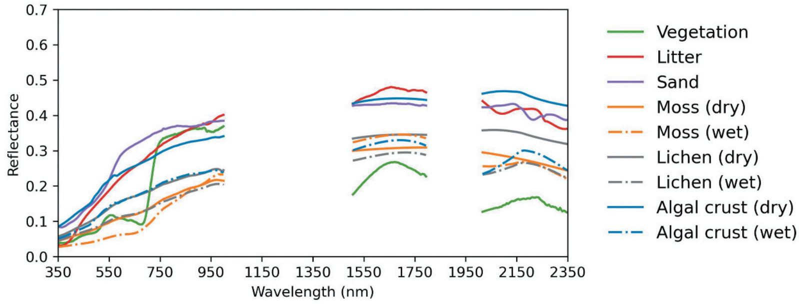

Figure 4. Measured spectral curves of different types of BSCs and other surface component types.

BSCs are in a dry state. Red-edge (RE) wavelengths (680–760 nm) represent the middle range of chlorophyll from the spectral range of maximum absorption to the spectral range of maximum reflectance. The reflectance of moss and vegetation increases rapidly in this wavelength range. Sand and plant litter have no RE effect, and algal crusts and lichens have no apparent RE effect. The slope of the wet BSCs in the RE wavelengths flattens with decreasing reflectance. Sand, vegetation, algal crusts and plant litter have high reflectance in the NIR wavelengths, while dry and wet lichens and mosses have low reflectance. In the shortwave infrared wavelengths, lichens and mosses show strong absorption at 1,720 nm, which is not present in sand and algal crusts. Cellulose and lignin in plant litter have absorption characteristics at 2,080 nm and 2,310 nm.

3.2. Relationship between dry and wet BSCs and spectral indices

There were differences in the indices of different types of BSCs before and after wetting. Figure 5 shows the NDVI, BI, CI and BSCI for the three types of BSCs under dry and wet conditions.

The NDVI of pure mosses reached 0.25 to 0.3. The NDVI of BSCs increased significantly after wetting, and the NDVI of wet mosses reached 0.5. There was no significant difference between lichens and algal crusts before and after wetting, and their NDVI values increased slightly after wetting. When the UAV images were taken at 13:00, the NDVI of the sand was slightly higher than that of algal crusts and lichens under strong solar radiation and high sand surface temperature. Among all surface components, vegetation had the highest NDVI values.

Under dry conditions, the order of BI for the three types of BSCs was as follows: moss < lichen < algal crust. Sand has the highest BI, with an average value of 0.65. When algal crusts and lichens were wet, the BI decreased. Unlike that of lichens and algal crusts, the BI of mosses increased after wetting. In addition, the BI of sand was higher than that of the BSCs. The BI value of vegetation is lower than that of algal crust and sand.

The CI was little affected by moisture, and the three types of BSCs showed little change before and after wetting. The CI of lichens and algal crusts was significantly higher than that of moss and sand, which indicated that the CI was very sensitive to phycocyanin. The CI of sand was only 0.63, and the CI of vegetation was the highest.

The lowest BSCI value was in sand, and the value gradually increased with BSC succession. The average BSCI values of mosses decreased by 2.9 after wetting, but the

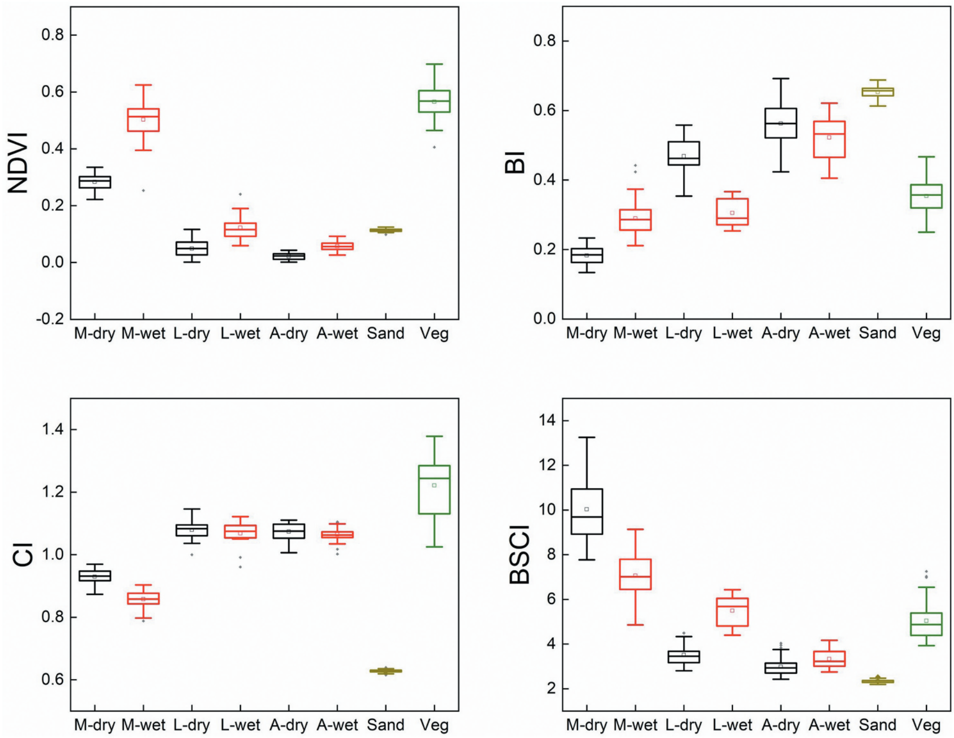

Figure 5. Different spectral indices for dry and wet BSCs, sand and vegetation, and data from UAV multispectral images. M, L and A in the horizontal coordinate represent moss, lichen and algal crust, respectively.

BSCI of algal crusts and lichens increased after wetting. The average values of lichens and algal crusts increased by 1.9 and 0.3, respectively. Changes in the three types of BSCs were most pronounced for mosses. In addition, the BSCI value of vegetation was low, with an average value of 5.

3.3. Spectral analysis of BSCs under different coverages

Figure 6 shows the spectral curves of the BSCs under coverage of 5% to 70%. The surface reflectance strongly depended on the BSC coverage, especially in the case of low fractional vegetation coverage, and the two showed a negative correlation. Specifically, when BSC coverage increased under dry and wet conditions, the surface reflectance decreased. As the coverage decreased, the BSC spectrum became closer to that of sand. In addition, the spectral variations of different types of BSCs were different. Compared to lichen and moss, the algal crust showed less variation in reflectance at different coverages due to its low biomass and insignificant physical characteristics (Figure 6). In contrast, changes in the coverage of lichen and moss had a greater impact on reflectance.

Under wet conditions, the decrease in reflectance led to a reduction in the reflectance difference between different BSC coverages. Due to the increase in chlorophyll and enhanced photosynthesis after wetting, the spectral curves of wet mosses were

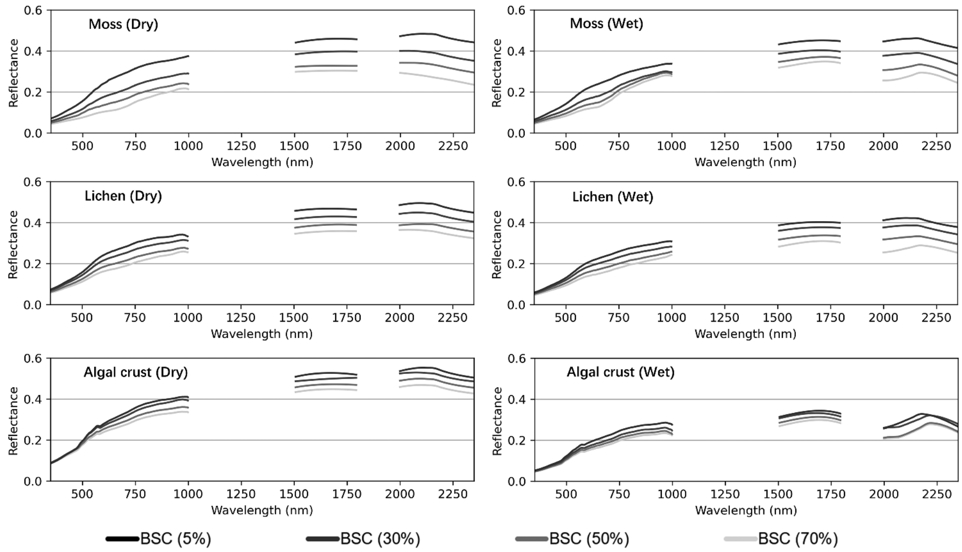

Figure 6. Spectral curves with BSC coverages of 5%, 30%, 50% and 70% were selected for different types of BSCs, including moss (dry), moss (wet), lichen (dry), lichen (wet), algal crust (dry) and algal crust (wet).

significantly different from those of other types of BSCs under different coverages and approached those of vascular vegetation (Figure 6). In addition, their spectral characteristics were gradually enhanced with increasing coverage, such as the absorption depth in the red wavelengths.

3.4. Relationship between BSC coverage and spectral indices

The relationship between four indices and the coverage of each BSC type was found to be linear (Figure 7). Under dry conditions, the correlation between moss coverage and the index was significant, and R^2 reached 0.9. NDVI was more sensitive to mosses than to lichens and algal crusts. Changes in moss coverage caused an increase in NDVI, and when the moss coverage increased by 50%, it caused NDVI to increase by 0.1 (Figure 7(a)). The NDVI values for low coverage lichens and algal crusts were similar to those for high coverage lichens and algal crusts at approximately 0.09. When the BSCs colonize the soil surface and the BSC coverage increases, the most intuitive change is the decrease in the brightness of the mixed pixel. In contrast, this change was not evident in algal crust dominated areas. A significant decrease in BI was observed in areas dominated by mosses and lichens (Figure 7(b)). The CI and BSCI increased with increasing coverage of the three types of BSCs, showing a positive correlation, with R^2 values higher than 0.9, and were more sensitive to mosses and lichens. The CI values varied by similar magnitudes for different types of BSCs (Figure 7(c)). In contrast, the BSCI was influenced by the brightness of the BSC. The increase in BSCI was higher in mosses and lichens than in algal crusts with increasing BSC coverage (Figure 7(d)).

The effect of moisture on the magnitude and change trend of the NDVI and BI of algal crusts and lichens was small, and the magnitude and trend of the change with

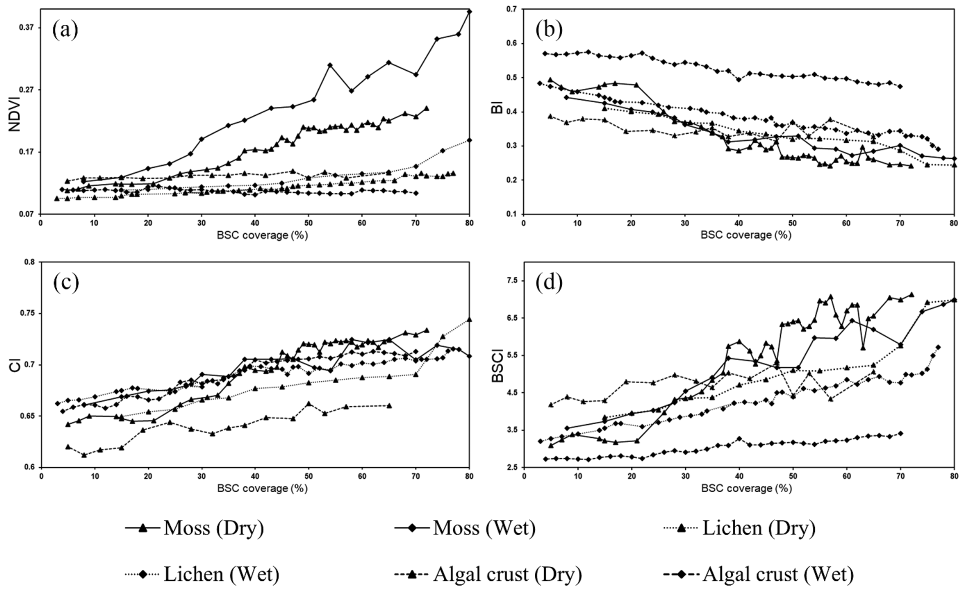

Figure 7. Line graphs show the relationship between the indices and coverage of different types of BSCs based on spectrometer data. (a) NDVI, (b) BI, (c) CI and (d) BSCI.

coverage after wetting was similar to that under dry conditions. In contrast, the change in NDVI for moss under wet conditions was more significant, and the slope of the change in coverage increased significantly. Moisture did not affect the change in the BI of moss. The magnitude of changes in the CI and BSCI for moss under wet conditions was less than that under dry conditions. Their correlation changes with moss coverage were different after wetting, the BSCI still exhibited a high correlation with moss coverage, and the CI showed a decrease in correlation with moss coverage. Moisture did not affect the trend and magnitude of the CI changes in algal crusts and lichens. The CI values were significantly related to the coverage of algal crusts and lichens before and after wetting, and R^2 was higher than 0.8. However, moisture had a greater effect on the change in the BSCI of algal crusts. The BSCI of wet algal crusts increased slowly and was significantly lower than that of other types of BSCs (Figure 7(d)).

4. Discussion

4.1. Influence of dry and wet BSCs and succession on indices

In arid areas, the moisture content of BSCs is at an extremely low level under natural conditions because evapotranspiration is much higher than precipitation; thus, photosynthesis is extremely inefficient or even stops. Because water molecules are part of the physiological structure of BSCs, the biomass and chlorophyll content of different types of BSCs increase after wetting, and net photosynthesis gradually returns to the normal level (Fang, Yu, and Qi 2015). On the other hand, the increase in moisture also changes the structure and morphology of BSCs because they can absorb up to several times their volume once moisture becomes available.

Moss has tiny vascular plant-like leaves on its surface, which are dense and dark in colour under dry conditions. A change from black to dark green was observed in the field after wetting. However, this change in the VIS bands was not obvious, and the reflectance of the green band only increased from 0.081 to 0.083 according to the UAV data. The moss leaves stretched after simulated precipitation, leading to an increase in reflectance in the NIR band, resulting in an increase in the BI values. The lichen and algal crust only absorbed a small amount of moisture, and the rest of the moisture remained on the surface because the BSCs prevent moisture from seeping down. Therefore, moisture affected the surface reflectance of the BSC areas, and the BI variation showed the differences between different types of BSCs after wetting (Weber et al. 2008). On the other hand, the increase in moisture content makes the spectra of the BSC areas have the absorption of chlorophyll in the red band and reflection in the NIR band, resulting in a change in NDVI, which is more evident in mosses (Karnieli et al. 1999). Zaady, Karnieli, and Shachak (2007) found similar phenomena and concluded that the NDVI is an important indicator of BSC succession. Therefore, the spectra of wet mosses are similar to those of vascular plants, making it difficult to distinguish wet moss from vegetation with low biomass. In areas with frequent rainfall, the dry and wet states of the BSCs alternate frequently, resulting in a state of dynamic change in the vegetation index. The increase in the NDVI can be mistaken for changes in vascular plant dynamics, which can lead to errors in estimating dryland productivity. Thus, this phenomenon cannot be ignored in areas with high BSC coverage. This finding is consistent with the seasonal and dry and wet analysis of mosses by Fang, Yu, and Qi (2015).

Biocrust indices were developed for BSC mapping, including the CI and BSCI. They were all sensitive to BSC change under dry conditions (R^2>0.8), indicating that these indices can reflect changes in BSC coverage, but this was not guaranteed after wetting; thus, it is necessary to consider the moisture state of the ground surface when using satellite images for BSC coverage studies. Unlike the NDVI and BI, the CI of moss decreased after wetting. Chen et al. (2020) also found that the CI value of moss decreased after wetting by calculating the simulated multispectral channel reflectance. This result was different from that of Fang, Yu, and Qi (2015). By observing the spectral data of the UAV after wetting, it was found that the red band reflectance after wetting had no obvious change compared with that under dry conditions. This may have been due to two reasons. The first reason may have been due to insufficient wetting time, which did not allow the absorption of the red band to reach its peak (Chen et al. 2020). The second reason may have been that the dense and dark shape of moss under dry conditions led to low VIS reflectance. The CI of lichens and algal crusts did not decrease significantly after wetting because their absorption in the red band was weak. The denominator of the BSCI increases after wetting for mosses, leading to a decrease in the BSCI values. When the moss coverage decreased, the BSCI value of the mixed pixels further decreased. Therefore, the BSCI was prone to misclassification in areas with low moss coverage after precipitation. In contrast, this phenomenon did not occur for algal crust and lichen because their BSCI values slightly increased after wetting. The BSCI values of sand and BSCs were significantly different, and the BSCI values of sand were lower than those of BSCs and vegetation. When using the biocrust indices, the CI and BSCI of BSCs varied before and after rainfall, which may affect the monitoring accuracy. To avoid such errors and conduct comparable measurements, satellite images with the same climatic conditions should be collected for BSC mapping in different areas. In addition, the common denominator of the currently widely used multispectral biocrust indices is that they only used the VIS to NIR bands. However, these indices have high requirements for the regional environments, such as a consistent underlying surface and few surface component types, making them difficult to apply to areas with high spatial heterogeneity. Therefore, multispectral data with additional spectral bands are recommended in areas where hyperspectral data are not available. To date, many multispectral satellites have provided multiple additional channels, such as RE to shortwave infrared channels, which may be helpful for BSC monitoring. Further research is needed to understand the differences between BSCs and other surface components in these spectral bands. However, using multispectral data to distinguish different types of BSCs is still a core problem that needs to be addressed urgently.

The above discussion implies that differences in physical structure and chemical properties between BSC types and their physiological adaptations to moisture will result in different spectra, which will affect some spectral indices. The variability of the BSC response to moisture makes it necessary to consider the distribution of precipitation when mapping BSCs or assessing their ecologicalfunctions. However, the distribution of rainfall is irregular in large-scale drylands. Thus, it is necessary to acquire a sufficient number of remote sensing images within a short phenological window, which is a challenge for many current satellite sensors.

4.2. Influence of BSC coverage and succession on indices

BSC coverage is an important ecological parameter that reflects the degree of BSC succession and surface stability. The spectral response of heterogeneous mixed areas observed from the instrumentation depends on the relative coverage of sand, plant litter, vegetation and BSCs. Therefore, variations in BSC coverage have a large effect on the sensor-based calculated spectral indices. On the other hand, BSC succession is associated with coverage, which is an important point that needs to be clarified in this study. Because BSC succession is a continuous process, for multispectral sensors with a wide shooting range and medium resolution, such as the Sentinel-2 multispectral instrument and the Landsat-8 operational land imager, this will involve implementing classification within pixels to determine the types of BSCs and other surface components contained in the image pixel. Usually, the BSC coverage in the mixed pixel is the sum of the coverage of all BSC types. Some explorations have been carried out in some studies, where they chose to classify the different types of BSCs and other surface components first and then calculate the BSC coverage (Rodríguez-Caballero, Escribano, and Cantón 2014; Théau, Peddle, and Duguay 2005). This method is suitable for areas where BSC development is in an early or late stage. In other words, it is usually assumed that image pixels contain only one type of BSC. However, BSCs are in constant succession in most cases, with different types of BSCs crossing each other. Thus, a single reflectance change is not valid for coverage estimation in such areas. Taking the BI as an example, the reflectance change degree in areas with only one BSC type and a few surface component types can reflect the change in BSC coverage. Rodríguez-Caballero, Knerr, and Weber (2015) found that the surface albedo strongly depends on the BSC coverage. They explained that this phenomenon is in the case of a single BSC type (cyanobacteria crust). In areas with mixed growth of multiple BSC types, the BI no longer has this ability.

Due to the sensitivity of the NDVI to chlorophyll content, the NDVI is effective in describing changes in moss coverage. In contrast, nonphotosynthetic bacteria, fungi and other large amounts of organisms with low chlorophyll content developed and mixed with sand in areas dominated by lichens and algal crusts; thus, the NDVI was not sensitive to changes in BSC coverage in these areas (Chen et al. 2020). Coverage change monitoring requires more sensitive bands or band combinations. In addition, the NDVI values of BSCs with low coverage were mostly in the range of 0.05 to 0.15. These values were also the spectral values of sand and sandy soil, meaning that it was not possible to distinguish between BSCs with low coverage and sand using the NDVI, which affected the accuracy of BSC coverage estimation.

The increase in phycobilin, the main photosynthetic pigment of algal crusts and lichens, reduced the slope between the red and blue bands, indicating that the increase in coverage emphasized the reflectance of the blue band (Karnieli 1997). This resulted in a positive correlation between the CI and coverage for algal crusts or lichens. However, as BSC coverage changed, the CI did not change significantly. In addition, as the coverage of BSCs in the early stages increased, the increased pigment and organic matter caused the BI values to decrease. As the degree of succession increased, the BI decreased more. This is also indicated by the experimental findings of Chamizo et al. (2012). In contrast, the effects of succession and coverage on the NDVI and CI were inconsistent with the effects on the BI. According to the definition of the BSCI, the BSCI value of BSCs is significantly higher than that of sand when the BSC coverage is higher than 33%, and it gradually increases as the BSC coverage increases (Chen et al. 2005). Under dry conditions, the BSCI was sensitive to changes in the BSC coverage during the late stage of BSC succession; thus, it was recommended to use the BSCI to estimate BSC coverage when BSCs are at this succession stage.

The spectral unmixing of mixed pixels is a common method for calculating the coverage. The results in Section 3 show that all variations in the indices and coverage conform to a linear relationship (Wang et al. 2019). This satisfies the prerequisite of spectral unmixing. In addition, a suitable index must reflect the degree of BSC succession and be sensitive to BSC coverage. In other words, it should be able to distinguish between different types of BSCs and determine the change in BSC coverage. However, the spectral characteristics of the mixed pixels containing BSCs that are in an early succession stage with high coverage are similar to those of the mixed pixels containing BSCs that are in a late stage of succession with low coverage. It is difficult to accurately determine BSC succession and coverage using only one index. Therefore, it is necessary to develop new methods to solve the coverage estimation problem considering BSC succession. We considered that the combination of several indices would provide the possibility for the estimation of coverage of different types of BSCs. Overall, the estimation of BSC coverage using appropriate models remains a major challenge.

4.3. Ecological significance of remote sensing for monitoring BSCs

Once a method for mapping the BSC abundance distribution is available, the BSC data obtained from remote sensing provide important support for follow-up ecological studies. We can establish ecological function models using the ground and satellite spectra according to the action mechanisms of BSC communities on the environment, to obtain the relevant ecological indicators. These indicators will help to further understand the importance of desert and sandy land ecosystems and help decision makers assess the impacts of environmental policies on biodiversity (Figure 8) (Xiao et al. 2019). This method can help to complete the evaluation of regional ecological function without damaging the surface.

We used the importance of BSCs for the carbon cycle as an example for discussion. Due to the sparse vegetation and low soil nutrient content in arid areas, especially in desert areas, carbon stored in BSCs cannot be ignored. At present, there are still large errors in the estimation of carbon content in arid areas. In addition, BSCs are an important way for CO_2 from the surrounding environment to enter the dryland ecosystem by absorbing light energy to convert CO_2 into organic matter and achieve carbon sequestration (Li et al. 2012). Although many factors affect carbon fixation, combined with other multidimensional remote sensing data, such as precipitation and temperature, we can establish a regional carbon sequestration model based on the principle of remote sensing observation. Therefore, spatial data on BSCs can help to calculate the carbon sequestration capacity of BSCs and quantitatively measure their contribution and influence on the carbon cycle.

Although we have made only slight extensions and explorations in this area, we can excavate more information with the help of further research to better explain some scientific problems associated with desert and sandy land ecosystems.

4.4. Limitations and perspectives

BSCs may have a seasonal effect due to climate change during the year (Kidron, Barinova, and Vonshak 2012; Fang, Yu, and Qi 2015). In the spring, with the melting of winter snowfall and spring precipitation, the physicochemical properties of the BSCs change, and chlorophyll and biomass increase significantly. In the summer, the chlorophyll content of

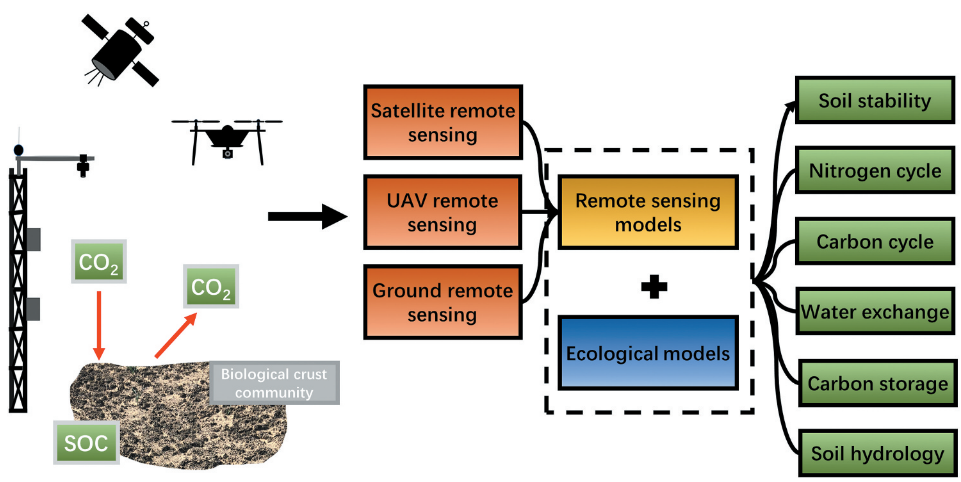

Figure 8. This section discusses the important role of remote sensing data in ecological research. Remote sensing models can be combined with ecological models to quantitatively calculate the environmental impacts of BSCs.

the BSCs decreases sharply, probably due to the high intensity of ultraviolet radiation and surface temperature in summer (Bowker et al. 2002; Stark, Brinda, and McLetchie 2011). Therefore, the seasonal factor of the sample selection area should be considered when selecting experimental samples. Our study was limited to the spectral response of different types of BSCs to coverage and moisture, and the potential effect of season on the spectra was not within the scope of our study due to the lack of a long time series of observational data.

In large-scale areas, when multispectral images are used for routine monitoring, the BSC types in mixed pixels appear in various combinations. This study can provide a basis for the classification and coverage estimation of BSCs. Additional efforts are needed to analyse the relationship between the biological structure and the spectral response in drylands. On the other hand, accurate monitoring of BSCs depends on the technical parameters of the sensor, which not only need to provide high spatial and spectral resolution but should also be able to collect images with sufficient frequency. Therefore, extra bands or algorithms need to be considered to accurately detect BSCs in the future.

5. Conclusions

Succession, moisture and growth are three main factors that affect BSC monitoring using remote sensing techniques. The degree of BSC succession needs to be considered when mapping BSCs; otherwise, the direct application of spectral indices in mixed BSC areas will result in misclassification because the effect of BSCs on spectra varies depending on their structure and chemistry. After precipitation, it is necessary to observe the changes in BSCs. The effect of moisture on the spectrum varies among BSC types. When assessing ecology using spectral indices, physical changes caused by moisture in BSCs can lead to misestimation. Precipitation or humidity should be considered when choosing the satellite image time to reduce the effect of moisture. In addition, an increase in BSC coverage leads to the enhancement of spectral absorption and reflection characteristics of different types of BSCs, which is obviously reflected in the values of the spectral indices. Combining multiple indices provides the possibility to estimate the BSC coverage of mixed pixels. The analysis of the effects of growth, succession and moisture on the spectra is important for conducting BSC monitoring techniques, such as image time selection and image interpretation. This study provides a theoretical basis for using spectral indices and multispectral remote sensing imagery to determine the succession stage and the coverage changes of BSCs and to provide accurate estimates for the ecological functions of the biological community in arid areas, which is important for improving our understanding of dryland functions.

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