Flood Monitoring Using Multi-Temporal AVHRR and RADARSAT Imagery

Chenghu Zhou, Jiancheng Luo, Cunjian Yang, Baolin Li, and Shixin Wang

Abstract
Multi-temporal NOAA AVHRR and RADARSAT images depicting flood conditions in the Nenjiang and Songhua River Basins during the summer of 1998 were used to monitor the floods and assess the damage. A knowledge-based RBFNN model was developed to extract the dynamic flooding information from AVHRR images. To map the flooded area more accurately, three RADARSAT ScanSAR images acquired at different times were used. Threshold-based image segmentation and texture analysis methods were utilized to process the SAR image, and to extract information on flooding duration and depth. This study shows that the integrated use of different remote sensing platforms images can provide real-time and all-weather monitoring of floods and provide necessary information for flooding control and disaster relief.

Introduction
Floods are arguably the most pervasive, diverse, and destructive natural hazards in China. China has seen several disastrous floods during the past century. Recent examples include the 1975 flooding of the Huaihe River basin, which claimed 26,000 lives, and the 1996 Yangtze River and Northeast Plain floods, which caused a direct economic loss of more than $3 billion.

Flood monitoring, damage evaluation, and disaster relief have become important topics addressed by Chinese scientists and engineers, and cause great concern among both the local and the central government.

Floods are a function of the location, intensity, volume, and duration of precipitation. Images from Earth-observing satellites provide the instantaneous and synoptic view necessary for accurate mapping of flood extent, and are therefore widely used in monitoring flood extent and evaluating flood damage. NOAA AVHRR images provide the majority of the available data at no charge. With the advantage of large coverage and high temporal resolution, meteorological SAR satellite imagery such as NOAA AVHRR has been intensively used to identify the flooding location and monitor the spatial distribution of flooded areas (Zhou, 1993; Zhou et al., 1996). High spatial resolution optical images, such as Landsat MSS/ETM, SPOT, and IRS, are also used to accurately delineate the flood extent and assess the flood damage (Yamagata and Akiyama, 1988; Nagarajan et al., 1993; Sharma et al., 1996; Wilson, 1997). However, optical imagery is constrained to favorable weather and daylight. Recently, satellite SAR images have been applied to map flooding extent due to SAR's ability to acquire timely images and its sensitivity to liquid. (Wang et al., 1995; Ramsey, 1995; Adam et al., 1998). Many successful applications showed that SAR is a very promising technology for accurately determining the extent of inundation during floods and under vegetation (Hess et al., 1990).

The Chinese central government and scientists have paid significant attention to the application of remote sensing to flood monitoring. In 1987, airborne remote sensing was initially introduced into the Yellow River real-time flood monitoring. Since then a series of experiments and applications have been conducted. For example, in the 1994 Taihu Basin flood, NOAA AVHRR, Landsat TM, and airborne SAR images were integrated and used to identify the flooded areas, estimate the flood water depth, and assess the damage, including damage to agriculture and public facilities. After five years of effort, a flexible airborne system equipped with a SAR system and satellite-based communication was established and put into use in 1995. This system can acquire real-time flood information, and then transmit the images from an airplane to flood control headquarters through a communication satellite and ground microwave lines. Many researchers are also developing methods for extracting flood information from the images. Dai and Tang, (1993) also developed a model based on water body spectrum characteristics to extract flooded areas from Landsat TM imagery, and Zhou et al., (1996) proposed a spectrum-vector model to automatically identify flooded areas on NOAA images.

This article first focuses on the NOAA AVHRR image processing and flood information extraction based on the RBFNN model. Multi-temporal RADARSAT images were utilized to accurately assess the extent of the flooding. The possibility and capability of remote sensing technology application to flood monitoring and damage analysis are also discussed.

Study Area and the 1998 Flood
Environmental Setting of the Study Area
The study area chosen for this research is located in the Nenjiang River Basin and the Lower Reaches of Songhua River. As the largest river in the Northeast Plain of China, the Songhua River drains 546,000 square kilometers. Physiographically, it ranges from the mountains in the Upper River to terrace plain and to the central lowlands in the Lower River. The Middle and Lower River basin is very flat with a relatively low elevation. Therefore, the hydraulic slope of the river course is very low. Climatologically, it has a humid-temperate monsoon climate. Multi-annual average precipitation reaches 400 to 500 mm, with a record of 767.4 mm. During the summer, warm and humid air masses from the south come in contact with cold air masses from the north, resulting in storm rainfall.

The Nenjiang River and second Songhua River are the main tributaries of the Songhua River. The Nenjiang River has
many tributaries, especially on its right bank as shown in Figure 1. The Upper River has a narrow channel while the Lower River has a wide and shallow channel with a maximum width of 10 km. There are many ancient river courses and depressions in the Lower reaches. Originally, these areas acted as temporary water flow channels during the flood season. As the numbers of inhabitants increased, these areas were cultivated. Consequently, these ancient river courses and depressions were disconnected and lost their ability to drain and store the flooding water. Water logging became common during the flood seasons in the area.

Great 1998 Flood Event

In 1998 severe flooding occurred in the Nenjiang River and the Lower Songhua River. In terms of precipitation amounts, river level records, flood duration, area of flooding, and economic losses, the 1998 floods surpassed all previous floods in this area, and were a hydrometeorological event without precedent in modern times.

Rainfall

During the period from June through August, 1999, a persistent atmospheric pattern of excessive rainfall occurred across much of the Songhua River Basin, and record and near record rainfall fell on the basin as seen in Table 1. Four heavy rainfall events greatly contributed to the river floods. The first three events occurred during 14–24 June, 06–09 July and, 18–26 July, respectively, on the upper river basin. Rainfall amounts reached an average of 250 mm. The fourth rainfall with multiple rainfall centers fell during 04–10 August over the entire river basin. Rainfall reached 388 mm at the Yinghe Reservoir Station, 266 mm at the Geli Station, and 220 mm at the Tongmeng Station.

River Flow

The deluge across the Nenjiang River Basin produced record setting peak flowrates and water levels in many tributaries and in the main-stem rivers. Flooding began on the upper Nenjiang River in late June and then moved southward to the middle reaches with the shifting of the rainfall storm and the travel of flood flows downstream in July. A deluge of heavy rainfall during early August over the whole Nenjiang River Basin led to the record flood on most portions of the River Basin, as indicated in Table 2. Flood control dikes were breached at Laojusi, Pang Tou Lake, and other places as shown in Figure 1.

Damage Reported

 Estimates of total damage in the flooded area during the 1998 flood range between $30 billion and $35 billion. Over half of this was agricultural damage to crops, livestock, aquatic farming, and equipment. The remaining damage was primarily to public facilities, residences, water resources engineering, and others. Estimates vary on the number of residents flooded and affected by the flood. The lower estimates are 5.5 million people affected, half a million people besieged, and 1.24 million people evacuated. About 7,125 villages and four towns were flooded to some extent in the 1998 floods.

| Table 1. Rainfall in the Nenjiang and Songhua River Basins During June-August, 1999 |
|---|---|---|
| Month | River Basin | Rainfall (A) (mm) | Annual Average (B) (mm) | Difference of A and B (mm) (%) |
| | | | | |
| June | Nenjiang | 133.6 | 79.1 | 54.5 | 68.0 |
| | Main Songhua | 96.5 | 88.5 | 8.0 | 9.0 |
| | 2nd Songhua | 120.2 | 108.5 | 11.4 | 10.5 |
| July | Nenjiang | 241.6 | 144.5 | 97.1 | 67.1 |
| | Main Songhua | 106.3 | 145.2 | -38.9 | -26.7 |
| | 2nd Songhua | 177.5 | 181.4 | -3.9 | -2.1 |
| August | Main Songhua | 159.0 | 122.1 | 36.9 | 30.2 |
| | 2nd Songhua | 208.7 | 140.0 | 68.7 | 49.0 |
Flood Monitoring by Using Multi-Temporal AVHRR Data

A Spectral-Vector Model for Flooded Area Extraction from AVHRR Images

The optical properties and states of a water body are primary factors influencing its spectral reflection on an AVHRR image. Theoretically, the water body has a high reflection in the visible band, and a very low reflection in the near-infrared and infrared bands. A large number of ground spectral tests also indicate that this characteristic does not change with region and time. With this prior knowledge, we collected hundreds of sub-image samples from AVHRR images covering different regions and from different seasons. Figure 2 is a typical spectrum curve for open water bodies on an AVHRR image. It can be ascertained from the sample spectral curves that the reflection rate decreases from Channel 1 to Channel 2, and then increases to Channel 3. At the same time, the reflection in Channel 2 is located at the lowest point in the spectral curve. If the flooded area is viewed as open water body, a simple and basic rule for identification of a flooded area on the AVHRR image can be expressed as follows:

\[
\text{IF} \ CH1 > CH2 \text{ and } CH2 < \text{mean, then Pixel is Water.}
\]

Of course, this rule needs to be modified when a composed pixel is processed. More research is needed.

Water Body Extraction Using an RBF Neural Network

Integrated with the spectral-vector model above, a Radial Basis Function (RBF) neural network was developed and used to identify the flooded area in this research. A RBFNN is a three-layer structure neural network (Figure 3), in which the output units form a linear combination of the radial basis (kernel) functions computed by the hidden (middle) units. Each hidden unit has a localized receptive field. Typically, learning in the hidden layer is performed by unsupervised methods such as K-means clustering and ISODATA, while learning in the output layer uses supervised methods such as the Least-Mean-Square (LMS) algorithm. The RBFNN can overcome the disadvantages of a slow training speed and potential convergence to a local minimum, incurred in most pervasive back-propagation neural networks (Benediktsson et al., 1990; Atkinson and Tatnall, 1997; Rollet et al., 1998).

Note: H.D = historical record

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**Table 2. Water Levels and Discharge for the Flood Peak**

<table>
<thead>
<tr>
<th>Station ID</th>
<th>Date</th>
<th>Water level (m)</th>
<th>Discharge (m³/s)</th>
<th>Station ID</th>
<th>Date</th>
<th>Water level (m)</th>
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<tr>
<td>(2)</td>
<td>20 Jun 08</td>
<td>2240</td>
<td>H.D</td>
<td>(10)</td>
<td>03 Jul 11</td>
<td>140.71</td>
<td>7480</td>
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<td>12 Aug 20</td>
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<td>30 Jul 10</td>
<td>141.71</td>
<td>142.37</td>
<td>25900</td>
</tr>
<tr>
<td>H.D</td>
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<td>7480</td>
<td>11 140.71</td>
<td>10 Aug 08</td>
<td>151.52</td>
<td>23700</td>
<td></td>
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<tr>
<td>(3)</td>
<td>27 Jun 06</td>
<td>197.22</td>
<td>10600</td>
<td>(11)</td>
<td>28 Jul 22</td>
<td>151.44</td>
<td>1110</td>
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<td>02 Aug 20</td>
<td>131.10</td>
<td>16100</td>
<td></td>
</tr>
<tr>
<td>H.D</td>
<td>10 Aug 11</td>
<td>210.47</td>
<td>25900</td>
<td>15 Aug 03</td>
<td>131.07</td>
<td>7880</td>
<td></td>
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<tr>
<td>(4)</td>
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<td>206.57</td>
<td>145.66</td>
<td>(12)</td>
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<tr>
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<td>100.21</td>
<td>8810</td>
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<td>15 Aug 03</td>
<td>100.21</td>
<td>16600</td>
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<td></td>
</tr>
<tr>
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<td>12200</td>
<td>10 Aug 11</td>
<td>12200</td>
<td>16600</td>
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<td></td>
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<td>27 Jun 14</td>
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<td>27 Jul 23</td>
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<td>120.05</td>
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<td>12 Aug 10</td>
<td>149.30</td>
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<td>148.61</td>
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<tr>
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<td>3700</td>
<td>(14)</td>
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<tr>
<td>(6)</td>
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<td>25 Aug 09</td>
<td>3500</td>
<td>120.05</td>
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<td>H.D</td>
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<tr>
<td>(8)</td>
<td>27 Jul 07</td>
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<td>80.34</td>
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<td>H.D</td>
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<td>80.63</td>
<td>27 Jul 07</td>
<td>145.21</td>
<td>3500</td>
<td>18400</td>
<td></td>
</tr>
</tbody>
</table>

Note: H.D = historical record

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**Figure 2.** Water body spectrum curve of a NOAA/AVHRR image.

**Figure 3.** Structure of the knowledge based RBF neural network.
Besides using training data, prior knowledge can be included by using rules defined in the water spectral vector model. First, we select a specific number of samples with prior spectral knowledge to identify the water information from a NOAA/AVHRR image using visual interpretation. Then, the vectors from the image are fed into the RBFNN pixel by pixel, and, by passing through the network, the classifying belief vector \( \mathbf{m}_1 \) is output to the output layer. Simultaneously, the vectors that represent spectral knowledge of water information, which is represented with a RULE format, are also serially input into the reasoning machine in order to output another classifying belief vector \( \mathbf{m}_2 \). Using the Dempster-Shafer Belief Functions method (Dempster, 1967; Shafer, 1976), the overall belief vector \( \mathbf{m}_3 \) can be acquired by \( \mathbf{m}_1 \mathbf{m}_2 \). Finally, the maximum dimensional value in the vector \( \mathbf{m}_3 \) can be chosen as the classification type (Figure 3).

Using a spectral-knowledge-based RBF neural network, the AVHRR image can be classified into three main land-cover types, including water area, cloud area, and land area. Based on multi-temporal AVHRR images, the different phases of water body can be extracted and overlaid on a single image to represent the dynamic flood process.

Result Analysis
During the flood period in 1998, ten cloud-free AVHRR images were received and processed. Based on the flood peak records, the images dated 30 July 14 August, and 24 August, 1998 were geo-referenced to a Gaussian projection at a 1.1-km resolution. Image registration accuracy was estimated at about \( \pm 1 \) pixel. The flooded areas were extracted from each image by using the above-described RBFNN method. Plate 1 is a composited image made from four-phase flooded areas and an AVHRR image dated 02 May 1998. The composited image clearly shows the increase in the flooded area as peak flows came one after the other. Especially significant, the increase of the inundated areas around the dikes revealed the locations of the dike breaches. It can be concluded that the NOAA/AVHRR images are of value in monitoring the dynamics of flooding.

Flood Monitoring and Analysis Using Multi-Temporal RADARSAT Imagery
Data Selection
In order to monitor the flood process and evaluate its damage in detail, higher resolution images are needed. Because of the lower resolution of AVHRR and the difficulty of acquiring Landsat TM images during the flood period, they cannot fully meet the requirements. Satellite SAR is designed to overcome the most common problem associated with monitoring flood events, that is, getting information when and where it is needed, regardless of weather conditions. Over the past few years, we have carried out research projects to investigate the methodology for application of Canadian RADARSAT satellite images for mapping floods. Based on the this experience, multi-temporal RADARSAT Scan SAR images (wide mode) were used in this study. These images, with a resolution of 50 meters, were acquired on 15, 23, and 29, August 1998 during the flood period.

Analysis of RADARSAT Imagery
In light of the distinct backscatter responses in the SAR data, the inundated area can be delineated using SAR images acquired during the flood period (Green et al., 1983; Imhoff et al., 1997). Flooded areas have a relatively smooth surface compared with the wavelength of RADARSAT Scan SAR. Thus, act as a specular reflector, directing the microwave energy away from the satellite, and creating the bright tones on the SAR images. Other areas such as farmland, grassland, areas of forest, and residential land show a relatively rough surface compared with the wavelength. They reflect more energy back to the satellite, creating the dark tones in the images. Therefore, it is possible for us to differentiate flooded areas from other areas.

Imagery Processing
All of the SAR images needed to be pre-processed before they were ready for use. First, all three images needed to be matched to each other, geo-registered, and radiometrically corrected. The ground control point (GCP) method was adopted for image matching and geo-referencing. About 12 GCPs were collected on the images and from the existing land-use map at the scale of 1:100,000. The registration accuracy was estimated to be less than two pixels. Meanwhile, a radiometric correction was carried out in the images.

Second, speckle noise needed to be removed from the images. Speckle appears as a granular texture on all radar images. The presence of speckle on SAR imagery reduces the ability to resolve fine details within the image. Many methods which have been developed to reduce SAR image speckle in order to improve image quality. Here the enhanced Frost filter was used with a 7 by 7 window. The enhanced images not only maintain edges and texture in the original image, but also increase image contrast and remove speckle noise, thus being more suitable for flood extent extraction and analysis (Yang et al., 1998).

Finally, the flooded areas were extracted from the filtered images. We can see the strong contrast between the flooded area and un-flooded area in the filtered image. Flooded areas have lower gray values, while un-flooded areas have high gray values. The histograms of the enhanced images appear as double peaks. The trough between two peaks can be used as a threshold to segment the images into flooded area and dry land.

A radar image depends heavily on the scatter from ground objects, and its textures sharply vary with different objects. This knowledge and the texture analysis method have been adopted by many scholars for land-use classification, for example, cultivated land and forest (Sun and Wee, 1982; Laws, 1985; Arai, 1991; Lee and Philpot, 1991) and ice discrimination (Barber and Ledrew, 1991; Sun et al., 1992). Here this method was also used in combination with the threshold method to improve the flooded area identification.

Dynamic Analysis of the Flood and Damage
In order to analyze the dynamics of the flood, multi-temporal images were needed at different dates. Here we used a composited image, as shown in Plate 2a, to combine the three images, taken on different days, in order to illustrate the flood area

Plate 2. (a) Dynamics of flood extent. (b) Land-use flooding map.
expansion with time. Table 3 lists the flood statistics data calculated from the above composited image above. On 15 August, the flood area covered about 996,899 ha, which was mainly distributed along Nenjiang River and its branches. On 23 August, the flood area had increased to 1,161,793 ha. The expanded area of 164,894 ha was mostly located in the middle Nenjiang River. Several dike breaches led to serious flooding downstream. The inundated area reached 1,262,737 ha by 29 August; another 100,944 ha of land had been flooded since 23 August. An overlay of the land-use map with the flooding image (Plate 2b) provided the statistics for the different types of land use, indirectly reflecting the flood damage (Table 4).

**Conclusion**

Remote sensing technologies are very useful in flood monitoring and damage evaluation. NOAA AVHRR images can be used to monitor flooding dynamics because of their higher temporal resolution. In this paper we have presented an RBFN method, which is integrated with a spectral-vector model, for automatic extraction of flooded areas. The successful application of multi-temporal RADARSAT images in flood damage assessment demonstrated the ability and potential of SAR remote sensing in monitoring floods and estimating the flood regimes. More research is needed to integrate other data such as digital topographic data and river networks with AVHRR images in order to improve the spatial accuracy, and to develop new algorithms for the pre-processing and thematic information enhancement of SAR images.

**References**


(Note: The customary western practice of listing author's family names last, except in the list of references where only the first author's name is listed family name first, is followed herein.)