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GMES4Mining – Description of a Flooding Process in Mining Areas using spectral Indices on multi-temporal Landsat Imagery

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Summary: The R&D project GMES4Mining aims to support particular tasks within the different phases of a mining life cycle. Within this project one task concentrates on vegetation monitoring in order to detect damages caused by mining. In Germany several mining districts have been exploited for a long time. Mining areas are associated with certain environmental hazards, such as surface subsidence and flooding. The change in substrate compaction due to mineral extraction provokes surface subsidence, down to the point that the surface can reach the groundwater level. This phenomenon provokes negative effects on vegetation, which can be observed using remote sensing. A temporal series of Landsat images from 1999 to 2012 has been used to detect temporal changes in vegetation by calculating 3 spectral indices. The spectral indices relate to vegetation greenness, leaf pigments and water content. The aim of this study is to detect early indications and to monitor the process of flooding in abandoned mining sites, to prevent environmental and civil hazards. Moreover, it is investigated whether these indices are appropriate to detect flooded areas and to describe the vegetation succession, once a flooded area is drained. It is expected that this methodology will be applicable to the future Sentinel-2 data, in order to monitor and prevent hazards in mining areas.

Zusammenfassung: GMES4Mining – Beschreibung des Flutungsprozesses in Bergbaugebieten durch Spektralindizes aus multitemporalen Landsat Daten. Das F&E Projekt GMES4Mining hat das Ziel, bestimmte Aufgaben in den verschiedenen Phasen des Bergbauzyklusses zu unterstützen. Innerhalb des Projektes besteht eine Aufgabe darin, ein Vegetationsmonitoring durchzuführen, um Schäden, die durch den Bergbau hervorgerufen wurden, zu detektieren. Dieses ist der Kontext der Studie, die hier beschrieben wird. Bergbau wird in verschiedenen Regionen Deutschlands seit langer Zeit durchgeführt. Der Bergbau ist jedoch auch mit bestimmten Umweltschäden wie Bodensenkungen und Überflutungen verbunden. Die Änderung der Bodenverdichtung durch den Abbau von Bodenschätzen bewirkt teilweise Bodensenkungen bis zum Erreichen des Grundwasserspiegels. Dieser Effekt kann mit Hilfe von Fernerkundung über die Auswirkung auf die Vegetation beobachtet werden. Eine multitemporale Serie von Landsat Bildern aus den Jahren 1999 bis 2012 wurde verwendet, um zeitliche Änderungen der Vegetation mit Hilfe von drei Vegetationsindizes zu detektieren. Die Indizes beschreiben Vitalität, Blattpigmentierung und Wassergehalt. Das Ziel dieser Methode ist es, erste Anzeichen und den Verlauf einer Überflutung in Bergbaugebieten zu beobachten und Schäden vorzubeugen. Die Methoden werden auch im Hinblick auf eine mögliche Nutzung des zukünftigen Sentinel-2 Satelliten entwickelt, um mit ihrer Hilfe Bergbauschäden vorzubeugen.

1 Background

The R&D project GMES4Mining is a joint project of four partners from the industry and the university sector which started in August 2011. GMES4Mining aims to support particular tasks within the different mining phases. The tasks for which new methods are developed and tested within the project are: monitoring of vegetation, detection of ground movements and the support of the exploration process. These tasks were identified during a

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user survey carried out within the project. Besides these tasks, a spatial data infrastructure (SDI) will be created to make the developed methods available to the users.

The work described here is part of the method developments for vegetation monitoring. The monitoring of post-mining impacts at a medium scale is related to the objectives of the European DIRECTIVE 2006/21/EC (2006) which exposes in Article 13 the monitoring of solid wastes and the minimization of impacts on ground waters.

The coal mine Prosper-Haniel serves as a test site. Although it covers only 165 km², there are several thousands of square kilometres affected by post-mining impacts throughout Germany, Southern Belgium and Northern France. This poses a great socio-economic impact and has political relevance for a highly populated area with estimated 20 million citizens.

This project aims to investigate the potential of multi-temporal satellite images to monitor vegetation in order to detect damages caused by mining. In a coming phase, hyperspectral images will be added for a combined vegetation monitoring approach. Therefore, the described study is the first part of the development of vegetation monitoring in mining areas.

2 Environmental Process

Adverse effects such as surface subsidence and flooding can be linked to mining activities. These impacts are related to the active water pumping during the exploitation of the mineral. The extraction of water from the ground water causes a change in the pressure of the granular structures of the ground. Without water, these materials present a lower cohesion and lose their buoyancy resulting in a compacting, provoking a subsidence of the ground surface (BUSCH et al. 2012, PREUSSE et al. 2008).

From an optical point of view, these phenomena can be indirectly monitored by the observation of changes in the vegetation. Vegetated areas undergo an increase of leaf productivity and water content in areas of high ground water level. However, if the ground water level is close to the surface, plant roots overwater, leading to the yellowing of leaves and the death of the plant. In the last step of the process, water emerges at the surface (Fig. 1).

Along these three flooding steps vegetation can be observed (greenness, yellowness and leaf water content) with remote sensed data through specific spectral indices, which provide enhanced information about chlorophyll (normalized difference vegetation index, NDVI), other pigments (plant senescence reflectance index, PSRI) and water content in leaves (normalized difference moisture index, NDMI) over time.

3 Objectives

Mining is one of the most important economic activities in Germany, and particularly in the Ruhr Valley area. Due to the intensive modification of the landscape, mining generates



Fig. 1: Mining activities can provoke ground subsidence up to the point where the ground surface reaches the ground-water table and water emerges.

environmental impacts that need to be monitored. The main goals of this study are the monitoring of mining impacts using remote sensing techniques such as the flooding process and the identification of flooded areas. Moreover, the ecological succession process of vegetation after drainage of the flooded areas is also monitored.

4 Methods

4.1 Study Site

Kirchheller Heide is a forested area located north of Oberhausen and Bottrop in the Ruhr area in Germany (Fig. 2). The area lies on the Low-Rhein sandstone plate, between the Lippe and Emscher valleys. Many streams run along the area, such as the Rotbach and the Schwarzbach. It is part of the Natural Park "Hohe Mark". The landscape had experienced many changes over time. In the 20th century, the area was reforested with pine trees, mainly, after several centuries of cattle and agricultural exploitation. Today, the area is a mosaic of different habitats, such as moors, heaths, coniferous and deciduous forests, and grasslands, and for this reason it is a protected area since 1926.

The Prosper-Haniel mine underneath the Kirchheller Heide is one of the most productive hard coal mines in Germany. It is operated by the Ruhrkohle Aktien Gesellschaft (RAG). Approximately 3.2 million tons per year of high-quality coal are extracted, which is primarily used for the production of electricity. The coal is planned to be gained until 2018 in four mining operations at depths between 700 m and 1246 m (RAG 2013).



Fig. 2: Location of the study site in Kirchheller Heide, in the Ruhr area (Germany). Enlarged, the flooded and the control areas A and B are shown.



Fig. 3: Study area in Kirchheller Heide (dashed-line box in Fig. 2) shown here as an RGB composite of bands B4-B5-B7 of Landsat. Solid line: test site for this study, dotted line: flooded area. 1999: pine forest, flooding started in the northern and southern surroundings; 2003: water flooded the pine forest; after 2006: pond shrinking; 2011: pond dried out.

Kirchheller Heide has been selected as a study site because several episodes of flooding occurred parallel to the coal mine exploitation. These flooding events are well known and documented in detail by local forestry authorities.

A pine forest area (*Pinus sylvestris*) within Kirchheller Heide was selected for the scope of the study (Fig. 2). In 2000, water emerged to the surface forming a pond.

Due to rising water levels and the danger of flooding a neighbouring road, the forestry and water authorities built a drainage pipe under the road in 2006. After this engineering action, the pond dried out and was initially colonized by shrubs, and followed by birch tree samples in a second phase of succession. In Fig. 3, the evolution of the flooded area can be observed. In 1999, water emerged at the surface in the surroundings of the test pine forest. In 2003, the test site was completely flooded and the pine forest totally gone. After 2006, the pond was actively shrunk, so in 2010 the extension of the flooded was considerably smaller. In 2011, no water in surface can be seen in the Landsat scene. Therefore, this study site permits the investigation of 1) the flooding process between 1999 and 2000, 2) the identification of flooded areas between 2000 and 2006 and 3) the ecological succession after the pond drainage from 2006 onwards.

4.2 Optical Remote Sensing for Monitoring Vegetation

4.2.1 Image acquisition and preprocessing

The main goal of this study is the monitoring of the flooding process, the identification of flooded areas and the monitoring of vegetation recovery in a test site in Kirchheller Heide, over a given period of time. Therefore, it was required to use satellite data covering the full study area with a high frequency since 2000, when the flooding occurred, and before. The most suitable option was to use a Landsat time series (Landsat-5 TM and 7 ETM+), covering the period between 1999 and 2012, with the exception of 2007, when there was no image available.

Moreover, Landsat covers a large spectral range, which enables the calculation of different spectral indices. Particularly, water content indices such as NDMI require the use of the short infrared spectra, which is not available in most current sensors.

Furthermore, one important goal of this study is to develop methods for monitoring flooding events which can be applied using future generations of satellites for vegetation monitoring at landscape scale, such as Sentinel-2. To date, Landsat is the most similar sensor available to Sentinel-2, regarding spectral range, temporal and spatial resolution (Tab. 1).

Landsat-7 ETM+ was preferred for this study. However, after the failure of the scan line corrector (SLC) in May 2003, Landsat-7

	Sentinel-2	Landsat-7 ETM+
Swath	290 km	185 km
Temporal resolution	5 days	16 days
Spatial resolution	10 m - 20 m - 60 m	30 m - 60 m
Spectral configuration	Multispectral	Multispectral
Spectral resolution (nm)	$\begin{array}{c} B1^{*}:433-453\\ B2^{**}:457-552\\ B3^{**}:557-612\\ B4^{**}:650-680\\ B5:690-720\\ B6:725-755\\ B7:773-793\\ B8^{**}:784-899\\ B8b^{*}:855-875\\ B9^{*}:935-955\\ B10:1365-1395\\ B12:1565-1655\\ B12:2100-2280\\ \end{array}$	B1: $450 - 520$ B2: $520 - 600$ B3: $630 - 690$ B4: $770 - 900$ (B4) (B4) (B4) B5: $1550 - 1750$ B7: $2090 - 2350$ B6*: $10400 - 12500$

Tab. 1: Comparison of Landsat-7 ETM+ and Sentinel-2.

* Bands with 60 m GSD (ground sampling distance) ** Bands with 10 m GSD

images have missing data lines. Therefore, cloud-free images of Landsat-5 TM were used after 2003. As an ultimate option, Landsat-7 ETM+(SLC-off) were used when no cloud-free Landsat-5 images were available. Thirteen images corresponding to the time window of high plant activity (May-September) were selected (Tab. 2). They were radiometrically calibrated to avoid differences in reflectance between sensors (Landsat 5 TM and 7 ETM+) and solar illumination conditions due to the date and hour of acquisition. Furthermore they were atmospherically corrected in FLAASH (Exelis Visual Information Solutions, Boulder, Colorado, USA) to remove atmospheric radiance. Clouds, cloud shadows and defective pixels of Landsat-7 ETM+ (SLC-off) were masked regarding the used test areas. No pixels were affected by the defective stripes of failed Landsat-7 SLC sensor. Fortunately, only few pixels of the 2005 image were affected by clouds. The whole Landsat collection was delivered at Level-1G by the USGS (United States Geological Survey). The pixel-wise geometric matching of all delivered scenes was checked. Only the image corresponding to 2012 needed to be co-registered, while the rest of the collection matched perfectly.

Tab. 2: List of applied Landsat scenes between
1999 and 2012.

Landsat scenes acquired for temporal vegetation monitoring		
9th September 1999	Landsat-7 ETM+	
6th May 2000	Landsat-7 ETM+	
25th May 2001	Landsat-7 ETM+	
16th August 2002	Landsat-7 ETM+	
11th August 2003	Landsat-5 TM	
6th September 2004	Landsat-7 ETM+ *	
24th August 2005	Landsat-7 ETM+ *	
18th July 2006	Landsat-5 TM	
31st July 2008	Landsat-7 ETM+ *	
19th August 2009	Landsat-7 ETM+ *	
27th June 2010	Landsat-5 TM	
2nd September 2011	Landsat-5 TM	
26th July 2012	Landsat-7 ETM+ *	

*(SLC-off)

Many environmental parameters can influence the spectral response of the observed targets such as the atmospheric conditions at the moment of the image acquisition, the soil type, the weather conditions in the year, the different radiation conditions (due to slope orientation), and the phenology. To discriminate spectral response caused by the flooding process or by other environmental variables, a control of the source of the spectral variability is needed. Some spectral variability can be controlled by selecting areas with similar conditions, i.e. soil type and orientation. The atmospheric correction of all Landsat images reduces the variability of atmospheric conditions. Moreover, the calibration of the Landsat scenes also reduces differences between Landsat-7 and Landsat-5. The selection of summer images was intended to reduce variability in phenology. Nevertheless, there are many other factors that cannot be controlled. For that reason, the flooded test site was compared to two control areas. It was assumed that variations in the spectral response from one year to the next may happen, while differences in the spectral signal between control and flooded sites are due to flooding (Fig. 5).

4.2.2 Spectral vegetation indices

The known flooded area was identified on the Landsat scene of 2006, when the flooding reached its maximum extension. Moreover, a nearby control area was selected as proposed by SALVADOR et al. (2000). It had the same forest composition as the test site before it was flooded (control area A, Fig. 2). An extra control area with similar forest composition and soil type but unaffected by the ground water rise was selected and digitized (4.5 km apart), to avoid any influence of anomalies in the ground water level (control area B). Orthophotos of Kirchheller Heide from 2001 together with GPS points gathered in a field campaign performed in October 2012 were used for the location and digitization of the flooded and the control areas. In order to avoid edge effects and reduce pixel mixing and light scattering from neighbouring pixels, only central pixels were used, both for test and control areas. In the case of the test area, pixels in the centre of the flooded area were selected, while in the case of the control areas, pixels in the core forest were used.

Three indices were used to describe the three stages of the flooding process (Fig. 1): the normalized difference vegetation index (NDVI), the plant senescence reflectance index (PSRI) and the normalized difference moisture index (NDMI) (Tab. 3). NDVI has

been widely used for research, in particular for detecting vegetation changes (SALVADOR et al. 2000). PSRI was selected because it performs well to identify senescent forests (CASTRO & SÁNCHEZ AZOFEIFA 2008). NDMI was selected because it is specifically designed for monitoring leaf water content using Landsat data (JIN & SADER 2005). These indices are based on the spectral properties of different physiological processes of the plants such as photosynthesis, plant necrosis, pigments, and water content. Therefore, they are sensitive to differentiate vegetation from other targets such as water surfaces. For this reason, they are useful for the identification of flooded areas. The indices are a ratio of two or more Landsat bands, corresponding to reflectance peaks or absorption areas in the spectral signature of the plant (Fig. 4, Tab. 3). In comparison to other materials, plants absorb visible light for photosynthesis and reflect infrared light (770 - 2500 nm). Chlorophyll and other photosynthetic pigments are responsible for the absorption of the visible light, mainly in the blue and the red spectra, while infrared light is reflected because of water present in the leaves mesophyll. The health of plants is expressed in their spectral signatures. Healthy plants are photosynthetically active with high water content leading to a large increase in spectral reflectance between the visible and the near infrared spectra. This dramatic change in reflectance from red to infrared is called "red edge". On the other hand, plants that show health problems, e.g. caused by plagues, drought or overwatering, reduce their absorption of visible light and reflectance of infrared. Here, the red edge is less evident. To the human eye, the combination of not absorbed blue, green and red light results in the yellowish colour in senescent leaves.

Some spectral vegetation indices, such as NDVI, are independent of the species composition and describe vegetation exclusively in terms of biomass and net primary productivity (NPP) (GAMON et al. 1995). Nevertheless, most spectral indices are sensitive to phenological changes in vegetation (DYMOND et al. 2002). For that reason, the selection of a control area of the same tree composition was used to monitor changes in the test area.

5 Results

The variation of spectral indices during the time series of the the flooded and the control areas was investigated, in order to describe the different flooding phases. The behaviour of each spectral index is represented in time graphs (Fig. 5).

For the correct interpretation of the graphs, it is necessary to consider that control areas and the test areas do not represent the same targets along the time. Control areas A and B are pine plantations dominated by *Pinus sylvestris* and did not change their status during the studied time period. However, the flooded test site changed its composition over time. In 1999, it was a forest dominated by pines (similar to control areas A and B). Between 2000 and 2006 it was flooded (water over the surface). Around 2006 it was drained (bare soil). After 2006 ecological succession took place (shrubs and birch samples). For all three spectral indices (NDVI, PSRI and NDMI), both control areas A and B present similar spectral responses over the monitored fourteen years (Fig. 5). This is an indicator that non-affected pine forests kept similar health conditions.

The spectral values of control forests A and B vary between expected values reported for healthy vegetation, confirming that they were not under environmental stress: values reported for NDVI for green vegetation vary between 0.2 and 0.9 (TUCKER 1979). Values reported for PSRI for green vegetation range between -0.1 and 0.2 (MERZLYAK et al. 1999) and values reported for NDMI for green vegetation extend between 0 and 0.5 (JIN & SADER 2005). The observed values for the three spectral indices of the control areas in the study site are 0.5 to 0.9 in NDVI, -0.1 to 0.2 in PSRI, and 0 and 0.5 in NDMI.

In 1999, NDVI and NDMI in the test area present lower values than the control areas A and B: 0.5 (test area) versus 0.75 (control areas

Tab. 3: Definition of the spectral indices used for flooding monitoring.

Greenness		
Normalized difference vegetation in	ndex $NDVI = \frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}}$	Tucker 1979
Leaf pigments		
Plant senescence reflectance index	$PSRI = \frac{R_{Red} - R_{Blue}}{R_{NIR}}$	Merzlyak et al. 1999
Leaf water content		
Normalized difference moisture inc	dex $NDMI = \frac{R_{NIR} - R_{SWIR}}{R_{NIR} + R_{SWIR}}$	Jin & Sader 2005
2000 1000 500 0.5 1.0 1.0 1.5 20 Wavelength (μm)	See Lectance See Lectance See Lectance See Lectance See Wavelength (µm)	See Getting See Ge
Normalized Difference Vegetation Index (NDVI)	Plant Senescence Reflectance Index (PSRI)	Normalized Difference Moisture Index (NDMI)

Fig. 4: Spectral bands involved in the spectral indices used for flooding monitoring.

A and B) for NDVI, and 0.2 (test area) versus 0.5 (control areas) for NDMI. On the other hand, PSRI showed a slightly higher value in the test area compared to the control areas, i.e. around 0.

The test area showed its lowest value for all spectral indices in 2000, coinciding with the emerge of water at the surface: around -0.5 for NDVI, -1.4 for PSRI and around -2.4 for NDMI (Fig. 5). NDVI values remained low compared to the control areas A and B until 2010. It showed values between -0.5 to 0.2 in the period 2000 - 2006 and 0.3 to 0.8 in the period 2008 - 2010. After 2010 the test area reaches similar NDVI values compared to the control areas (Fig. 5). A gradual recovery of NDVI values from 2000 to 2010 is observable. PSRI and NDMI values showed only a low value compared to the control areas A and B in 2000. For all other years, PSRI and NDMI are within the same range as the control areas (Fig. 5).

6 Discussion

Mining activities are an important sector of the German economy. Like other human activities, they can cause environmental impacts that need to be monitored and controlled. Mining can cause for example subsidence and flooding that affect infrastructures, croplands and forestry resources, and thus generate a social and economic impact.

For this reason, there is an urgent need to develop methods and tools to support the surveillance and risk management, in order to follow civil and environmental policies.

Three spectral indices were tested in a German mining area in order to 1) monitor the previous phases of a flooding process of a pine forest in 2000 due to terrain subsidence caused by mining activities, 2) to identify water masses, and 3) to monitor the process of succession after the pond dried out in 2006.

The variation of the spectral indices was observed at two control sites of pine forests to limit confusion with other sources of spectral variability such as phenology or weather conditions.

The three indices were selected to identify different stages of the flooding process over time with respect to the health status of the vegetation before the flooding (NDVI), the yellowing and senescence of trees when ground water level is close to the surface (PSRI), and the presence of surface water during flooding (NDMI) (Fig. 1). They were also expected to show deviating values with respect to the control areas during the flooding period from 2000 to 2006.

In 1999 lower values of NDVI and NDMI were observed compared to the control areas, especially in NDVI, but still within the normal range reported for vegetation targets, between 0.2 and 0.9 for NDVI and between 0 and 0.5 for NDMI, meaning that trees were partially defoliated in 1999. As observed in Fig. 3, in 1999 areas north and south of our test site were flooded. Thus, it is assumed that the ground water level is close to surface under the pine forest under study. The lack of air in the rooting zone provoked the decease of the trees, which is expressed at this early stage as defoliation. The low values of NDVI in comparison to the control areas are caused by the decrease in leaf biomass and chlorophyll content in the test forest canopy. The lower NDMI values are caused by a reduction of the water content in the mesophyll of leaves in senescent leaves, plus a reduction of leaves in the observed test forest. Therefore, NDVI and NDMI seem to be good predictors of early effects of flooding in vegetation.

On the other hand, trees in the test area presented similar values to the control areas A and B for PRSI. This observation implies either that 1) this index is not appropriate for detecting early signs of flooding, or 2) trees are defoliated but leaves do not turn to yellow, or 3) a higher spatial or temporal resolution is needed to observe the yellowing of leaves (Fig. 5).

All three tested spectral indices, NDVI, PSRI and NDMI, showed a strong decrease in 2000, when the test site flooding occurred. However, NDMI and PRSI showed similar values to the control areas A and B, except for the year 2000 (Fig. 5). Therefore, PSRI and NDMI are not good enough to identify flooded areas, nor to describe the succession process after the drainage of the flooded area.

An explanation for this quick spectral response recovery may be linked to the fact that these indices are capturing the spectral reflectance of other vegetation types such as algae during the flooding period until 2006, or shrub and birch saplings after 2006, when terrestrial vegetation re-colonized the drained area.

NDVI appeared to better identify flooded areas and better describe the succession process since it presents lower values than reported for healthy vegetation from 2000 and 2006, and presents values for healthy vegetation (TUCKER et al. 1979) between 2006 and 2010, due to the presence of shrub and birch saplings in the test area.

This different behaviour of NDVI in comparison to PSRI and NDMI may respond to the fact that NDVI is not only related to pho-



Fig. 5: Spectral behaviour of the test area and two control areas (A and B) expressed through spectral indices.

tosynthetic activity, but also to biomass. However, PSRI and NDMI respond to variations in pigments and water content, which can be very high in smaller photosynthetic organisms such as algae, cyanobacteria or aquatic plants, and are not only related to terrestrial vegetation.

Another conclusion that can be extracted from our results is that changes in vegetation related to flooding are very well delimited in extension, since the control area A presented very similar spectral behaviour to the control area B, located 4.5 km away. Control area A did not show any indication of being affected by a rising ground water level (close to the surface), in which case the control area A would have shown similar spectral response to the flooded test site.

These results encourage further research on monitoring floodings using remote sensing sensors to define in a more accurate manner of finding affected areas and of developing time sequence of early flooding effects on vegetation. Landsat presents a medium resolution (30 m), which partially limits the accurate estimation of flooding in the study site. The use of higher spatial resolution imagery with a high temporal availability such as RapidEye (5 m) might improve the determination of affected areas. However, Rapid-Eye was not launched until 2009, so it was not adequate for this study site, flooded in 2000. Our study showed that the flooding process occurred over a relatively short time. In addition to the use of sensors with higher spatial resolution, it is also recommended to analyse a higher number of images per year in order to calculate the time frame between the first indications of flooding in vegetation (senescence and yellowing) and the moment when water emerges at the surface.

Moreover, we encourage the exploration of different spectral indices that are more independent on environmental variability and related only to forest biomass, in order to better discriminate flooding effects on trees.

As mentioned initially, hyperspectral images will be also used for vegetation monitoring within the GMES4Mining project. A combination of hyperspectral and multi-temporal satellite images will be used to enhance the information retrieved using Landsat data. It is expected that the methods developed here can be applied to future Sentinel-2 images because of comparable spatial, temporal and spectral resolutions of the Sentinel-2 and Landsat sensors. The smaller pixel size in the visible and near infrared bands (Tab. 1) of Sentinel-2 will enhance the estimation of flooding effects using NDVI and similar spectral indices.

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