Using GF-2 Images to Detect Tamarix Chinensis Community within a Vegetation Patch

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Abstract. The quasi-circular vegetation patches (QVPs) are mainly composed of *suaeda salsa*, *Tamarix chinensis*, and *Phragmites australis* in the Yellow River Delta, China. The previous studies indicate that the shrubs within a vegetation patch play an important role in the establishment and disappearance of vegetation patch. Therefore, in this work, the method based on the tasselled cap brightness and greenness components derived from the April image and the August GF-2 image acquired after water replenishment with the decision tree classifier was developed for quickly detecting the *Tamarix chinensis* community. The detection rate was 73.5%, and the misclassification rate was 12.1%. In the future, more samples of plant community and multi-seasonal images such as the late fall-early winter leaf-off data needs to be applied to further improve the detection accuracy.

1. Introduction
The quasi-circular vegetation patches (QVPs) was firstly found in the Yellow River Delta (YRD), China in 2011 [1], which are regarded as the important research object for understanding re-vegetation mechanism and developing adaptive restoration strategies for the degraded wetland ecosystem in this region [2-3]. In general, *suaeda salsa*, *Tamarix chinensis*, and *Phragmites australis* are the three main plant species composed of the QVPs in this region. The previous studies indicated that the establishment and disappearance of vegetation patch are associated with the growth and death of the shrubs and trees within them in arid and semi-arid regions [4-5]. Therefore, it is necessary to monitor the dynamics of *Tamarix chinensis* community within the QVPs.

Except traditional field survey methods which are expensive and arduous, high resolution satellite remote sensing have been proved to be a cost-effective way to monitor the spatial and temporal dynamics of *Tamarix chinensis* community [6-15]. The images acquired in the late fall-winter season are helpful for identifying *Tamarix chinensis* [16, 17], and hyperspectral imagery acquired at 1-2 m spatial resolution during early July and late August are useful in determining the effectiveness of biological control of tamarisk in several western USA states [18], and high spatial resolution multispectral data are more effective in *Tamarix chinensis* detection [19]. However, no matter how successful in the reported studies, *Tamarix chinensis* community mapping from remote sensing imagery is still not easy [20], which may be attributed to the acquisition difficulty of ideal resolution and seasonal imagery, and the spectral confusions between *Tamarix chinensis* and associated vegetation.

The aim of this work is to detect *Tamarix chinensis* community within the QVPs from the Chinese Gaofen 2 satellite (GF-2) fused multispectral images using the tasselled cap transformation and...
decision tree classifier, which will be an easy way to quickly map *Tamarix chinensis* community in the YRD, China.

2. Materials and Methods

2.1. GF-2 Images Pre-Processing

GF-2 satellite has two panchromatic-multispectral cameras (two-camera stitching width of 45 km, a repetition cycle of five days), which images the Earth by one panchromatic band (Band 1, 450-900 nm) with a spatial resolution of 1 m, and four multispectral bands (Band 2, 450-520 nm; Band 3, 520-590 nm; Band 4, 30-690 nm; Band 5, 770-890 nm) with a spatial resolution of 4 m. Because of cloud contamination and limitations of data acquisition, two scenes of GF-2 images acquired on April 30 (spring season) and August 26 (summer), 2016 were used in this work.

The modified intensity-hue-saturation pansharpening approach in commercial ERDAS imagine v9.2 software was used to sharpen four low resolution multispectral bands with high resolution panchromatic band, which can better preserve spectral information of the original multispectral bands while improving image spatial resolution [21]. The subsets of the fused images were shown in Figure 1 and Figure 2). The coefficients of tasselled cap transformation (TCT) for GF-2 digital number data were derived based on April image using the Gram-Schmidt method [22], which was used to calculate the brightness (TCB) and greenness (TCG) of the TCT (see Table 1).

![Figure 1. GF-2 fused colour image (RGB543, acquired on April 30 2016) of the study site](image)

![Figure 2. GF-2 fused colour image (RGB543, acquired on August 26 2016) of the study site](image)

2.2. Classification

The decision tree (DT) classifier was used to discriminate the vegetation patch from the background, which is a simple and easy way to classify land covers [23]. Because the eutrophication of standing
water in bare soil area produced spectral confusions between vegetation patches and bare soils in the August image acquired after the water replenishment for ecosystem conservation (see the middle part of Figure 2), it was not suitable for mapping the vegetation patches. Thus, the splitting thresholds (793 < TCB of the April image < 1073 and -70 < TCG of the April image < -24) from the April image was used to map the vegetation patches, which was determined by many tests and visual inspections on classification result. Then, the classification result of vegetation patches was used as a mask to remove the non-vegetation objects. Although the August image was not suitable for classifying the vegetation patches, Tamarix chinensis community presented unique spectral features in the August image. The colour tone of Tamarix chinensis community was brighter than that of the other vegetation, which may be due to the small impact of water because they are taller than the other vegetations within vegetation patches (see Figure 3). Again, the splitting thresholds (365 < Band 2 of the August image < 400 AND -10 < TCG of the August image < 130, or Band 2 of the August image > 400 AND TCG of the August image > 75) was determined to detect Tamarix chinensis community through visual inspections on classification result.

| Table 1. Tasseled cap coefficients for the digital number data of the mIHS pansharpened GF-2 multispectral imagery |
|-----------------------------------------------------------|
| Band 2  | Band 3  | Band 4  | Band 5  |
| The brightness | 0.435 | 0.450 | 0.604 | 0.493 |
| The greenness | 0.048 | -0.237 | -0.525 | 0.816 |

Figure 3. Part of the GF-2 fused image (RGB432) acquired on August 26, 2016

3. Results and Discussions
Figure 4 presents the DT classification result based on the TCB and TCG of the April image, which mapped the vegetation patches very well. Figure 5 shows the distribution of Tamarix chinensis community within the vegetation patches detected by the splitting thresholds.

A total of forty-nine samples of Tamarix chinensis community and 107 samples of other plant communities from two field surveys implemented in October 2013, and August 2017, located in lower left and middle right of the image, were used to evaluate the detection accuracy of Tamarix chinensis community. Thirty-six of the forty-nine samples of Tamarix chinensis community were correctly detected (the detection rate was 73.5%), and thirteen of 107 samples of other plant communities was mistakenly classified into Tamarix chinensis community (the misclassification rate was 12.1%).

4. Conclusions
It allowed for easy and quick detection of Tamarix chinensis community within vegetation patches using the DT classifier through integrating the spring fused image and the summer fused image acquired after water replenishment of GF-2 satellite. For the follow-on research, field validation needs
to be carried out to further assess the detection results of this work. In addition, more samples of *Tamarix chinensis* community and other plant species needs to be collected to optimize the splitting thresholds of the decision tree, and multi-seasonal images such as the late fall-early winter leaf-off data needs to be applied to improve the detection accuracy.

![Classification Result](image1)

**Figure 4.** The classification result of vegetation patches from the decision tree based on the brightness and greenness components of TCT of the GF-2 fused image acquired on April 30, 2016

![Distribution Map](image2)

**Figure 5.** The distribution of *Tamarix chinensis* community within the vegetation patches detected by the splitting thresholds in this study

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