The Effect of Lossy Compression on Feature Extraction Applied to Satellite Landsat ETM+ Images

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ABSTRACT

Lossy compression is preferred for many of applications; however, it is not preferred in the remote sensing community, because the use of lossy compression may change the features of remote sensing data. In this paper, we study the effect of lossy compression on two of the most common indices for vegetation feature extraction; Normalized Difference Vegetation Index (NDVI), and Normalized Difference Water Index (NDWI). The study is performed over several Landsat ETM+ images, and our experimental results show that the different transformations used in lossy compression techniques exhibit different impacts on the reconstructed NDVI and/or NDWI. We have also observed that, for certain compression techniques, a low PSNR may represent more vegetation features. This work shows the recommended compression techniques related to Landsat image vegetation quantity. Results and discussion provide helpful guidelines for joint classification and compression of remote sensing images.

Keywords: Multispectral image, NDWI, NDVI, Lossy compression.

1. INTRODUCTION

Using satellite images for extract information from Earth's surface has become an important study in the remote sensing community. In the science of remote sensing, satellite multispectral imagery is one of the best sources of surface observation data, especially over large areas. It represents the reflected solar radiation, and by altering fluxes of heat, water vapor, carbon dioxide and other trace gases.

Today, satellite multispectral image compression is one of the important fields in a wide range of applications, due to the common limitations of storage and transmission in remote sensing scenario. Lossy compression techniques have been used with high compression ratios. However, lossy compression coding may affect the features of the original multispectral images, and hence we need ensure that the quality of the reconstructed images is still adequate for the intended scientific use. Therefore, there are many works on joint classification and compression of remote sensing images [1]–[3].

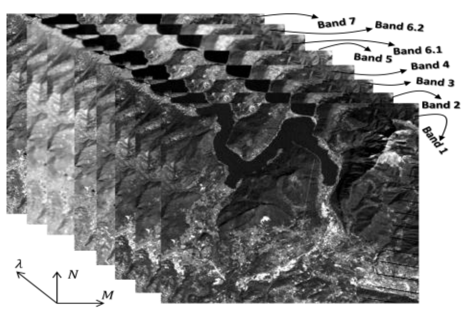

Figure 1. The 3-D structure of Landsat multispectral image.

The research in [1] demonstrated the effectiveness of proper principal component image rate allocation, which enabled compression at high ratios without producing significant classification differences. However, they used one technique only in the lossy compression is JPEG2000, and all results performed over hyperspectral images. Two techniques are used in [2], JPEG2000 and CCSDS; the paper [2] presented a comparison between the different techniques and its effects on the hyperspectral images classification. In [3], the researcher used different lossy compression techniques to

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study the effect of lossy compression on hyperspectral image data also on two standards for hyperspectral data exploitation: spectral unmixing, and supervised classification using support vector machines (SVM). They showed different stages of the linear spectral unmixing chain exhibit different sensitivities to lossy data compression. They also concluded that, for certain compression techniques, a higher compression ratio may lead to more accurate classification results.

In this paper, we select two of the most common indices for extraction of features from satellite multispectral images; Normalized Difference Vegetation Index (NDVI) [4] and Normalized Difference Water Index (NDWI) [5], and study the effect of lossy compression techniques on the reconstructed satellite multispectral images, especially over reasonably high compression ratios (up to CR 80:1, i.e., 0.1 bits per pixel per band (bpppb)). We use a dataset from one of the most important NASA Earth-observing missions [6], [7] (Landsat 7 with Enhanced Thematic Mapper Plus (ETM+)). The dataset in our experiments include four Landsat ETM+ images from different locations as shown in Table 1. All images contain 8 bands (see Fig. 1). These images are publicly available for download form [8].

Table 1. Selected Landsat ETM+ images.

Name	Technical name (Scene id)	Size(x×y×z)	Bit rate
Image 1: Egypt (EG).	LE71760392003068SGS00	7931×7171×8	8
Image 2: France (FR1).	LE71980282013297ASN00	8231×7311×8	8
Image 3: Brazil (BR).	LE72240702014226CUB01	8031×6931×8	8
Image 4: France (FR2).	LE71980282013345ASN00	8231×7311×8	8

The rest of this paper is organized as follows: Section 2 covers the two methods used for extraction of features from satellite images, and briefly reviews the lossy compression techniques used in our experiments. Section3 presents the experimental results and discussions. Finally, Section 4 gives the concluding remarks.

2. VEGETATION INDICES AND COMPRESSION TECHNIQUES

In this section, we briefly define NDVI and NDWI that are used in the simulation experiments, and introduce the compression techniques used in our experiments.

2.1 Vegetation Indices

Two of the most important indices for remote sensing of vegetation and vegetation liquid water from space are NDVI, and NDWI. These indices have been widely used to study the features of Landsat images [9]–[13].

2.1.1 Normalized Difference Vegetation Index

NDVI [4] is one of the oldest, most well-known, and most frequently used indices in the remote sensing of vegetation. This index uses radiances or reflectance from a red channel R_{RED} (0.63–0.69 µm) and a near-IR channel R_{NIR} (0.77–0.90 µm). The use of the highest absorption and reflectance regions of chlorophyll makes it robust over a wide range of conditions, while the near-IR channel is located in the high reflectance plateau of vegetation canopies.

The common range for green vegetation is 0.2 to 0.8, and the value of this index ranges from -1 to 1.

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

2.1.2 Normalized Difference Water Index

The NDWI was first proposed in [5]. This index uses two narrow channels centered to detect surface waters in wetland environments and to allow for the measurement of surface water extent. NDWI for the Landsat multispectral images; uses a near-IR channel R_{NIR} (0.77–0.90 µm), and a shortwave infrared channel R_{SWIR} (1.55–1.75 µm).

$$\mathrm{NDWI} = \frac{R_{NIR} - R_{SWIR}}{R_{NIR} + R_{SWIR}} \tag{2}$$

The values of this index also range from -1 to 1, and if the value is greater than zero, it represents water surfaces, while values less than, or equal to, zero may be assumed as non-water surfaces.

2.2 Lossy Compression Techniques

Image compression techniques can be divided into lossless and lossy. Lossless compression typically achieves a limited compression ratio, while lossy compression achieves a high compression ratio [14]. We are concerned with the up-to-date lossy techniques in our experiments. Three well-defined lossy compression techniques are selected in our experiments.

2.2.1 JPEG2000

JPEG2000 [15] standard provides a multi-component extension in Part2 [16], which has been posited by several authors to design compression algorithms for satellite multispectral and hyperspectral images [17]–[19].

The standard is based on the wavelet coding. JPEG2000 supports the 9/7 and the 5/3 integer wavelet transforms. After transformation, coefficient quantization is adapted to individual scales and sub-bands, and then quantized coefficients are arithmetically coded. In addition, in order to improve the coding performance of these techniques, a common strategy for satellite images is to decorrelate first the image in the spectral domain. After that, decorrelate every band in the spatial domain. DWT and PCA are often used as spectral decorrelators [20], and 2D-DWT is used as spatial decorrelators. The JPEG2000 with DWT in the spectral decorrelator is implemented in [21] and JPEG2000 with PCA in the spectral decorrelator is implemented in [22].

2.2.2 SPIHT

SPIHT [23] is one from the first coding systems which benefited from the DWT transform. The effectiveness of the SPIHT algorithm originates from the efficient subset partitioning and the compact form of the significance information.

SPIHT algorithm contains four steps, initialization, sorting pass in list of insignificant points (LIP), sorting pass in list of insignificant sets (LIS), and refinement pass. Firstly, in the initialization step, the algorithm sets the list of significant points (LSP) as empty, and then sets the roots of similarity trees in the LIP and LIS. Secondly, each coefficient in the LIP is checked and the significant coefficients are moved to the LSP, and then the sign bits of the significant coefficients are encoded. Thirdly, if an entry in the LIS is significant, a one is sent and then its two offspring are checked like an entry in the LIP. If an entry in the LIS is insignificant, a zero is sent. Finally, each old entry of LSP is checked. If it is significant under current threshold, a one is sent and its magnitude is reduced by the current threshold. If it is insignificant, a zero is sent. For more details of the SPIHT algorithm you can see the original reference [23].

2.2.3 CSDS-IDC

In the last few years, CCSDS [24] has defined several techniques for data compression. The IDC recommendation (CCSDS 122.0-B-1 [25]) is one of the lossy compression algorithms for multi/hyper-spectral images.

The compression technique described in this Recommended Standard can be used to produce both lossy and lossless compression. CCSDS-IDC is implemented in [21]. The compressor in CCSDS-IDC consists of two functional parts, described in [25], a DWT module that performs decorrelation, and a Bit-Plane Encoder (BPE) which encodes the decorrelated data. The 9/7 biorthogonal filter is employed in the lossy compression and the numerical values of the analysis filter coefficients are specified in [25].

3. EXPERIMENTAL RESULTS

We show and discuss here the performance of the different lossy compression techniques in terms of two indices for extraction of features from satellite multispectral images (i.e., NDVI and NDWI). In all cases, the evaluation has been performed on a representative bit-rate range 0.1– 1.0 bpppb, (i.e., a compression ratio ranging from 80:1 to 8:1), with a bitrate step of 0.1 bpppb.

In the remote sensing classification, the most important aspect of any classifier is its error; as shown in [9], [26], [27]. In our experiments, we used two metrics for performance evaluation of an error estimator for NDVI and NDWI indices; Root Mean Square Error (RMSE), and coefficient of determination (R^2).

$$\mathrm{MSE} = \frac{1}{M \cdot N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[A(i,j) - B(i,j) \right]^2 \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \tag{4}$$

where A and B are the original and reconstructed NDVI/NDWI, respectively. M is the number of rows and N is the number of columns in the image.

$$\mathrm{R}^2 = \left(\frac{\sum (A - \overline{A})(B - \overline{B})}{\sqrt{\sum (A - \overline{A})^2} \sqrt{\sum (B - \overline{B})^2}} \right)^2 \tag{5}$$

where $\overline{A}$ and $\overline{B}$ denote the mean values of A and B, respectively. RMSE and R^2 are very important measures to show how the lossy compression at a certain bitrate may effect on the NDVI and/or NDWI indices related to the coding and transformation used. We calculate the NDVI and NDWI indices mean values for the selected images (Implemented in ENVI [28]) in Table 2. Image 1 (EG) represents high vegetation data and Image 4 (FR2) represents low vegetation data in our experiments.

Table 2. NDVI and NDWI Indices Mean Values for the Selected Multispectral Images.

Name	NDVI	NDWI
Image 1	0.747540 (high vegetation)	0.482874 (more water surfaces)
Image 2	0.443875	0.246093
Image 3	0.376618	0.273858
Image 4	0.260911 (low vegetation)	-0.075317 (more non-water surfaces)

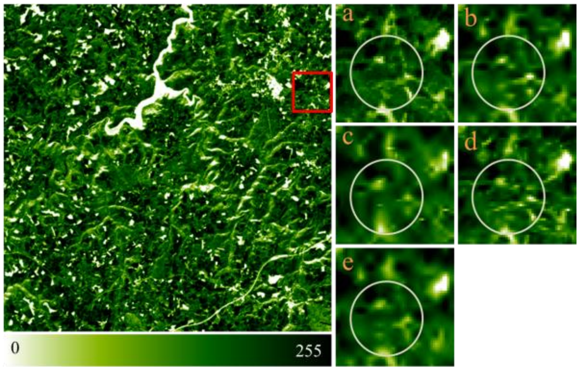

Figure 2. NDVI index for Landsat Image 2 (FR1), (a) Original, (b-e) Compression techniques in Table 3, respectively. Bit rate = 0.3 bpppb, most vegetation value is 255)

Three experiments were used to quantify the impact of lossy compression on NDVI and NDWI for Landsat data sets.

In the first experiment, we investigate the relation between averages Peak Signal to Noise Ratio (PSNR) and (NDVI and NDWI) indices mean difference for compressed images with different lossy compression techniques for the same compression ratio, as reported in Table 3.

The results in Table 3 indicate that high PSNR does not necessarily mean good vegetation features. However, for certain compression techniques, a low PSNR may represent more vegetation features. Figure 2 shows the NDVI index for Image 2 at bit rate = 0.3 bpppb with different lossy compression techniques. Notice that CCSDS-IDC obtains more impacts on the NDVI features than most of the other compression techniques in spite of it have the best PSNR = 49.15dB. As indicated by this experiment, we conclude that the effect of lossy compression on NDVI and NDWI mainly depends on the coding and the transform used in different compression techniques. Also, the high PSNR does not means good vegetation features.

Table 3. NDVI and NDWI Indices Mean Difference Values for the Reconstructed Images, and the Average PSNR.

Image 1 *Image 2* *Image 3* *Image 4*	**Bit rate = 0.3 bpppb**			**Bit rate = 0.7 bpppb**		
	PSNR (dB)	**NDVI**	**NDWI**	**PSNR (dB)**	**NDVI**	**NDWI**
SPIHT by [23]	32.12	0.0020	**0.0007**	36.18	0.0009	**0.0004**
	47.55	0.0014	**0.0007**	50.90	**0.0003**	**0.0005**
	32.79	0.0053	0.0076	36.92	0.0035	0.0053
	29.92	**0.0003**	0.0008	33.64	**0.0006**	**0.0002**
JPEG2000-DWT by [21]	38.85	0.0053	0.0038	42.40	0.0013	0.0019
	47.32	0.0095	0.0034	49.84	0.0042	0.0050
	36.63	0.0167	0.0178	39.82	0.0067	0.0083
	30.70	0.0104	**0.0005**	32.59	0.0047	0.0018
JPEG2000-PCA by [22]	**41.17**	**0.0013**	0.0020	**45.00**	**0.0007**	0.0010
	48.94	**0.0006**	0.0014	**52.71**	0.0006	**0.0005**
	39.62	**0.0020**	**0.0044**	**42.67**	**0.0006**	**0.0032**
	32.74	0.0016	0.0015	**35.81**	0.0016	0.0008
CCSDS-IDC by [21]	41.14	0.0076	0.0022	44.61	0.0046	0.0020
	49.15	0.0056	0.0008	51.96	0.0039	0.0014
	39.17	0.0080	0.0097	42.31	0.0054	0.0064
	32.70	0.0053	0.0015	35.62	0.0028	0.0005

In the second experiment, we measure the RMSE between the NDVI and NDWI indices from the original Landsat data sets and those measures after compressing, as a function of the compression ratio (see Fig. 3).

In the final experiment, we measure the R2 between the original (NDVI and NDWI) and the compressed Landsat images. The results of this experiment are presented in the form of R2 with different lossy compression techniques and compression ratios, as show in Fig. 4.

The results reported on Fig. 3 and Fig. 4 revealed the following aspects. First, we should note that the vegetation features affects by the compression ratio, direct correlation. (i.e., NDVI and NDWI indices were better for lower compression ratios (high bit rates).

Second, the use of the spectral decorrelation affected on the NDVI and NDWI indices for all Landsat images. We can observe that compression technique applying PCA in the spectral decorrelation achieves the best results on the average compared to other methods. On the other hand, for the DWT spectral decorrelation, we can observe that JPEG2000 (with DWT in spectral decorrelator) has the worst average results for RMSE, so this method is poor in vegetation features extraction than other techniques.

Third, despite the poor PSNR values for SPIHT technique, but it achieved good results in the vegetation features extraction (NDVI and NDWI) compared to other compression techniques and it is mainly related to its bit rate regardless of the vegetation values.

Finally, one of the most interesting aspect that, for all data set, all rang of compression ratios, and all compression techniques used in our experiments, there is a direct correlation between the value of NDVI and NDWI indices (i.e., if the NDVI index affected by factor x the NDWI index also affected by factor very closed to x). This aspect can provide helpful guidelines to the further development of a simple filter for removing noise from NDVI and NDWI indices, the main idea behind this filter is to get a relationship between the original NDVI and/or NDWI indices and the reconstructed ones knowing the bit rate and the compression method used

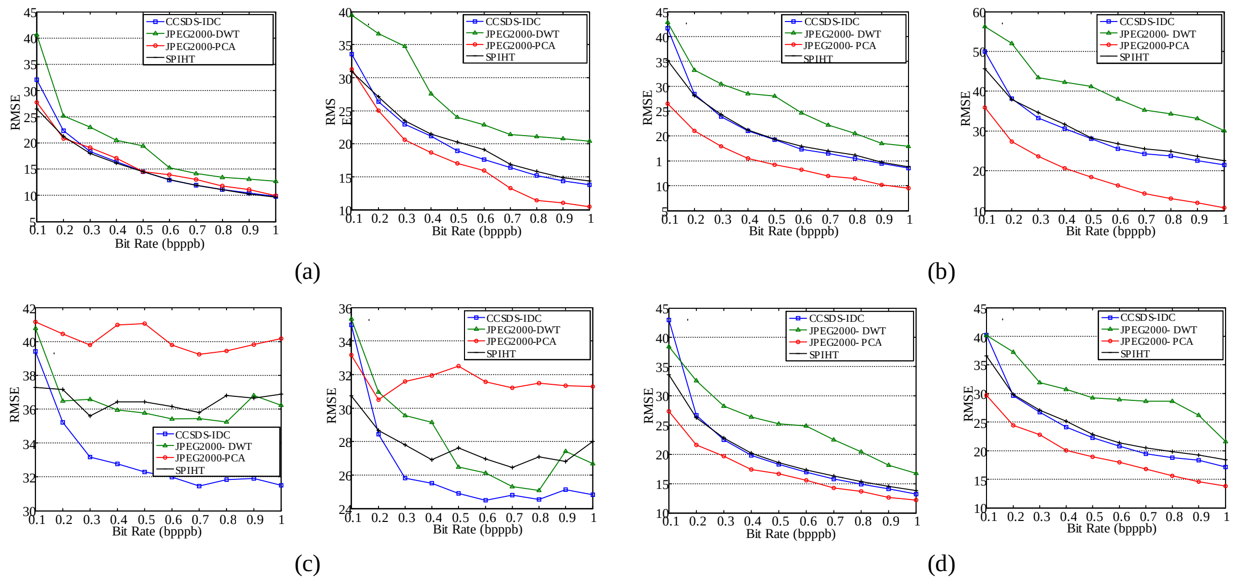

Figure 3. RMSE measures between the NDVI (left) and NDWI (right) indices from the original Landsat data sets and those measures after compressing, (a-d) images from Table 1, respectively.

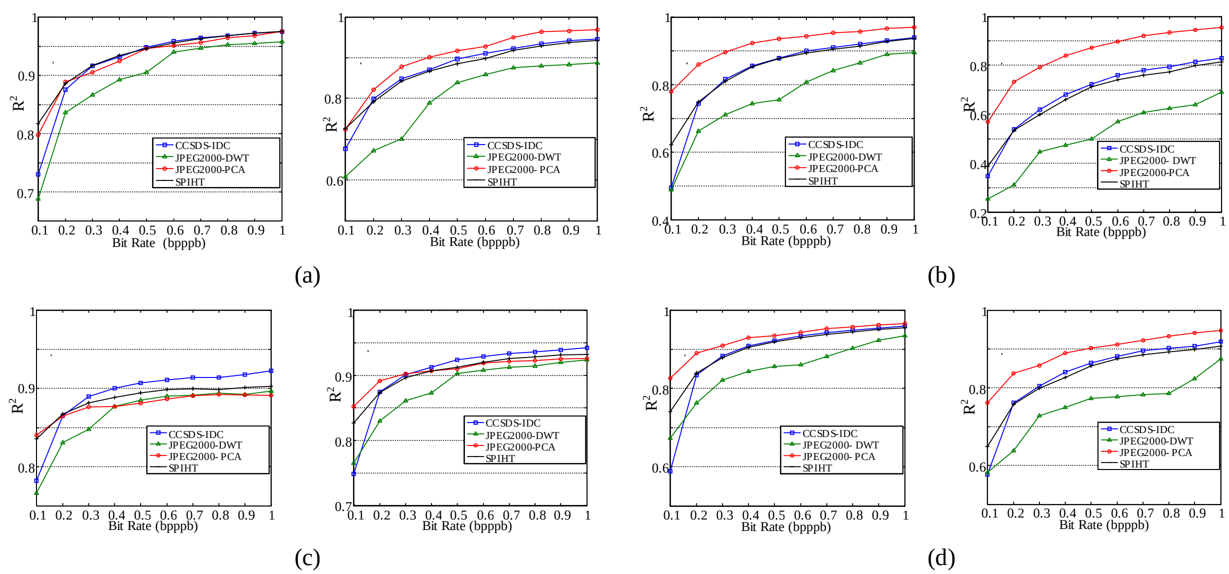

Figure 4. R^2 measures between the NDVI (left) and NDWI (right) indices from the original Landsat data sets and those measures after compressing, (a-d) images from Table 1, respectively.

4. CONCLUSIONS

In this paper, we studied the effect of existing lossy compression techniques on feature extraction for remote sensing imagery using several multispectral Landsat ETM+ images. Specifically, three different lossy compression techniques, JPEG2000, SPIHT, and CCSDS-IDC are used for compressing remote sensing images and the impact of compression is studied on two common indices (NDVI and NDWI) for vegetation features extraction.

The results show that these metrics do not directly correspond monotonically with the PSNR achieved by the compression technique for the image data. Also, we conclude that JPEG2000 with PCA in the spectral decorrelation has a small effect on the NDVI and NDWI indices for Landsat images compared to other compression techniques.

Finally, we show that, regardless of the method used for compression, there is a direct correlation between NDVI and NDWI indices all rang of compression ratios. Further experimentation with additional Landsat images and compression techniques may allow extrapolating the observations in this work to join classification and compression of these data.

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