Improved mapping and understanding of desert vegetation-habitat complexes from intraannual series of spectral endmember space using cross-wavelet transform and logistic regression

Qiangqiang Sun, Ping Zhang, Hai Wei, Aixia Liu, Shucheng You, Danfeng Sun

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

ARTICLE INFO

Keywords:
Desert vegetation-habitat complex
Endmembers fraction series
Cross-wavelet transform
Feature parameters
Logistic regression

ABSTRACT

Desert vegetation-habitat complexes in dryland systems are fragile ecosystems with complex vegetation-habitat feedback, and have significant implications for natural environment protection and global climate change mitigation. However, a spatial-detailed and high-precision remote sensing method for the identification of desert vegetation-habitat complexes and characterization of their biophysical processes remain scarce. Here, we developed an innovative cross-wavelet transform (XWT)-based approach coupled with logistic regression to extract critical vegetation-habitat interaction characteristics in order to identify, map, and understand their complex ecological processes. Fine intraannual profiles between the green vegetation (GV) fraction and habitat fractions including dark material (DA), saline land (SA), sand land (SL) were unmixed by Multiple Endmember Spectral Mixture Analysis (MESMA) from 16-period Gaofen-1 (GF-1) wide field of view (WFV) images in Minqin County, after which XWT was performed to extract feedback characteristics as feature parameters. Major principal components (PCs) were obtained from those feature parameters to reduce dimensions and solve multicollinearity, logistic regression was applied for mapping. The results demonstrate that the proposed procedure efficiently reproduced desert vegetation-habitat complexes with high accuracy (overall accuracy: 87.33%; Kappa coefficient: 0.86) in the entire Minqin County, representing a 3.42% overall accuracy increase relative to a previously published decision tree (DT) method. The new method also had a lower quantity and allocation disagreement. Moreover, this procedure not only achieved comparable accuracy to that of an optimized Support Vector Machine (SVM) and superior to a Convolutional Neural Network (CNN)-based U-net model, but also explored biophysical processes and complex relationships with better interpretability. Therefore, the developed approach has the potential for accurately monitoring the highly heterogeneous dryland landscape and characterizing the land degradation processes in the spectral endmember space of fine spatial-temporal remote sensing data.

1. Introduction

Dryland systems are sensitive and fragile ecosystems which are constantly threatened by land degradation (Millennium Ecosystem Assessment (MEA), 2005). Given the land surface structure and pattern changes resulting from human-environment interaction, land use/land cover (LULC) mapping has become a common approach for integrated environmental monitoring and assessment (LADA, 2013; Hessel et al., 2014), resource management and policy (Ghil et al., 2000; Grainger, 2015), and to determine dryland system degradation processes (Reynolds et al., 2011; Rodríguez-Caballero et al., 2014). Desert vegetation-habitat complexes, integrating sparse desert vegetation with exposed surface as cover complexes in dryland systems (Sun et al., 2018), play a crucial role for sand fixation, carbon sequestration, and the overall stability of desert and oasis ecosystem (Aguiar and Sala, 1999; Okin et al., 2016). Thus, mapping desert vegetation-habitat complexes and understanding their underlying interactive biophysical processes, is key to regional sustainable dryland systems management and decision-making (Sun and Liu, 2015; Sun et al., 2018).

In recent decades, time-series metrics, i.e., Normalized Difference
Vegetation Index (NDVI), typically selected to enrich phenology information and capture dynamic features at various vegetation growth stages (Maxwell et al., 2002; Zhou et al., 2013), have also been widely utilized for LULC classification and detection (Reed et al., 1994; Fuller, 1998; Bradley and Mustard, 2010; Piccoli et al., 2018; Teluguntla et al., 2018). However, due to the inherent low coverage of desert vegetation, the subtle differences between NDVI of sparse vegetation and bare soil matrix insufficiently support desert vegetation subdivision (Huego, 1988), and constrain the understanding of processes (Sun et al., 2018).

Thus, there are very few datasets that describe desert vegetation and their associated habitats, as this topic has been seldom addressed in the field of remote sensing. Consequently, the role of sparse vegetation and soil in the regulation of ecological environment and carbon sequestration in the global dryland systems remains unclear and likely underestimated.

Devoting to endmembers (EMs) fractions at subpixel level (Roberts et al., 1993; Small, 2004), Spectral Mixture Analysis (SMA), offers a valuable approach to account for considering both sparse vegetation and associated habitat information in SVD (i.e., substrates, vegetation, and dark) space (Small and Milesi, 2013; Sousa and Small, 2017). The spectral dominant EMs can be standardized for intercomparison of fraction estimates from different sensors across space and time (Small and Milesi, 2013; Sun and Liu, 2015), and unmixing physically-based EMs fraction images can promote better understanding of the related biophysical processes (Quintano et al., 2012). In dryland systems, Sun and Liu (2015) developed a fixed four-EM space comprised of green vegetation (GV), dark material (DA), sand land (SL), and saline land (SA) in Landsat images to map temperate dryland cover and its growth form (i.e., the length and the maximum growth season of vegetation throughout the year). Moreover, biannual differences in typical EMs were validated for assessing surface degradation processes at landscape level (Sun, 2015).

Nonetheless, the temporal characterization of EM dynamics to understand intraannual processes has been limited by the landscape-scale temporal resolution of conventional broadband remote sensing. For example, the plant types produced by typical phenological EMs in Landsat imagery exhibited a relatively low producer’s accuracy ranging from 63% to 75% (Sun and Liu, 2015). As a latest broadband satellite, the wide field of view camera (WFV) on Gaofen-1 (GF-1), can provide optical imageries with both high spatial (16 m) and temporal (4-day revisit) resolution (China Centre for Resources Satellite Data and Application (CRESDA), 2015). Thus, an intraannual 16-period series of vegetation EM (GV) and habitat EMs (DA, SA, and SL) were achieved by Multiple Endmember Spectral Mixture Analysis (MESMA). Then, range, rate and mean of each EM during the growing season were empirically selected and calculated from respective profile to classify desert vegetation-habitat complexes (Sun et al., 2018). Nevertheless, the detailed interactive information between vegetation and soil-related EM time series has not been fully explored, resulting in relatively lower mapping accuracy. Thus, a method that would automatically and accurately extract the interactive characteristics of vegetation and associated habitat would facilitate dryland cover mapping and understanding.

Focusing on detailed characteristics of a time series signal, the wavelet transforms (WT) has been widely and maturely applied within multi-resolution analysis and wavelet transforms (WT) has been widely and maturely applied within multi-resolution analysis and wavelet power spectrum within time (Small and Milesi, 2013; Sousa and Small, 2017). The wavelet power spectrum within time on the cross-wavelet spectrum effectively captures wavelet power spectrum within time–frequency space (Torrence and Compo, 1998). WT can approximate the mutation of unsteady signals or discrete discontinuous signals with local characteristics, so as to reflect the changes of the original signals in a certain time scale more truthfully (Grinsted et al., 2004; Stoy et al., 2005). Recently, WT has been proven useful for remote sensing processing, as demonstrated by their application in vegetation phenology feature analysis (Sakamoto et al., 2005; Galford et al., 2008), image denoising (Wang et al., 2003; Mohideen et al., 2008), image fusion and compression (Devore et al., 1992; Li et al., 2002; Cheng et al., 2015), multi-resolution analysis and processing (Martinez and Gilabert, 2009; Wang et al., 2012), and texture extraction and classification (Xiong and Zhang, 1999; Zhang and Zheng, 2010; Prabhakar and Geetha, 2017; Han et al., 2018). Following WT, designed to reveal the detailed relationship between two nonstationary signals (Grinsted et al., 2004), the cross-wavelet transform (XWT) is an efficient approach for electrocardiogram feature extracting and signals distinguishing (Dey et al., 2008, 2010; Banerjee and Mitra, 2014), and exploring interaction and feedback between multiple time series (Soon et al., 2014; Issartel et al., 2015). Thus, XWT based approach, which has not been applied for remotely sensed LULC classification, raises new opportunity to quantify the interactive dynamic processes in intraannual EMs time series concretely for desert vegetation-habitat complexes with different power and angle in the scale and time on the cross-wavelet spectrum effectively.

Conceptually, the structure, process, and evolution of ecosystem dynamics can be described using simple response functions mathematically (Oliver and Larson, 1996), to help ecologists and decision makers understanding ecosystem phenomena. A supervised learning algorithm improved from binary logistic regression, named as logistic regression (Bishop, 2006), provides a reliable and efficient tool for multi-class classification (Greene, 2013; Tao et al., 2015; Wolte et al., 2017), and describes the relationship between independent and dependent variables for understanding their feedbacks and mechanism (Bai et al., 2017). Currently, the logistic activation function was applied for establishment of the classification model, integrated with deep learning model, i.e., convolutional neural network (CNN) and Recurrent Neural Network (RNN) (e.g., Hu et al., 2018; Huang et al., 2018).

Therefore, this paper attempted to develop an innovative approach, coupling XWT with logistic regression for mining and integrating interactive features in the profiles of EM pairs in order to improve dryland cover classification. The specific aims were 1) to establish XWT for quantifying the interactive features in EM time series pairs, 2) to integrate feature parameters in EM pairs by principal component analysis (PCA) for reducing dimensions and solving multicollinearity, and 3) to map and characterize desert vegetation-habitat complexes with logistic regression, finally 4) to compare the proposed procedure with previously developed decision tree (DT) and other state-of-the-art machine learning methods.

2. Materials

2.1. Experimental area

Minqin County, located in the east end of Gansu Corridor, northeast China (Fig. 1), consists of alluvial oasis for agricultural production and various desert vegetation-habitat complexes (Sun et al., 2018), was chosen as experimental area. Table 1 shows five desert vegetation-habitat complexes, individual composed by one of three desert vegetation types (i.e., shrub, shrub/undershrub, desert meadow) and one of three habitats (i.e., xerophyte and psammophyte, xerophyte and halophyte, hygrophyte and halophyte). Three field surveys of desert vegetation with soil properties and surface geomorphology were implemented, from 11 September 2016 to 20 September 2016, from 17 August 2017 to 27 August 2017, and from 11 August 2018 to 13 August 2018 (Fig. 1C), respectively.

2.2. Data and preprocessing

The 16-period GF-1 WFV time series imageries in study area, from October 2014 to November 2015, were downloaded from China Centre for Resources Satellite Data and Application (CRESDA). The pre-processing, including radiometric correction, atmospheric correction, registration, seamless mosaic and mask, was performed for these reflectivity images. With spatial and spectral heterogeneity, and a limited number of GF-1 WFV bands, MESMA was performed to adaptively...
unmix four-EM time series information from the 16 aforementioned imageries. Variance and eigenvectors calculated from PCA of the 16 imageries were applied to determine the EMs types (i.e., GV, DA, SA, and SL), and their representative periods. The EMs for each representative period were acquired directly from the GF-1 WFV images at corners of scatter plot constructed by representative PCs, and standard EMs spectrums were derived from the mean EMs spectra of all representative periods. Fully Constrained Linear Spectral Mixture Analysis (FCLS) was then used for any three combinations of the four EMs, and the least RMSE (root-mean-square error) for each pixel was regarded as a criterion for final optimal fitting with the most suitable EMs fractions. A more detailed description of the MESMA data processing procedure can be found in Sun et al. (2018).

To visualize seasonal variations and spatial distribution of corresponding EMs (Sun and Liu, 2015), the fractional abundance of three temporal EMs (2015-04-29, 2015-08-22, and 2015-11-29) were composited (Fig. 2). GV distributed mainly in the cultivated area of Minqin Oasis in summer with green color (Fig. 2A). Locations in the hill shade and water body showed brighter indicating little seasonal variability in the DA fractions, while oasis was purple due to higher soil bareness in spring and winter without crop cover (Fig. 2B). Higher fraction of SA was concentrated in the lower reaches of Minqin County as dry salt lakes with white color, whereas, in the summer inundated playas, SA accumulated in surface in spring season with red color (Fig. 2C). And SL represented brighter intensity with gray tone with slight seasonal change in the desert, while it had saturated red color in oasis because of little crop cover in spring (Fig. 2D). The highest spatial heterogeneity existed at desert-agriculture ecotone covered by desert vegetation-habitat complexes with various phenology change (Fig. 2).

The fractional abundance images, from October 2014 to November 2015, were organized into layer stacks as time-series profiles of GV, DA, SA, and SL images, respectively. And the Harmonic Analysis of Time Series (HANTS) algorithm was used to smooth the four EMs fraction time series, respectively. The time series curves of each pixel were constructed and furtherly applied to XWT pixel by pixel (Fig. 3A).

3. Methodology

3.1. XWT of three pairs of two-EM for vegetation phenology and associated habitats

By decomposing a signal onto certain functions, WT can both focus on detail of the signal and fully highlight features of variability (Torrence and Compo, 1998). In mathematics, for a discrete time series signal \( x(n) \) \( (n = 1, 2, \ldots, N) \), the Continuous Wavelet Transform (CWT) is commonly employed to divide the signal into wavelets and expressed as a function of \( n \) and \( s \):

\[
W_{\psi}^s(n) = \frac{1}{s} \sum_{n=0}^{N-1} x_n \psi^* \left( \frac{n'-n}{s} \right)
\]

(1)

where \( N \) is the signal length, \( s \) is the wavelet scale, \( n \) is the localized time index, \( \delta n \) is the time interval, \( (\delta n/s)^{1/2} \) is the standardization factor of wavelet function, \( \psi \) is the mother wavelet which provides a source function to recover the original signal \( x(n) \) with multi-scale flex and transition, and * indicates the operation of complex conjugate. With specific wavelet scale \( s \), CWT outcome, \( W^s_{\psi}(n) \) can be regarded as various coefficients related to the localized time index \( n \) (Lindsay et al., 1996).

Morlet wavelet is a common mother wavelet with both
nonorthogonality and complex exponential multiplied by a Gaussian window (Bernardino and Santos-Victor, 2005), resulting in a better equilibrium between the time and frequency (Grinsted et al., 2004). Thus, Morlet wavelet was used in our study as mother wavelet and expressed as follows:

$$\psi_\pi(\eta) = \pi^{-1/4} e^{-\eta^2/2} e^{i\omega_0 \eta}$$  \hspace{1cm} (2)$$

where $\omega_0$ and $\eta$ are dimensionless frequency and time, respectively. When $\omega_0 = 6$, the wavelet scale is basically equal to the Fourier period ($\lambda = 1.03s$) to meet admissibility conditions (Farge, 2003).

Given the two series signals $x(n)$ and $y(n)$, XWT based on WT is used to analyze correlation between two signals and defined as:

$$W^\omega(s) = W^\omega_x(s) W^\omega_y(s)$$  \hspace{1cm} (3)$$

where $W^\omega(s)$ is the complex conjugate of $W^\omega(s)$. Since the Morlet wavelet is a complex wavelet, the $W^\omega(s)$ is also complex (Torrence and Compo, 1998). Consequently, $|W^\omega(s)|$ represents the cross-wavelet power, the phase is accordingly defined as

$$\phi^\omega(s) = \arctan \frac{\text{Im}[W^\omega(s)]}{\text{Re}[W^\omega(s)]}$$  \hspace{1cm} (4)$$

Where $\text{Im}[W^\omega(s)]$ and $\text{Re}[W^\omega(s)]$ were imaginary and real of $W^\omega(s)$, respectively.

In our experimental design, the GV series was selected for vegetation phenology, and SL, SA, and DA for habitat characteristics. Thus, the cross-wavelet spectrum for GV and DA, GV and SA, GV and SL at each pixel were figured out using MathWorks Matrix Laboratory (MATLAB) R2018b software, respectively, and serve to quantify and decompose the interaction between vegetation and habitat in a given wavelet scale and time domain.

With time-series curves obtained from samples of five desert vegetation-habitat complexes for GV, DA, SA, and SL fractional abundance previously published by Sun et al. (2018) (Fig. S1), cross-wavelet spectrum between GV and SL, GV and SA, GV and DA, respectively, were calculated and visualized (Fig. S2). There existed errors in the beginning and end of cross-wavelet spectrum as an edge effect for wavelet power spectrum, it was thus worthy to pay attention to a “Cone of Influence” (COI) (Torrence and Compo, 1998). Additionally, modeled with a first order autoregressive (AR1) process, red noise was commonly used as background spectrum to test statistical significance of wavelet power spectrum at a 5% significance level (Grinsted et al., 2004; Torrence and Compo, 1998). In Fig. S2, value of wavelet power in the time-frequency space was plotted and represented through different colors (blue represents lower wavelet power, red is higher wavelet power). The black colored line and ‘U’ shape were significant level and COI respectively. Black arrows, illustrated in Fig. S2 and Fig. 3B, indicate the phase angle $\phi^\omega(s)$. For different desert vegetation-habitat complexes, the wavelet power and phase angle presented a distinct volatility and even stagnation, which could provide foundation for the identification of complexes via XWT feature parameters. For example, for the XWT wavelet power between GV and DA for HHDM, illustrated in the upper right corner of Fig. S2, the higher wavelet power represented by red colors indicated higher correlation and interaction between GV and DA at specific time (approximately 512) and scale.

Fig. 2. Three-temporal false-color composite images, where red, green, and blue represent EM fractional abundance in 2015–04-29, 2015-08-22, and 2015-11-29, repetitively, unmixed from GF-1 WFV images for GV (A), DA (B), SA(C), and SL(D). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
(approximately 23) with a 5% significant level, the black arrows with 180° phase angle indicated the lag effect between GV and DA.

3.2. Feature parameters extraction and processing

Cross-wavelet spectrum, highlighting regions in which common power in the time-frequency space is high, and providing insights on phase angle relationship information (Grinsted et al., 2004), can be extracted as various features of the cross-wavelet spectrum. The feature parameters proposed by Dey et al. (2008) were reconstructed as feature images of the cross-wavelet spectrum for each EM pair as described below.

\[
F_1 = \frac{\sum_{x} \sum_{y} W_{xy}}{\sum_{x} \sum_{y} W_{xy}^2} \quad \text{(5)}
\]

\[
F_2 = \frac{\sum_{x} \sum_{y} \sqrt{W_{xy}^2}}{\sqrt{\sum_{x} \sum_{y} W_{xy}}} \quad \text{(6)}
\]

Fig. 3. The flowchart of the developed approach. A is acquisition of time series of EMs abundance, including GV, DA, SA, and SL with MESMA and construction of EMs time series curves pixel by pixel; B is XWT for achieving cross-wavelet spectrum of three pairs of two-EM, including GV and SL, GV and SA, GV and DA; C is feature parameters extraction for each cross-wavelet spectrum and dimension reduction using PCA; and D is mapping with logistic regression and major PCs transformed from feature parameters images.
\[
F_3 = \frac{\sum_{s} \sum_{n} |W_{xy}^s(n)|}{|W_{xy}^s(n)|_{\text{peak}}} \\
F_4 = \frac{\sum_{s} \sum_{n} |W_{xy}^s(n)|}{(s_{\text{max}} - s_{\text{min}})(n_{\text{max}} - n_{\text{min}})} \\
F_5 = \frac{\sum_{s} \sum_{n} s^n |p_{xy}^{s}(n)|}{\sum_{s} \sum_{n} |p_{xy}^{s}(n)|} \\
F_6 = \frac{\sum_{s} \sum_{n} s^n |p_{xy}^{s}(n)|}{\sqrt{\sum_{s} \sum_{n} |p_{xy}^{s}(n)|}} \\
F_7 = \frac{\sum_{s} \sum_{n} |p_{xy}^{s}(n)|}{|p_{xy}^{s}(n)|_{\text{out}}} \\
F_8 = \frac{\sum_{s} \sum_{n} |p_{xy}^{s}(n)|}{(s_{\text{max}} - s_{\text{min}})(n_{\text{max}} - n_{\text{min}})} \\
F_9 = \alpha \text{at peak of } |W_{xy}^s(n)| \\
F_{10} = n\text{at peak of } |W_{xy}^s(n)|
\]

where \( |W_{xy}^s(n)| \) is the cross-wavelet power and \(|p_{xy}^{s}(n)|\) is the cross-wavelet phase angle, peak represents the \(|W_{xy}^s(n)|\) maximum, ‘s’ and ‘n’ are ‘scale’ and ‘time’, respectively.

XWT parameter images were displayed in Fig. S3, both F1 and F2 represented cross-signal interactive power in the time-frequency space weighted by ‘scale’ and ‘time’, that is, F1 and F2 quantified interaction extent between two signals. F3 was proposed to enhance peak of \(|W_{xy}^s(n)|\) inversely, while the larger peak of \(|W_{xy}^s(n)|\), the smaller peak of \(\omega\) is the cross-wavelet power and \(|p_{xy}^{s}(n)|\) is the cross-wavelet phase angle, peak represents the \(|W_{xy}^s(n)|\) maximum, ‘s’ and ‘n’ are ‘scale’ and ‘time’, respectively.

The multicollinearity among feature parameters is crucial for multiple-linear regression, where true synergistic relationships among the variables or spurious correlations are difficult to measure (Graham, 2003). Sparse-PCA (SPCA) and Non-Negative Matrix Factorization (NMF) are suitable methods for dimension reduction with interpretability due to their sparse representation of PCs and non-negative basis vectors (Yousef et al., 2018a, 2018b). However, the explicit interactive information from sparse vegetation and habitats may be ignored using Sparse-PCA, because PC coefficients tend to become zero. Thus, after noise and outlier removal with HANTS, PCA, as an effective method to solve multicollinearity problem coupling with dimensionality reduction (Hotelling, 1933), was thus performed to transform parameters images into independent variables (Fig. 3C). Although feature mixing and negative elements resulted after PCA, PCs were linearly expressed with original parameters multiplied by the corresponding eigenvector matrix. The cumulative variance of the twelve primary PCs (PC1 to PC12), was greater than 99% (Fig. 4), meaning nearly all the image parameter information can be represented by these PCs.

3.3. Logistic regression for desert vegetation-habitat complexes

In addition to the dominant desert vegetation-habitat complexes in Minqin County (i.e., XPSH, XPSU, XHSU, XHDM, and HHDM) presented in Table 1, the other covers in the study area (i.e., Moving sand, Salinized land, Oasis, Water/Shadow) were also mapped.

Training sets selected from various complexes can be shown as:

\[
T = \{(x_1, y_1), \ldots, (x_i, y_i), \ldots, (x_n, y_n)\}
\]

where \((x_i, y_i)\) is training samples \(i\) and \(y_i\) is its class label.

Logistic regression is an efficient approach which can not only predict the classification of samples, but also calculate the probability of classification. For binary classification using logistic regression, the probability of \(y = 1\) is defined as

\[
p(y = 1|x, \omega) = \frac{\exp(\omega'x)}{1 + \exp(\omega'x)}
\]

where \(\omega \in \mathbb{R}^n\) is the weight parameter belonging to class \(k\) and \(n\) is each vector length. The essence of multi-category logistic regression is the estimation of weight parameters \(\omega = [\omega_1, \omega_2, \ldots, \omega_k]\). With training samples, the likelihood function of \(\omega\) is:

\[
L(\omega) = \prod_{i=1}^{m} p(y|x_i, \omega)
\]

where \(\omega\) can be estimated iteratively with the maximizing log-likelihood function Eq. (19) using gradient descent method Eq. (20) as follows:

\[
L(\omega) = \sum_{i=1}^{m} \log p(y|x_i, \omega) = \sum_{i=1}^{m} \sum_{k=1}^{K} 1(y_i = k) \log \left( \frac{\exp((\omega_k' x_i))}{\sum_{j=1}^{K} \exp((\omega_j' x_i))} \right)
\]

\[
\omega_j = \omega_j - \frac{\alpha}{m} \sum_{i=1}^{m} [x_i'(1[y_i = j] - p(y_i = j|x_i'; \omega))] + \alpha \omega_j
\]
were used as input dataset to train via logistic activation function for desert vegetation-habitats complexes and other land covers mapping. The loss profiles were applied for assessment with convergence criterion set to 0.00001. Learning rate and maximum iterations determine fitting degree and efficiency of the model. To reach a minimum steady-state value, the low learning rate was indicative of high maximum iterations with low fitting efficiency (Fig. 5A, D). Conversely, high learning rate and low maximum iterations indicated a large probability skipping convergence criterion (Fig. 5C, F). The optimum maximum iterations and learning rate for experimental areas were 300 and 20 (Fig. 5B, E), respectively, and the cross-validation results indicated high overall accuracy (98.85%) and Kappa coefficient (0.98) (Table 2), signifying that XWT-based logistic regression achieved satisfactory performance with high training accuracy.

### 3.4. Accuracy assessment and comparisons

A total of 4500 pixels, selected from high-resolution Google Earth images based on sampling sites/lines and textural features (See Sun et al., 2018 for a detailed description), were applied for accuracy assessment with a confusion matrix. Quantity and allocation disagreement were also calculated because of limitations of Kappa coefficient (Pontius et al. 2011). To verify the advantages of our proposed approach, comparisons with DT-based mapping from our previous study (Sun et al., 2018) were conducted with mapping accuracy assessment and a representative sampling route.

Additionally, two schemes (S1 and S2) were designed to compare our methodology with state-of-the-art approaches, with the same training datasets as this study. S1 evaluated the performance of a trained Support Vector Machine (SVM) classifier coupled with Sequential Minimal Optimization (SMO; Platt, 1998), an optimized SVM model was trained, based on linear kernel, using 300 maximum number of iterations and 0.00001 tolerance. S2 evaluated the performance of the U-Net model, an improved convolutional neural network (CNN) trained end-to-end from few training samplings (Ronneberger et al., 2015), this approach was applied for directly mining features of multiband fractional images composited by four EMs series (64 bands). Because of small patch size of desert vegetation-habitats complexes, training samplings for each desert vegetation-habitats complex and others with a size of 8 × 8 pixels were extended from training datasets of this study. To ensure accuracy, the corresponding training samplings labels were obtained from mapping results of XWT and logistic regression, screening and verified with Google Earth. Finally, 3626 training samplings were determined after mirrored transform approaches (i.e., left and right, up and down) and rotated transform approaches (i.e., 0°, 90°, 180°, 270°) (Hu et al., 2018). Furthermore, with $8 \times 8 \times 64$ training sampling as input, a U-Net containing 32 filters (3 × 3 in size) was then constructed in MATLAB R2018b. Epoch, learning rates, and mini batch parameters were respectively set to 10, 0.05, and 2. The model was then trained, using the Adam optimization algorithm (Kingma and Ba, 2014) and L2 regularization to avoid overfitting (Ng, 2004).

### Table 2

The cross-validation results of multi-category logistic regression classifier obtained from respectively setting the values of maximum iterations and learning rate to 300 and 20.

<table>
<thead>
<tr>
<th>References for cross-validation</th>
<th>Moving sand</th>
<th>Salinized land</th>
<th>Water/Shadow</th>
<th>XPSH</th>
<th>XPSU</th>
<th>XHSU</th>
<th>XHDM</th>
<th>HHDM</th>
<th>Oasis</th>
<th>Total</th>
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<td>33</td>
<td>57</td>
<td>60</td>
<td>392</td>
</tr>
</tbody>
</table>

Overall accuracy = 96.17%; Kappa coefficient = 0.96.
4. Results

4.1. Desert vegetation-habitat complexes mapping using XWT and logistic regression

Fig. 6 illustrated the mapping results in Minqin County and detailed results in three typical zones (i.e., Z1, Z2, and Z3; Fig. 6E, F, and G). Within severe soil and water environment, the *Nitraria tangutorum*, that is an XPSH with few leaves and magnanimous dark branches present in Z1. It exhibited low reflectivity in remote sensing images (Fig. 6B), however, was extracted with high accuracy using XWT and logistic regression (Fig. 6E). Moreover, XPSH in other zones with relatively abundant water resources and higher reflectivity can also be identified effectively (Fig. 6F and G). XPSU, which occurs in the same soil habitat as XPSH, is generally distributed around XPSH (Fig. 6). Benefiting from the seasonal accumulation of upstream water and salt, HHDM, intensively distributes in the historical playa lakes, such as Z3 (Fig. 6D). As the negative successional type of HHDM, XHDM and XHSU also

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*Fig. 6. Mapping results using XWT and multi-category logistic regression classifier. B, C, and D are false color composite images (red, green, and blue are Band 4 [770–890 nm], Band 3 [630–690 nm], and Band 2 [520–590 nm]) of GF-1 images from 30 August 2015 in three typical zones (Z1, Z2, and Z3). E, F, and G are detailed mapping results in Z1, Z2, and Z3, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)*
Quantity disagreement = 4.42%; Allocation disagreement = 8.24%.

occur around playas and the oasis fringe (Fig. 6).

Overall accuracy = 87.33%; Kappa coefficient = 0.86.

Quantity disagreement exhibited nearly no change. The difference in allocation disagreement decreased by 3%. However, the overall accuracy of XWT and logistic regression improved by 3.42%, respectively. Quantity disagreement and allocation disagreement were statistically significant (F = 4.73, p = 0.06, N = 9). The largest significant improvement was observed in the detection of XPSH. In desert areas, sparse XPSH, XPSU and Moving sand are challenging for mapping approach (Fig. 7). Assisting with transitional landscape plots indicating psammophyte coverage changes (e.g., Fig. 7D, E, and F with photos), the complexes with lower vegetation coverage could be effectively identified and classified via XWT based approach, such as in plot 7-3, which was covered by *Nitaria tangutorum* and plot 7-6 with lower coverage of XPSU. There was no understimation of moving sand observed in plot 7-8, compared to the scattered and sparse mapping derived from DT (Fig. 7B). Furthermore, salinized land, presenting bright color on Google Earth (Fig. 7C), was also mapped effectively using XWT based approach.

DT-based mapping depends on the acquisition of detailed phenology, habitat knowledge, and threshold segmentation. In this case, XWT can facilitate the elucidation of detailed interactive information between vegetation phenology and associated habitats to improve desert vegetation-habitat complexes mapping. Due to the sparsity of vegetation in desert and the restrictions on spatial, temporal and spectral resolution of GF-1 images, the developed approach only had a 3.42% improvement compared to DT-based mapping. However, the results derived from our proposed approach may be reasonably close to the detailed information available in practice.

### 4.2. Comparisons with DT based mapping

Compared to the DT-based mapping in our previous study, the overall accuracy of XWT and logistic regression improved by 3.42%, and the allocation disagreement decreased by 3%. However, the quantity disagreement exhibited nearly no change. The difference of correct pixels (diagonal lines of confusion matrixes) between the two approaches was statistically significant at a 10% level (F = 4.73, p = 0.06, N = 9). The largest significant improvement was observed in the detection of XPSH. In desert areas, sparse XPSH, XPSU and Moving sand are challenging for mapping approach (Fig. 7). Assisting with transitional landscape plots indicating psammophyte coverage changes (e.g., Fig. 7D, E, and F with photos), the complexes with lower vegetation coverage could be effectively identified and classified via XWT based approach, such as in plot 7-3, which was covered by *Nitaria tangutorum* and plot 7-6 with lower coverage of XPSU. There was no understimation of moving sand observed in plot 7-8, compared to the scattered and sparse mapping derived from DT (Fig. 7B). Furthermore, salinized land, presenting bright color on Google Earth (Fig. 7C), was also mapped effectively using XWT based approach.

DT-based mapping depends on the acquisition of detailed phenology, habitat knowledge, and threshold segmentation. In this case, XWT can facilitate the elucidation of detailed interactive information between vegetation phenology and associated habitats to improve desert vegetation-habitat complexes mapping. Due to the sparsity of vegetation in desert and the restrictions on spatial, temporal and spectral resolution of GF-1 images, the developed approach only had a 3.42% improvement compared to DT-based mapping. However, the results derived from our proposed approach may be reasonably close to the detailed information available in practice.

### 4.3. Understanding interactive processes based on logistic regression

Using the Python programming language, regression coefficients between each complex and 12 independent PCs were calculated (Table 4). PC1, a comprehensive PC containing various interactive information of sparse vegetation and different habitats, contributed largely to each complex (Table 4). However, other PCs for complexes with different habitats were radically different. For instance, PC3 and PC5 were characteristically reflective of XPSH and XPSU, and PC2 and PC6 were more consistent with XHDM and XHSU (Table 4). Compared to XPSH, representative PCs of HHDM were similar, but PC1 and PC3 were dissimilar (Table 4).

Moreover, coupling PC regression coefficients in Table 4 with their corresponding eigenvectors (Table S1), the contributions of XWT feature parameters for each complex were calculated. The five parameters with the largest contributions were listed in Table 5, which could clarify and understand the local distinctive interactions between the desert vegetation communities and associated habitats. Compared to the empirical selection of critical growth period from time series curves in Sun et al. (2018), the scale of the peak of cross-wavelet power (F9) among time series curves of EM pairs was the most significant features in XWT based linear logistic regression classifier (Table 5). The most important explanatory variable for XPSH and XPSU was F9 parameter obtained between GV and SL, while F9 from GV and DA reflected differences in peak scale of XHSU, XHDM, and HHDM with different soil and water resource condition (Table 5).

As the widely distributed in study area, XPSH was usually constrained into sandbags with low coverage and scarce natural resources adjacent to moving sand (Aguiar and Sala, 1999; Schnber et al., 2003). Moreover, XPSH was more sensitive to SL changes in terms of both extent and speed. Thus, F1 and F4 derived from GV and SL, as well as F2 and F1 from GV and DA indicated the interactive extent between vegetation and sand/gravel dunes, simultaneously with the surface darkening or lighting (Table 5). Compared to XPSH, F8 extracted from GV and SL reflected better resilience of XPSU to SL changes in XPSU (Table 5). HHDM, concentrically distributed in regions surrounding playas-lake with relative water abundance (Castañeda et al., 2013), thus the extracted parameters focused on interaction between GV and DA for water availability (Table 5). As the negative successional complexes of HHDM, XHSU and XHDM further depended on XWT features between GV and SA series for their identification (Table 5). Therefore, the distinctive interactive processes and characteristics between EMs can be effectively quantified by XWT, and organized in logistical regressions for accurate mapping of desert vegetation-habitat complexes.

### 5. Discussion

#### 5.1. Comparisons with state-of-the-art approaches

After SVM optimization, the cross-validation result achieved 97.19% overall accuracy, which was slightly higher than that of logistic regression. After 18000 iterations, Fig. S4 was the accuracy and loss profiles of U-net model, representing approximately 80% accuracy and loss approaching 0. Using the aforementioned optimized trained model
and U-net, the desert vegetation-habitat complexes and other land covers were mapped. Compared to the mapping results derived from logistic regression performed in this study, the spatial pattern and area proportion of the optimized SVM model based on PCs derived from XWT parameters (S1) were largely similar (Fig. 8C, D, G), and the overall accuracy and Kappa coefficient of SVM were only slightly and non-significantly increased by 0.75% and 0.01, respectively (Fig. 8C). There was no significant difference between correct pixels indicated by the diagonal lines of confusion matrices of two approaches (F = 0.06, p = 0.81, N = 9). Nevertheless, without explicit interpretability, the optimized SVM cannot reveal interactive ecological processes.

As a black-box deep learning model (Geirhos et al., 2018), CNN may extract abstract texture features through continuous convolution for image recognition (Krizhevsky et al., 2012). Because of the high spatial heterogeneity characterized by small and sparse vegetation patches, constant max-pooling may lose various detailed feature information (Sabour et al., 2017). Thus, the output of U-net (S2), was unsatisfactory, with only 81.97% overall accuracy and 0.79 Kappa coefficient (Fig. 8F), which were significantly lower than those of logistic regression and SVM approaches. This also resulted in both higher allocation and quantity disagreement. Furthermore, XPSU and salinized land with small patches were not effectively distinguished and mapped, compared to that of logistic regression and SVM (Fig. 8C, D, E). For large patches (i.e., oasis and moving sand), the deep learning model performed well (Fig. 8B), reproducing almost the same area among the three mappings (Fig. 8G). These differences may also be attributed to the low number of training samples (only 3626 samples), which was further limited by the high costs of time, labor and hardware equipment. Additionally, although the U-net model has been widely used in image segmentation and classification researches, other deep learning models (e.g., standard CNN) may be compared with our proposed method in the future.

### 5.2. Advantages of the proposed approach

As a physically based approach, SMA can allow the decomposition of mixed spectral space into easily understandable EMs fraction to characterize vegetation-habitat interactions (Small, 2004). Combined with higher spatial resolution and temporal frequency of observations,

<table>
<thead>
<tr>
<th>Complexes</th>
<th>Constant</th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>PC4</th>
<th>PC5</th>
<th>PC6</th>
<th>PC7</th>
<th>PC8</th>
<th>PC9</th>
<th>PC10</th>
<th>PC11</th>
<th>PC12</th>
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<td>-0.09</td>
<td>-0.03</td>
<td>0.11</td>
<td>-0.02</td>
<td>-0.02</td>
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<td>-0.06</td>
<td>0.05</td>
<td>-0.04</td>
<td>-0.02</td>
</tr>
<tr>
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<td>-0.21</td>
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<td>0.00</td>
<td>0.04</td>
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<tr>
<td>XHDM</td>
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<td>-0.19</td>
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<td>0.02</td>
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<td>-0.02</td>
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<tr>
<td>HHDM</td>
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<td>0.13</td>
<td>-0.06</td>
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<td>0.12</td>
<td>0.09</td>
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<td>-0.05</td>
<td>-0.12</td>
<td>0.08</td>
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such as GF-1 imagery (China Centre for Resources Satellite Data and Application (CRESDA), 2015), the vegetation and soil habitats in intrannual series of spectral endmember space can meet the requirements of phenology-based approaches. Thus, this approach facilitates high-accuracy desert vegetation-habitat complexes mapping (Table 3), as well as inferring ecological irregularities and processes.

With the aid of physical EMs, XWT-derived parameters clearly established the interaction processes between vegetation and associated habitats by considering the wavelet variance synthetically, providing insight into the structure of signal interaction (Bradshaw and Spies, 1992; He et al., 2007) and time variance, and also revealing the average contributions of wavelet coefficients for a given time or position (Dale

### Table 5
The most important feature parameters and responding coefficient calculated from regression coefficient between each complex and PCs and PCA eigenvectors matrix.

<table>
<thead>
<tr>
<th>XPSH</th>
<th>Parameters</th>
<th>GV&amp;SL F9</th>
<th>GV&amp;SL F1</th>
<th>GV&amp;SL F4</th>
<th>GV&amp;DA F2</th>
<th>GV&amp;DA F1</th>
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<tr>
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<th>XPSU</th>
<th>Parameters</th>
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<th>GV&amp;SL F8</th>
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<td>0.12</td>
<td>0.12</td>
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</table>

<table>
<thead>
<tr>
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<th>Parameters</th>
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<th>GV&amp;SA F9</th>
<th>GV&amp;SA F6</th>
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<tr>
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<td>0.08</td>
<td>−0.08</td>
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<th>XHDM</th>
<th>Parameters</th>
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<th>GV&amp;DA F1</th>
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<th>GV&amp;SA F1</th>
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<tbody>
<tr>
<td>Coefficient</td>
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<tr>
<th>HHDM</th>
<th>Parameters</th>
<th>GV&amp;DA F9</th>
<th>GV&amp;DA F8</th>
<th>GV&amp;DA F10</th>
<th>GV&amp;DA F6</th>
<th>GV&amp;DA F5</th>
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<tbody>
<tr>
<td>Coefficient</td>
<td>−0.12</td>
<td>0.07</td>
<td>−0.06</td>
<td>0.06</td>
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Fig. 8. Comparison of state-of-the-art approaches, including XWT and optimized SVM based mapping (S1), and EM fractional abundance coupled with U-net based mapping (S2). A and B are mapping results of S1 and S2. C, D, and E are the mapping results of our proposed approach, S1, and S2, respectively, in a typical zone located in Minqin County represented by red box in B. F and G represent disagreement and area proportion using three different approaches, where OA is overall accuracy, and Kappa is Kappa coefficient. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
and Mah, 1998). It is thus that the XWT based algorithm has potential for LULC classification and object detection with coupled and interactive time-series images.

Inherent deep learning limitations in some black-box based machine learning approaches (i.e., SVM, CNN) lack theoretical research on their fundamental principles, leading to difficulties in processes and outcomes interpretation (Goodfellow et al., 2015; Zhu et al., 2018). However, to reveal land cover properties, understand ecological processes and feedbacks is crucial to the functional characterization of state and pattern of ecosystem (Reynolds et al., 2011). Compared to the aforementioned machine learning approaches, the advantage of our newly developed approach is not only that it achieves ideal accuracy, but also that it quantifies the interactive processes of each desert vegetation-habitat complex via a series of regression equations (Table 5). Thus, our developed approach may provide an additional opportunity to monitor dryland heterogeneous landscapes and evaluate degradation processes for dryland systems restoration and management.

5.3. Limitations and prospects

Because of the sparsity of vegetation and restrictions on spatial, temporal, and spectral resolution of remote sensing images, the detailed information available for mapping is limited, resulting in an 87.33% and 88.08% overall accuracy using logistic regression and an optimized SVM model, respectively (Fig. 8F). Therefore, with the higher frequency time-series images (such as GF-1/6, Sentinel-1), and/or spatial-temporal image fusion approaches (e.g., Gao et al., 2006; Zhao et al., 2018), the proposed approach may provide more accurate mean for monitoring heterogeneous landscapes in drylands. Within water-limited dryland systems, for characterized by rapid and short-lived vegetation occurrence and abrupt state transition, the proposed approach needs to be enhanced by implementing high-frequency components of WT and XWT derived from unsmoothed time-series signals.

The PCA approach was adopted in this study to determine the tradeoff between classification accuracy and interpretability. It will likely be necessary to develop the efficient mapping approaches with more understanding and interpreting biophysical processes in further studies. Moreover, by integrating high spatial resolution images (i.e., WorldView, QuickBird, and GF-2), explicitly reflecting spatial patterns and textures characteristics of LULC, deep learning models, such as the standard CNN, Fully Convolution Networks (FCNs), SegNet, U-Net, and DeepLab model, might provide better solutions for mapping small patches of desert vegetation-habitat complexes in sensitive landscapes (e.g., Huang et al., 2018; Marcos et al., 2018).

6. Conclusions

In this study, an innovative procedure was developed with XWT and logistic regression to extract the characteristics of detailed feedbacks and interactions between sparse vegetation and associated habitats in a spectral endmember space for their mapping and understanding feedbacks and mechanism.

Based on EM fraction time series derived from GF-1 images using MESMA, XWT was adopted to extract feature parameters of detailed interactions between sparse vegetation and associated habitats from cross-wavelet spectrum between GV and SL, GV and SA, and GV and DA. Logistic regression was applied for mapping desert vegetation-habitat complexes using major PCs transformed from feature parameters with higher accuracy in the entire Minqin County (overall accuracy is 87.33%, the kappa coefficient is 0.86). Compared to DT-based mapping from our previous study, the mapping was improved by approximately 3.42%, and simultaneously presented lower allocation disagreement. The performance of proposed approach was largely equal to that of the optimized SVM, and better than the U-net model.

According to the mapping results in Minqin County, our proposed procedure has the potential to become a stable tool for accurately quantifying the characteristics of desert vegetation phenology and habitat complexes. Thus, organizing explicitly interactive ecological processes via a series of regression equations in a spectral endmember space may provide more opportunities for monitoring heterogeneous landscapes and evaluating the land degradation processes in dryland systems.

Declarations of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Acknowledgments

We are very grateful to the reviewers of this manuscript for their valuable comments to greatly improve the content and clarity of this manuscript considerably. We also extend our appreciation to Editor-in-chief Dr. Emilio Chuvieco and associate editor Dr. Marta Yebra for their helpful suggestions and patience during the review and revision processes. This work was partly funded by “Land Resources Monitoring with Standard Endmember Space” of China Land Surveying and Planning Institute [2018111332], and the National Natural Science Foundation of China [41071146].

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2019.111516.

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