Dynamic monitoring of flood disaster based on remote sensing data cube

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Abstract
High-frequency dynamic monitoring of flood disaster using remote sensing technology is crucial for accurate decision-making of disaster prevention and relief. However, the current trade-off between spatial and temporal resolution of remote sensing sensors limits their application in high-frequency dynamic monitoring of flood disaster. To deal with this challenge, in this study, we presented an approach to conduct high-frequency dynamic monitoring of flood disaster based on remote sensing data cube with high spatial and temporal resolution. The presented approach included two steps: a, removing the cloudy areas in original MODIS data to construct the cloud-free MODIS data cube by using the information provided by GPM rainfall data; b, fusing the cloud-free MODIS data cube and Landsat-8 data by using the spatiotemporal data fusion algorithm to construct the high spatiotemporal resolution (Landsat-like) data cube. The approach was tested by conducting high-frequency dynamic monitoring of flood disaster occurred in Henan Province, PR China. Our study had three main results: (1) the presented cloud removal algorithm in the first step was able to retain flood information and performed well in removing clouds during consecutive rainy days. The differences between cloud-free MODIS data cube and original MODIS data were small and the cloud-free MODIS data cube could be used for constructing high spatiotemporal resolution data cube. (2) Our presented approach could be used to conduct high-frequency dynamic monitoring of flood disaster. (3) Testing results showed that there were two floods occurred in the study area from July 17, 2021, to October 16, 2021; the first flood occurred from July 17, 2021, to September 15, 2021, with maximum affected area of 668.36 km²; the second flood occurred from September 18, 2021, to October 16, 2021, with maximum affected area of 303.88 km². Our study provides a general approach for high-frequency monitoring of flood disaster.

Keywords Flood disaster · Data cube · Remote sensing · Spatiotemporal data fusion algorithm
1 Introduction

Flood disaster is one of the most common and destructive disasters in the natural world (Khan et al. 2011), which can have a serious impact on the ecological environment, agriculture and economy of the flood-affected region (Chen et al. 2012; Gianinetto et al. 2006). Timely and accurate monitoring of flood disaster is essential for rapid response, effective decision-making, and disaster mitigation (Chen et al. 2018). Due to the large inundated area, it is tough to monitor the flood disaster by traditional ground survey methods (Dao and Liou 2015; Sanyal and Lu 2004). Therefore, an effective monitoring method is in need to conduct the dynamic monitoring of flood disaster.

In recent years, remote sensing technology has played a huge role in disasters monitoring, because it can achieve simultaneous monitoring of large area and this technology is economical (Zhang et al. 2014). Generally, there are two kinds of remote sensing technologies to monitor flood disaster, including active remote sensing and passive remote sensing. Active remote sensing realizes flood disaster monitoring by transmitting microwave to flood and receiving backscatter signal. Among most of the active remote sensing sensors, Sentinel-1 (Tsyganskaya et al. 2018; Mehrabi 2021) and TerraSAR (Cruz et al. 2010; Voormansik et al. 2014) are widely used in flood disaster monitoring. Active remote sensing can work in cloudy weather because of the ability of microwave’s penetrating clouds and water vapor (Henry et al. 2006; Mallinis et al. 2013), which makes active remote sensing more efficient for flood disaster monitoring during rainy days (Pulvirenti et al. 2011). Compared to active remote sensing, passive remote sensing conducts flood disaster monitoring by using visible bands emitted by the sun; it has great potential in flood disaster monitoring because of higher spatial or temporal resolution, abundant band information and low cost. Over the past years, Landsat series data (Diaz-Delgado et al. 2016; Olthof 2017), MODIS data (Fuentes et al. 2019; Hu et al. 2021) and Sentinel-2 (Guo et al. 2021; Zhang et al. 2021) data have arisen great attention in monitoring flood disaster because of their longer time coverage and easier access. However, the existence of clouds during passive remote sensing satellites’ monitoring makes passive remote sensing invalid because of the poor ability of visible wavelengths’ penetration, which limits the application of passive remote sensing.

One effective approach to resolve the impact of clouds on passive remote sensing is to remove clouds from passive remote sensing images and then fill the cloud pixels using information provided by neighboring similar cloud-free pixels. Based on this idea, some cloud removal algorithms have been proposed. For example, Neighborhood Similar Pixel Interpolator (NSPI) proposed by (Chen et al. 2011) removes clouds based on the assumption that same class neighboring pixels are similar pixels and exhibit similar patterns of spectral differences between date. Zeng et al. (2013) proposed a weighted linear regression (WLR) algorithm which uses multi-temporal images as referable information and builds a regression model using similar pixels within a local search window. Yan and Roy (2018) developed a spectral-angle-mapper-based spatiotemporal similarity (SAMSTS) algorithm which selects similar pixels by using spectral-angle-mapper metric. SAMSTS deals with the challenge of low efficiency by firstly segmenting image time series and then grouping segments into different clusters; similar pixels are searched within a cluster that includes gap pixel. Up to now, these cloud removal algorithms have been used in land use change monitoring (Liu et al. 2021), land surface temperature retrieval (Ebrahimi et al. 2022) and urban heat island effect monitoring (Shen et al. 2016).
High-frequency monitoring of flood disaster can help decision-makers to make disaster mitigation policies and rescue plans in time. However, there are some limitations in traditional remote sensing technology and cloud removal algorithms when used in dynamic monitoring of flood disaster with high-frequency. First, although active remote sensing performs well during rainy days, due to the low spatial and temporal resolution, active remote sensing data cannot always be obtained during the flood period; as a result, it fails to conduct high-frequency dynamic monitoring of flood disaster. Second, it is impossible for passive remote sensing to obtain images with both high spatial and high temporal resolution because of the limitation of current technology. For example, Landsat provides images with a spatial resolution of 30 m, but its temporal resolution is 16 days, which makes it impossible to conduct intensive dynamic monitoring of flood disaster; in contrast, MODIS images’ temporal resolution is 1 day and its spatial resolution is 250–1000 m (Wang et al. 2020), which makes it hard to capture fine flood disaster information. The trade-off between spatial and temporal resolution has become a barrier for application of passive remote sensing in high-frequency flood disaster monitoring. Last, traditional cloud removal algorithms may fail to search similar pixels in images containing emergency events such as flood disaster, which makes traditional cloud removal algorithms not suitable for the monitoring of flood disaster.

In this study, the main objectives were as follows: (1) to resolve the challenge that traditional cloud removal algorithms are not suitable for the monitoring of flood disaster, and (2) to resolve the difficulty that monitoring of flood disaster by remote sensing technology cannot take into both high spatial and high temporal resolutions account. We presented an approach to conduct high-frequency dynamic monitoring of flood disaster based on remote sensing data cube with high spatial and temporal resolution. First, the approach constructed the low spatial but high temporal cloud-free MODIS data cube by removing clouds combined with rainfall information. Then, based on spatiotemporal data fusion algorithm, the approach fused the cloud-free MODIS data cube and Landsat-8 data by using the spatiotemporal data fusion algorithm to construct the high spatiotemporal resolution (Landsat-like) data cube. And finally, the approach was tested by conducting high-frequency dynamic monitoring of flood disaster occurred in Henan Province, PR China.

2 Study area and data

2.1 Study area

We selected Anyang City, Hebi City, Jiaozuo City, and Xinxiang City in Henan Province, PR China, as our study area which is located in the north of Henan Province (Fig. 1) and has the total area of 21,759.7 km². Main land use types of study area are cultivated land, forest land, construction land, and water bodies. The climate in study area is the temperate continental monsoon climate. From July 17, 2021, to July 30, 2021, under the influence of typhoon “Yanhua,” a heavy rainstorm occurred in the study area and caused flood disaster. In September 2021, there was a second flood disaster due to consecutive rainy days. Two flood disasters had a huge side impact on ecological environment and production activities in the study area. During the flood periods, there were few remote sensing data that could be used to monitor the flood. Therefore, this study area was selected to test our presented approach.
As shown in Table 1, seven kinds of data were used. The Landsat-8 data on May 22, 2020, and MODIS daily reflectance data (MOD09GA) were used as input data of spatiotemporal data fusion algorithm to generate high spatial and temporal resolution Landsat-like data cube; GPM rainfall data were used to construct weights for removal of cloud areas in MODIS data; Sentinel-1 data, Sentinel-2 data, some of the Landsat-8 data, GF-1 data and GF-3 data were used to evaluate the accuracy of the extracted flood results.

### 3 Methods

#### 3.1 The presented method

##### 3.1.1 Constructing cloud-free MODIS data cube

There are data-missing areas in MODIS images due to the influence of clouds. In this study, cloud areas in MODIS images were removed according to the “Fill–Fit” method.

![Image: a: the location of study area in Henan Province, b: Landsat-8 OLI image of study area, c: flood photograph taken in study area](image_url)

**Table 1** Data used in this study

| Data                | Spatial resolution | Time range               | Usage                                               |
|---------------------|--------------------|--------------------------|----------------------------------------------------|
| Landsat-8           | 30 m               | 5.22.2020, 9.30.2021, 10.16.2021 | Input of spatiotemporal data fusion algorithm     |
| MODIS               | 500 m              | 5.22.2020                | Evaluating the extracted flood results             |
| GPM rainfall data   | 0.1°               | 7.17.2021–10.17.2021     | Constructing cloud-free MODIS data cube           |
| GF-3                | 10 m               | 7.24.2021                | Evaluating the extracted flood results             |
| Sentinel-1          | 5 m × 20 m         | 7.17.2021–10.17.2021     | Constructing weights to remove clouds in MODIS data|
| Sentinel-2          | 10 m, 20 m, 60 m   | 7.17.2021–10.17.2021     | Evaluating the extracted flood results             |
| GF-1                | 16 m               |                          |                                                    |
proposed by (Yan and Roy 2020). Different from “Fill” step in “Fill–Fit” method which uses similar pixels to fill the data-missing areas, our “Fill” step constructs weighting factors by using GPM rainfall data and then makes use of the information provided by the valid pixels before and after the data-missing areas to fill the data-missing areas.

The pixel value in the remote sensing image is the reflectance value of a ground object corresponding to the pixel at a certain wavelength. As described in (Liu et al. 2002), with the increase in the water content of a ground object, the reflectance value of this ground object will decrease for all the wavelengths. Therefore, we propose that the rainfall increases the water content of the ground objects, which reduces the reflectance values of the ground objects, and the more rainfall, the faster the reflectance values of the ground objects decrease; when there is flood on the ground, the reflectance values will be close to that of the flood water. In addition, we suppose that the reflectance values of ground objects change linearly during a short time period. For a pixel, its time series are as follows:

\[
[r_m, r_n, r_{n+1}, r_{n+2}, r_k]
\]

where \(r_n\), \(r_{n+1}\) and \(r_{n+2}\) are the reflectance values at time \(t_n\), \(t_{n+1}\) and \(t_{n+2}\), respectively, and these values are missing because of the influence of clouds; \(r_m\) and \(r_k\) are the reflectance values at time \(t_m\) and \(t_k\), respectively, and these values are valid. Furthermore, the rainfall of this pixel at time \(t_n\), \(t_{n+1}\) and \(t_{n+2}\) are \(p_n\), \(p_{n+1}\) and \(p_{n+2}\), respectively. Then, \(r_n\) can be calculated by the following equation:

\[
r_n = r_m + (r_k - r_m) \times w
\]

\[
w = \frac{p_n}{p_n + p_{n+1} + p_{n+2}}
\]

After all the pixels of missing data filled by employing the above equations, the time series reflectance values of each pixel were fitted by linear harmonic model. The fitted results constituted a cloud-free data cube with low spatial and high temporal resolution in time dimension.

### 3.1.2 Constructing Landsat-like data cube

We used spatiotemporal data fusion algorithm to construct Landsat-like data cube. Among all spatiotemporal data fusion algorithms, we selected the FSDAF algorithm which can predict land use changes well (Zhu et al. 2016). As shown in Fig. 2, the input data of FSDAF algorithm are as follows: Landsat-8 OLI image and MODIS image at \(t_0\), another MODIS image at \(t_1\) (Zhu et al. 2016); the output of FSDAF algorithm is Landsat-like image with both high spatial and high temporal resolution which constitutes the Landsat-like data cube in time dimension. It should be pointed out that, when running the FSDAF algorithm, a MODIS image at \(t_1\) is taken from the cloud-free MODIS data cube.

FSDAF algorithm includes five main steps: (1) Classify Landsat-8 OLI image at \(t_0\), and calculate the proportion of each class in each pixel of MODIS image at \(t_0\). (2) Estimate temporal change of each class. (3) Predict initial Landsat-like image \(t_1\). (4) Interpolate the MODIS image at \(t_1\) by using thin plate spline method, and calculate the residual of each band. (5) Predict the final result by using neighboring similar pixels (Zhu et al. 2016).
3.2 Extracting flooded area

By using the random forest algorithm, we extracted the flooded area from Landsat-like data cube. Since the generated flood spatial distribution did not change obviously in the adjacent time, we took out the extracted results at a certain interval as our final results.

3.3 Evaluating cloud-free MODIS data cube

We evaluated the cloud-free MODIS data cube from quantitative and qualitative aspects. In quantitative evaluation, we simulated the cloud areas using observed data and used the method in Section 3.1.1 to remove the simulated cloud areas; then, we calculated root-mean-square error (RMSE), mean difference (MEAN_DIFF) and correlation coefficient (R) between observed data and the results of cloud removal. In qualitative evaluation, we visually compared the images with cloud areas with their corresponding results after cloud removed.

3.4 Evaluating Landsat-like data cube

Evaluations are usually performed by comparing Landsat-like images in Landsat-like data cube with its corresponding Landsat images. However, most Landsat images in the period of this study were covered by cloud areas and could not be used. Therefore, we evaluated Landsat-like data cube from three aspects: (1) visually evaluated the Landsat-like data cube; (2) evaluated the accuracy of flood extraction results, which could indirectly reflect the quality of Landsat-like cube; (3) compared flood results extracted from Landsat-like data cube with those from reference data.
3.5 Evaluating the accuracy of flood extraction results

Due to the small number of available reference images, it was impossible to evaluate the accuracy of each flood extraction result by using the corresponding reference image of the same date. We adopted a compromising scheme, that was, using reference images close to the date of flood extraction results to evaluate the accuracy. After evaluation, flood extraction results were compared with each other and adjusted manually, and finally, reliable flood extraction results were obtained.

4 Results

4.1 Evaluation results of cloud-free MODIS data cube

Table 2 shows the RMSE, MEAN_DIFF and R at different wavelengths. First, the RMSE and MEAN_DIFF at short wavelengths (Band3, Band4, and Band1) were lower than those at long wavelengths (Band2, Band6, and Band7), and they were lower than 0.007 and 0.003, respectively, which indicated that the method in Section 3.1.1 can achieve better results at short wavelengths. Second, MEAN_DIFF values at short (Band3, Band4 and Band1) and long wavelengths (Band2, Band6 and Band7) were lower and higher than 0, respectively, indicating that reflectance values after cloud removal were lower than the original reflectance values at short wavelengths and higher than the original reflectance values at long wavelengths. Therefore, the flood area extracted from images at short wavelengths would be larger than that from images at long wavelengths. Third, the correlation coefficient R at Band3 and Band4 were 0.75 and 0.71, respectively, which might be caused by high variances of Band3 and Band4; while the correlation coefficients at other bands were all higher than 0.85, indicating that there was a strong linear correlation between reflectance values after cloud removal and the real reflectance values. As can be seen from Fig. 3, thin cloud and thick cloud were well removed using method in Section 3.1.1, and flood information was well retained in the generated cloud-free MODIS image.

In general, using method in Section 3.1.1 to generate low spatial, high temporal resolution cloud-free MODIS data cube could achieve a good effect, and the results could be used for subsequent studies.

| Band   | RMSE     | MEAN_DIFF | R   |
|--------|----------|-----------|-----|
| Band1  | 0.0061   | -0.0009   | 0.89|
| Band2  | 0.0143   | 0.0061    | 0.94|
| Band3  | 0.0068   | -0.0017   | 0.75|
| Band4  | 0.0093   | -0.0024   | 0.71|
| Band6  | 0.0117   | 0.0057    | 0.86|
| Band7  | 0.0074   | 0.0033    | 0.93|
The spatial resolution of both observed Landsat images and images in Landsat-like data cube generated by the spatiotemporal data fusion algorithm was 30 m. However, the temporal resolution of observed Landsat images was 16 days, relatively low; there were large areas of missing data in images because of the influence of clouds, which resulted in discontinuous spatial coverage. Therefore, it was impossible to capture the dynamic changes of flood disasters by observed Landsat images in detail. On the contrary, the temporal resolution of Landsat-like data cube could reach 1 day, and the effects of clouds were eliminated. High-frequency dynamic monitoring of flood disasters could be achieved by using Landsat-like data cube.

We randomly selected eight Landsat-like images between July 17, 2021, and October 17, 2021, for display (Fig. 4). In general, Landsat-like data cube generated by the spatiotemporal data fusion algorithm were in good effect. Its spatial coverage was complete and continuous, and it reflected the spatial distributions of each land use type (such as vegetation, construction land, water body, and cultivated land). The extent of flood disasters in each image was clearly visible. However, some noises appeared in Landsat-like images, which was mainly caused by cloud shadows in some MODIS images; it did not affect the high-frequency dynamic monitoring of floods using Landsat-like data cubes.

In terms of the accuracy evaluation of flood extraction results, most of the overall accuracy, producer accuracy and user accuracy were higher than 0.80 (Fig. 5), indicating that the flood extraction results were good; most of Kappa coefficients were higher than 0.75 (Fig. 5), indicating that there were a good consistence between flood extraction results and reference data. The flood extraction result on July 31 was the best, and its overall accuracy, producer accuracy and user accuracy were the highest. In addition,
its Kappa coefficient was 0.83, indicating that the reference data had a good consistency with the extraction result. This was mainly because the weather on July 31 was clear, and MODIS image had no data-missing areas, which made the generated Landsat-like image on July 31 close to the real image. But there was an undesired evaluation results on July 24, the overall accuracy, producer accuracy and user accuracy were 0.78, 0.79 and 0.76, respectively, and its Kappa coefficient was 0.73, which mainly due to the adopted compromising evaluation scheme of flood extraction results and the small number of reference images before July 24.

Figure 6 shows the comparisons between reference images and Landsat-like images. In general, the flood extents from the three kinds of reference images were consistent
with those from the Landsat-like images on the corresponding date. Among them, flood extraction results from reference images on July 27 and September 30 had the best consistency with those from the corresponding Landsat-like images, while there was a slight difference on September 14 between flood extraction results from reference image and Landsat-like image.

Above analyses verify the quality of Landsat-like data cube generated by spatiotemporal data fusion algorithm and the accuracy of flood extraction results.

4.3 High-frequency flood disaster monitoring results based on Landsat-like data cube

Figures 7, 8, 9 and 10 show the statistics of flood areas and the spatial distribution of flood disaster, respectively. High-frequency monitoring of flood disaster could be achieved very well by Landsat-like data cube.

There are two peaks in Fig. 7, indicating that the study area experienced two flood disasters from July 17 to October 16 and the first was more severe than the second. The first flood disaster happened during July 17 to September 15. The growth period and the recession period of the first flood disaster were July 17–31 and July 31–September 15, respectively. The area increased from 95.53 to 668.36 km$^2$ and the spatial distribution gradually expanded from north to south, from scattered point distribution to concentrated plane distribution in the growth period (Fig. 8); while in the recession period, the flood area decreased from the maximum value of 668.36–0.56 km$^2$, and the spatial distribution gradually shrank from south
Fig. 7 Flood areas

Fig. 8 Flood extents during July 17 to August 19
to north and from outside to inside until August 22 when the flood distribution turned into point-like distribution (Figs. 8, 9). The second flood disaster occurred from September 15 to October 16. During the growth period which was from September 15 to September 24, the flood area increased from 0.56 to 303.88 km², with the spatial distribution reaching the widest range on September 24 (Fig. 9); while in the recession period which was from September 24 to October 16, the flood area decreased to 3.95 km², and the spatial distribution shrank from west to east (Figs. 9, 10).
5 Conclusions and discussion

Despite the wide application of remote sensing technology in monitoring flood disaster, there are two limitations that make remote sensing technology fail to conduct high-frequency monitoring of flood disaster. On the one hand, although cloud removal algorithms have been widely proposed, due to the neighboring similar pixels selected to fill cloud pixels, it may lose flood information when applied to flood monitoring. On the other hand, the limitation of current technology makes it impossible for remote sensing technology to monitor flood disaster with both high spatial and high temporal resolution. Therefore, in order to overcome these limitations, we presented an approach to conduct high-frequency dynamic monitoring of flood disaster based on remote sensing data cube with high spatial and temporal resolution. We proposed to remove clouds by using the information provided by rainfall data. Subsequently, the cloud-free MODIS data cube was constructed by the proposed cloud removal algorithm, and the evaluation results verified the ability of this proposed algorithm in monitoring flood disasters. In addition, Landsat-like data cube with both high spatial and high temporal resolution was constructed by fusing the cloud-free MODIS data cube and one Landsat image based on the spatiotemporal data fusion algorithm; the evaluation results of Landsat-like data cube indicated that Landsat-like data cube could be used to monitor flood disaster in high-frequency. We tested our approach by conducting high-frequency dynamic monitoring of flood disaster occurred in Henan Province, PR China. And testing results showed that two flood disasters occurred in the study area from July 17 to October 16. The first was during July 17 to September 15 with maximum affected area of 668.36 km². The second was from September 15 to October 16 with maximum affected area of 303.88 km². Our study can provide a general method for high-frequency monitoring of flood disaster.

Unlike NSPI (Chen et al. 2011), SMASTS (Yan and Roy 2020) and other cloud removal algorithms which use neighboring similar pixels for cloud removal, our proposed cloud removal algorithm makes good use of the information provided by rainfall data which can reflect the change of reflectance value of a ground object corresponding to the pixel. Beforehand, (Liu et al. 2002) proposed that the increase in water content of a ground object can reduce reflectance value at all wavelengths due to the absorption effect of water. Based on this conclusion, we proposed the hypothesis that the rainfall increases the water content of the ground objects, which reduces the reflectance values of the ground objects, and the more rainfall, the faster the reflectance values of the ground objects decrease; when there is flood on the ground, the reflectance values will be close to that of the flood water. This is the foundation of the following proposed cloud removal algorithm using the information provided by rainfall data. Moreover, the linear harmonic model was used after filling the cloud pixels, which further removed outliers (Roerink et al. 2000; Zhou et al. 2015) and made the cloud removal results more reliable. This is why the proposed cloud removal algorithm is more effective when in monitoring flood disaster.

It should be pointed out that many spatiotemporal data fusion algorithms have been developed, such as STARFM (Gao et al. 2006), ESTARFM (Zhu et al. 2010) and the like. Although they have excellent performance in vegetation phenology monitoring, they are unable to monitor land cover changes because they were proposed under the assumption that no land cover changes. In contrast, the FSDAF algorithm we used solves this problem by using thin plate spline (TPS) interpolation method to downscale MODIS data so that spatial changes can be well predicted (Zhu et al. 2016), which makes FSDAF algorithm effective in monitoring sudden change of land use types caused by flood disaster.
Therefore, the Landsat-like data cube with both high spatial and high temporal resolution generated by FSDAF algorithm can reflect the temporal and spatial changes of flood disaster and can be used to achieve high-frequency monitoring of flood disaster.

In addition, although we achieved high-frequency monitoring of flood disaster based on Landsat-like data cube in this study, there was a limitation. When evaluating the accuracy of flood extraction results, due to a lack of enough real observed remote sensing data, we adopted a compromising scheme, that was, using reference images closed to the date of flood extraction results to evaluate the accuracy. The adopted scheme could bring errors to the evaluation results. In our future work, evaluating the accuracy of flood extraction results by employing other types of data will become the focus of our research.

Author contributions All authors have made a substantial contribution to this research and have approved the final manuscript. ZW contributed to data processing and writing; ZG contributed to data acquiring, checking results of data processing and checking manuscript.

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Declarations

Conflict of interest None.

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