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This study describes the development of a semi-automatic object-based image analysis approach for the detection and quantification of deforestation in Zalingei, Darfur, in consequence of the increasing concentration of refugees or internally displaced persons (IDPs) in the region. The classification workflow is based on a multi-scale approach, ranging from the analysis of high resolution SPOT-4 to very high resolution IKONOS and QuickBird satellite imagery between 2003 and 2008. The overall accuracy rates for the classification of the SPOT 4 data ranged from 92% up to 95%, while those for the QuickBird and IKONOS classification have shown values of 88 and 87%, respectively. The resulting trends in woody vegetation cover were compared with the development of the local population and the variability of precipitation. The results show that the strong increase in human population in the Zalingei IDP camps can be associated with considerable decrease in woody vegetation in the camp vicinity.

Keywords: deforestation; object-based image analysis (OBIA); refugee camp monitoring; land cover; impact assessment

Introduction

According to estimates of the UN Refugee Agency (UNHCR 2014), there were about 51.2 million displaced people worldwide at the end of 2013, including 16.7 million refugees, 1.2 asylum seekers and 33.3 million internally displaced persons (IDPs). As a result of the numerous conflicts, there were between 4.5 and 5.2 million IDPs across Sudan, before it split in July 2011 (Enough 2012) – the largest displaced population in the world. Today, more than six million people are in need of humanitarian assistance in Sudan, while at least two million people are estimated to be internally displaced in Darfur (UN OCHA 2014).

On the whole, these people seek refuge in camps because they had to flee their homes due to complex conflict situations or human-made or natural disasters. Most of these camps are under supervision of national and/or international relief organizations, which provide support by supplying the camps with the essential facilities for survival. Living conditions in these camps are extremely difficult. In many cases, there is only

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limited access to food, water, sanitation and shelter (UNHCR 2012). Despite this, most refugee/IDP camps are operated for years and sometimes even decades. The long-lasting and high concentration of people in camps often affects the surrounding environment due to the pressure on natural resources such as wood, water and grazing areas (Tearfund 2007; UNEP 2007; Gorsevski et al. 2012). Thus, especially in vulnerable environments like the semi-arid region of Central Darfur, sustainable management of this impact on the areas surrounding refugee/IDP camps is necessary. This is especially true since the growing pressure on land and water resources, including fire wood and building timber, is an important factor in regional conflicts (Nordås & Gleditsch 2007; Raleigh & Urdal 2007; Salehyan 2008; Bronkhorst 2011; Benjaminsen et al. 2012) and related population movements (UNEP 2007). However, for effective camp management and decision-making, humanitarian organizations require reliable and up-to-date information about the situation on the ground (Bouchardy 1995; UNHCR 2000, 2005). This also comprises the aforementioned assessment of the impact on local and regional resources in order to develop effective mitigation strategies.

Consequently, the main focus of this study is the development of methods for the generation and provision of land cover information for a more reliable and precise documentation of the environmental situation around refugee/IDP camps and changes therein. The major aim is not merely the provision of a profound documentation of land cover changes. This would to a certain extend accuse those people having no alternative to just battling for their existence every day. Rather it is important to utilize the generated Earth observation (EO)-based information as a basis for the provision of a better management of natural resources, the development of mitigation and conflict prevention as well as provisionary measures. Since respective projects are still limited, the United Nations recommend supporting reforestation and afforestation efforts of local, regional and national institutions (UN Sudan 2010). Some projects have already been set up responding to growing pressure on natural resources – amongst tree plantations also focussing on fuel conservation measures (UNEP 2007; Gafaar 2011).

The demand for EO-based information

International relief organizations working globally and supporting people in need sometimes have only very limited knowledge of the prevailing circumstances in the countries and landscapes they are operating in. Thus, geographic information is one of the key factors that need to be assessed for effective humanitarian relief operations (Bouchardy 1995; Bjorgo 1999; UNHCR 2000). Especially in remote areas or regions where geospatial information and detailed map material tends to be inaccurate or even fails to exist, satellite imagery may provide objective and up-to-date information about a given area and thus complement the information about the on-ground situation, which is usually collected by field missions (Bouchardy 1995). In cases like Darfur where field assessments are extremely dangerous, if at all possible, due to the complex conflict situations, satellite imagery may be the only reliable source of information. In addition, satellite data provides a unique historical record for examining spatial and temporal changes in the environment. In the context of refugee camp mapping, repeated acquisitions are crucial in order to assess changes in the population of camps as well as the impact on the environment resulting from human activities (e.g. Lodhi et al. 1998; Giada et al. 2003; Tiede & Lang 2009; Kranz et al. 2010, 2015; Lang et al. 2010; Hagenlocher et al. 2012).

Conflict and environment – The role of wood

The crisis in Darfur demonstrates that environmental stress can be strongly related to conflict. On the one hand, the long-lasting conflict over environmental resources is one of the major causes of the crisis; on the other hand, the displacement of millions of people and their concentration in camps and at the outskirts of urban settlements has a significant impact on the respective environments (O'Fahey 2004; Tearfund 2007; UNEP 2007; Bromwich 2008; Magnus Theisen 2008; Leroy 2009; UN Sudan 2010; Oxfam 2014; UNEP/OCHA 2014). Thus, the monitoring and quantification of such impacts can be of high value for conflict prevention and the mediation of clashes of interest between the local population and refugees/IDPs.

Although previous studies have indicated that refugees/IDPs have had a negative impact on natural resources in the vicinity of resettlement camps, only few studies have quantified the environmental impact of the growing number of internal and external refugee/IDP flows caused by political, economic or environmental crises (e.g. Lodhi et al. 1998; Kranz et al. 2010, 2015; Spröhnle et al. 2010; Hagenlocher et al. 2012). However, the detection and the quantification of the impact may provide important information for the management of the camps and thus contribute to a sustainable usage of land resources and the protection of the environment, which in turn, will have a positive impact on the situation of the camp population.

People living in camps are forced to collect wood as source of energy for cooking, brick-making and the construction of dwellings. In addition, for many IDPs, wood is the only source of income (UNEP 2008). Due to the uncontrolled exploitation of woody vegetation in Darfur, IDPs may walk up to 15 km (Tearfund 2007; UNEP 2007) or even 75 km (UNEP 2008) to collect wood. This can be extremely dangerous, especially for women and girls who are at risk of rape, harassment and other forms of violence (Women's Commission 2006).

Study area and data

The study area is located in the central part of Darfur, Sudan, and is part of the western Jebel Marra Foreland, in the middle course of the Wadi Azum System between longitudes 23°17.7′E and 23°47.2′E and latitudes 12°41.5′N and 13°5.7′N (see Figure 1). With an area of 1200 km^2, it comprises the Zalingei IDP camps and town as well as the surrounding environment.

The Zalingei region is characterized by a semi-arid environment with moderate annual rainfall but a high seasonal variability (eight arid months per year in average). The average total yearly precipitation of about 500–800 mm is generated by a limited number of strong rainfalls and highly concentrated on the wet season during summer, from June to September, with August as the month of maximum rainfall (Ibrahim 1984; Giessner 1989; UNEP 2007; Funk et al. 2011; Sorooshian et al. 2014). Apart from wood harvesting, the landscape around Zalingei is mainly used as grazing land during the summer rainfall period. The alluvial areas of the major wadi systems are, due to their morphology, more favourable for intensive land use such as cattle herding, rain-fed cultivation and irrigated horticulture (Schrenk 1989).

Multispectral SPOT-4 scenes, acquired on 5 October 2003, 6 August 2005 and 26 September 2007, with a spatial resolution of 20 m in the multispectral bands were used for the high resolution (HR) image analysis, covering the Zalingei IDP camps and the surrounding areas with a study area of 40 km × 30 km (see Figure 1). The very high

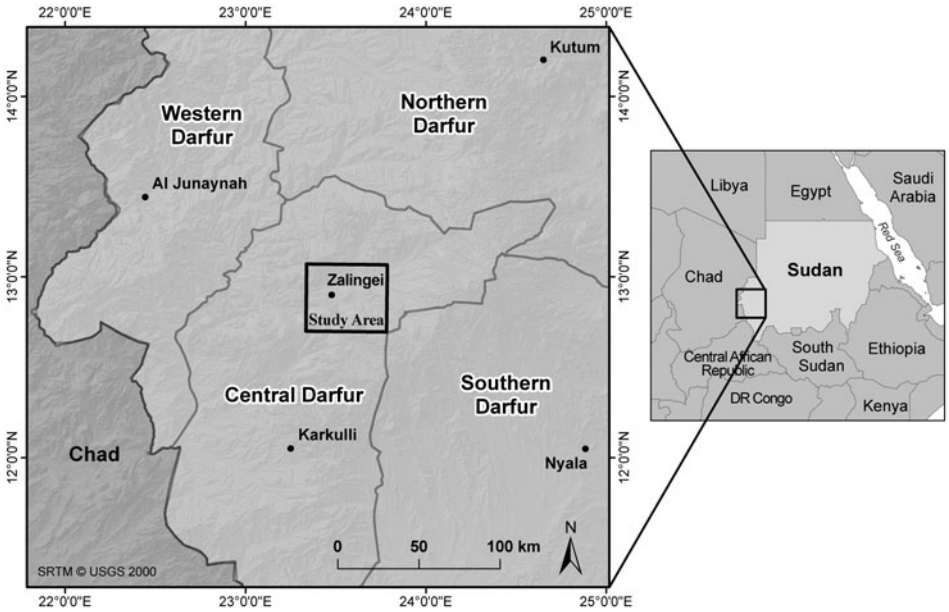

Figure 1. Overview of the study area (black box = extent of HR satellite data).

resolution (VHR, cf. Moeller 2011) analysis was conducted based on IKONOS data acquired on 14 September 2004 and a QuickBird scene from 6 July 2008 covering an area of 10 km × 10 km. An overview on the EO data used and the preprocessing steps applied to the imagery is given in Table 1.

An important factor influencing the growth and vitality of vegetation – including wood resources – is the rainfall variability (Ibrahim 1984; UNEP 2007; Funk et al.

Table 1. Overview of satellite data specifications and image preprocessing steps.

Acquisition date	Sensor[a]	Spatial resolution (m)	Image type	Preprocessing steps	Coverage
05/10/2003 06/08/2005 26/09/2007	SPOT-4	20	MS	Geometric correction Orthorectification Atmospheric correction using ATCOR[b]	40 km × 30 km
14/09/2004	IKONOS	1	PAN/ MS	Geometric correction Orthorectification Pan-sharpening Resampling Co-registration	10 km × 10 km
06/07/2008	QuickBird	1	PAN/ MS	Geometric correction Orthorectification Pan-sharpening Resampling Co-registration	10 km × 10 km

[a]SPOT-4 © CNES 2003/2005/2007, Distribution Astrium Services/Spot Image S.A., France, all rights reserved; IKONOS © DigitalGlobe 2004; QuickBird © Digital Globe 2008 distributed by EURIMAGE 2008.
[b]Atmospheric/Topographic Correction for Satellite Imagery (Richter 1996).

2011; UN Sudan 2010; Sorooshian et al. 2014). This variability leads to varying phenological conditions throughout the year and even within the different seasons. Due to the high seasonal rainfall variability in Darfur, even satellite data from the same season during consecutive years can be influenced by different phenological conditions. Therefore, for a better understanding of the conditions at the image acquisition dates and for the evaluation of results, precipitation data provided by the Hydrologic Data and Information System (HyDIS; cf. Sorooshian et al. 2014) have been used (see Figure 7).

When assessing the influence of refugee/IDP camps on their surrounding environment, it is necessary to consider the population dynamics in the camps of the study area over the period of investigation. Thus, population figures have been taken into account to examine if there is a correlation between population growth and vegetation trend patterns. The population data were obtained from the Humanitarian Information Centre Darfur (HIC Darfur 2006) and the United Nations Office for the Coordination of Human Affairs (UN OCHA 2009). Additional information has been used to gather reliable population figures between 2009 and 2013 to complete the picture (UN OCHA 2012, 2013). The figures for the camps in Zalingei are visualized in Figure 10.

Methodology

The methodological workflow of this research is illustrated in Figure 2. The structure of this chapter follows the sequence presented in this figure (see sections 'Image preprocessing' and 'Image analysis – Object-based feature extraction'). The approach follows a multi-scale impact assessment in order to evaluate possibilities and limitations for the identification of major influencing factors (with the focus on wood resources) at different scales. The aim is not to initially detect 'hot spots' of human activity for large regions on HR data that will subsequently further be analysed using higher resolution data. Instead, this study aims to assess the feasibility of using satellite data on different scales and to evaluate the possibilities and limitations of the different data scales for the selected application. In this sense, the analyses at different scales are not depending on each other, which allow the definition of different land cover classes in order to reflect the higher granularity of the VHR imagery.

Image preprocessing

Preprocessing steps applied to the HR imagery included ortho-rectification and geometric correction to UTM Zone 34 N (WGS 84) as well as an atmospheric correction using ATCOR (Atmospheric/Topographic Correction for Satellite Imagery after Richter 1996). Although data procurement focused on image acquisitions from corresponding seasons in order to reduce the seasonality effect, influences of phenological differences remain, which affect the analysis.

Concerning the VHR data, image preprocessing included geometric correction, ortho-rectification as well as pan-sharpening. Both images were resampled to a common resolution of 1 m using nearest neighbour resampling. This could be regarded as a loss of detail of the QuickBird image, but was necessary to avoid detecting false changes in the subsequent change detection (cf. Serra et al. 2003). Atmospheric corrections were not performed, due to the clear sky conditions. In addition, the approach follows a post-classification change detection where atmospheric corrections are not mandatory (Singh 1989; Song et al. 2001). Finally, the IKONOS and QuickBird images were co-registered to a Ground Sample Distance (GSD) of 1 m in the UTM-Zone 34 N

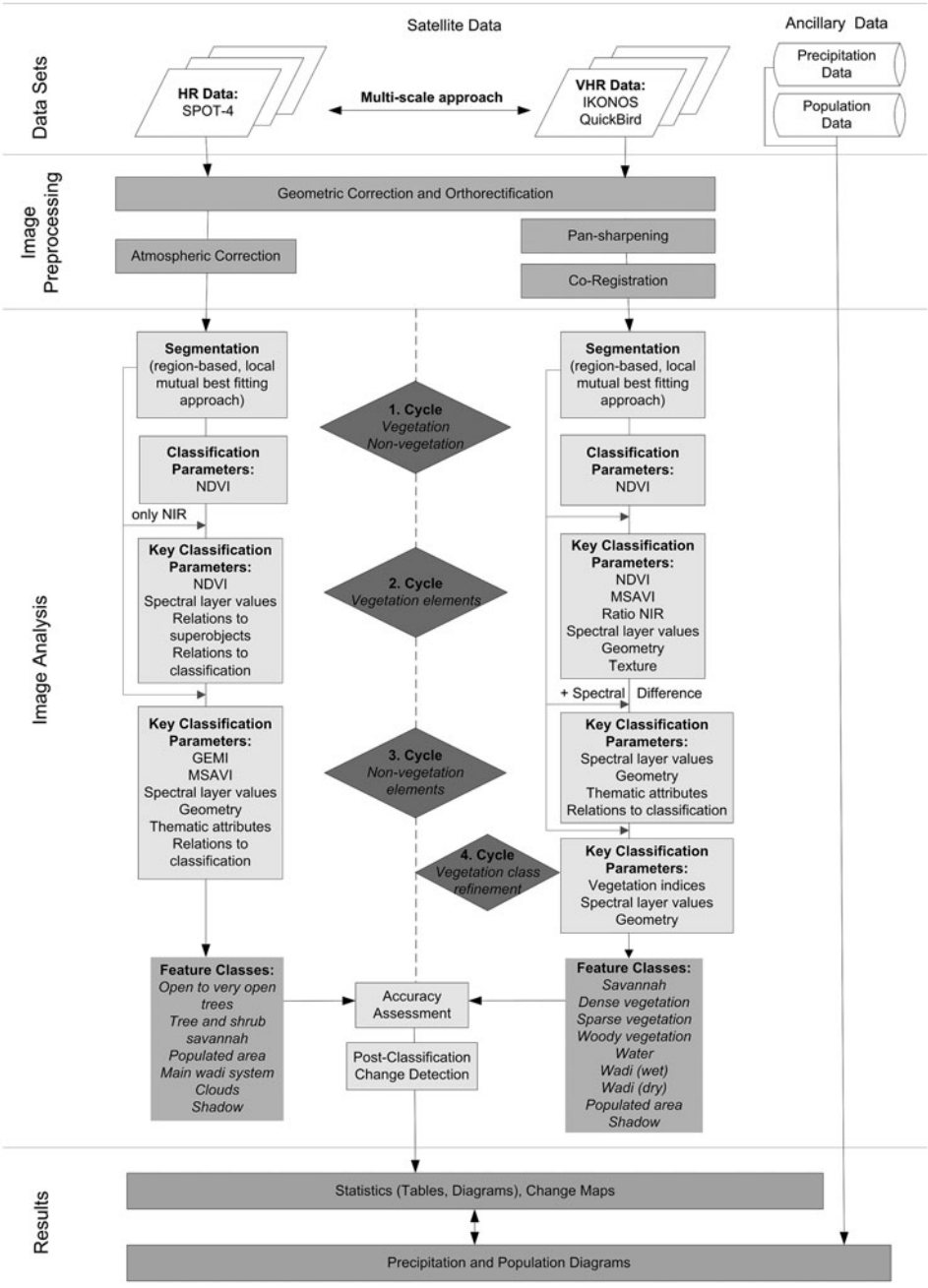

Figure 2. Methodological workflow.

(WGS-84) in order to avoid registration errors. The co-registration was carried out by using a second degree polynomial transformation with 52 ground control points and nearest neighbour resampling with a Root Mean Square Error of 0.76 pixels. A high precision geometric registration was difficult to achieve, because accurate ground control points are scarcely available within this region.

Image analysis – Object-based feature extraction

In the underlying multi-scale approach, first, a broad land cover characterization was conducted analysing a large area around the camps using HR SPOT-4 data. Next, the hierarchical classification was refined by the analysis of VHR QuickBird and IKONOS data, which provided additional information for distinguishing vegetation classes in detail. Although the analyses of the different scales were conducted independently from each other, most of the spectral features used for the HR classification procedure could also be applied for the analysis of the VHR imagery, while geometrical features proved primarily suitable for the VHR analysis.

The object-based image analysis (OBIA, cf. Blaschke 2010) was performed using the software eCognition (Trimble Geospatial). Emphasis was put on the definition of a rule set for a hierarchical classification based on stable object characteristics to ensure – to the extent deemed possible – the transferability to other scenes and sensors as well as to diminish the influence of different acquisition times.

Figure 2 gives an overview of the image analysis workflow showing the essential steps of the rule set development including the key classification parameters and the final feature classes. In case of the SPOT data, the rule set was developed for the 2003 scene and transferred to the other scenes with minor adaptations in order to compensate for differences in off-nadir angles, acquisition dates and atmospheric conditions. The rule set for the VHR images was developed for the 2008 QuickBird imagery and transferred to the 2004 IKONOS scene.

The analyses were based on an iterative multi-scale segmentation (Baatz & Schäpe 2000) and supervised rule-based classification approach of image objects. Complex class descriptions used for this classification contain spectral information, as well as spatial, geometrical and textural features. Furthermore, thematic attributes, contextual and hierarchical relationships of the image objects as well as object- and pixel-based resizing algorithms were used. Especially for the analysis of vegetation, the Normalised Difference Vegetation Index (NDVI) (Rouse et al. 1973) and the Modified Soil Adjusted Vegetation Index (MSAVI) (Qi et al. 1994) as well as ratios and textural features have proved suitable. The designated land cover classes refer – within the first hierarchical level, which is based on the SPOT data – to the nomenclature of the UNEP/FAO AfriCover Land Cover Classification System (cf. Di Gregorio & Jansen 1998) and have been adapted in order to meet the parameters of the HR data. Within the second hierarchical level, based on the VHR data, this classification is broken down to an even finer subdivision.

The image analysis has been conducted in several cycles, with each cycle starting with a bottom-up, region-growing segmentation (Baatz & Schäpe 2000) grouping surrounding pixels according to pre-defined criteria of homogeneity through a combination of different parameters, i.e. scale, colour and shape, to objects of interest. The overall values of the parameters at each cycle were determined by visual inspection of the objects resulting from variations in the parameter weighting. While in most cases, colour was preferred to shape, the scale parameter was set to different values starting with a very fine segmentation (small objects) in the first cycle and steadily increasing, according to the size of objects to be classified.

The initial segmentation was conducted using all available layers. The resulting image objects were considered for the classification and class refinement. The classification process follows a hierarchical scheme, starting with the detection of general land cover categories, i.e. ‘vegetation’ and ‘non-vegetation’ (Figure 2, 1. Cycle) using

the NDVI. These basic classes are further subdivided during the following classification cycles.

The second cycle aims at the detailed extraction of vegetation elements (see Figure 2, 2. Cycle), so that only the vegetation class was taken into consideration. For the HR data, it proved suitable to only use the near infrared channel for segmentation. This cycle was most challenging, since difficulties were found in distinguishing between arboreal and grassy vegetation, due to the similar spectral characteristics of these classes. In case of the SPOT data, vegetation indices as well as the information of the green band and the near- and shortwave infrared bands were useful for the detection and distinction of vegetation objects. Thus, for the 2003 image, the separation of closed, open and very open trees was possible. However, due to the different image quality, this detailed classification could not be applied for the 2005 image, since no suitable threshold could be determined to detect trees with a satisfactory result. As a consequence of the high degree of uncertainty, the classes were finally subsumed to the class 'open to very open trees'. For the VHR data, the separation of vegetation classes was also challenging. However, in contrast to the HR data analyses, the higher spatial resolution of the VHR data allowed the application of additional features, in order to reduce the confusion amongst the vegetation classes. Besides the spectral information of the imagery (vegetation indices, ratios, spectral layer values), textural feature characteristics as well as geometrical features proved suitable for further class distinction. A detailed overview of the extraction scheme for vegetation objects – exemplarily for the QuickBird scene – is given in Figure 3. The combination of features allowed the detailed distinction of the classes 'savannah', 'dense vegetation', 'sparse vegetation', 'dense trees and shrubs' and 'single trees and shrubs'.

In the third cycle, the non-vegetation elements were further investigated focussing on the detection of the main wadi system and the populated area. Due to the existence of clouds in the 2005 SPOT image, the classes 'clouds' and 'cloud shadow' were additionally introduced. In the first step, the populated area was classified using a thematic layer depicting the camp border. For the HR classification, especially the MSAVI and the Global Environment Monitoring Index (GEMI, Pinty & Verstraete 1992) have proved successful for separating the wadi area from the bare soil. Misclassified wadi objects could be removed using geometry features, e.g. *length/width* and *area*. In the VHR images, the water could be classified straightforwardly using the information of the near infrared band in combination with the brightness of image objects. The distinction between further wadi classes (wet and dry wadi areas) was more complicated since the spectral characteristics of dry and wet soil are the same in the wadi area as in the surrounding area. In this case, applying knowledge about the spatial behaviour of objects of interest (i.e. the spatial representation of objects as well as the spatial relationship between objects of different classes, e.g. neighbourhood conditions) enabled a more detailed classification. Thus, geometrical and class-related features were used to overcome spectral similarity. For the QuickBird image, which is characterized by dry climatic conditions, a spectral difference segmentation was applied additionally, in order to allow the separation of the dry riverbed and the surrounding dry soil.

Finally, the woody vegetation classes of the VHR classification were refined in a fifth cycle. There were some misclassifications of baobabs and small shrubs, which had no green leaves due to the dry climatic conditions at image acquisition of the QuickBird scene and thus were assigned to the classes 'savannah' or 'sparse vegetation'. The classification could be improved using spectral layer values (MSAVI, green band) in combination with geometrical features such as *asymmetry*, *area* and *roundness*.

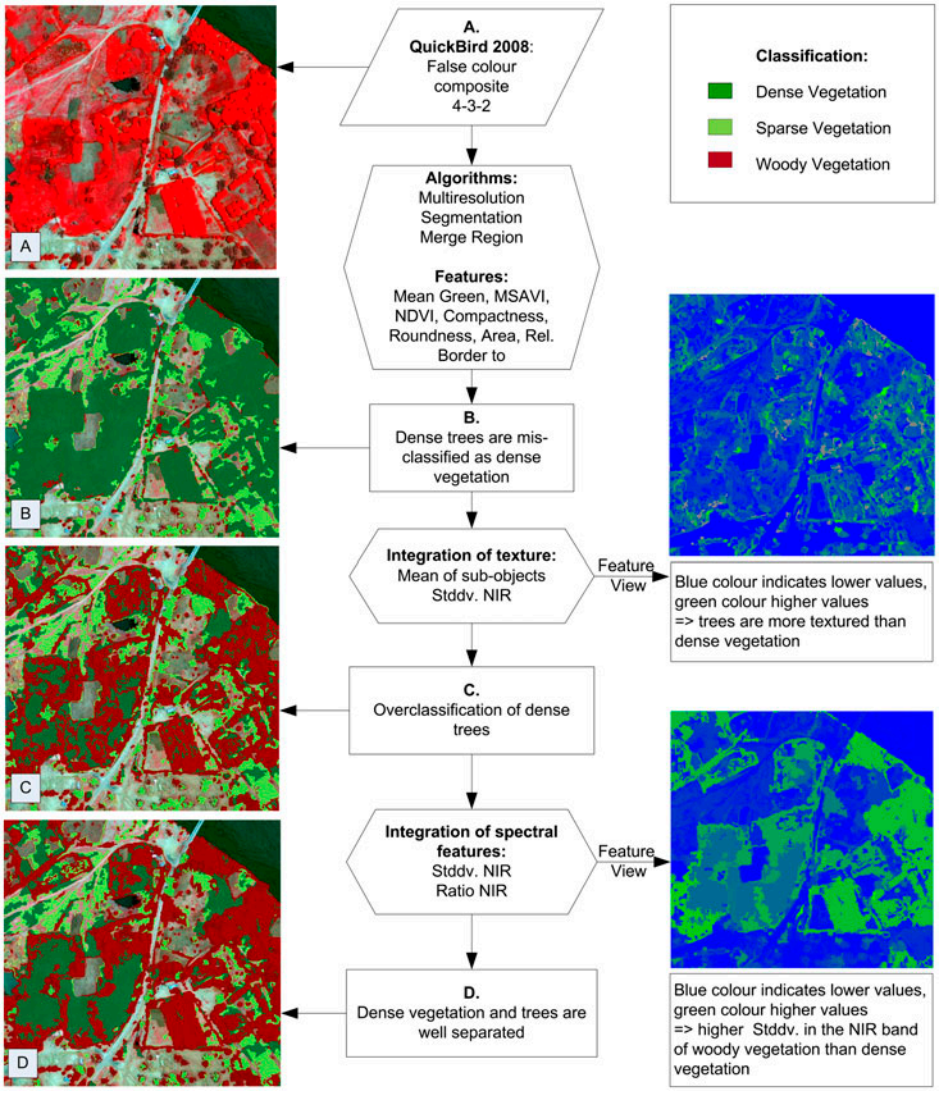

Figure 3. Workflow for the separation of vegetation elements.

Final class refinement could be reached by the application of object- and pixel-based resizing algorithms.

Since the study focuses on the changes in woody vegetation cover, the tree and shrub classes were finally merged to the class 'woody vegetation'.

Accuracy assessment

There are numerous publications dealing with the design and the most important factors to be taken into consideration when carrying out an accuracy assessment either on single data classifications or on change detection analyses results (Congalton & Macleod 1994; Dobson et al. 1995; Khorram et al. 1999; Congalton & Plourde 2002; Lu et al. 2004;

Congalton & Green 2009; Wickham et al. 2013) also reflecting on object-based approaches (Aguirre-Gutiérrez et al. 2012; MacLean & Congalton 2012; Hussain et al. 2013). In summary, one can state that most commonly used methods such as error matrices strongly build upon ground reference information (Congalton & Macleod 1994; Khorram et al. 1999; Congalton & Plourde 2002; Lu et al. 2004). Congalton and Plourde 2002 indicate five factors that need to be taken into consideration for a reliable accuracy assessment – amongst them ground reference data collection as the single most important factor (Congalton & Plourde 2002). Congalton (1991) points out that already one missing factor will result in significant shortcomings for the accuracy assessment itself (Congalton 1991).

Due to the crisis situation in Darfur, no ground reference data were available, even not through NGOs and UN agencies working in the region. For a statistical validation and quantification of the accuracy of the land cover classifications, an accuracy assessment was performed according to Congalton (1991). The classified images were compared to the original satellite data and evaluated by visual interpretation. Stratified random sampling was employed to choose a minimum of 50 sampling points for each category. Using the original satellite data as a basis, producer's accuracy, user's accuracy and Kappa coefficients were calculated.

Change detection

In order to quantify the change in woody vegetation in the vicinity of the Zalingei IDP camp, a post-classification comparison was carried out on both the HR and the VHR data. The main aim was to compare the analysis result at different scales in order to identify the major factors influencing the reliability of the results. Additionally, the possibilities and limitations at different scale should be evaluated. Different phenological status, for example, makes a comparison of the HR images difficult, but has only minor influence at single tree detection level on the VHR scenes.

As the main focus of this study is the assessment of the influence of refugee/IDP camps on their surrounding wood resources, only the classes 'open to very open trees' for the HR data and 'woody vegetation' in case of the VHR imagery served as input for the change detection. Shadows influence the detection of trees, because they partly cover them – especially in clusters of trees. For that reason, the change detection was conducted in two iterations: first including the shadow and second only considering the woody vegetation class.

Results and discussion

In general, the multi-scale image analysis approach and the hierarchical classification schemes developed show promising results, which are underlined by the high accuracy values. While for the HR scenes only broad land cover categories could be extracted and phenological differences hampered the analysis, the complex picture of structural elements characterizing the landscape pattern of Zalingei has been delineated through the analysis of the VHR data (see Figure 4).

Feature extraction

As a general observation of the image classification procedure, the potential of the object-based image analysis could be verified. Using expert knowledge and an iterative

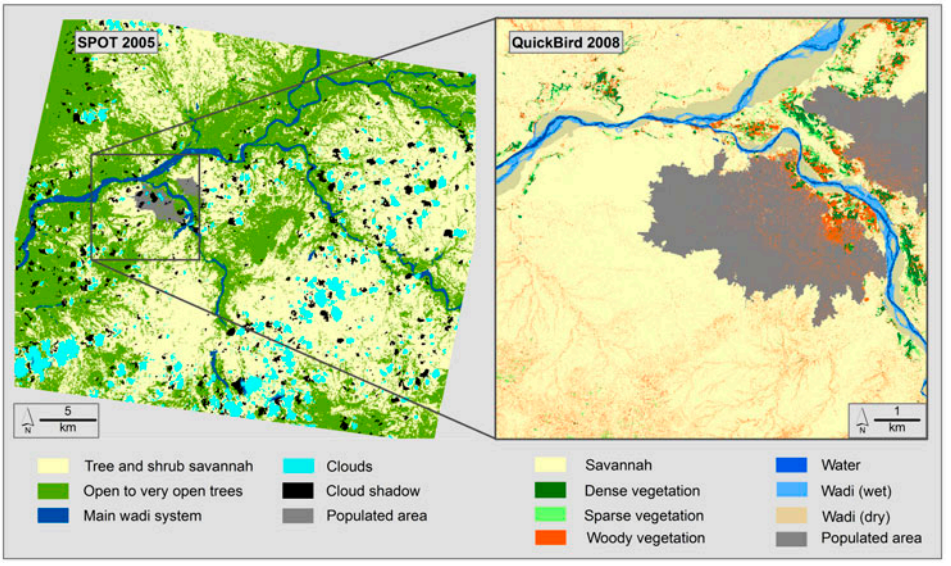

Figure 4. Results of the land cover classifications.

analysis process, a satisfactory detection of land cover classes (cf. Figure 4) could be obtained.

The study also demonstrates the suitability of additional features (e.g. spatial and contextual information) for the semi-automatic classification of high and very high spatial resolution satellite images in order to overcome the limited spectral resolution. The results from this research agree with previous studies (e.g. Laliberte et al. 2004; Puissant et al. 2005; Carleer & Wolff 2006) which also report an improvement in classification results through the integration of textural features.

Through the region-based classification of the HR SPOT-4 data, the non-vegetation classes have been delineated with a high level of reliability. In contrast, the extraction of vegetation classes was limited by the spatial and spectral resolution of the imagery, different phenological phases during the image acquisition and the higher humidity and cloud coverage in the 2005 data-set which resulted in poorer image quality. Consequently, vegetation elements could hardly be distinguished, even by visual interpretation, and no suitable and transferable threshold could be defined to detect trees with a satisfactory result.

The VHR data analysis was also influenced by different states of phenology at the acquisition dates. In summary, it can be stated that dry seasonal conditions during the QuickBird image acquisition favoured the extraction of single trees, except those with no green leaves. While baobab trees and shrubs could be well identified within the IKONOS image, due to their green leaves, the spectral mixture with the sparse grassland and the savannah led to an underestimation of these classes in the QuickBird classification. However, the relatively high density of the vegetation within the IKONOS image caused confusion amongst the vegetation classes. Especially the distinction of small patches of dense vegetation and close-standing trees was challenging.

Accuracy assessment

A summary of the accuracy values for the classifications is presented in Tables 2 and 3. All images have a Kappa value of about 0.85, indicating that most of the classes are well described by the developed class descriptors. However, only ground reference data could give absolute evidence of the assumptions. In general, it can be stated that in all images the vegetation classes are not as well identified as the non-vegetation classes, due to the spectral confusion amongst these classes.

The values for the overall classification accuracies of the HR data range from 92.75 to 95% and the overall Kappa statistics from 0.91 to 0.92%.

With an overall accuracy of 88.09% for the QuickBird and 86.87% for the IKONOS scene, the results obtained for both images are very convincing, especially when taking into account the number of classes and the complexity of the landscape. This conclusion is supported by the high overall Kappa coefficients of 0.86 for the QuickBird and 0.85 for the IKONOS scene.

Change detection

The change detection results of the HR data analysis (Figure 5) reveal that for the period from 2003 to 2005, there is a drastic decrease in open to very open trees of about 16,866 ha (23%), resulting from an increase of 6456 ha and a decrease of 23,322 ha for that LULC class.

From 2005 to 2007, a total increase in the open to very open trees area of about 10,116 hectares (18%) could be observed, with an increase of 19,363 ha and a decrease of 9247 ha, respectively. However, analysing the vegetation change from 2003 to 2007, an overall decrease of open to very open trees of about 6750 ha (9.2%) is indicated.

The change maps (see Figure 6) show that most areas characterized by vegetation decrease within the years 2003 and 2005 show an increase of vegetation in the years 2005–2007. Furthermore, it can be noticed that within a buffer zone of 10 km around the camp, the area in the south-east and especially in the south-west is most affected by the vegetation degradation during the entire period.

Table 2. Results of the accuracy assessment for the HR analysis.

Class name	Producer's accuracy (%)			User's accuracy (%)			Overall accuracy (%)	Overall Kappa coefficient (%)
	2003	2005	2007	2003	2005	2007		
Open to very open trees	94.12	89.90	90.91	97.56	97.80	96.77		
Tree and shrub savannah	93.18	95.51	95.49	93.18	85.00	89.44	2003: 95.00 2005: 92.75 2007: 94.50	2003: 0.91 2005: 0.91 2007: 0.92
Main wadi system	100.00	100.00	100.00	90.74	90.38	98.11		
Populated area	97.96	100.00	98.00	96.00	90.00	98.00		
Clouds	–	85.25	–	–	96.30	–		
Cloud shadow	–	89.83	–	–	100.00	–		

Table 3. Results of the accuracy assessment for the VHR analysis.

Class name	Producer's accuracy (%) 2004	Producer's accuracy (%) 2008	User's accuracy (%) 2004	User's accuracy (%) 2008	Overall accuracy (%)	Overall Kappa coefficient (%)
Dense vegetation	81.67	78.95	75.38	92.31		
Sparse vegetation	82.86	85.48	89.23	81.54	2004: 86.87 2008: 88.09	2004: 0.85 2008: 0.86
Woody vegetation	79.03	80.33	75.38	75.38		
Savannah	79.66	94.00	94.00	94.00		
Wadi (dry)	100.00	100.00	92.00	82.00		
Wadi (wet)	93.75	95.65	90.00	88.00		
Water	87.27	84.75	96.00	100.00		
Populated area	87.72	96.00	100.00	96.00		
Shadow	100.00	–	76.00	–		

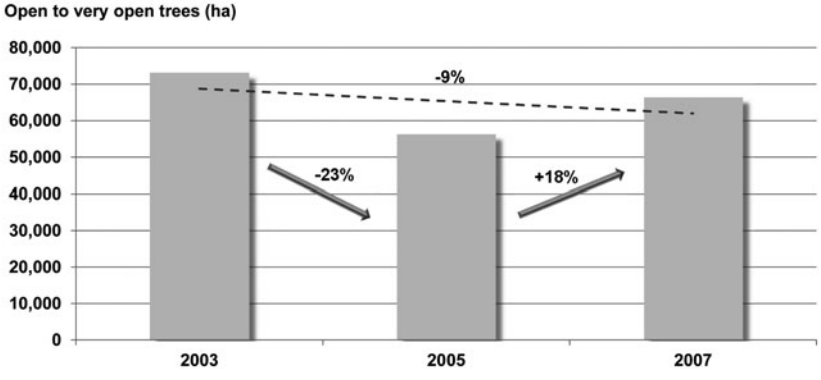

Figure 5. Change in open to very open trees from 2003 to 2007 based on SPOT-4 data (from Spröhnle et al. 2010, modified).

Due to the broad structure of the land cover class 'open to very open trees', it is not possible to detect subtle changes and to differentiate between arboreal and grass vegetation. Thus, the strong vegetation increase from 2005 to 2007 could be caused by several factors. A feasible explanation for a fractional vegetation increase within this period might be an increase in the agricultural crop land. An additional factor influencing the change detection result can be read from the accuracy assessment: the introduction of the classes 'clouds' and 'cloud shadow' caused additional confusion in the 2005 scene. It has been assessed that clouds and cloud shadow are slightly underestimated. As a result, there are more areas covered by clouds and cloud shadow in the 2005 scene than are masked out in the other scenes. This could lead to an underrepresentation of vegetation within the 2005 scene. However, these difficulties cannot explain the overall dimension of vegetation increase. The change detection results may rather have been influenced by different precipitation and consequent phenological conditions. For

this reason, the precipitation data has been used to get a better estimation of the phenological status at the time of data acquisition (see Figure 7). The SPOT data in 2005 was acquired during the main rainy season while the data in 2003 and 2007 were acquired after the main rainy season, in months with a lower rainfall rate. This

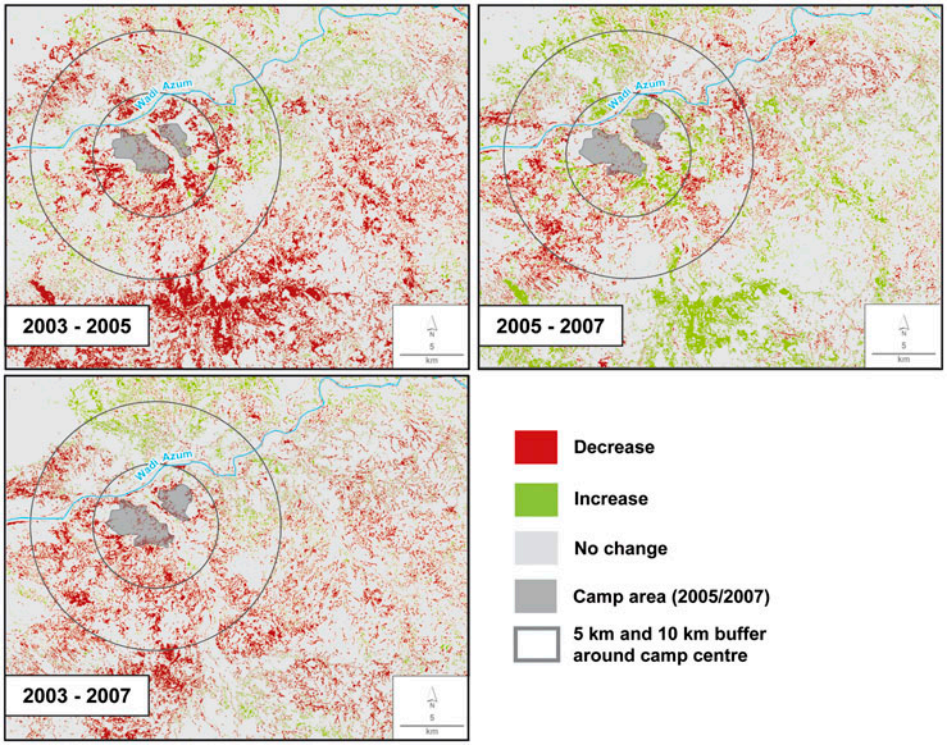

Figure 6. Change maps of open to very open trees resulting from the SPOT-4 data analysis.

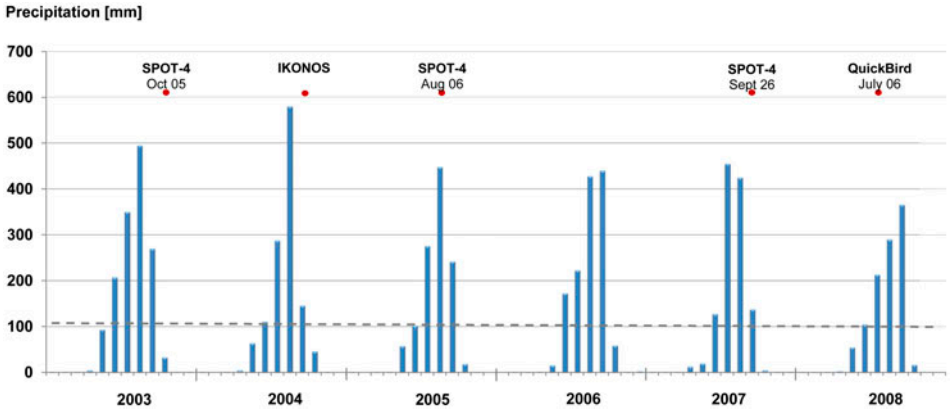

Figure 7. Precipitation data for Zalingei derived from HyDIS-Data (Sorooshian et al. 2014).

obviously resulted in different phenological stages of the vegetation which are clearly visible in the respective image.

Based on the SPOT data, it was not possible to verify whether the trend is caused by decrease/increase of woody vegetation or by a general decrease/increase of the green vegetation cover. Therefore, the VHR data were used to explicitly analyse the tree cover.

The land degradation becomes evident when comparing the VHR data of 2004 and 2008, which show an obvious decline in woody vegetation in the area surrounding the IDP camps. While areas were still scarcely covered with trees in 2004, they are basically deprived of vegetation in 2008 (see exemplarily Figure 8).

The change detection of the VHR classification results (see Table 4) revealed that in 2004, between 809 (without shadow) and 944 ha (with shadow) were covered with woody vegetation. By 2008, the cover reduced to 654 ha. Hence, there is a drastic decline of about 19 (without shadow) to 31 (with shadow) per cent in just four years. Most differences between the two iterations (regarding shadow) can be identified in the direct vicinity of the camp since there is a high accumulation of close standing trees, which are particularly influenced by shadow.

Severely degraded areas can be found in the south and southwest of the camp, within a distance of approximately 5 km. The vicinity of the camp is more secure for gathering wood hence, these areas are exploited most. However, also a vegetation

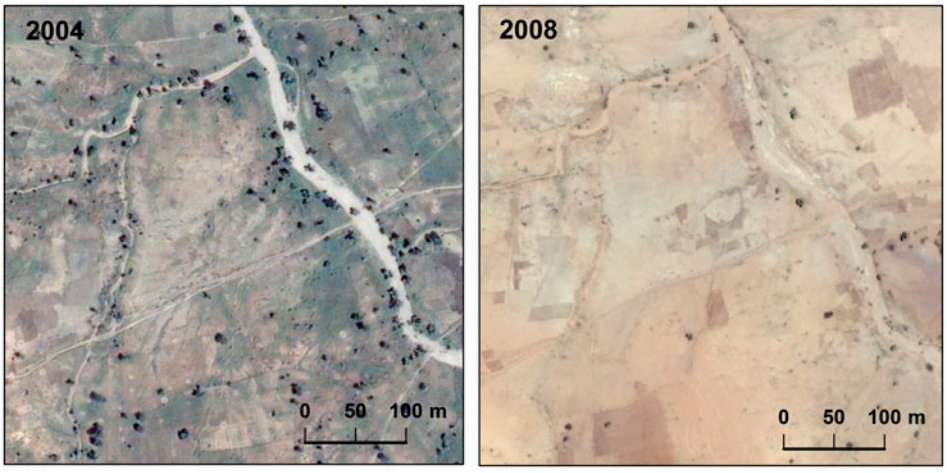

Figure 8. Example for decrease in woody vegetation within the study area between 2004 and 2008.

Table 4. Change detection results of the VHR data analysis.

Category	Change 2004–2008			
			Difference	
Woody vegetation	2004 (ha)	2008 (ha)	(ha)	(%)
Including shadow	944	654	290	30.7
Excluding shadow	809	654	155	19.2

increase within the camp can be observed, which can be explained by the cultivation of trees. This positive trend interferes with the mentioned exploitation of wood resources and explains another observation: The change map (see Figure 9) reveals that the elimination of woody vegetation occurred predominantly further away from the IDP camp, especially in those areas where woody vegetation cover originally was more dense due to favouring geographic conditions (e.g. groundwater, soils). In contrast, in the direct vicinity (especially close to the wadi areas), a partial increase in vegetation could be observed which might reflect reforestation and afforestation activities.

In general, the observed decrease in woody vegetation correlates well with the IDP situation in the Zalingei camps. Population dynamics in the camps between January 2004 and October 2008 (see Figure 10) show a considerable increase in the number of IDP's during this time period; from approximately 30,000 (HIC Darfur 2006) to more than 100,000 people while the number of permanent residents stayed constant during the same time (UN OCHA 2009).

The post-classification change detection technique presented here is less sensitive to radiometric variations between the scenes and more appropriate when dealing with data captured at different dates (see also Mas 1999). In addition, while other techniques only provide change/no-change information, the post-classification comparison provides complete matrices of change information (cf. Lu et al. 2004). Nevertheless, it has to be mentioned that change detection is limited by spatial, spectral, thematic and temporal constraints (c.f. Lu et al. 2004), especially in semi-arid environments exhibiting a high degree of landscape fragmentation and small structures like individual trees and shrubs.

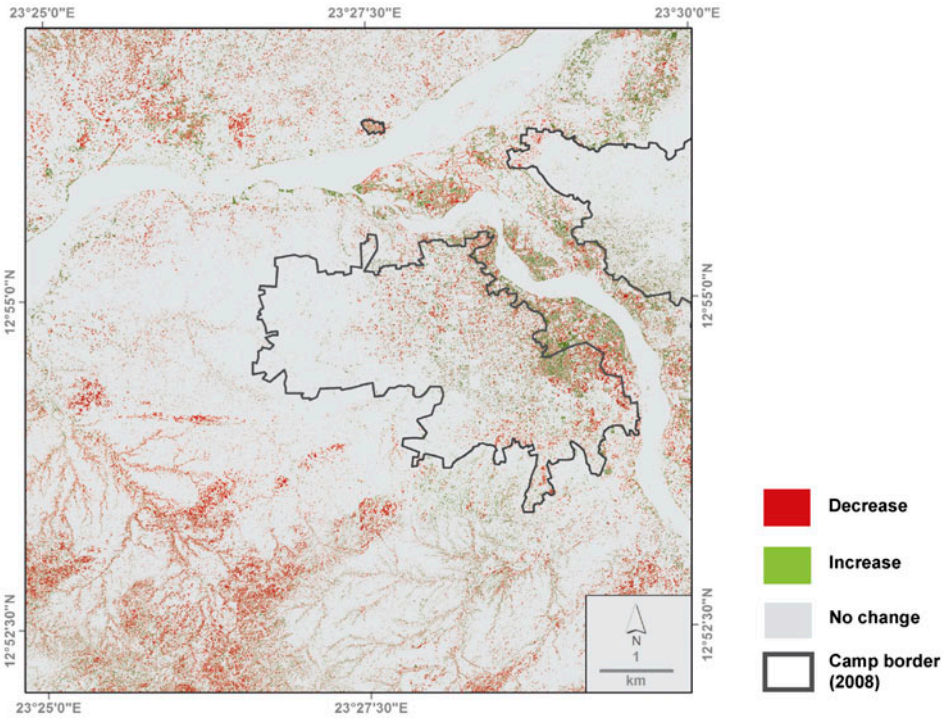

Figure 9. Change map of woody vegetation resulting from the VHR data analysis.

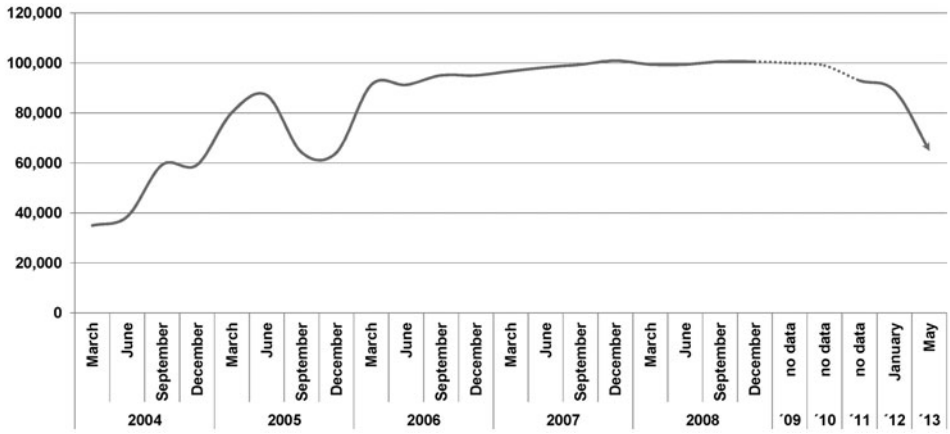

Figure 10. IDPs in the camps around Zalingei from 2004 to 2013 (HIC Darfur 2006; UN OCHA 2009, 2012, 2013).

The assessment of the environmental impact of IDP/refugee camps was based solely on a small number of satellite imagery. Thus, the comparison is influenced by different states of phenology. This is especially true for the HR analysis. More robust results could be obtained with a higher temporal resolution, i.e. a high frequency time series.

Finally, it can be ascertained that the described approach and its results have proven to be suitable to verify a substantial impact of IDP camp population on the environment and its natural resources.

Conclusion and outlook

The study demonstrates that the analysis of multi-temporal remote sensing data, supported by ancillary data, is an effective tool for monitoring human-induced environmental changes and degradation of natural resources in the vicinity of refugee/IDP camps. Furthermore, the potential of object-based image analysis for the extraction of different land cover types using HR and VHR satellite data could be demonstrated. It can be stated that the SPOT satellite data were suitable to detect broad land cover classes and the change in vegetation cover, if combined with additional information (e.g. precipitation data). However, for a detailed analysis of land cover changes, VHR satellite imagery is required. Finally, the results suggest that despite the restricted availability of large-scale maps and ground reference data, the predominant land cover changes in woody vegetation in the study area could be monitored accurately by the presented remote sensing approach.

In general, it can be stated that the high increase in human population in the Zalingei IDP camp in 2004 can be associated with considerable changes in the vegetation cover. Woody vegetation appears to have been cleared to generate timber, fuelwood and livestock forage for the local population (UNEP 2007). The quantitative information derived from this analysis may be used to enhance the qualitative information available so far (UNEP 2008).

The results of this study agree with several previous studies, which assessed a negative influence of the concentration of people in IDP camps on their surroundings. Substantial impact on vegetation has already been observed around camps in Darfur as a

whole (UNEP 2008; Kranz et al. 2010, 2015; Spröhnle et al. 2010; Hagenlocher et al. 2012). A major concern is that in the future almost all fuelwood supplies within walking distance of the camps will be exhausted. This should raise the awareness of decision-makers and should cause relief organizations active in this domain to work towards solutions to the deforestation problem around the IDP camps. The trend patterns derived from the EO-based assessment of the impact of refugee camps on wood resources can provide substantial support to decision-makers in developing strategies mitigating these impacts.

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