Operational Identification of Inland Excess Water Floods Using Satellite Imagery

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1 Introduction

Inland excess water is a type of flood where large areas are temporary inundated by water remaining in local depressions due to a surplus of water, which is caused by lack of runoff, insufficient evaporation and low infiltration capacity of the soil or by upwelling of groundwater (VAN LEEUWEN et al. 2012). Scientifically and operationally, this type of flood is different from for example river floods. The extent and duration of inland excess water floods depend on a complex set of inter-related meteorological, geomorphological, pedological, geological, hydrological and anthropogenic factors (KUTI et al. 2006).

It is important to acquire knowledge of the exact location and extent of the inundations for several reasons: (1) authorities need to have this information to be able to prevent and/or respond to inland excess water, (2) their size and location are needed to understand the role of the different natural and anthropogenic factors in the formation of the inundations, and (3) to develop models to estimate when and where inland excess water will develop.

Traditionally, fieldwork was executed to acquire information on the locations of inland excess water occurrences. More recently, remote sensing techniques have been applied to measure the extent of the inundations more efficiently and with higher accuracy. Scientific studies using remote sensing have been published, mainly in Hungarian. Examples are among others CSEKŐ (2003) who used radar data to identify inland excess water, and LICSKÓ & DITZENDY (2003) who visually identified inundations on near infrared colour aerial photographs. Scientific results in English have been published by MUCSI & HENITS (2011) who applied advanced image processing techniques on Landsat imagery, and VAN LEEUWEN et al. (2013) who showed that satellite data can be suitable for classifying inland excess water. The aim of this study is to evaluate RapidEye imagery and to find a (semi-) automatic image processing method to identify inland excess water inundations on large areas in an operational manner.

2 Methods

To be able to identify inland excess water inundations on an operational basis, remote sensing data with sufficient spatial, temporal and spectral resolution is necessary. Although aerial imagery is suitable to identify inland excess water for smaller areas (VAN LEEUWEN et al. 2009), it was not included in this study due to the relatively high costs, and because it requires considerable processing time compared to satellite data.

Vogler, R., Car, A., Strobl, J. & Griesebner, G. (Eds.) (2014): GI_Forum 2014. Geospatial Innovation for Society.

Depending on the specifications, satellite images cover large areas and are nowadays affordable, even in circumstances where several images of the same area need to be acquired over a short period of time. Earlier research showed that the spatial and spectral resolution of LANDSAT data is sufficient to identify and classify inland excess water (RAKONCZAI et al. 2001, MUCSI & HENITS 2010), but that its low temporal resolution of only 16 days is insufficient for operational use. To study the phenomenon, a platform is required with a high temporal resolution and with programming capability. The recent very high resolution satellite systems like IKONOS or GeoEye would provide more than sufficient spatial resolution and high enough spectral and temporal resolution, but to regularly purchase their data for a large area is financially unrealistic.

The RapidEye satellite consortium provides data with daily temporal resolution, 5 meters spatial resolution, and 5 spectral bands from the visible to near infrared part of the electromagnetic spectrum, which is sufficient to perform (semi-)automatic classification. The data is reasonably priced and therefore it is possible to acquire data on a regular basis. For this study, test data sets were acquired during three periods (see table 1). For each period, the individual images were atmospherically corrected and mosaicked together.

Tab. 1: Parameters of the programmed RapidEye acquisitions

Date	**Total acquisition area (km^2)**	**Number of images**	**Number of acquisition days**	**Amount of inland excess water**
March 2011	9000	25	2	Severe
March 2013	8000	25	3	Some
April 2013	8000	25	6 acquisition days (April 8 – April 20)	Severe

Besides requirements regarding the base data, also the image processing technique to derive the inland excess water patches needs to be suitable for the application. The method should be accurate, easy to implement, fast to execute and not require too much ancillary data. Four methods were tested: (1) ISODATA; an unsupervised clustering method that does not require any training ahead of the classification. This method is fast and robust, but requires interpretation of the output classes. (2) Maximum likelihood; a commonly used supervised classification method that assumes normal distribution of the classes within the image. It does not require further input from a user other than the training set. (3) Spectral mixture analysis; a method that aims to determine the spatial ratio of spectrally homogeneous land cover types within one pixel. These so called end-members are selected by taking the extremes in a point cloud that results from transforming the original data set using the principal component transformation. The resulting end-member composite is reclassified using the maximum likelihood classification. The method provides fuzzy class information, but is sensitive to systematic errors in the input data set. (4) Feed forward artificial neural network; a mathematical approach that is a simplified model of the functioning of the brain where the aim is to train a network of interconnected nodes to store knowledge on the combination of inputs which results in a certain output. The training is computationally intensive, but the network itself is robust and can cope with outliers and other errors in the training data set.

The results of the ISODATA classification were only visually interpreted and evaluated, because it is not possible to statistically evaluate the accuracy of the unsupervised method.

No external field data was available from the study area; therefore, the accuracy of the other three methods was evaluated using internal validation.

3 Results

The mosaic of the 2011 data set was classified using all four classification methods (VAN LEEUWEN et al. 2013). The ISODATA methods resulted in severe over-classification of the inland excess water areas. Therefore the method was rejected, even though from the perspective of operability, this method is very suitable. The results of the other classifications are given in table 2.

Tab. 2: Supervised classification results of the 2011 data set

Method	Overall accuracy	Cohen's Kappa
Maximum Likelihood	0.95	0.94
Spectral mixture analysis	0.75	0.71
Artificial neural network	0.96	0.96

The result of the spectral mixture analysis was strongly influenced by the haze in the study area, resulting in misclassification of soil, and in a low overall accuracy. The results of the maximum likelihood and artificial neural network classifications were good. The maximum likelihood method gave similar results as the artificial neural network method, but is simpler, can be executed faster and is more practical in operational circumstances. Therefore, for further classification only the maximum likelihood method was used.

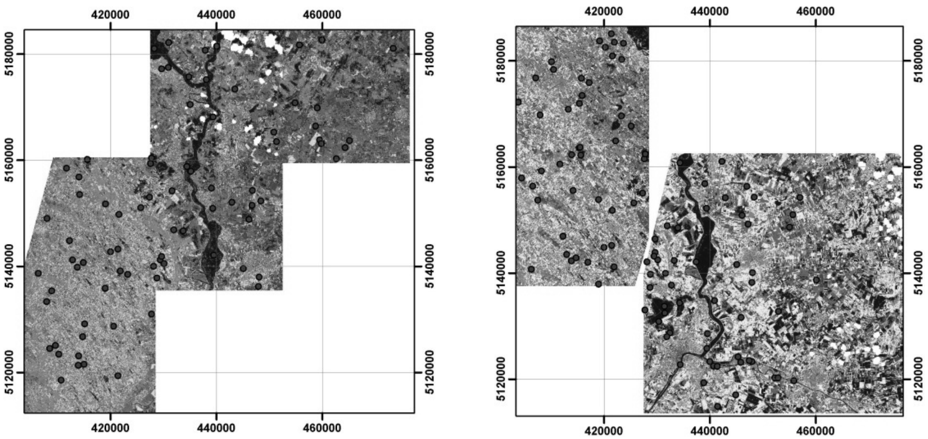

Fig. 1: Classification results of the mosaic of April 13-20, 2013 (left) and of April 8, 2013 (right). The red dots are the locations of the evaluation points.

The March 2013 data set was acquired during a period with minor inland excess water. The maximum likelihood classification resulted in only small amounts of inland excess water, and is therefore not presented here. The April 2013 mosaic was acquired on 6 different days during a period of 13 days with large atmospheric differences. This resulted in severe problems during the processing of the data, because the different days showed large radiometric differences for similar areas. To be able to classify the images, the area was split into three subareas which were classified separately. The results for two mosaics were evaluated at 179 points (see figure 1). The April 13-20 classification had an accuracy of 0.90 for the inland excess water class, while the April 8 showed an accuracy of 0.98.

4 Conclusion

Inland excess water inundations cover large areas but fluctuate in size rapidly. RapidEye imagery is suitable for operational identification of inland excess water due to its high temporal resolution, its sufficient spectral and spatial resolution, and its affordability. The maximum likelihood classification provides the best results in terms of accuracy and applicability under operational circumstances because it is fast and requires limited auxiliary data. Nowadays, affordable satellite images with high temporal and sufficient spatial resolution can be acquired to study inland excess water. As with other extreme weather related phenomena; it is difficult to acquire and process good quality satellite images.

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