Determination of inundation area based on flood hazard for a global water risk assessment

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Abstract The authors determined flood areas accurately in emergency response efforts as soon as possible. Estimation of a flood periphery is important to determine a fundamental hazard for risk management. The purpose of this study was to accurately extract the spatial distribution of nationwide flood risk using MODIS time series images and to estimate a simple algorithm for computing the flood inundation depth using DEM, flow direction and river network. The authors improved the accuracy of the water extent boundary using flood inundation depth (FID) data from a one-year time series of MODIS data.

Key words flood risk; flood inundation depth (FID); MODIS; time series

INTRODUCTION

Real-time determination of flood inundation has been limited to large-scale events such as nationwide inundation. The geographic information system (GIS) including satellite images is an effective method to interpret and analyse a nationwide flood risk assessment. Moreover, satellite images are also necessary to analyse flood disasters. Remote-sensing images are an effective tool to determine flood inundation areas. Estimation of a flood periphery is important to determine a fundamental hazard for water risk management. Many studies have been conducted by using remote sensing data to detect spatial and temporal changes in the extent of flood inundation, including the delineation of wetlands (Martineza *et al*., 2007; Islam *et al*., 2010). The normalized difference water index (NDWI), a satellite-derived index from near-infrared (NIR) and short-wave infrared (SWIR) channels (Gao, 1996), is used to derive water fraction and a flood map from MODIS data. The land surface water index (LSWI) uses a red channel in place of NIR (Delbart *et al*., 2005; Xiao *et al*., 2005, 2006). Islam *et al*. (2010) used enhanced vegetation index (EVI), LSWI and DVEL (difference value of EVI and LSWI). However, NDWI is not necessarily the best way to extract water bodies. In some cases, NDWI is not very effective in extracting flooded sites because water bodies such as rivers and lakes show higher reflectance levels than vegetation. In this study, the proposed method was applied to extract water body from a channel reflectance by using Moderate Resolution Imaging Spectrometer (MODIS) time-series images and flood inundation depth (*FID*). This simple approach was to determine nationwide inundation areas from a geomorphologic point of view, rather than a hydrological model.

Objective

The purpose of this study was to accurately estimate an inundation area based on the spatial distribution of flood hazard for nationwide flood risk assessment using GIS data and MODIS time-series images. To determine the water extent boundary more accurately, the authors suggest an improved extraction method of surface water bodies with a simplified decision tree algorithm using MODIS channel 1 (CH1, Red), channel 2 (CH2, NIR) and channel 7 (CH7, SWIR) reflectance acquired from a regional flooding. The improved method was then applied to the Indus River basin in Pakistan, which was selected as the prime research focus area. The selected area suffered from a huge, severe flood caused by abnormally heavy rainfall from late July to early August 2010.

METHODOLOGY

Used data

MODIS MYD09A1 The MODIS Surface Reflectance products provide an estimate of the surface spectral reflectance as it would be measured at ground level in the absence of atmospheric scattering or absorption. MYD09A1 provides channels 1–7 at 500-m resolution in an 8-day gridded level-3 product in the Sinusoidal projection. Each MYD09A1 pixel contains the best possible L2G observation during an 8-day period as selected on the basis of high observation coverage, low view angle, the absence of clouds or cloud shadow, and aerosol loading. Science data sets provided for this product include reflectance values for channels 1–7, quality assessment, and the day of the year for the pixel, along with solar, view, and zenith angles (USGS, 2011).

Potential flood inundation depth Topography is an essential factor for hydrological models to simulate flooding and runoff. One of the most obvious factors controlling streamflow is the gradient, or slope, of the stream channel. The definition of potential *FID* is the accumulated level index overflowing the banks of a main river. It is clear that potential *FID* indicates the depth due to overflowing the banks of a river and can be defined as the accumulated level index. Kwak & Kondoh (2010) developed and proposed potential *FID* for basin-wide flood risk assessment at the national level. Actual calculation of potential *FID* required a dataset composed of DEM, flow direction and river network. Potential *FID* was determined based on DEM and the highest water level (*HWL*) of the main stream, as shown in equation (1) below:

$$H_{ij\ FID} = H_{ij(DEM)} - H_{ij(HWL\ of\ river)} \tag{1}$$

where, H is the height of surface, i is the number of pixels, and j is the number of lines.

Extraction of water body

MODIS channels were strongly absorbed by water, providing information on the inundation pattern. However, in the case of the NDWI method, this method has some weaknesses and errors in extracting the water body by using MODIS. For instance, the water value of spectral reflectance rate is higher than a forest value (e.g. forest = 0.14, clean water = 0.1). A new simple approach in this study was to determine nationwide inundation areas. A quantitative analysis was divided into three steps. In the first step, the decision tree method was applied to the main stream and surface water in the Indus River basin to discriminate each pixel with either of the two categories: water body and land surface. The classified pixel of water body was used to composite images derived from MODIS observation data during 2009. Based on the images resulting from the decision tree method, the pixels were further categorized into five relevant classes: soil, vegetation, snow, cloud, and water (clean water, muddy water and flooded water). The water body pixels satisfying the conditions of CH7 < 10%, CH1 + 10% > CH2 and CH3 < 20% were identified as water area, where MODIS L3 8-day composite surface reflectance product (MYD09A1) was computed from the MODIS Level 1B land channels 1, 2, 3, 4, 5, 6 and 7, which were centred at 0.648 μm, 0.858 μm, 0.470 μm, 0.555 μm, 1.24 μm, 1.64 μm, and 2.13 μm. In the next step, the flooding extent boundary was extracted from MODIS time-series images acquired on July and August 2010. For improved extraction of water bodies, the main stream was integrated with other thematic data. Based on the flood water extent results, the authors attempted to identify expected flood inundation depth per 250-m mesh. Finally, we calculated and estimated flooding extent area located in flood plains under potential *FID* of 9 m.

RESULTS

Figure 1 illustrates that the reflectance rate of clean water was the lowest among the classification of soil, vegetation, snow, cloud and clean water (Fig. 1(a)). In particular, the authors found that the reflectance rates of CH6 and CH7 were lower than the other channels in the case of surface water such as clean water, muddy water and flooded water (Fig. 1(b)).
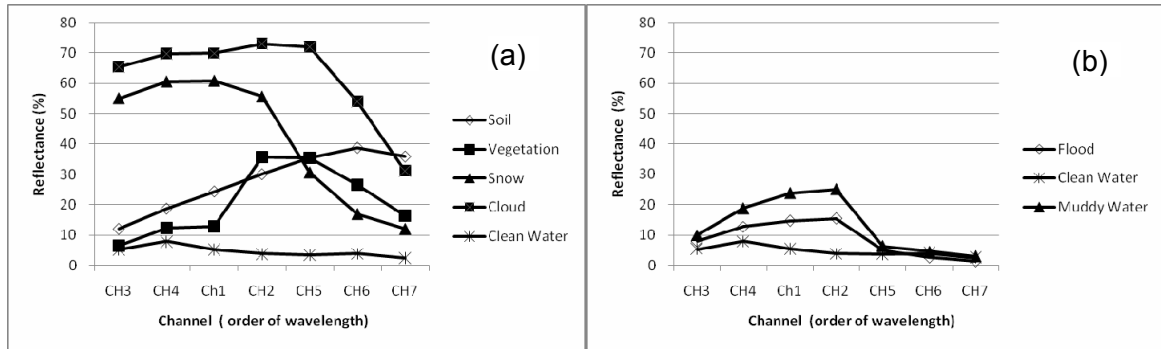
Fig. 1 (a) Surface reflectance of MODIS Level 1B land channels, and (b) reflectance rate in case of surface water.
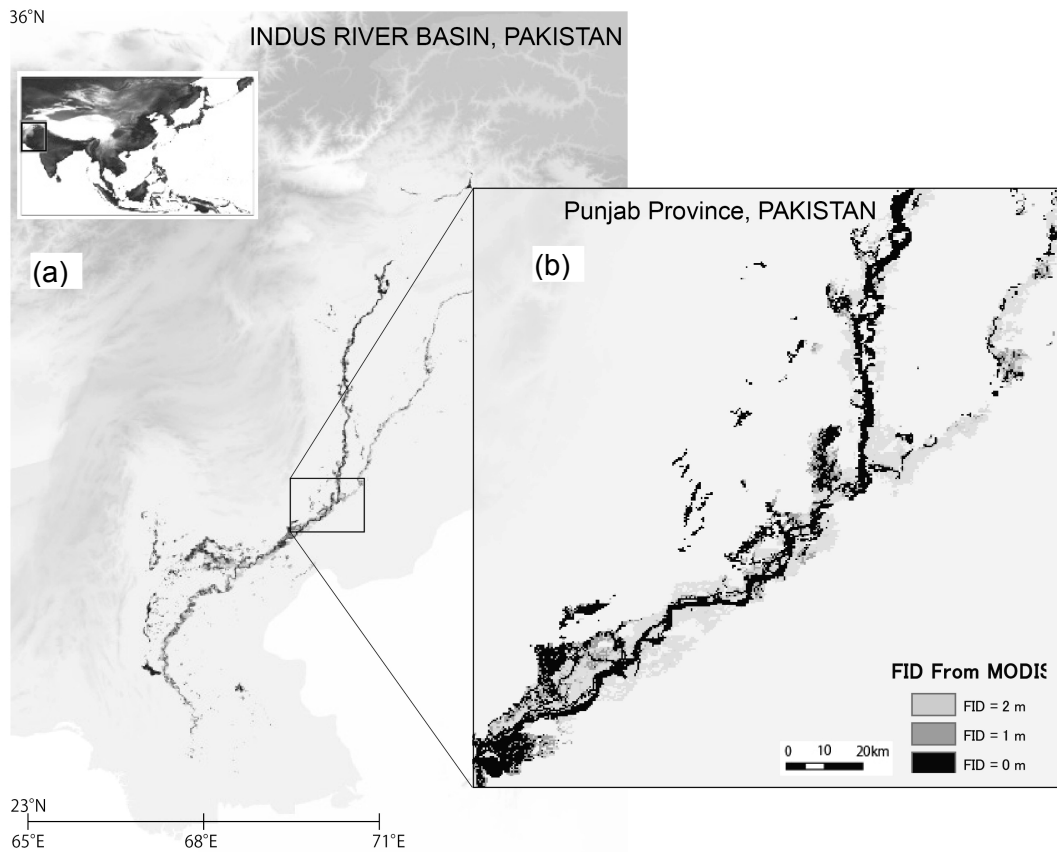
Fig. 2 Distribution of inundation map affected by flooding using potential *FID* data based on water extent boundary from MODIS MYD09A1 time series data (250-m horizontal grid spacing).

Based on the flood water extent results, the authors identified expected potential flood inundation depth per 250-m mesh. The periphery of flooded areas is directly correlated with an inundation depth around the river. Therefore, it was clear that potential flood inundation depth (*FID*) indicates the depth due to overflowing of the banks of a river and can be defined as the accumulated level index. From Fig. 2(a) (Indus River basin), it can be concluded that the potential *FID* of inundation area has a value ranging from –1 m to 9 m. Examining the relationship between *FID* ranges and MODIS images under the flooding, it was found that the inundation area was 70 253 pixels, 4390.8 km^2 in the Indus River basin from late July to early August in 2010. For instance, Fig. 2(b) shows that the inundation area under the condition of *FID* = 0 m was estimated

to be 31 444 pixels, about 4390.8 km^2. The inundation area under the condition of *FID* = 1 m was also estimated to be 8622 pixels, about 538.9 km^2. The inundation area under the condition of *FID* = 2 m was also estimated to be 6468 pixels, about 404.3 km^2. In detail, Fig. 2(b) shows the enlarged view of a partial Punjab Province, Pakistan.

CONCLUSION

This is a case study considering the independence of the data sources and the resolution of the data available at the national level. Although flood is controlled by various risk factors, the flood vulnerable area was extracted from GIS-derived data such as potential *FID* and satellite images. To conclude flood risk assessment, the authors focused on improvement of the accuracy in determining a vulnerable inundation area using a simplified decision tree method based on MODIS time-series images in the Indus River basin, Pakistan. This new approach can be a very useful tool in emergency response efforts since it can conduct extreme value analysis and predict when and what size of flooding event may occur. The water extent area can be classified as a category of land cover for flood risk assessment affecting nationwide flood damage based on potential *FID*. In the future, the authors are planning to improve the proposed assessment to be applicable on a national as well as a global level.

REFERENCES

Delbart, N., Kergoat, L., Le Toan, T., Lhermitte, J. & Picard, G. (2005) Determination of phenological dates in boreal regions using normalized difference water index. *Remote Sens. Environ.* **97**, 26–38.

Gao, Bo-Cai (1996) NDWI a normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sens. Environ.* **58**, 257–266.

Islam, A. S., Bala, S. K. & Haque. M. A. (2010) Flood inundation map of Bangladesh using MODIS time-series image. *J. Flood Risk Management* **99**(4), 333–339.

Kwak, Y. J. & Kondoh, A. (2010) A study on the assessment of multi-factors affecting urban floods using satellite image: a case study in Nakdong Basin, S. Korea. *Adv. Geosci.* **17**, Hydrological Science (HS), 265–278.

Martineza, J. M. & Toanb, T. (2007) Mapping of flood dynamics and spatial distribution of vegetation in the Amazon floodplain using multitemporal SAR data. *Remote Sens. Environ.* **108**(3), 209–223.

Xiao, X., Boles, S., Frolking, S., Li, C., Bau, J. Y. & Salas, W. (2006) Mapping paddy rice agriculture in South and Southeast Asia using multitemporal MODIS images. *Remote Sens. Environ.* **100**, 95–113.

Xiao, X., Boles, S., Liu, J., Zuang, D., Frolking, S. & Li, C. (2005) Mapping paddy rice agriculture in southern China using multitemporal MODIS images. *Remote Sens. Environ.* **95**, 480–492.

USGS (2011) United States Geological Survey https://lpdaac.usgs.gov/lpdaac/products/modis_products_table/surface_reflectance/8_day_l3_global_500m/myd09a1 (accessed January 2011).