Application of remote-sensing technology in atmospheric environmental assessment

W. Xuemei¹, D. Ruru² & H. Zhijian²
¹Department of Environmental Science of Zhongshan University, China
²Remote-sensing Center of Zhongshan University, China.

Abstract

In this study, remote-sensing technology was applied to investigate the air pollution concentration distributions in the area of Shajiao Power Station in Guangdong Province, China. Based on the analysis of satellite physical mechanism of remote-sensing information, a model for remote-sensing identification and processing of emitted gas was established in order to extract information about pollution diffusion. It is the first time in China that the accumulative concentration information was retrieved from TM Satellite data. The image shows pollutant distribution and impact area clearly. The method is useful in area atmospheric environmental quality survey.

1 Introduction

Shajiao Power Station, located in the north of the Pearl mouth, is one of the largest Power Stations in Guangdong Province, which is near Hong Kong. It consists of 3 sub-stations (A, B, C). Total capacity is 3880MW. This station is fueled by coal. To its northeast are low hills. According to monitoring data in this district, the PH value in precipitation is 4.94, and the frequency of acid rain is more than 56.6%. Besides Shajiao Power Station, Mawan Power Station in Hong Kong and Qingshan Power Station also have an influence upon this district. In order to study the atmospheric environmental quality of this district synthetically, satellite remote-sensing technology is used in this region to investigate atmospheric environmental quality. However, because the atmospheric information is very weak and is superposed on complex terrain information, it is difficult to retrieve it from satellite remote-sensing data. Many researchers have worked on this subject since the 1980s. Sun Tianzong et al. [1] estimated the
522 Air Pollution LX

atmospheric pollution situation in urban area according to the heat-island effect. Fujii Hisao et al [2] and Fujii Toshio [3] estimated the atmospheric pollution information by using the relationship between SO\textsubscript{2} concentration in leaves and vegetation index in remote-sensing data. In this paper, we divided the surface of the studied area into several basic terrain types, namely, soil, vegetation, water, and so on according to field observation. By assuming the pixel information to be the simple superimposition of the information of polluted gas and those of these terrain types, we then quantitatively separated the information of atmospheric pollution from those of various terrain types after making image radiation calibration, atmospheric calibration, compensation of data voids and image intensification. District pollutant concentration distribution can be drawn directly and quantitatively.

2 Remote-sensing information model

2.1 Remote-sensing data and their characteristics

The remote-sensing data used in this paper was observed by the Land Satellite No.5 of US(TM) on 29 August 1997. The Satellite orbits over the studied region at 9:40 AM every 16 days. TM data consist of 7 bands. The radiation resolution in every band is 256 grades. Bands and surface resolution are shown in Table 1.

Table 1: TM bands and surface resolution.

<table>
<thead>
<tr>
<th>Number of bands</th>
<th>Confines of band (μm)</th>
<th>Surface resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM\textsubscript{1}</td>
<td>0.45—0.52</td>
<td>30</td>
</tr>
<tr>
<td>TM\textsubscript{2}</td>
<td>0.52—0.60</td>
<td>30</td>
</tr>
<tr>
<td>TM\textsubscript{3}</td>
<td>0.63—0.69</td>
<td>30</td>
</tr>
<tr>
<td>TM\textsubscript{4}</td>
<td>0.76—0.90</td>
<td>30</td>
</tr>
<tr>
<td>TM\textsubscript{5}</td>
<td>1.55—1.75</td>
<td>30</td>
</tr>
<tr>
<td>TM\textsubscript{6}</td>
<td>10.4—12.5</td>
<td>120</td>
</tr>
<tr>
<td>TM\textsubscript{7}</td>
<td>2.08—2.35</td>
<td>30</td>
</tr>
</tbody>
</table>

2.2 Spectrum characteristics in polluted air

The polluted gas emitted from the power station mainly contains SO\textsubscript{2}, NO\textsubscript{x}, and dust. The spectrum characteristic of SO\textsubscript{2} is similar to that of NO\textsubscript{x}. In the TM spectrum scope, there is almost no absorption in near infrared band, so SO\textsubscript{2} and NO\textsubscript{x} are colorless and transparent when we observe them. But they can induce Mie scattering, and the scattering intensity is directly proportional to the
concentration of polluted gas and $\lambda^2$, where $\lambda$ is electromagnetic wavelength. Therefore, the strongest scattering intensities of $SO_2$ and $NO_x$ exist in blue light band, whose wavelength is the shortest. The scattering intensities decrease rapidly while wavelength increases. When wavelength is longer than 1$\mu$m, the scattering intensity of $SO_2$ and $NO_x$ is nearly zero. Hence, the information of $SO_2$ and $NO_x$ in $TM_1$ are the strongest, and become weak in $TM_2$ and $TM_3$, while in $TM_4$, $TM_5$, $TM_6$ and $TM_7$ there is no reflection. In this paper, we consider $SO_2$ and $NO_x$ as the same polluted gas. The conception of spatial vertical accumulative concentration in unit surface area is used as pollutant concentration in the studied region. Dust has middle absorption in visible band, but it has stronger reflection in the near infrared band. According to these characteristics, we can separate the polluted gas information from background information.

2.3 Remote-sensing information model

2.3.1 Pixel spectrum

Every pixel spectrum is composed of reflected rays and scattering rays, which are responsive to the reflective route. Atmospheric scattering light includes light scattered by normal air and scattered by polluted gas. Terrestrial reflected rays change with different location. In the studied area, there are four basic terrain types: soil (including rock), vegetation, water and water suspension materials. Although the components of water suspension materials are similar to that of soil, their reflectivity is higher than normal soil in visible band. Therefore, we can distinguish them from normal soil. The surface response in every pixel includes the four basic terrain types in different ratios. Reflected light of pixel can be expressed in the following equation,

$$I=I_0ApR_p+I_0AsRs+I_0AwR_w+I_0A_dR_d+I_0AuRu+I_0Z$$

(1)

where, $I$ is the intensity of reflected light in pixel, which come into the sensor; $I_0$ is the intensity of incident light; $A_p$, $A_s$, $A_w$ and $A_d$ are area ratio of soil, vegetation, water and water suspension materials in pixels respectively; $R_p$, $R_s$, $R_w$, $R_d$ are reflectivity of soil, vegetation, water and water suspension materials respectively; $R_u$ and $Z$ are scattering coefficient of polluted gas and that of normal air respectively.

Define $Pu$ is relative accumulative concentration index, which has linear relationship with polluted gas concentration $Cu$. It can be written as

$$Pu = a \cdot Cu + b$$

(2)

Where $a$ and $b$ are constant coefficients. The scattering light scattered by normal air $I_0Z$ can be eliminated by air calibration, and thus, eqn (1) can be written as

$$I/ I_0=ApR_p+AsRs+AwR_w+A_dR_d+AuRu$$

(3)

Where $I/ I_0$ is pixel brightness.
2.3.2 Decomposition of pixels

We can calculate the basic terrain type ratio in every pixel from the infrared band information that includes only weak or even no polluted gas information, such as from TM3, TM4, TM5 and TM7. Then we calculate the normal brightness of TM1 from the known surface reflectivity. Pu is obtained from real brightness of TM1 minus normal brightness of TM1. This process can be realized through resolving the following equations:

\[
\begin{align*}
TM_1 &= A_{p1}R_{p1} + A_{s1}R_{s1} + A_{w1}R_{w1} + A_{d1}R_{d1} + Pu_{1} \\
TM_2 &= A_{p2}R_{p2} + A_{s2}R_{s2} + A_{w2}R_{w2} + A_{d2}R_{d2} + Pu_{2} \\
&\cdots \cdots \\
TM_5 &= A_{p5}R_{p5} + A_{s5}R_{s5} + A_{w5}R_{w5} + A_{d5}R_{d5} + Pu_{5}
\end{align*}
\]

Where \( TM_i \) (i varies from 1 to 5) is pixel brightness of 5 bands. A and R are area ratio of one surface type in pixel and reflectivity respectively. Subscripts of s, w, d represent vegetation, soil, water and water suspension materials, respectively. Two methods are used to calculate \( R_{pi}, R_{si}, R_{wi}, R_{di}, \) and \( R_{ui} \). One is observation through a spectrum meter, another one is to choose typical surface types in the image and read their brightness in different bands. The second method is easy to carry out and avoids the error in the first method caused by different observation time and light conditions. In this paper the second method was adopted, while the first method used as an alternative. There are 5 unknown variables (\( A_p, A_s, A_w, A_d \) and \( Pu \)) in the equation set (4), so we can solve it easily. We put the TM data observed on 29 August 1997 into equation set (4), and can got the following formula,

\[
Pu = 18.429TM1 - 31.350TM2 + 5.749TM3 + 2.779TM4 - 2.810TM5
\]

With the formula, we can get the whole field distribution of \( Pu(x,y) \). If we superpose the image of Pu on the image of TM3, TM4 and TM7, the intensified image of the pollutant diffusion can be obtained. Figure 1 shows the image of pollutant distribution (A).

Although we have calculated the value of Pu, it is not the accumulative concentration \( Cu \). Pu only has linear correlation with the accumulative concentration \( Cu \). According to eqn (2), before solving \( Cu \), we must know the coefficients of \( a \) and \( b \), that is to say, we must know at least two \( Cu \) values in the region. It is difficult to observe the accumulative concentration directly, so we theoretically simulated the accumulative concentration with model according to the emission source intensity and meteorological condition. At the same time, we observed the surface concentration, which is used to evaluate the model performance. On the basis of the evaluated model, we simulated the accumulative
concentration at the same time with the Satellite observation and calculate a and b.

3 The simulated accumulative concentration in imaging time

Gaussian plum model is used to simulate the pollutant spatial distribution at 9-10AM on 29 August 1997. The emission parameters are shown in Table 2. At that time, wind direction was NNE, wind velocity is 2.0m/s. Figure 2 shows the vertical accumulative concentration contours of SO$_2$, NO$_x$ and dust.

Table 2: The emission parameters.

<table>
<thead>
<tr>
<th>emission parameters</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>SO$_2$ (g/s)</td>
<td>370.48</td>
<td>347.84</td>
<td>673.03</td>
</tr>
<tr>
<td>NO$_x$ (g/s)</td>
<td>689.93</td>
<td>690.16</td>
<td>1380.65</td>
</tr>
<tr>
<td>Dust (g/s)</td>
<td>52.32</td>
<td>32.22</td>
<td>44.33</td>
</tr>
</tbody>
</table>
Figure 2: The vertical accumulative concentration contour of $\text{SO}_2$, $\text{NO}_x$, and dust (unit: $\text{g/m}^2$).

4 Identification of absolute pollutant concentration from remote-sensing information

We have calculated the $Pu(x, y)$. As what we mentioned above, if we know two $Cu$ values, we can calculate coefficients of $a$ and $b$, consequently we can then calculate whole field of $Cu$. Because of the difficulty in observing the accumulative concentration directly, we simulated the accumulative concentration theoretically. We assume that the distribution area of the accumulative concentration keeps unchanged if wind velocity is stable or its variation is limited. Using area as a standard, we established the relationship between simulated accumulative concentration and $Pu$, which is shown in Table 3. It is easy to get $a=1/60$ and $b=-1/30$. Therefore we have

$$Cu(x, y)=\frac{[Pu(x, y)-2]}{60}.$$

According to $Cu$, we divided the accumulative concentration into 5 grades as shown in Figure 3. The criteria used to make division is listed in Table 4.

Table 3: The relationship between simulated accumulative concentration and $Pu$.

<table>
<thead>
<tr>
<th>Simulated accumulative concentration ($\text{g/m}^2$)</th>
<th>$Pu$</th>
<th>Distribution area ($\text{km}^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.5</td>
<td>170</td>
<td>1.0134</td>
</tr>
<tr>
<td>2.0</td>
<td>140</td>
<td>2.1533</td>
</tr>
<tr>
<td>1.5</td>
<td>110</td>
<td>5.4081</td>
</tr>
<tr>
<td>1.0</td>
<td>80</td>
<td>12.9285</td>
</tr>
</tbody>
</table>
Figure 3: Atmospheric pollution remote-sensing image and its contour (partially).

Table 4: Classification for air pollution.

<table>
<thead>
<tr>
<th>Class</th>
<th>Slight</th>
<th>Low</th>
<th>Middle</th>
<th>Middle-high</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accumulative</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>concentration</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(g/m²)</td>
<td>0.01–0.5</td>
<td>0.5–1.0</td>
<td>1.0–1.5</td>
<td>1.5–2.0</td>
<td>&gt;2.0</td>
</tr>
</tbody>
</table>

Looking at Figure 3, we can identify the high concentration zone and its domain clearly.

5 Conclusion

In this study, the atmospheric environmental quality in the Shaojiao Power Station area was evaluated by analyzing satellite remote-sensing data (TM). In the area, the terrain information in TM contains basic information of soil, vegetation, water and water suspended matters in different ratios. The information of gaseous atmospheric pollutant is regarded as simple superposition on these basic terrain types. After making image radiation calibration, atmospheric calibration and image intensification, we established an equation set
to decompose the image information. The information of atmospheric pollution can be retrieved from surface basic information effectively and quantitatively. By making a comparison between simulated accumulative concentration and pixel brightness, we can draw the contours of polluted gas diffusion from remote-sensing image. Therefore we can identify the concentration distribution and the area influenced by the power station. It can be used as a tool of dynamic monitor in area air pollution control.

References