Performance of Landsat TM in ship detection in turbid waters

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Abstract:

The visible and near infrared bands of Landsat have limitations for detecting ships in turbid water. The potential of TM middle infrared bands for ship detection has so far not been investigated. This study analyzed the performance of the six Landsat TM visible and infrared bands for detecting dredging ships in the turbid waters of the Poyang Lake, China. A colour composite of principal components analysis (PCA) components 3, 2 and 1 of a TM image was used to randomly select 81 dredging ships. The reflectance contrast between ships and adjacent water was calculated for each ship. A z-score and related p-value were used to assess the ship detection performance of the six Landsat TM bands. The reflectance contrast was related to water turbidity to analyze how water turbidity affected the capability of ship identification. The results revealed that the TM middle infrared bands 5 and 7 better discriminated vessels from surrounding waters than the visible and near infrared bands 1–4. A significant relation between reflectance contrast and water turbidity in bands 1–4 could explain the limitations of bands 1–4; while water turbidity has no a significant relation to the reflectance contrast of bands 5 and 7. This explains why bands 5 and 7 detect ships better than bands 1–4.

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1. Introduction

Dredging is an important economic activity with significant environmental impact. The potential of remote sensing for monitoring dredging impact has been long recognized. Dredging impacts are typically inferred from increased water turbidity patterns revealed by remote sensing images (e.g., Merry et al., 1988; Jorgensen and Edelvang, 2000). Wu et al. (2007), however, argued that it remains difficult to infer dredging impact from remotely sensed water turbidity patterns alone, as increased turbidity might reflect natural variability. They suggested that the plausibility of inference of dredging impact would be corroborated when ships could be associated to the observed turbidity patterns. Thus, ideally a remotely sensed dredging impact assessment system would combine water turbidity assessment and ship detection.

Basically two remote sensing techniques have been employed for ship detection. The potential of optical remote sensing has been explored since the launch of Landsat in 1970s. McDonnel and Lewis (1978) demonstrated the possibility to detect ships of 100 m length using Landsat MSS. Burgess (1993) applied Landsat TM and SPOT data to identify smaller ships. McDonnel and Lewis (1978) suggested that water turbidity might complicate and possibly inhibit ship detection while decreasing the signal-to-noise contrasts of the visible and near infrared bands of Landsat MSS. In addition, optical remote sensing has a limited potential in operational monitoring since it does not work at night and in the presence of clouds. As a consequence, a second technique, Synthetic Aperture Radar (SAR) with capacity to image day and night under most meteorological conditions (Winokur, 2000), became the state of the art technique for ship detection (Crisp, 2004). For example, Liu et al. (2003) used ERS SAR to monitor illegal fishing ships, Tunaley (2004) employed RADARSAT-2 SAR to detect ships, and Tello et al. (2006) applied space-borne SAR to assist authorities in monitoring ship traffic. However, Zhang et al. (2006) reported limitations of SAR in identifying smaller ships in inland waters.

Dredging impact assessment based on the association between ships and water turbidity patterns requires the simultaneous monitoring of ships and water turbidity. Simultaneity is necessary because both the location of ships and water turbidity patterns might change rapidly. Which remote sensing system(s) would be the most appropriate to achieve this simultaneous monitoring of ships and water turbidity? Greidanus (2006) concluded that SAR was most suitable for ship detection. However, SAR has no capability in water
turbidity assessment due to its strong absorption by water. Optical remote sensing has been employed successfully to map water turbidity (e.g., Fraser, 1998; Gan et al., 2004; Vignolo et al., 2006). However, it is difficult to combine SAR with optical remote sensing simultaneously, because the overpass time of the platforms carrying these sensors is not synchronous. Simultaneity could be achieved when deriving the information of ships and water turbidity from the same sensor system. In this view, it is interesting to reconsider the capability of traditional optical remote sensing systems for ship detection.

Landsat TM has two bands in the middle infrared spectrum, which are less influenced by water turbidity. The potential of these middle infrared bands for ship detection has so far not been investigated. This paper, with the northern Poyang Lake as a case study, analyzes the performance of six Landsat TM bands for detecting dredging ships in turbid water.

2. Materials and methods

2.1. Study area

Poyang Lake (115°47′–116°45′E, 28°22′–29°45′N), the largest freshwater lake in China, is located south of the Yangtze River (Fig. 1). Intensive sand dredging for construction started around 2001 in the northern Poyang Lake (Zhong and Chen, 2005). Recent reports (e.g., Zhong and Chen, 2005; Fok and Pang, 2006) suggest that dredging has a negative impact on this ecosystem. Since 2003 hundreds of dredging ships have been found between Hukou and Sand Hill. Due to these intensive dredging activities, the water turbidity in this region decreased from Secchi disk depths of 1.5 m in the past to less than 0.5 m at present (Wu et al., 2007).

2.2. Landsat TM image

One Landsat TM image (path 121/row 40) of 30 July 2006 was obtained from the Chinese Remote Sensing Satellite Ground Station. The cosine approximation model (COST) described by Chavez (1988, 1996) and Chen et al. (2004) was applied to atmospherically correct the image. Topographic maps of 1:50,000 were employed to register the image to the Beijing 54/Gauss–Kruger projection using a first-order polynomial and nearest neighbour approach. The root mean square error (RMSE) for positional accuracy was within half a pixel. Land areas and small water bodies were removed using a binary mask created through visual interpretation of an unsupervised classification of the image. Only bands with 30 m resolution (bands 1–5 and 7) were used in this study. We subjected the water areas of the northern Poyang Lake and Ganjiang River to a principal component analysis to enhance the visibility of vessels.

2.3. Sampling vessels

During repeated field visits to Poyang Lake, we noted that barges transporting sand passed by in regular order with distances of several hundreds of meters between individual ships. We further observed that these barges had a carrying capacity of 2000–4500 ton and a size of around 60 m by 20 m. A colour composite of principal components analysis (PCA) components 3, 2 and 1 (Fig. 2A) of the processed TM image revealed around 180 regular spaced linearly arranged objects. We concluded these objects to be barges because their uniform size and linear arrangement perfectly matched the size and linear arrangement of vessels observed during our field observations. Eighty-one of these 180 objects were randomly selected for further analysis.

![Fig. 1. Map of Poyang Lake and the study area (dashed rectangle) in the northern Poyang Lake.](image)
2.4. Reflectance contrast

For each ship, we defined the reflectance contrast \( c \) as the ratio of the reflectance of a ship object \( R_o \) to its background \( R_b \):
\[
c = \frac{R_o}{R_b}
\]
We selected the brightest pixel of each ship to represent \( R_o \) and calculated mean of the reflectance of 16 pixels (Fig. 2B) around each selected ship to represent \( R_b \) of the surrounding water while avoiding selection of other ships or land.

2.5. Secchi disk depth

Wu et al. (2008) developed a regression model describing the relation between the natural logarithm of Secchi disk depth \( (\text{SDD}) \) and the blue and red bands of a time-series of five Landsat TM images of 2004 \( (\ln(\text{SDD}) = 1.13 - 10.5 \times \text{Blue} - 13.8 \times \text{Red}) \) for the Poyang Lake National Nature Reserve, which combines with Poyang Lake during higher water levels in summer. The model explained 83% of the variance of the natural logarithm of Secchi disk depth. We applied this model to predict the Secchi disk depth of water in the northern Poyang Lake and Ganjiang River.

2.6. Statistical analyses

We first used analysis of variance (ANOVA) to test whether the six Landsat bands differed in average reflectance contrast. Following rejection of the null hypothesis, a post-hoc Bonferroni corrected multiple comparison test was used to reveal differences between pairs of bands.

Fig. 2. (A) Colour composite of principal components 3, 2 and 1 of Landsat TM image showing the regularly spaced linearly arranged objects (pink dots) and selected ships (identified by black circles) in Ganjiang River and the northern Poyang Lake; (B) 16 water pixels (*) around each selected ship (+) to represent the adjacent water. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

Fig. 3. Figure showing that Landsat TM bands 5 and 7 not influenced by turbidity do show vessels (white dots), while bands 1–4 revealing turbidity patterns do not. Note that some vessels are visible in bands 3 and 4 in clear water.
Next, for each ship, we calculated a z-score ($z$) which expresses how many standard deviations ($s$) the reflectance contrast ($c$) differed from one:

$$z = \frac{c - 1}{s}$$

The magnitude of the $z$-score expresses how well a band contrasts the ships from their surrounding water. The $p$-value derived from the $z$-score can be interpreted as the probability of not identifying a ship when using a contrast greater than one as the classification rule. Hence, assuming normality we used $p$-values to assess the ship detection performance of the six Landsat TM bands.

We then performed the analysis of covariance (ANCOVA) of reflectance contrast with the six TM bands as categories and Secchi disk depth as covariate to test the homogeneity of the slopes for the six TM bands. Following rejection of the equal slope hypothesis, we performed a two-sided $t$-test of the slope of the regression of each TM band to test whether slope deviated from zero in order to analyze how water turbidity influenced the performance of ship detection in each band. All statistical analyses were performed in Statistica 6.0.

3. Results

Fig. 2 reveals the variation in water turbidity in the northern Poyang Lake with a turbid plume amidst clear water. This turbidity pattern is clearly visible in TM band 1–4, but not in the middle infrared bands 5 and 7 (Fig. 3). Fig. 3 further shows vessels in turbid water in bands 5 and 7, but not in bands 1–4, and vessels in clear water are visible in bands 3–5 and 7, but not in bands 1 and 2.

Table 1 describes the mean and standard deviation of the reflectance for the 81 ships and their adjacent water for the six Landsat TM bands. The reflectance of water is low with low variability in the middle infrared bands 5 and 7 (see also Fig. 3), while it is higher with relatively high standard errors in other bands, especially the visible ones. The table also shows that the difference in reflectance between the bands for pixels with ships is less pronounced, and the difference in reflectance between water and ships increases from the visible towards the near and middle infrared bands.

The widths of the vessels we studied were smaller (20 m by 60 m) than a TM pixel, and pixels with vessels are thus expected mixtures of the spectral signatures of water and ships. When sampling pure pixels of vessels one would expect no relation between the reflectance of a ship and its surrounding waters ($H_0$: $\beta = 0$). The significance of the relation (Fig. 4) between the reflectance of ships and that of their adjacent water at a significant level of $< 0.001$ (TM 1: $R^2 = 0.90$; TM 2: $R^2 = 0.89$; TM 3: $R^2 = 0.89$; TM 4: $R^2 = 0.53$; TM 5: $R^2 = 0.26$; TM 7: $R^2 = 0.26$) thus confirms that the ships we studied did not occupy a whole pixel. Based on this, we concluded that these pixels were mixtures of the signals from ships and their surrounding waters.

![Fig. 4. Scatter plots of the reflectance of ships versus that of the surrounding water for six Landsat TM bands ($n = 81$).](image-url)

**Table 1**

<table>
<thead>
<tr>
<th>Band</th>
<th>Spectrum (μm)</th>
<th>Water Mean</th>
<th>Water S.D.</th>
<th>Ship Mean</th>
<th>Ship S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM 1</td>
<td>0.45–0.52</td>
<td>0.0677</td>
<td>0.0140</td>
<td>0.0721</td>
<td>0.0133</td>
</tr>
<tr>
<td>TM 2</td>
<td>0.52–0.60</td>
<td>0.0869</td>
<td>0.0197</td>
<td>0.0930</td>
<td>0.0185</td>
</tr>
<tr>
<td>TM 3</td>
<td>0.63–0.69</td>
<td>0.0920</td>
<td>0.0308</td>
<td>0.1110</td>
<td>0.0263</td>
</tr>
<tr>
<td>TM 4</td>
<td>0.76–0.90</td>
<td>0.0460</td>
<td>0.0199</td>
<td>0.0877</td>
<td>0.0263</td>
</tr>
<tr>
<td>TM 5</td>
<td>1.55–1.75</td>
<td>0.0264</td>
<td>0.0099</td>
<td>0.0820</td>
<td>0.0255</td>
</tr>
<tr>
<td>TM 7</td>
<td>2.08–2.35</td>
<td>0.0249</td>
<td>0.0081</td>
<td>0.0796</td>
<td>0.0199</td>
</tr>
</tbody>
</table>
Fig. 5 shows the histograms and derived normal distributions of the reflectance contrasts for the six TM bands. Analysis of variance (ANOVA, $F = 368.21$, d.f. = 5,480, $P < 0.0001$) revealed a significant difference in mean reflectance contrast between the six TM bands. Subsequent post hoc Bonferroni corrected two sample $t$-tests further reveals that the means of these reflectance contrasts differ significantly for all pairs of bands apart from the combinations of bands 1–3.

A reflectance contrast of one indicates lack of contrast between pixels with and without ships. The results in Fig. 5 reveal that the reflectance contrasts of bands 1–3 centres almost on one; while that a contrast of one is located in the tail of the frequency distributions of bands 5 and 7. The $z$-scores in Table 2 confirm the results in Fig. 5. The $p$-values reveal that reflectance contrasts below one occur frequently in the visible and near infrared bands 1–4, while the middle infrared bands 5 and 7 have extremely low probabilities of reflectance contrasts below one. These results indicate that the middle infrared bands discriminate ships better than the visible and near infrared bands.

Figs. 5 and 6 show that the absolute value of reflectance contrast ranges approximatively from 1 to 2 for bands 1–3, from 1 to 4 for band 4 and from 2 to 7 for bands 5 and 7. Fig. 6 also suggests that the slope of the relation between the reflectance contrast and water turbidity differs between the bands. A test for homogeneity of slopes (ANCOVA, Table 3) reveals a significant interaction term. This implies that the slope of the relation between reflectance contrast and water turbidity differs significantly between the TM bands.

The coefficients of the ANCOVA model (Table 4) reveal a general positive slope of 0.263 for the relation between reflectance contrast and water turbidity. This slope holds for band 7. The slopes of bands 1–3 do not significantly differ from this general slope, while bands 4 and 5 have significantly higher and lower slope, respectively. The results of separate $t$-tests in Table 5 reveal that the slope of the relation between reflectance contrast and water turbidity differs significantly from zero in bands 1–4, but not in bands 5 and 7. These results indicate that reflectance contrast is significantly influenced by water turbidity in bands 1–4, but not in bands 5 and 7.

We used an estimated reflectance contrast threshold of 1.5 to automatically identify ships from bands 5 and 7 of Landsat TM image. As an example, a small region with high ship density
displayed in Fig. 7. From this figure highly consistent results are observed through the comparison of ship information revealed in the colour composite of principal components 3, 2 and 1 with those derived bands 5 and 7 of Landsat TM image.

Fig. 7. Visual comparison of ship location in (A) the colour composite of principal components 3, 2 and 1, and as predicted by classification of bands 5 (B) and 7 (C) of the Landsat TM image.

Table 4

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>S.E.</th>
<th>t</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.937</td>
<td>0.052</td>
<td>37.34</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>TM 1</td>
<td>-0.924</td>
<td>0.116</td>
<td>-7.97</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>TM 2</td>
<td>-0.949</td>
<td>0.116</td>
<td>-8.18</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>TM 3</td>
<td>-0.999</td>
<td>0.116</td>
<td>-8.61</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>TM 4</td>
<td>-0.687</td>
<td>0.116</td>
<td>-5.92</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>TM 5</td>
<td>1.950</td>
<td>0.116</td>
<td>16.80</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>SDD</td>
<td>0.263</td>
<td>0.094</td>
<td>2.78</td>
<td>0.0056</td>
</tr>
<tr>
<td>TM 1 × SDD</td>
<td>-0.143</td>
<td>0.211</td>
<td>-0.68</td>
<td>0.4973</td>
</tr>
<tr>
<td>TM 2 × SDD</td>
<td>-0.079</td>
<td>0.211</td>
<td>-0.38</td>
<td>0.7096</td>
</tr>
<tr>
<td>TM 3 × SDD</td>
<td>0.383</td>
<td>0.211</td>
<td>1.82</td>
<td>0.0699</td>
</tr>
<tr>
<td>TM 4 × SDD</td>
<td>1.414</td>
<td>0.211</td>
<td>6.71</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>TM 5 × SDD</td>
<td>-0.814</td>
<td>0.211</td>
<td>-3.86</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

Table 5

<table>
<thead>
<tr>
<th>Band</th>
<th>Slope</th>
<th>S.E.</th>
<th>t</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM 1</td>
<td>0.119</td>
<td>0.031</td>
<td>3.91</td>
<td>&lt;0.0005</td>
</tr>
<tr>
<td>TM 2</td>
<td>0.184</td>
<td>0.035</td>
<td>5.19</td>
<td>&lt;0.0005</td>
</tr>
<tr>
<td>TM 3</td>
<td>0.646</td>
<td>0.080</td>
<td>10.81</td>
<td>&lt;0.0005</td>
</tr>
<tr>
<td>TM 4</td>
<td>1.677</td>
<td>0.208</td>
<td>8.07</td>
<td>&lt;0.0005</td>
</tr>
<tr>
<td>TM 5</td>
<td>-0.552</td>
<td>0.401</td>
<td>-1.38</td>
<td>0.1723</td>
</tr>
<tr>
<td>TM 7</td>
<td>-0.498</td>
<td>0.333</td>
<td>-1.50</td>
<td>0.1383</td>
</tr>
</tbody>
</table>
4. Discussion

In this study, we showed that the middle infrared bands 5 and 7 of Landsat TM effectively discriminated dredging ships from the surrounding water, while the visible and near infrared bands 1–4 poorly discriminated the ships. These results differ from those of Burgess (1993) who concluded that Landsat TM red (band 3) and near infrared (band 4) bands were the most useful for ship detection in marine clear water environments. To our knowledge, this is the first evidence that the Landsat TM middle infrared bands effectively discriminate ships in turbid water.

Why do the middle infrared bands discriminate ships from turbid water, while the visible and near infrared bands are not effective? It is well known that the reflectance of water, irrespective of turbidity, is extremely low in the middle infrared bands 5 and 7, since these bands are located close to the strong water absorption peaks at approximately 1.4 and 1.9 μm (Richards and Jia, 2005). Turbid water, however, has higher reflectance in the visible and near infrared bands compared with middle infrared bands due to multiple scattering of radiation by suspended silt (Gupta, 2003). We observed that the ships, which may or may not hold sands, have a much higher reflectance in the middle infrared bands. The reflectance of dry or wet sand is high in the middle infrared bands, and becomes low in the near infrared bands, even approaching that of turbid water (Sabins, 1997). This results in a lower contrast for the visible and near infrared bands of the spectrum, but higher contrast for the middle infrared bands.

Our results revealed that water turbidity influenced the detectability of ship in the visible and near infrared bands, but not in the middle infrared bands. This observation is consistent with the result of McDonnell and Lewis (1978) who argued that the capacities of visible and infrared bands of Landsat MSS image in detecting ships were limited in more turbid water.

Strong positive relations between water turbidity and Landsat TM visible or near infrared band values have been reported by many studies (e.g., Lathrop and Lillesalde, 1986; Lathrop, 1992; Zhao et al., 2003; Hellweger et al., 2004). In this study, we observed that the reflectance of ship was significantly and positively related to those of their adjacent water in these bands (Fig. 4). Thus, we infer that the contrast between ships and their adjacent waters would reduce with increasing water turbidity. This may explain why the potential of ship detection in the visible and near infrared bands is influenced by water turbidity. Although there are significant relations between ships and their adjacent waters in the middle infrared bands, these relations are really weak (Fig. 4). Most importantly, the middle infrared bands have no clear relations with water turbidity due to strong absorption by water. Thus, water turbidity has no impact on the performance of ship detection in the middle infrared bands of Landsat TM. This makes these bands particularly suited for detection of dredging infrastructure as this commonly occurs in turbid waters.

5. Conclusion

In this study, we analyzed the performance of the Landsat TM visible, near and middle infrared bands for detecting dredging ships in the turbid water of the northern Poyang Lake, China. The principal results obtained can be summarized as: the Landsat TM visible and near infrared bands showed limitation in ship detection especially in turbid water, while the middle infrared bands better contrasted ships; and that water turbidity has no significant impact on the reflectance of the middle infrared bands, which explains why the middle infrared bands provides stronger capacity compared with the visible and near infrared bands in ship detection.

SAR has frequently and successfully been applied to detect ships, because it can be applied day and night under most meteorological conditions. However, SAR does not allow simultaneous ship detection and water turbidity assessment. Although Landsat TM images are often hampered by cloud cover, it is possible to detect ships, even in turbid waters. We thus recommend using the middle infrared bands of Landsat TM for operational ship monitoring for dredging impact assessment in turbid water.

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