Extraction of Urban Green Spaces Based on Gaofen-2 Satellite Imagery

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Abstract: Urban green space (UGS) plays indispensable role to maintain the ecological balance of a city. Remote sensing & GIS techniques can play vital role in the accurate estimation of the UGS. This study attempts at a new method of extracting the UGS from high resolution imagery data of Gaofen-2 satellite. The proposed method combines the strength of different transformation techniques i.e. KT transform, principal component analysis and NDVI in order to accurately map UGS. Different combinations were checked to classify the Gaofen-2 satellite imagery of Lanzhou city. The classified image was assessed for classification accuracy and it was observed that the overall accuracy was 89.78% with the kappa coefficient of 0.8125. It was observed that the proposed method can yield relatively high accuracy compared to the individual transformations such as NDVI thresholding.

1. Introduction
Urban green space is an important component of ecological system and plays central role to improve the city’s ecological environment. Facts on the structure and type of urban green space are necessary for protection and management projects of city. In the past, this information was obtained by a combination of field measurements and aerial photos interpretation. This approach typically required intensive interpretation by expert analysts, and cross validation methods to ensure the consistency. Recently, satellite imagery has become available for estimates of urban green space characteristics at different spatial resolutions. The application of satellite imagery for mapping urban green space with moderate spatial resolution from the Landsat and SPOT satellites have produced limited results because the spatial resolution of the sensors is too coarse to delineate narrow bands of vegetation along streams (Congalton et al. 2003).

Reported studies on UGS mapping have mostly used medium and high resolution images such as Landsat-TM, ETM, Sentinel-2A, IKONOS, etc. However, studies on the use of very high resolution images for UGS extraction are comparatively limited. Xu et al (Xu et. al 2020) has recently suggested phenological features contraints for urban green space extraction using GF-2. The phenological features of vegetation were used as auxiliary bands to the deep learning network for training and classification. The experimental results show that the introduction of phenological features into HRNet model training can effectively improve urban green space classification accuracy by solving the problem of misclassification of evergreen and deciduous trees. The improvement rate of F1-Score of deciduous trees, evergreen trees, and grassland were 0.48%, 4.77%, and 3.93%, respectively, which
proved that the combination of vegetation phenology and high-resolution remote sensing image can improve the results of deep learning urban green space classification.

Liu, (Liu et al. 2019) described a multilevel architecture which targets urban green space extraction from GF-2 imagery. Semantic segmentation model (DeepLabv3plus) was used for satellite imagery classification of three different locations and one other for verification. Then, five comparative methods are carried out for monitoring urban green space distribution. The accuracy indexes of each method were found as the difference of prediction and the ground truth. The results showed that the architecture with DeepLabv3plus outperformed the other five methods to better extract urban green space accuracy of 89.46%.

Canran, C et al (2017) proposed new method of extract green land information in urban area which improvised on K-T transform and ICA transform using Gaofen-1 data. The study compared the result of green space extraction through new method and classical approach of utilizing NDVI thresholding. The classification accuracy of the prosed method was found to be very promising, i.e the overall accuracy of 94.97 and 0.9195.

SUN Shiya et al (Sun et al 2019) formulated a scheme of shadow detection applying to GF-1 images. The shaded and non-shade areas were identified based on near infrared, then transforming RGB to HLS and performing PCA. The non-shaded areas and shade areas were separated using band math and threshold method. Logical operations and morphological filtering algorithm were applied on the two compound shaded areas. The results showed that method to be efficient, higher extraction accuracy and also showed better operability and universality for GF-1 images.

This research specifically suggests method of extracting the UGS from high resolution imagery data of Gaofen-2 satellite. Compared to previous studies, this study exploits only the spectral information in the High Resolution Gaofen-2 Imagerys to accurately delineate the UGS. The previous studies have problem with the shadow, and in the situation where the water and vegetation can not be accurately classified. The proposed method combines the strength of different transformation techniques such as KT transform, principal component analysis and NDVI in order to accurately map UGS.

2. Materials and Methods

2.1 Study Area

Lanzhou is the capital city of Gansu Province Located at 35.983° Latitude and 103.767° Longitude. It is located on the ancient Silk Road in the Yellow River valley on the east side of the Qinghai-Tibet Plateau. Lanzhou is located in a temperate continental climate zone and has an altitude of 1783.32 m. It is the famous for four peach production bases in China and is known as the “Tenli Taoxiang”. Lanzhou is also an important industrial base and comprehensive transportation hub in northwestern China; it is among the important central cities in western China. Lanzhou in total covers an area of 13,100 square kilometres, including a built up area of 321.75 square kilometres with the urbanization rate of 81.03%.

This paper selects Anning District, which accounts for more green land in Lanzhou City, as the research area.(Figure 1).
2.2 Imagery Data

The image data of Gaofen-2 for this research was used which has the collection time of May 27, 2017. (Figure 2). The dataset consisted of multispectral data with 4 m resolution and panchromatic data with 1 m resolution. The position of the band is 0.45 μm to 0.69 μm which is suitable for vegetation monitoring (Table 1). The data was then uploaded to the Envi environment and prepared for the analysis.

| Bands    | Wavelength Range | Resolution |
|----------|------------------|------------|
| Blue     | 0.450-52 μm      | 4 m        |
| Green    | 0.52-0.59 μm     | 4 m        |
| Red      | 0.63-0.69 μm     | 4 m        |
| NIR      | 0.77-0.89 μm     | 4 m        |
| Panchromatic | 0.45-0.90 μm | 1 m        |

In order to show the experimental results and details, this article selects the study area of 517 meters * 335 meters as the test area. (Figure 2).
In order to obtain the surface reflectance values, the process of atmospheric correction was executed using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH) (Cooley et al., 2002). The FLAASH module can convert the raw quantized calibrated pixel values to surface reflectance (Hu and Tang, 2012). The FLAASH model was selected to calibrate the radiation of GF-2. The DN values of the GF-2 were then transformed into the radiation values. The RPC model was also used to correct the 2-m panchromatic image of GF-2. Finally, the Gram Schmidt algorithm was adopted to fuse the processed multispectral and panchromatic images. The image was clipped based on the boundary of the Anning district and further image processing techniques were applied on the clipped image.

2.3 Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) is one of the most commonly used methods for extraction of vegetation coverage. It is usually used to detect the land cover changes caused by human activities and natural hazards. The NDVI is based on the red and near infrared (NIR) bands reflectance in the electromagnetic spectrum and is the balance between the energy obtained and emitted by earth objects using these bands. It is calculated by taking the ratios of red and NIR bands from remote sensing data. The values of NDVI vary between −1 (water body and snow) and +1 (full vegetation coverage). The conversion function was shown in formula (1).

\[
\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}
\]  

Where R and NIR are the red and near-infrared bands of the image, respectively. The zero value of NDVI indicates that there is vegetation cover, The higher the value the dominance is the vegetation cover and its health. The threshold value of the NDVI specifies the vegetation and non-vegetation categories. (Figure 3).

![Figure 3. NDVI image](image)

2.4 Principal Component Analysis (PCA)

The PCA is a technique of dimensionality reduction which transforms the data into smaller set of uncorrelated variables. The variables represent most of the image information and are easier to interpret. Principal components are derived such that the first PC accounts for much of the variation of the original data. The second accounts for most of the remaining variation. Minimum noise fraction (MNF) method can be used with hyper spectral data for noise reduction.

The PCA transform is one of the commonly used mathematical methods of dimension reduction. It recombines many original relevant variables into a new set of mutually irrelevant variables. After PCA transformation, remarkable characteristics of the original data will mainly focus on the first principal component, which is convenient for the subsequent processing. In order to perform Image fusion scheme based on PCA, first the multispectral image is transformed and then the first principal component of multispectral image is replaced by panchromatic band. (Figure 4)
Figure 4. PCA Band 1

2.5 K-T Transformation Technique

The KT or “Tasselled Cap” transform was developed originally using Landsat Multi-Spectral Scanner data for agricultural applications (Kauth 1976). Similarly like PCA, the K-T transform is a transformation/rotation of axes such that certain features are more distinguishable in the new coordinate system. The method is useful for highlighting the phenomena of crop development in a way that allows discrimination of specific crop from other vegetative covers. The KT is a sensor-specific; different sets of coefficients are invoked depending on the data are used. Collins and Woodcock (1996) compared KT and PC transforms with Gramm Schmidt (GS) orthogonalization for mapping pest-induced forest mortality in the Lake Tahoe Basin, concluding that the KT transform was most sensitive to changes in vegetation condition. They found also the KT transform yielded better performance than GS orthogonalization and the PC transform, citing sensitivities of KT wetness to vegetation status. The K-T transform is based on observing the relationships between band 3 versus band 2, and band 2 versus band 1. (Figure5,6)

3.Methodology

The flow chart of this experiment is as follows:(Figure 7)
After preparing the required data, the data is processed accordingly, and the extracted green space is analyzed. The GF-2 satellite image taken consisted of panchromatic and multispectral bands. The data is preprocessed first, and then the preprocessed image is cropped using the vector boundary of Anning District of Lanzhou City to obtain the image of the study area. Then, the calculated NDVI, K-T transformed brightness band, vegetation band, and the first principal component of PCA transform are band-fused to obtain a new image (Figure 8). Perform PCA transformation again on the new image obtained, and select the first band.

The resultant output image was converted into vegetation and non-vegetation categories by applying band math through the formula $(b1 \leq -340)$ and $(b1 \geq -450)$ (Figure 9). According to the above method, the vegetation in Anning District is extracted (Figure 10).
Accuracy assessment was formed using 179 random points in the polygon of study area. The random points were taken by using ArcMap random points command. The confusion matrix for three categories of Water, Vegetation and non-vegetation matrix were generated and the points were assigned through visual interpretation. The interpretation was first attempted through google earth imagery; however it was found that there was dominant shift between the google earth and the image used in the analysis. The visual interpretation was therefore performed with the Multi spectral image.

4. Results
The impact of classification accuracy was evaluated using confusion matrix and Cohen’s kappa coefficient.(Table 2).
It can be seen that the overall classification accuracy reaches 89.78%, Kappa the coefficient is 0.81, the classification result was found to be suitable owing to the all features, the classification accuracy of water bodies and green spaces is high, and the user accuracy and the manufacturer’s accuracy is 100% and 99.92% respectively. The user’s accuracy of Greenland and the precision of the producer is 92.95% and 94.66% respectively. However, by Then there is an obvious misjudgement phenomenon; the same phenomenon also exists in the green, between land and construction land. Further research found that it was mainly due to the presence of shadows will cause construction land and green land to have a similar spectrum feature. In summary, the new method of green space extraction proposed in the thesis has a significant impact on green space information. The extraction accuracy of information is high, and it is feasible and effective green space information. Information extraction method normally monitor green space information for high-resolution remote sensing images Information changes provide accurate and effective technical means. Image fusion and other pre-processing, Urban green images with rich green space information use NDVI-based typical type of green space extraction new method proposed in this paper the images of the experimental area were extracted from the green space information, so that the new methods of accuracy evaluation.

5. Conclusions
In order to solve the problem of NDVI based typical green space extraction method in this paper, a new method based on K-T transform and PCA transform is used to extract the green space, and the results are compared with the typical green space extraction results based on NDVI. From this study it is concluded that the best combination of KT greens band, PC1 band and NIR band is feasible, accurate and effective to extract green space information. As compared to the NDVI based typical green space extraction method, the new green space extraction method based on K-T transformation and PCA transformation proposed in this paper can significantly the accuracy of extraction results. It is further observed that the classification method in this paper is only to distinguish green space from other features, but the study of urban green space ecosystem also needs to distinguish different types of green space. It is therefore suggested that the studies on other objects extraction may also be carried out in order to accurately map all the objects in urban environment.

6. Acknowledgments
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7. References
[1] Cheng, Miaomiao, Hong Jiang, Jian Chen, Zheng Guo, and Zishan Jiang. 2009. “Extraction of the Urban Green Space Based on the High Resolution Remote Sensing Image.” MIPPR 2009: Remote Sensing and GIS Data Processing and Other Applications 7498:749813.
[2] Congalton, Russell G., Kevin Birch, Rick Jones, and James Schriever. 2003. “Evaluating Remotely Sensed Techniques for Mapping Riparian Vegetation.” Computers and Electronics in Agriculture 37(1–3):113–26.

[3] Johansen, Kasper, Stuart Phinn, Ian Dixon, Michael Douglas, and John Lowry. 2007. “Comparison of Ground Based and Image Based Assessments of Riparian Zone Health in Australian Tropical Savannas Comparison of Image and Rapid Field Assessments of Riparian Zone Condition in Australian Tropical Savannas.” Forest Ecology and Management 240(2007):42–60.

[4] Kauth, R. J. 1976. “Tasselled Cap - a Graphic Description of the Spectral-Temporal Development of Agricultural Crops As Seen By Landsat.” 41–51.

[5] Liu, Wenya, Anzhi Yue, Weihua Shi, Jue Ji, and Ruru Deng. 2019. “An Automatic Extraction Architecture of Urban Green Space Based on DeepLabv3plus Semantic Segmentation Model.” 2019 IEEE 4th International Conference on Image, Vision and Computing, ICIVC 2019 311–15.

[6] Vigneshwaran, S. and S. Vasantha Kumar. 2019. “Comparison of Classification Methods for Urban Green Space Extraction Using Very High Resolution Worldview-3 Imagery.” Geocarto International 0(0):1–14. Retrieved (https://doi.org/10.1080/10106049.2019.1665714).

[7] ZHOU Zhi-yong, XING Ying-mei, DONG Qi-liang, etc. Information Extraction of urban green land using GF-1 remote sensing data[J]. Mineral Exploration, 2015.

[8] Canran C, Shuwen Y, Pengqing S, et al. Comparative research on urban green space extracting based on GF-1 satellite images[J]. Mine Surveying, 2017.

[9] Hongshun C, Hui H, Hongyu X. Extraction of Urban Green Space from High Spatial Resolution Remote Sensing Images[J]. Environmental ence & Management, 2016.

[10] Bo F, Danlin Y, Yaojun Z. The livable urban landscape: GIS and remote sensing extracted land use assessment for urban livability in Changchun Proper, China[J]. Land Use Policy, 2019, 87.

[11] CHEN Y, ZHAO J S, CHEN Y. ENVI based urban green space information extraction with high resolution remote sensing data[J]. Engineering of Surveying and Mapping, 2015, 24: 33.