PFG 2016 / 4, 211 – 223
Stuttgart, October 2016

Report

Impact Assessment of Oil Exploitation in South Sudan using Multi-Temporal Landsat Imagery

Alexander Mager, Oberpfaffenhofen, Lars Wirkus, Bonn & Elisabeth Schoepfer, Oberpfaffenhofen

Keywords: remote sensing, natural resources, land cover change, landscape monitoring, South Sudan

Summary: This scientific report examines the spatial impacts of oil exploitation in Melut County, South Sudan, at six points in the time span between 1999 and 2011, based on Landsat satellite data. Three features were analysed: cropland, oil well pads and roads. Feature extraction consisted of pixel- and object-based classification approaches as well as on-screen digitization. Land cover classification was performed as a base for further object-based classification of cropland areas and oil well pads. Spatial analysis of the relationship between the detected features was performed. Apart from a sharp decline in cropland areas between 1999 and 2002, croplands increased steadily over time and more than doubled in size. Oil infrastructure grew enormously in size throughout the whole time series from a single pad in 1999 to 555 pads in 2011. The example exhibited the potential of Earth observation as a tool to support the field of peace and conflict research (Mager 2013).

Zusammenfassung: *Untersuchung des Einflusses der Erdölförderung im Süd-Sudan auf die räumliche Entwicklung basierend auf multitemporalen Landsat-Bildern*. Dieser Beitrag untersucht die räumlichen Auswirkungen der Erdölförderung in Melut County im Süd-Sudan anhand von sechs verschiedenen Zeitpunkten zwischen 1999 und 2011 basierend auf Landsat Satellitendaten. Drei Objektarten wurden analysiert: Ackerflächen, Ölbohrstellen und Straßen. Die Objekterfassung bestand aus pixel- und objektbasierten Klassifikationsmethoden sowie Digitalisierung. Landbedeckungsklassifikationen wurden als Basis für weitere Klassifikationen von Ackerland und Ölbohrstellen durchgeführt. Eine Analyse bezüglich der räumlichen Zusammenhänge zwischen den erfassten Objekten wurde durchgeführt. Abgesehen von einem starken Rückgang der Ackerflächen zwischen 1999 und 2002 stieg die Fläche der landwirtschaftlich genutzten Gebiete stetig an und verdoppelte sich in ihrer Größe. Über die gesamte Zeitreihe hinweg wuchs die Erdölinfrastruktur enorm, und zwar von einer Ölbohrstelle im Jahr 1999 auf 555 Ölbohrstellen im Jahr 2011. Die Studie zeigt das Potential der Erdbeobachtung als unterstützendes Werkzeug in der Friedens- und Konfliktforschung auf (Mager 2013).

1 Introduction

Oil plays a vital role in the economy of the Republic of South Sudan, which gained independence from the Republic of Sudan only in 2011. Six years after the conclusion of the 'Comprehensive Peace Agreement' (CPA) between the government of Sudan und the Sudan People's Liberation Movement/Army (SPLM/A) in 2005, a referendum on the 9th of July 2011 ended not only this six-year interim phase and four decades of bloody North-South conflict but even more so sealed the split of South Sudan from Sudan. Since its secession South Sudan is the most oil-dependent country in the world. Almost all of the state bud-

DOI: 10.1127/pfg/2016/0300 1432-8364/16/0300 $ 3.50

get is oil revenue. Right after its independence oil represented 98% of South Sudan's state revenue. In the more recent years, the exact share is unclear because of the frequent disruptions to the country's oil production (EIA 2014). According to the World Bank (2015) the oil revenues currently account for around 60% of South Sudan's gross domestic product. Most of the oil production capacity is located in South Sudan, whose proved oil reserves account for 3.5 billion barrels, being more than twice as high as those of Sudan (EIA 2014). Nevertheless, being a landlocked country, South Sudan still remains dependent on Sudan. It still is forced to use Sudan's pipelines and port to export its oil. Armed civil conflicts within South Sudan and continued tensions between the two countries, partly violent, but also disagreements over oil revenue sharing have cut down oil production from both countries over the past few years with the consequence of severe economic crisis in both countries (EIA 2014, Grawert 2013).

The development of the oil fields took place against the backdrop of Sudan's second civil war, which lasted from 1983 to 2005. The discovery of oil added a major economic component to the conflict and deepened the divide between North and South. The central government in Khartoum tried to achieve full control of the oil fields, a majority of which is located in the South. Hence, oil exploration was mostly limited to the central and south-central regions of the unified Sudan at that period. Thousands of people were evicted from their homes in order to secure undisturbed development of the fields. Villages were destroyed, people killed and thousands forcefully displaced (Robinson 2003, Terminski 2011). Apart from the bloodshed, oil field development led to big-scale environmental problems. Crop patterns changed, poorly constructed roads led to drain blockages which caused droughts and floods and polluted ponds pose a danger for humans and animals alike (BICC 2013, ECOS 2006, ECOS 2009, ECOS 2014).

Earth observation is capable of providing important information about such processes on the ground. Remote sensing data are used as an independent source of data to complement local information. This is in particular important for regions where traditional means of survey are not possible due to geographic or financial considerations, or limitations in time. Other hindering factors might be great travel distances, security concerns, or both. In the above-described context the use of satellite images seems to be most suitable. However, so far only a few studies have documented the benefits of remote sensing within the context of impact assessment of oil exploitation. Prins (2009) compared Landsat satellite data for the years 1999, 2000, 2001 and 2005 for parts of Melut County in Sudan and utilized Quickbird data in order to investigate the land use development during the preliminary phase of oil exploration. Sergey & Oganes (2009) and Aksyonov (2006) investigated the impacts of oil extraction on the Russian landscape using Landsat data. Even though they focus on oil spills, which is not of concern for this study, they also captured oil infrastructure from satellite data and analyzed the possibilities and limits of doing so. Russia was also the focus for Hese & Schmullius (2009) who, amongst other features, classified oil well pads from Landsat-5 data. Landsat-7 data was used by Duncan et al. (2014) to assess the impact of oil exploration activities in the Sahara. In 2014, Plank et al. presented an automated feature extraction procedure based on the combination of a pixel-based unsupervised classification of polarimetric synthetic aperture radar data (PolSAR) and an object-based post-classification. All these studies utilize the principle of change detection, i.e. the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh 1989), for monitoring the different features of interest.

This paper provides an overview of oil-related developments in Melut County, located in the Upper Nile region, in South Sudan for the period from 1999 to 2011. The objective of the study was to map human activity in the context of oil extraction and to assess its impacts in the area of interest (AOI). In order to document the spatio-temporal development of the oil fields and impacts on their surroundings, six points in time were chosen. The study aimed at answering the following research questions: What changes can be observed by means of remote sensing? What spatial connections exist between those observed changes? Can they be explained with existing knowledge about events related to oil production? In order to answer the questions, a three-step approach was followed: (1) An initial land cover classification was performed in order to gather core environmental information; (2) classes of interest were extracted using both semi-automatic (pixel- and object-based) and manual classification techniques, and (3) the extracted features were being used to map the state of the AOI at the aforementioned points in time and to analyse the relationships between them. One key assumption of this study is that the development of oil infrastructure leads to a loss of cropland areas (ECOS 2011, 2014). Taken together, an overall picture of the situation and its development over time was expected to emerge.

2 Study Area

The majority of south-sudanese oil reserves are located in the oil-rich Muglad and Melut rift basins, which extend also into the Republic of Sudan (EIA 2014). The study area (Fig. 1) is located in Upper Nile state, one of South Sudan's ten states, which cover large parts of the Melut basin. It includes Melut County, one of the thirteen counties of Upper Nile State, comprising of 478 villages as well as parts of the counties Renk, Maban, Baliet, Fashoda. Melut County historically has been inhabited by Dinka. After the signing of the CPA and the formation of the Government of Southern Sudan (GOSS) the former seven sections, which were governed by paramount chiefs of various Dinka sub-groups, were turned into seven Payams. Two Paymas, Melut and Paloich, are of special interest to this study.

The Dinka of the northern Upper Nile region practise agriculture more than cattle breeding and hunting. They adopted to the climate conditions in this area in a way that they move between areas near to the river Nile during dry seasons and the areas of their origins during rainy seasons where they then practised agriculture (ECOS 2014). Agriculture, which was largely practised in this area, vanished almost entirely during wartime due to forced displacement of locals by the Sudanese Armed Forces (SAF). According to Prins (2009), the same is true for the Western Upper Nile region of South Sudan, where oil concession Block 5A is located.

The size of the AOI is approximately 10,500 km^2 (104 km × 101 km). BICC (2013) estimates the number of persons living in Melut County to be approximately 70,000 for mid-2013. As of 2011, the AOI comprises four oil

Fig. 1: The study area (red square) with the two subsets for cropland classification (yellow squares) and the regional setting of South Sudan.

fields: Paloich, Adar Yale, Gumry and Muleeta. Exploration of the Paloich field began in 2001. In order to make way for oil exploration and to ensure undisturbed oil production, the government of Sudan continued to forcefully displace thousands of people in Melut and Maban Counties after the signing of the CPA in 2005. Hundreds of villages were affected by the construction of oil well pads, roads, ponds and other infrastructure. Some villages vanished completely (BICC 2013, ECOS 2011, ECOS 2014, Human Rights Watch 2003). ECOS (2014) states that "Assuming that on average a village consists of 100 people, this means that the lives of about 38,000 people have been affected by oil industry development in some way or another in Melut County."

3 Data

The main data sources for this study were Landsat-5 TM and Landsat-7 ETM+ images. The area of interest is completely covered by Landsat paths 173 and 172 of row 53. Six points in time (1999, 2002, 2004, 2006, 2009, 2011) were chosen based on events that occurred in the study area as well as data availability (Tab. 1). The first one – 1999 – was of interest because it showed the state of the area before oil production started. The second point in time – 2002 – supposedly not only showed the first stages of oil field expansion but also the effects of the heavy fighting that took place between 1999 and 2002 as mentioned in chapter 1. In the year 2004, displaced people and persons that had fled the areas started to return to Melut County (BICC 2013). The last date in the list – 2011 – was set as an endpoint of the time series upon design of the study in mid-2012. The fact that early 2011 was the last time for which Landsat-5 imagery of the area of interest was available also contributed to this decision. The two remaining dates in-between – 2006 and 2009 – were chosen in order to keep the time interval of two to three years between dates. In May 2003 the Scan Line Corrector (SLC) in the ETM+ instrument failed. Thus, additional data were selected for the years 2004 and 2006 in order to fill the data gaps which are caused by the SLC's failure.

Landsat-5 data was available for 2009 and 2011, which were used to keep the number of images that contain gaps to a minimum. For

Tab. 1: Overview of satellite imagery. Additional data used to overcome the SLC's failure are marked with an asterisk.

Satellite	Sensor	Acquisition date	Spatial resolution	Path/Row
Landsat-7	ETM+	29.11.1999	15 m (pansharpened)	172 / 053
Landsat-7	ETM+	06.12.1999	15 m (pansharpened)	173 / 053
Landsat-7	ETM+	23.12.2002	15 m (pansharpened)	172 / 053
Landsat-7	ETM+	30.12.2002	15 m (pansharpened)	173 / 053
Landsat-7	ETM+	26.11.2004*	15 m (pansharpened)	172 / 053
Landsat-7	ETM+	12.12.2004	15 m (pansharpened)	172 / 053
Landsat-7	ETM+	03.12.2004*	15 m (pansharpened)	173 / 053
Landsat-7	ETM+	19.12.2004	15 m (pansharpened)	173 / 053
Landsat-7	ETM+	18.12.2006	15 m (pansharpened)	172 / 053
Landsat-7	ETM+	04.02.2007*	15 m (pansharpened)	172 / 053
Landsat-7	ETM+	25.12.2006	15 m (pansharpened)	173 / 053
Landsat-7	ETM+	10.01.2007*	15 m (pansharpened)	173 / 053
Landsat-5	TM	18.12.2009	30 m	172 / 053
Landsat-5	TM	09.12.2009	30 m	173 / 053
Landsat-5	TM	06.01.2011	30 m	172 / 053
Landsat-5	TM	13.01.2011	30 m	173 / 053

preprocessing, a tasseled cap transformation as developed by KAUTH & THOMAS (1976) was performed on all images. It resulted in a three-band feature space. The first band corresponds to brightness. The second represents greenness. The third band indicates wetness and relates to soil and surface moisture (LILLESAND et al. 2008). For this study, the third band proved to be suitable for identifying human-made structures with very little or no surface moisture such as oil well pads. Landsat-7 data was pansharpened by merging the panchromatic 15 m-band with a layer stack of the bands 1-2-3-4-5-7 to produce colour images, which in turn feature a resolution of 15 m instead of 30 m (LILLESAND et al. 2008).

4 Methodology

The methodological workflow (Fig. 2) consisted of three main steps: (1) Classification, (2) feature extraction as well as (3) analysis and visualization. The objective of the first step was to assess the applicability of semi-automatic classification approaches both pixel- and object-based. In the second step the features of interest (cropland, roads and oil well pads) for the impact assessment of oil exploitation were derived. In order to achieve the highest accuracy possible the classes were manually digitized. The derived classes served as input for the third step that focused on the mapping of the state of the oil fields for every point in time as well as on analysing their spatial connections to the extracted features.

4.1 *Classification*

Land cover was classified using pixel-based and object-based approaches for two selected time periods, i.e. 2002 and 2009 with 15 m and 30 m spatial resolution, respectively. Five classes were defined: 'Water', 'Wetland', 'Burned Area', 'Savanna-Dense' and 'Savanna-Sparse'. Burned areas can be seen as indicator for grazing activities (PRINS 2009, GRAWERT 2012). The two savanna classes were introduced to account for vegetation density trends that frequently occur in such landscapes.

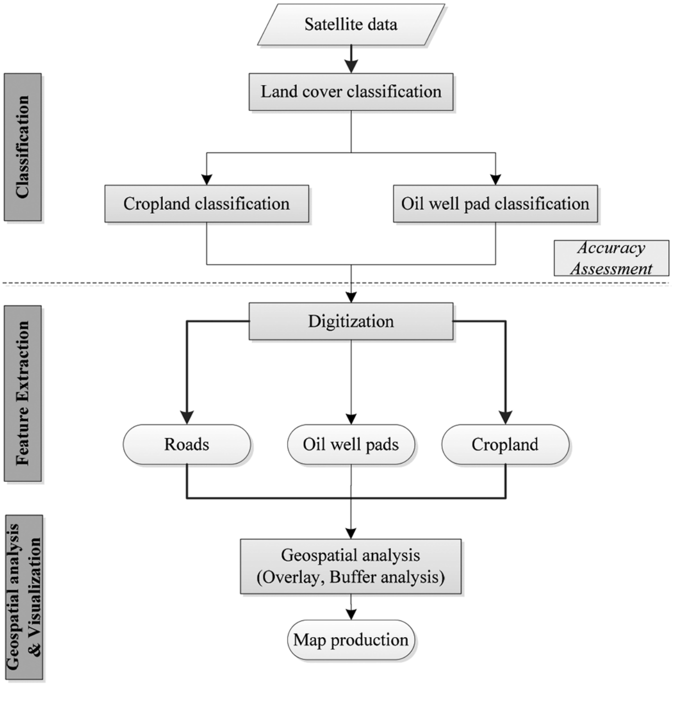

Fig. 2: Methodological workflow.

For the pixel-based classification a supervised maximum-likelihood approach was selected. The method is based on training areas, which numerically describe the spectral attributes of the classes to be mapped (Lillesand et al. 2008).

At the turn of the millennium the concept of image segmentation, which is not new in computer vision (Haralick & Shapiro 1985, Pal & Pal 1993), was transferred to the remote sensing domain in order to complement the more traditional pixel-based methods (Baatz & Schäpe 2000, Blaschke & Strobl 2001, Addink et al. 2012). Object-based image analysis (OBIA) (Blaschke 2010, Chen et al. 2012, Hussain et al. 2013, Blaschke et al. 2014) was employed using the Cognition Network Language (CNL) (Baatz et al. 2008). The segmentation algorithm used is a multiresolution segmentation as defined in Baatz & Schäpe (2000). An initial segmentation was applied to separate water from vegetation followed by a second segmentation with a smaller scale parameter. The class descriptions are mainly based on spectral features and various ratios of the bands. The following indices proved to be highly suitable for the class separation: Normalized Difference Vegetation Index (NDVI) (Rouse et al. 1974), Modified Soil-Adjusted Vegetation Index (MSAVI) (Qi et al. 1994), Burned Area Index (BAI) (Chuvieco et al. 2002) and Bare Soil Index (BSI) (Azizi et al. 2008).

Two additional classifications were performed to test the identification of further classes. The distinction of cropland and non-cropland areas was tested on two subsets measuring 25 km × 25 km each. The previously defined ruleset in CNL was enhanced by introducing geometrical and contextual information and applied accordingly. In addition, a ruleset was developed to classify oil well pads in the whole study area. The well pads are characterized by flattened, unvegetated squares measuring 100 m × 100 m. Accordingly, the class description is based on geometrical information and brightness values.

To quantify the quality of the classifications, an accuracy assessment was performed (Congalton 1991). Since no ground reference data were available, the classified images were compared to the original satellite imagery and evaluated by visual interpretation. A stratified random sampling approach was chosen to perform the accuracy assessment. For each land cover classification, a minimum of 50 sample points per class and a total of 500 sample points were randomly selected. The number of sample points increased with the total number of pixels per class, ranging from 50 in the least populated class ('Water') to more than 200 in the 'Savanna-Sparse' class.

4.2 *Feature Extraction*

Based on visual inspection of the imagery as well as the expert knowledge of involved researchers, three landscape features were found to be of interest for the analysis of the impact of oil exploitation, namely 'Cropland', 'Roads' and 'Oil well pads'. The features can be described according to the satellite data as follows: (1) 'Oil well pads' are mostly clear and distinct features. The oil well pads measure approximately 100 m in width and length and are used to drill for oil. Oil pads are characterized by a squared shape and bright ground. It has to be noted that no information of the status, i.e. active or inactive, of the pad can be given. Pads which are used for water injection were also considered under the same category. This is permitted in the context of this study since man-made structures themselves were more important than the exact use of the pads. (2) The feature class 'Road' covers a variety of features that are used for transport between different places. They include paved and unpaved roads, simple tracks as well as routes specifically built to connect oil well pads to the road network. Due to their long and narrow shape, roads are most often easily identifiable. (3) The feature class 'Cropland' covers all areas used for agricultural purposes. It includes small and big scale farming. Small scale farming comprises rain fed agriculture being done without the help of motorized machinery. The plots of land that are cultivated this way are quite small and heterogeneous. On the other hand big scale farm lands have a distinctive shape and compactness.

For all six points in time (1999, 2002, 2004, 2006, 2009, 2011), cropland, roads, and oil well pads were digitized. The manual interpretation was supported by the use of high resolution satellite imagery available in Google Earth as well as by information provided by experts with local knowledge about the area.

4.3 *Analysis and Visualization*

Geospatial feature analysis comprised (1) cropland change analysis, (2) buffer-distance analysis and visual overlay analysis regarding the relationship between cropland and road network, and (3) grid-based oil field development analysis.

For step (1), a variety of GIS operations based on overlaying different data layers were employed to create new vector layers containing gained, lost and unchanged cropland areas. These areas were then visualized in change maps (Fig. 5). Step (2) aimed at investigating the changes of cropland areas and their relation to the road network. In order to determine whether road development influenced cropland areas in positive or negative ways, buffer-distance analyses as well as overlay analyses were performed. For buffer analysis, distances of 500 m, 1,000 m, 2,500 m, 5,000 m, 10,000 m and 20,000 m were chosen. Overlay analysis consisted of superimposing the 'new roads layer' with the 'lost cropland areas layer' to visually determine whether or not spatial connections can be observed. For the final feature analysis step (3), the area of interest was divided into 10,200 grid cells measuring 1 km^2 each. For each grid cell, the number of oil well pads contained therein was counted. The values were then separated into five classes, based on the distribution of the data (Fig. 3). For an analysis of the oil wells' influence on cropland, lost and gained cropland areas were laid on top of a similar grid which contained newly set up oil well pads only.

5 Results

To quantify the quality of the land cover classifications, an accuracy assessment was applied. The land cover classifications reached a generally high level of accuracy with the object-based approach being slightly more accurate than the pixel-based approach (Tab. 2).

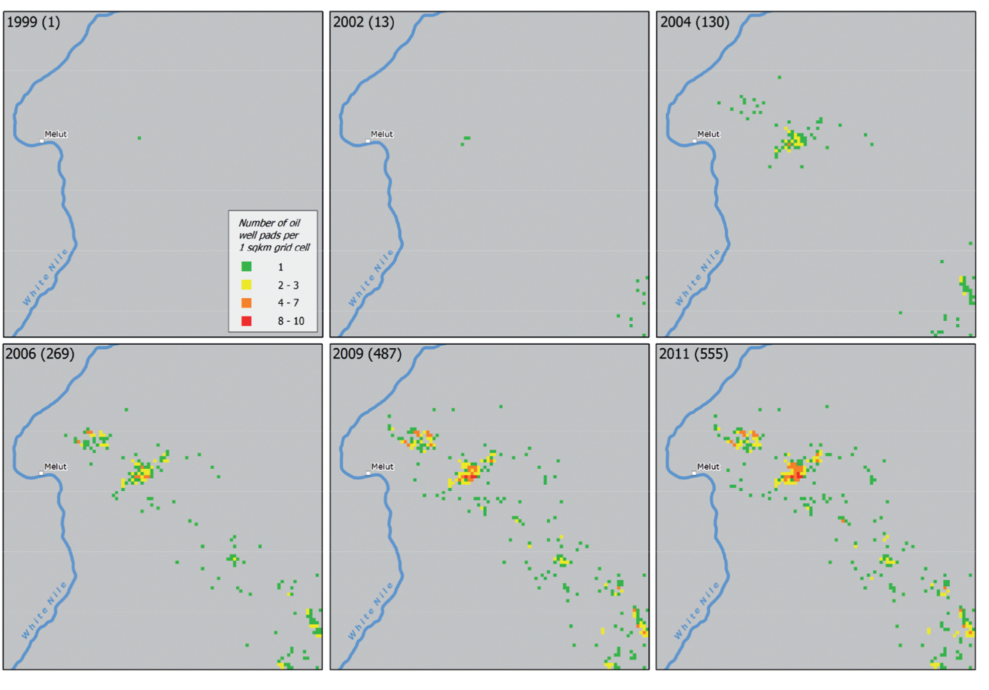

Fig. 3: Oil field development from 1999 to 2011 (number of oil well pads per 1 km^2 grid cell; grey: 0, green: 1, yellow: 2 – 3, orange: 4 – 7, red: 8 – 10).

Spectral similarity caused some confusion between the classes 'Savanna-Dense' (densely vegetated) and 'Savanna-Sparse' (sparsely vegetated). Tabs. 3 and 4 show that, in the maps of 2002, the approaches based on both, pixels and objects, led to low levels of accuracy for the classification of densely vegetated savanna. This confusion was also reported in other vegetation mapping approaches conducted in savannas, e.g. by Cord et al. (2010). Classification of the 2009 image resulted in very similar outcomes.

As mentioned above, the land cover was classified in order to create an additional source of information as well as a base for further classification of cropland and oil well pads. With regard to the first purpose, large scale land cover changes could not be linked to oil exploitation activities. The main reason for major changes in land cover appearance were different states of vegetation as well as different burned area patterns. While the former were caused by seasonal conditions at image acquisition time, the latter can be linked to agricultural activities (Grawert 2012) as well as grazing and bush fires (Prins 2009).

Cropland was classified on two subsets of 25 km × 25 km each. The accuracy assessment (Tab. 5) indicates the challenge of mapping cropland in savanna landscapes, where fire scars can seldom directly linked to one natural land cover (natural bush fire) or land

Tab. 2: Overall accuracy of the land cover classifications using pixel- and object-based approaches.

	2009, Pixel (30 m)	**2009, Object (30 m)**	**2002, Pixel (15 m)**	**2002, Object (15 m)**
Overall Accuracy	85.00 %	86.20 %	84.60 %	86.40 %
Overall Kappa	0.7978	0.8123	0.7827	0.8071

Tab. 3: Class-wise accuracy of the 2002 land cover classifications using pixel-based approaches.

	Water	**Wetland**	**Burned Area**	**Savanna-Dense**	**Savanna-Sparse**
Producer's Accuracy	89.58 %	90.20 %	82.86 %	78.95 %	84.52 %
User's Accuracy	86.00 %	85.19 %	86.14 %	60.81 %	91.40 %
Kappa	0.8451	0.8350	0.8245	0.5577	0.8353

Tab. 4: Class-wise accuracy of the 2002 land cover classifications using object-based approaches.

	Water	**Wetland**	**Burned Area**	**Savanna-Dense**	**Savanna-Sparse**
Producer's Accuracy	100.00 %	89.47 %	85.15 %	93.33 %	82.40 %
User's Accuracy	94.00 %	96.23 %	89.58 %	51.85 %	93.64 %
Kappa	0.9338	0.9574	0.8695	0.4709	0.8727

Tab. 5: Accuracy of the cropland classifications.

Subset	**Producer's accuracy**	**User's accuracy**
A	68.25 %	83.02 %
B	69.01 %	43.90 %

use activities, and in general a high spectral confusion among cropland and natural vegetation classes occur (Cord et al. 2010, Forkuor et al. 2014). This result also supports the use of visual feature extraction for a more accurate delineation of cropland areas in the study region.

The accuracy of the object-based classification of the oil well pads for the whole study area reached low accuracies (Producer's accuracy: 54.62%, User's accuracy: 34.68%). Locally, classification results were satisfying, however, again, visual features seemed to be preferable for accurate mapping of oil well pads using Landsat data.

5.1 *Feature Extraction*

A significant decrease in cropland areas occurred as observed on images dating from 1999 and 2002. More than 160 km^2 of former farm lands were not used as such anymore. Similar cropland area decline was observed by Prins (2009) in another part of South Sudan. From this base, the size of cropland areas rose steadily throughout the years, already before the end of the war in 2005. The level of 1999 was surpassed as identified on the 2006 image. After that, the sum of areas used for agricultural purposes more than trebled to reach 593 km^2 in 2011, of which 464 km^2 are located in Melut County (Fig 4a).

The number of oil well pads in the entire study area as identified on the imagery rose from a single one in 1999 to 555 in 2011 (Fig. 4b). According to a report by the Nile Research Initiative (2013), the combined number of oil well pads from all four oil fields was 601. Taking into account that parts of the Adar Yale field are located outside the AOI and further expansion of the fields between 2011 and 2013 seems likely, the number of 555 identified oil well pads for 2011 suggests a very high level of accuracy. Road length expanded from 190 km to 1,085 km.

5.2 *Analysis and Visualization*

The key objective of the study was to map human activity in the context of oil extraction and to assess its impacts in the area of interest. Thus, focus was put on the analysis of derived features and the visualisation of results. In total, 19 maps were generated to visualize the results of the study. The outcomes of the cropland change analysis were visualized in five maps, which show new, lost and unchanged areas for every change period. Fig. 5 gives an example for the change period 2006 – 2009, when the strongest increase of cropland occurred. A detailed description of the locations of lost and gained cropland can only be given with the help of the maps since no distinctive change pattern emerged that can be transferred to the entire AOI.

According to ECOS (2014) 37 villages in Melut County were lost due to expulsions during war time and over a hundred villages were affected by oil related infrastructure, particularly by the presence of rigs, pipelines, feeder lines and roads, often hampering traditional means of livelihood such as agriculture and cattle grazing or in the worst case even destroying properties of local communities. Returnees or those who managed to stay in their villages during war time and displacement periods usually could not practise agriculture. Security personnel of the oil companies has been preventing locals from carrying out agriculture or other livelihood activities close to

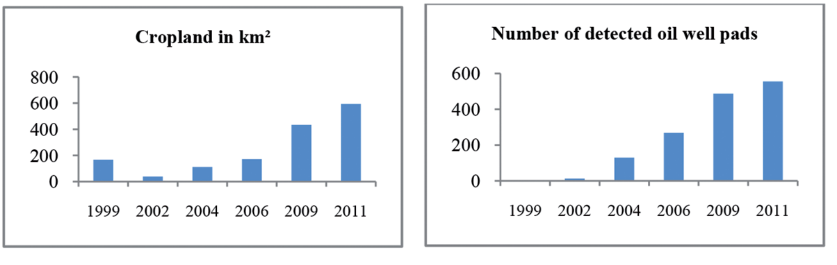

Fig. 4: (a) Changes in cropland and (b) oil well pads in the area of interest.

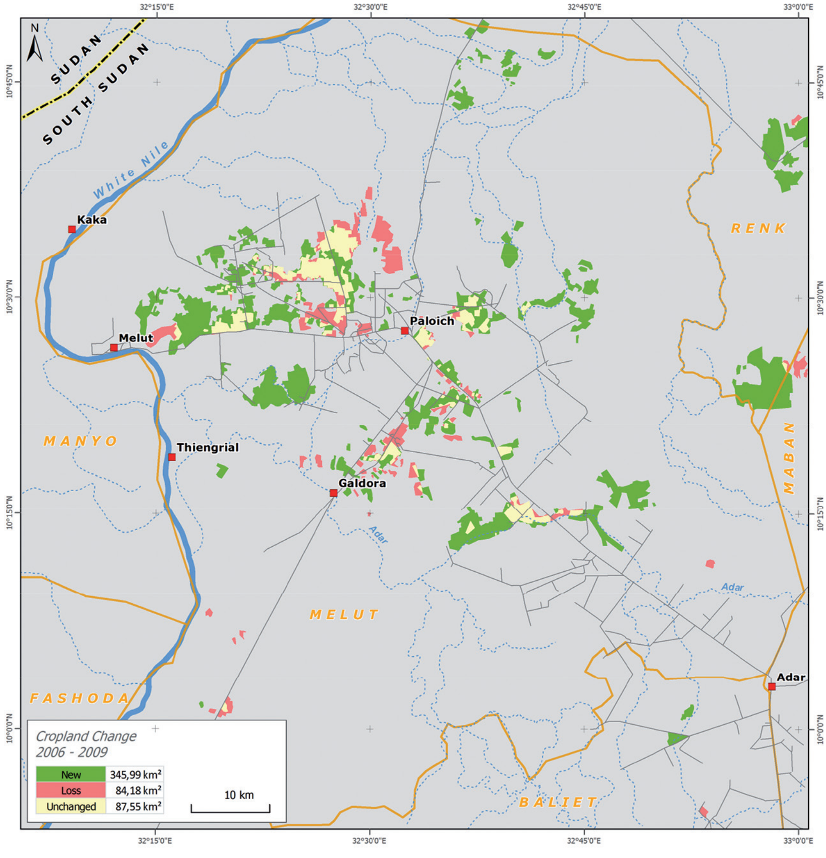

Fig. 5: Change map of cropland for the period of 2006 – 2009 showing the highest increase of cropland after the end of the war in 2005.

rigs and pipelines (ECOS 2014). Those people, whose villages were either lost or affected by activities or infrastructure of the oil industry, were therefore forced to cultivate areas in farer surroundings of their villages.

Spatial analyses of the relationship between the road network and cropland areas alone did not provide clear answers. A mixed picture emerged with many examples where road construction led to a loss of cropland areas. This is also stated in ECOS (2011), i.e. "Agricultural lands were used for roads, pipelines, oil wells, airports in relation to oil exploitation." On the other hand, examples for new cropland areas that sprung up in close proximity to newly constructed roads abounded. Road construction has enabled access to hitherto inaccessible areas. For some years – 2004, 2006 and 2009 – a lot of new cropland areas were closer located to new roads than to previously existing ones. One possible explanation seems to be that many of the new roads built in subsequent years often were elevated roads, which unintentional but effectively acted as dams in the rainy season either causing floodings or droughts (ECOS 2014). Because of both effects new cropland areas arose further afield – often times along the new roads which made it easier for the people to access more distant areas.

The same applies for the influence of oil well pads on cropland areas. While many examples for oil well pads replacing croplands were found, new cropland areas seemed to have emerged around newly created oil well pads. Aside the afore mentioned explanation that the forced development of new areas followed the new roads, a lot of cropland also sprung up as a consequence of the return flow of displaced persons as well as the influx of refugees since 2006 (BICC 2013, ECOS 2014).

Summarizing, satellite data can only provide an "as is" picture, documenting the status quo as shown in the oil field development map (Fig. 3).

6 Discussion

The observed changes are in line with what is known to have happened in the area. As stated above, the period between 1999 and 2002 saw vicious fighting with displacement and flight of thousands of people. A sharp decline of cropland reflects these circumstances. From the year 2004 on, thousands of refugees returned which in turn led to new cropland areas being cultivated all over Melut County. Cropland losses (after war) and parts of newly cultivated areas were direct consequences of the oil field exploration and exploitation activities in the past years, which for various reasons forced people to look for new land. Apart from all the negative effects on people and the environment, the development of the oil fields brought also benefits to the area like improved transport possibilities through the extended and improved road network and as a follow-up access to local and regional markets as well as the extension of the mobile network coverage (ECOS 2014). After the expulsions during war times, numerous villages vanished completely, others like New Paloich were newly established (ECOS 2014). Some began to exhibit signs of socio-economic change with emerging local and regional market integration (BICC 2013).

The observation of both, decrease and increase of cropland where new roads were constructed showed only weak evidence of causal spatial relationships between the development of roads and oil well pads on the one and cropland on the other side. It is beyond dispute that the erection of oil well pads led to the disappearance of croplands and even whole villages. On the other hand, new cropland areas sprung up in very close proximity to new well pads, often alongside the newly built roads. The distance analysis concerning proximity of new roads to new cropland areas showed that for some years it was likely that new roads enabled new croplands to emerge. Thus, explicit conclusions about the interplay between certain developments could not be made, however, the maps can support site specific discussion and complement ground-truth data as well as local knowledge.

From the methodological point of view, it was shown that Landsat data and related semi-automatic analysis (OBIA) are highly suitable for monitoring land cover classes. It was also demonstrated that object-based image analysis has advantages in the identification of the desired features (cropland, oil wells) as it offers the integration of geometrical and contextual information. However, due to the coarse resolution of the input data semi-automatic approaches are limited in the classification of subtle features such as oil well pad structures. In that case, visual feature extraction may be more suitable.

The oil-rich South Sudan represents a country in transition. A process of nation-building occurs that involves a high level of violence (Grawert 2013, Wimmer & Min 2006). The results revealed in this study show that Earth observation can provide valuable information in such situations, e.g. for conflict research. Due to its unique point of view from space, remote sensing puts apparently isolated incidents into a larger context and adds a new perspective. Earth observation not only provides evidence for the impacts associated with violent conflicts but furthers the understanding of related processes, especially in situations when field access is limited. If combined with secondary or ground truth information a more reliable analysis is possible. The results provided in this research helped to better understand important processes related to oil exploitation in South Sudan by visualizing changes in land use patterns over time.

A potential next step for research would be, based on the geospatial analysis of the oil field evolution, its impacts and changes on land cover and land use (oil pads, road network, cropland, villages), to superimpose other geo-referenced data, such as data about the spatial-temporal evolution of violent incidences, or data on refugee camps and migration routes to even further the analysis of interlinkages between organized violence and oil exploration.

Acknowledgement

We would like to express our special thanks to Lena Guesnet and Elke Grawert from BICC for their support and fruitful discussions. We would like to thank Fabian Selg for preceding work.

References

Addink, E.A., van Coillie, F.M.B. & de Jong, S.M., 2012: Introduction to the GEOBIA 2010 special issue: From pixels to geographic objects in remote sensing image analysis. – International Journal of Applied Earth Observation and Geoinformation **15:** 1–6.

Aksyonov, D.E., 2006: Cumulative Environmental Impact Assessment of Oil Production Using Space Imagery Products. – http://scanex.com/en/publications/pdf/publication15.pdf (20.4.2016).

Azizi, Z., Najafi, A. & Sohrabi, H., 2008: Forest canopy density estimating, using satellite images. – The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, **XXXVII**, Part B8: 1127–1130.

Baatz, M., Hofmann, P. & Willhauck, G., 2008: Progressing from object-based to object-oriented image analysis. – Blaschke, T., Lang, S. & Hay, G.J. (eds.): Object-based image analysis. – Spatial concepts for knowledge-driven remote sensing applications, Springer, Berlin.

Baatz, M. & Schäpe, A., 2000: Multiresolution Segmentation: an optimization approach for high quality multi-scale image segmentation. – Strobl, J., Blaschke, T. & Griesebner, G. (eds.): Angewandte Geographische Informationsverarbeitung, Heidelberg, Wichmann: 12–23.

BICC, 2013: Oil Investment and Conflict in Upper Nile State, South Sudan. – Bonn International Center for Conversion (BICC), Brief 48, Bonn.

Blaschke, T. & Strobl, J., 2001: What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. – GeoBIT/GIS **6:** 12–17.

Blaschke, T., 2010: Object based image analysis for remote sensing. – ISPRS Journal of Photogrammetry and Remote Sensing **65:** 2–16.

Blaschke, T., Hay, G.J., Kelly, M., Lang, S., Hofmann, P., Addink, E., Feitosa, R.Q., van der Meer, F., van der Werff, H., van Coillie, F. & Tiede, D., 2014: Geographic Object-Based Image Analysis – Towards a new paradigm. – ISPRS Journal of Photogrammetry and Remote Sensing **87:** 180–191.

Chen, G., Hay, G.J., Carvalho, L.M.T. & Ulder, M.A., 2012: Object-based change detection. – International Journal of Remote Sensing **33** (14): 4434–4457.

Chuvieco, E., Martin, M.P. & Palacios, A., 2002: Assessment of different spectral indices in the red-near-infrared spectral domain for burned land discrimination. – International Journal of Remote Sensing **23** (23): 5103–5110.

Congalton, R.G., 1991: A review of assessing the accuracy of classifications of remotely sensed data. – Remote Sensing of the Environment **37** (1): 35–46.

Cord, A., Conrad, C., Schmidt, M. & Dech, S., 2010: Standardized FAO-LCCS land cover mapping in heterogeneous tree savannas of West Africa. – Journal of Arid Environments **74:** 1083–1091.

Duncan, C., Kretz, D., Wegmann, M., Rabeil, T. & Pettorelli, N., 2014: Oil in the Sahara: mapping anthropogenic threats to Saharan biodiversity from space. – Philosophical Transactions of the Royal Society B-Biological Sciences **369** (1643): 1–12.

EIA, 2014: Country Analysis Brief: Sudan and South Sudan. – U.S. Energy Information Administration, https://www.eia.gov/beta/international/analysis_includes/countries_long/Sudan_and_South_Sudan/sudan.pdf (20.4.2016).

ECOS, 2006: Oil development in Northern Upper Nile, Sudan. – European Coalition on Oil in Sudan, http://www.ecosonline.org/reports/2006/melut.pdf (20.4.2016).

ECOS, 2009: Sudan, Whose oil? Facts and Analysis. – European Coalition on Oil in Sudan, http://www.ecosonline.org/reports/2008/dossier%20final%20groot%20web.pdf (20.4.2016).

ECOS, 2011: Sudan's Oil Industry after the Referendum. Conference Report. – European Coalition on Oil in Sudan, http://www.ecosonline.org/reports/2011/Oil_conference_report_Dec2010.pdf (20.4.2016).

ECOS, 2014: Scrutiny of South Sudan's oil industry – Community Relations, Labour Practices and Impact on Land Use Patterns. – European Coalition on Oil in Sudan, http://www.ecosonline.org/reports/2014/Scrutiny_of_South_Sudans_Oil_Industry.pdf (20.4.2016).

Forkuor, G., Conrad, C., Thiel, M., Ullmann, T. & Zoungrana, E., 2014: Integration of Optical and Synthetic Aperture Radar Imagery for Improving Crop Mapping in Northwestern Benin, West Africa. – Remote Sensing **6:** 6472–6499.

Grawert, E., 2012: Information on burned areas. – (Personal communication, October 23, 2012).

Grawert, E. (ed.), 2013: Forging two nations – Insights on Sudan and South Sudan. – 1st ed., 270 p., Organisation for Social Science Research in Eastern and Southern Africa, Addis Abbeba, Ethiopia.

Haralick, R.M. & Shapiro, L., 1985: Survey: image segmentation techniques. – Computer Vision, Graphics, and Image Processing **29:** 100–132.

Hese, S. & Schmullius, C., 2009. High spatial resolution image object classification for terrestrial oil spill contamination mapping in West Siberia. – International Journal of Applied Earth Observation and Geoinformation **11:** 130–141.

Human Rights Watch, 2003. Sudan, Oil, And Human Rights. – https://www.hrw.org/reports/2003/sudan1103/sudanprint.pdf (20.4.2016).

Hussain, M., Chen, D., Cheng, A., Wei, H. & Stanley, D., 2013. Change detection from remotely sensed images: From pixel-based to object-based approaches. – ISPRS Journal of Photogrammetry and Remote Sensing **80:** 91–106.

Kauth, R.J. & Thomas, G.S., 1976: The Tasseled Cap – A Graphic Description of the Spectral-Temporal Development of Agricultural Crops as Seen by LANDSAT. – Symposium on Machine Processing of Remotely Sensed Data, Purdue University of West Lafayette, IN, USA. 4B-41 - 4B-51.

Lillesand, T.M., Kiefer, R.W. & Chipman, J.W., 2008: Remote sensing and image interpretation. – 6th ed., John Wiley & Sons Ltd., Chichester, Great Britain.

Mager, A., 2013: Impact assessment of oil exploitation in Upper Nile State, South Sudan, using multi-temporal Landsat-data. – MSc thesis, Paris-Lodron-University Salzburg, Austria.

Nile Research Initiative, 2013: Research on oil business in Melut County in Upper Nile State. – Study report, Catholic Diocese of Malakal, Justice and Peace Department.

Pal, N.R. & Pal, S.K., 1993: A review on image segmentation techniques. – Pattern Recognition **26** (9): 1274–1294.

Plank, S., Mager, A. & Schoepfer, E., 2014: Monitoring of Oil Exploitation Infrastructure by Combining Unsupervised Pixel-Based Classification of Polarimetric SAR and Object-Based Image Analysis. – Remote Sensing **6:** 11977–12004.

Prins, E., 2009: Satellite Mapping of Land Cover and Use in relation to Oil Exploitation in Concession Block 5A in Southern Sudan 1987 – 2006; http://www.ecosonline.org/reports/2009/Satellite_mapping_Block5a_small.pdf (20.4.2016).

Qi, J., Chehbouni, A., Huete, A.R., Kerr, Y.H. & Sorooshian, S., 1994: A Modified Soil Adjusted Vegetation Index. – Remote Sensing of Environment **48:** 119–126.

Robinson, C.W., 2003: Risks and Rights: The Causes, Consequenses, and Challenges of Development-Induced Displacement. – Occasional Paper, The Brookings Institute-SAIS Project of Internal Displacement, Washington DC, USA.

Rouse Jr., J.W., Haas, R.H. , Schell, J.A. & Deering, D.W., 1974: Monitoring vegetation systems in the Great Plains with ERTS. – Goddard Space Flight Center 3d ERTS-1 Symp, Vol. **1**, Sect. A: 309–317.

Sergey, M. & Oganes, T., 2009: Landscape Impact Assessment of the Oil and Gas Industry in the Russia using space images interpretation. – XIV Simpósio Brasileiro de Sensoriamento Remoto, Natal, Brasil, INPE: 6711–6717.

Singh, A., 1989: Digital change detection techniques using remotely-sensed data. – International Journal of Remote Sensing **10:** 989–1003.

Terminski, B., 2011: Oil-Induced Displacement and Resettlement: Social Problem and Human Rights Issue. – http://ssrn.com/abstract=2029770 (20.4.2016).

Wimmer, A. & Min, B., 2006: From Empire to Nation-State: Explaining Wars in the Modern World, 1861 – 2001. – American Sociological Review **71** (6): 867–897.

World Bank, 2015: South Sudan Overview. –http://www.worldbank.org/en/country/southsudan/overview (20.4.2016).

Addresses of the Authors:

Alexander Mager, German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), D-82234 Oberpfaffenhofen, e-mail: alexander.mager@dlr.de

Lars Wirkus, Bonn International Center for Conversion (BICC), D-53121 Bonn, e-mail: wirkus@bicc.de

Elisabeth Schoepfer, German Aerospace Center (DLR), German Remote Sensing Data Center (DFD), D-82234 Oberpfaffenhofen, e-mail: elisabeth.schoepfer@dlr.de

Manuskript eingereicht: Dezember 2015
Angenommen: Juli 2016