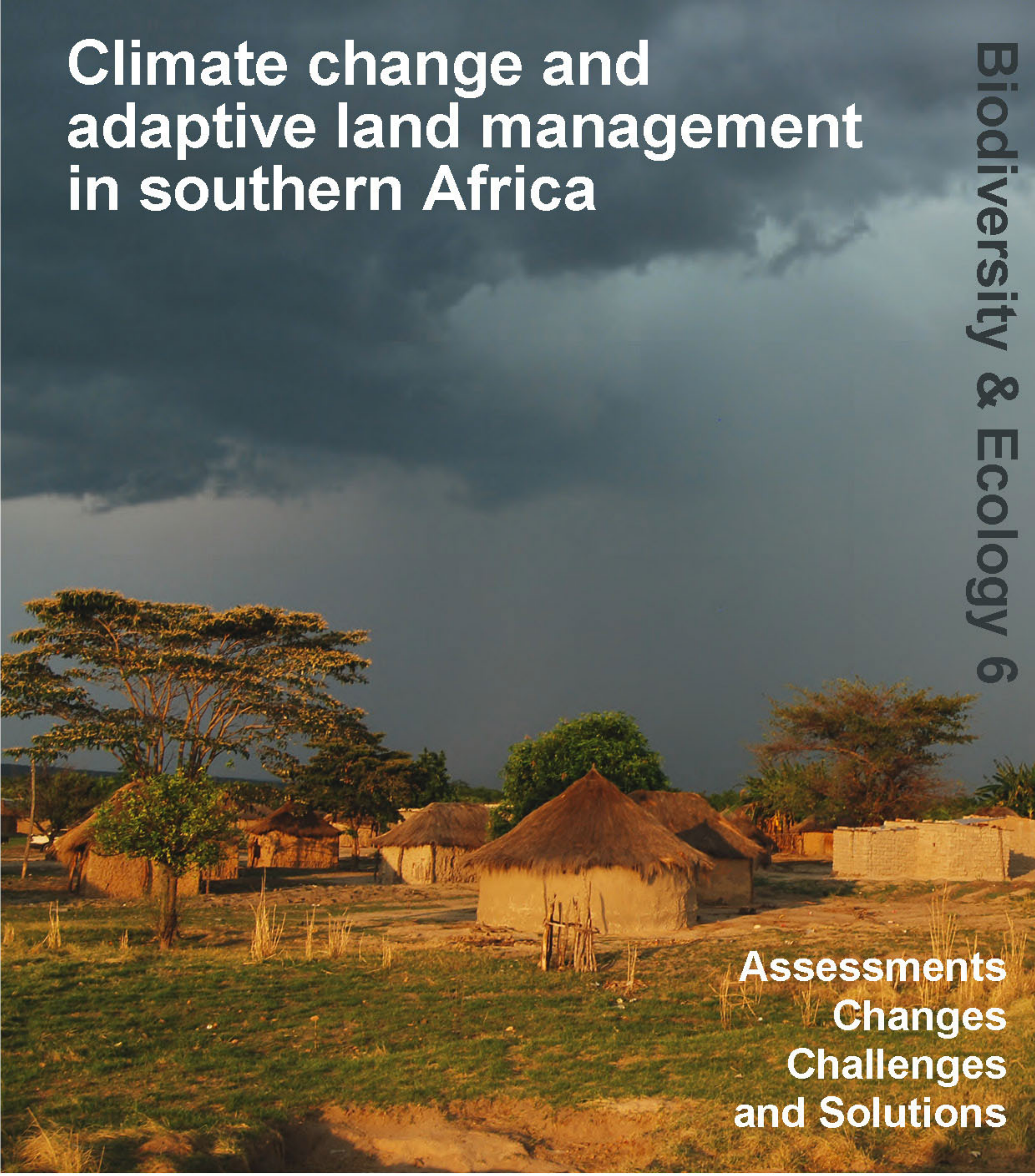
Climate change and adaptive land management in southern Africa

Biodiversity & Ecology 6



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Changes
Challenges
and Solutions

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Climate change and adaptive land management in southern Africa

Assessments, changes, challenges, and solutions

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Risk management

Monitoring flood and drought events – earth observation for multiscale assessment of water-related hazards and exposed elements

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Abstract: Disaster management is dependent on comprehensive information about the hazard's nature and the elements exposed – independent of the location and extent of the hazard. This work explores methods to monitor water-related hazards and identify exposed elements based on multisensorial earth observation (EO) and auxiliary data in southern Africa. For the *hazard-related perspective*, we present methods to monitor floods based on radar data (Sentinel-1, TerraSAR-X) and droughts based on time series MODIS satellite data. For the *exposure-related perspective*, we classify exposed settlements from TerraSAR-X (TSX) and TanDEM-X (TDX) data. We assess people at risk and their respective locations, combining earth observation and census-based geoinformation. The datasets and methods are explored in two case studies investigating a flood in northern Namibia in 2011 and drought events in South Africa and Botswana in 2015 and 2016. The case studies show that the methods developed are crucial tools for hazard and exposure identification, assessment, and monitoring.

Resumo: A gestão de catástrofes está dependente de informação detalhada sobre a natureza do risco e dos elementos expostos, independentemente da localização e da extensão do perigo. Este trabalho explora métodos para a monitorização de riscos relacionados com a água e para a identificação de elementos expostos na África Austral, com base na observação multi-sensorial da Terra (EO) e em dados auxiliares. Para a *perspectiva relacionada com os riscos*, apresentamos métodos para monitorizar cheias, baseados em dados de radar (Sentinel-1, TerraSAR-X), e secas, baseados nas séries temporais dos dados de satélite MODIS. Para a *perspectiva relacionada com a exposição*, classificamos povoados vulneráveis a partir de dados de TerraSAR-X (TSX) e TanDEM-X (TDX). Avaliamos pessoas em risco e as suas respectivas localizações, ao combinarmos a observação da Terra com a geoinformação baseada em censos. Os conjuntos de dados e métodos são explorados em dois casos-de-estudo que examinam uma cheia no Norte da Namíbia em 2011, e eventos de seca na África do Sul e Botswana em 2015 e 2016. Os casos-de-estudo mostram que os métodos desenvolvidos são ferramentas cruciais para a identificação, avaliação e monitorização de riscos e da exposição.

Introduction

Natural hazards have been and will always threaten our societies. Although we have a profound knowledge on historic extreme natural events and their frequency, magnitude or spatial distribution, the earth system is in constant change (Munich Re, 2017). As a consequence, one aspect is climate change, which does not just influence patterns of natural hazards, but also patterns of vulnerability and exposure. At the same time, elements at risk are at constant change. Urbanization processes (Taubenböck et al., 2012) as one example, concentrate more and more people and assets in often hazard-prone areas. However, monitoring the components of risk (Birkmann, 2006), is often limited by temporal and spatial data gaps.

In the past decades, space-borne remote sensing technologies along with geographic information systems (GIS) have become key tools for the assessment of climate change induced risks (Taubenböck et al., 2008). A large body of literature shows, that remote sensing not just holds the capabilities for analyzing hazards such as droughts (Rhee et al., 2010; Winkler et al., 2017) and floods (Martinis et al., 2015; Taubenböck et al., 2009), but also holds the capabilities for deriving exposed elements (Aubrecht et al., 2013; Geiß & Taubenböck, 2013) and assessing the related vulnerability of exposed elements (Geiß et al., 2014). *Exposure* can generally be considered as the location and characteristics of the "elements at risk," *vulnerability* is defined as "the conditions determined by physical, social, economic and environmental factors or processes, which increase the susceptibility of a community to the impact of a hazard" (UN/ISDR, 2004).

This study presents the capabilities of multisource earth observation data, techniques, and applications in the context of water-related hazards. We (1) show the potential of rapid mapping activities for reliable spatial assessments of flood impacts at the community level and (2) show the potential for identifying agricultural droughts and quantifying potentially affected elements at national levels.

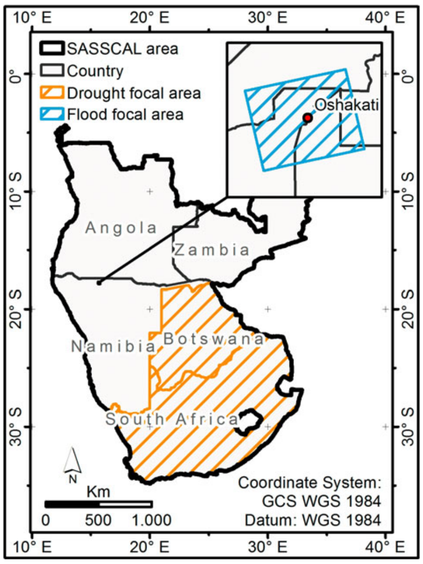

Figure 1: Study area

Study Area

The SASSCAL study area is southern Africa including the countries of Angola, Zambia, Namibia, Botswana, and South Africa (Fig. 1). In this study we work on three different scales: On the *continental scale*, which includes all five southwestern countries of SASSCAL, we monitor water-related hazards and assess potentially exposed elements.

The methods and information gathered on a continental scale are presented in two case studies, of which one is on a national and one on a local scale. The study area on a *national scale* focuses on droughts in 2015–2016 in South Africa and Botswana, whereas the study area on a *local scale* focuses on a flood event in northern Namibia in 2011. This study area, which is located in the most populous area of the Cuvelai-Etosha Basin, covers 143 km² in the Oshana region of Namibia and contains the town of Oshakati, which is the fifth-largest city of Namibia (Mendelsohn et al., 2013).

Data

Regarding hazard management, the availability of reliable, area-wide, up-to-date data is crucial for decision making. In the following we present and give reasons for the selection of a suite of satellite and sociodemographic data for monitoring the specific hazard (floods and droughts) as well as the identification and localization of potentially exposed elements (settlements, people, land cover). Table 1 provides an overview of the data used within this study.

Earth observation data

Satellite data are based on either passive optical systems or active radar (radio detection and ranging) or lidar (light detection and ranging) systems. The selection of the system for specific applications is influenced by various characteristics such as the geometric and temporal resolution. In this study we use radar and optical data for different applications as well as ready-to-use datasets (see Tab. 1).

Hazard-related remote sensing data

Flood

For the detection of surface water and thus, in exceptional circumstances, flooded areas, radar data are often the first choice. In contrast to optical data, they provide continuous all-weather day/night imagery (Brakenridge et al., 2003). In this study we rely on data from the Sentinel-1 mission, operated by the European Space Agency (ESA) in the framework of the European Union's Copernicus Programme. Because floods are relatively short-lived events, a satellite image acquired during and/or shortly after the peak of a flood event is required to obtain up-to-date information. Sentinel-1 is capable of providing this timeliness via a six-day exact repeat cycle and a repeat frequency (ascending/descending) of three days at the equator.

Drought

Since the detection of agricultural droughts using remote sensing is based on different spectral characteristics of healthy and stressed vegetation, optical earth observation (EO) data are applied for the approach suggested here. The assessment of areas affected by droughts was based on 8-day series (MOD09A1) of the moderate resolution imaging spectroradiometer (MODIS). MODIS is a scientific instrument aboard the research satellites Terra and Aqua operated by NASA, and the spatial resolution of the data is 500 meters per pixel (NASA, 2016).

Exposure-related remote sensing data

Settlements

For the classification of potentially exposed human settlements, we use very high-resolution (VHR) synthetic aperture radar (SAR) images of the German TerraSAR-X and TanDEM-X missions that have been collected between 2011 and 2013 (Esch et al., 2013). The vertical spatial resolution is 2 meters (relative) and 10 meters (absolute) within a grid of 12 square meters. Thanks to the globally uniform elicitation and very high resolution, the dataset is very suitable for the computation of settlement areas on a global scale.

Table 1: Multisource geodata applied in this study

Hazard monitoring		Exposure assessment	
Flood	Sentinel 1	Settlements	TerraSAR-X, TanDEM-X
Drought	MODIS	Landcover	Land Cover Map
		Population	WorldPop
		Auxiliary data for test site	In situ population data Infrastructure data

Risk management

Land cover

The land cover map of the ESA Climate Change Initiative provides a detailed overview of the annual global distribution of land cover types from 1992 to 2015. The spatial resolution of the dataset is 300 meters, and land cover classes were obtained from the processing of the full archives of 300 m MERIS, 1 km SPOT-VEGETATION, 1 km PROBA-V, and 1 km AVHHR surface reflectance 7-day composites. We use this product to assess land cover classes potentially affected by droughts.

Auxiliary sociodemographic data

Besides satellite-based data, we use auxiliary data to assess the exposure and vulnerability of people and elements in both study areas.

For the analyses of sociodemographic situations, we rely on population data originating from the WorldPop project (Tatem, 2017), which provides detailed and open-access population distribution data sets. Peer-reviewed, transparent, and fully documented methods are used to transform and disaggregate population counts at administrative unit levels to 100 m x 100 m grid cells (Tatem, 2017).

While the previous dataset is available for the entire SASSCAL area, we rely for our detailed case study at the local level on in-situ collected population data. They were collected in ground surveys by a mapping team after the 2011 flood in the relevant area.

For the socioeconomic vulnerability analyses, a georeferenced dataset of infrastructure comprising dwelling units and commercial and public services was obtained from the Namibia Statistics Agency (NSA, 2014).

Methods

Hazard-related classification using EO data

The selection of the data and the method of processing the data are strongly dependent on the nature of hazards. Since floods can occur at short notice and droughts, in contrast to this, over long periods of time, different methods of monitoring these events are necessary.

Floods

The Sentinel-1 Flood Service developed at the German Aerospace Center (DLR) is designed for flood detection and monitoring in near-real time (NRT). By user-defined criteria, a Python-based script routinely queries the ESA Sentinel Data Hub for new acquisitions. If the user-defined criteria on location, time, and so on match, the data are automatically downloaded and transferred into a fully automatic processing chain for surface water classification. The workflow consists of geometric correction and radiometric calibration of the Sentinel-1 data, initial classification using automatic thresholding, fuzzy-logic-based classification refinement, and final classification including auxiliary data. The fully automated processing chain allows time-critical disaster information in less than 45 minutes after a new dataset is available. The methodological details are published in Twele et al. (2016).

Droughts

Droughts are conceptually defined as an extended period of deficit rainfall related to the long-term average condition for a specific region (Schneider et al., 2011). Nevertheless, no standard definition of drought exists. The monitoring of spectral information using EO data relies on indices used as proxies to assess the conditions of the vegetation. For the analyses of spatial-temporal patterns of droughts, we used a dataset produced by Winkler et al. (2017). It is based on the Vegetation Condition Index (VCI) calculated from MODIS 8-day series (MOD09A1) of the time period 2000 to 2016. The VCI compares the current NDVI to the values observed in the same time periods in previous years. Lower and higher values (expressed as percentages) indicate bad and good vegetation conditions, respectively (Kogan, 1990). As proposed by Kogan (1995) and widely adopted by the drought-monitoring community (Deng et al., 2013; Gebrehiwot et al., 2011), a threshold of 35% for classifying droughts was applied (Winkler et al., 2017). Phenological information is retrieved from previously generated NDVI time series using the software package TIMESAT 3.2 (Eklundh & Jönsson, 2015). To assess all relevant growing seasons, each dataset refers to an extended year that spans from August of the previous year to December of the current year. In the finally used datasets, the severity of the droughts is indicated by the percentage of time of the growing seasons affected by droughts. More details on the drought dataset and its derivation can be found in Winkler et al. (2017).

Exposure-related classification using EO data

For the classification of human settlements, we use the original backscatter information as well as related texture information in TSX and TDX data. Highly textured surfaces such as vertical settlement structures lead to an increase of directional, non-Gaussian backscatter with comparably high values. In turn, homogeneous surfaces without any true structuring such as grassland show almost no true texture. By this procedure, using local speckle statistics in the SAR data, we localize highly textured regions. Based on this input information, we derive the thematic, binary mask identifying built-up areas and non-built-up areas by analyzing the texture layer by means of a pixel-based image classification procedure (Esch et al., 2013). The localized settlement areas are used as proxy for assessing potentially exposed elements.

Case studies: application of hazard and exposure products

Space defines whether elements are exposed to certain natural hazards, whereas the condition of the elements exposed defines whether they are vulnerable to the specific natural hazard. Based on two case studies, we analyze the elements exposed to a flood and drought event. Regarding droughts, however, it must be considered that people located in areas affected by droughts are not always exposed as a consequence.

Floods

On a local scale we approach the assessment of exposed people and cultivated land related to a flood that occurred in northern Namibia in 2011. Because Sentinel-1A and Sentinel-1B were launched in 2014 and 2016, the flood mask used

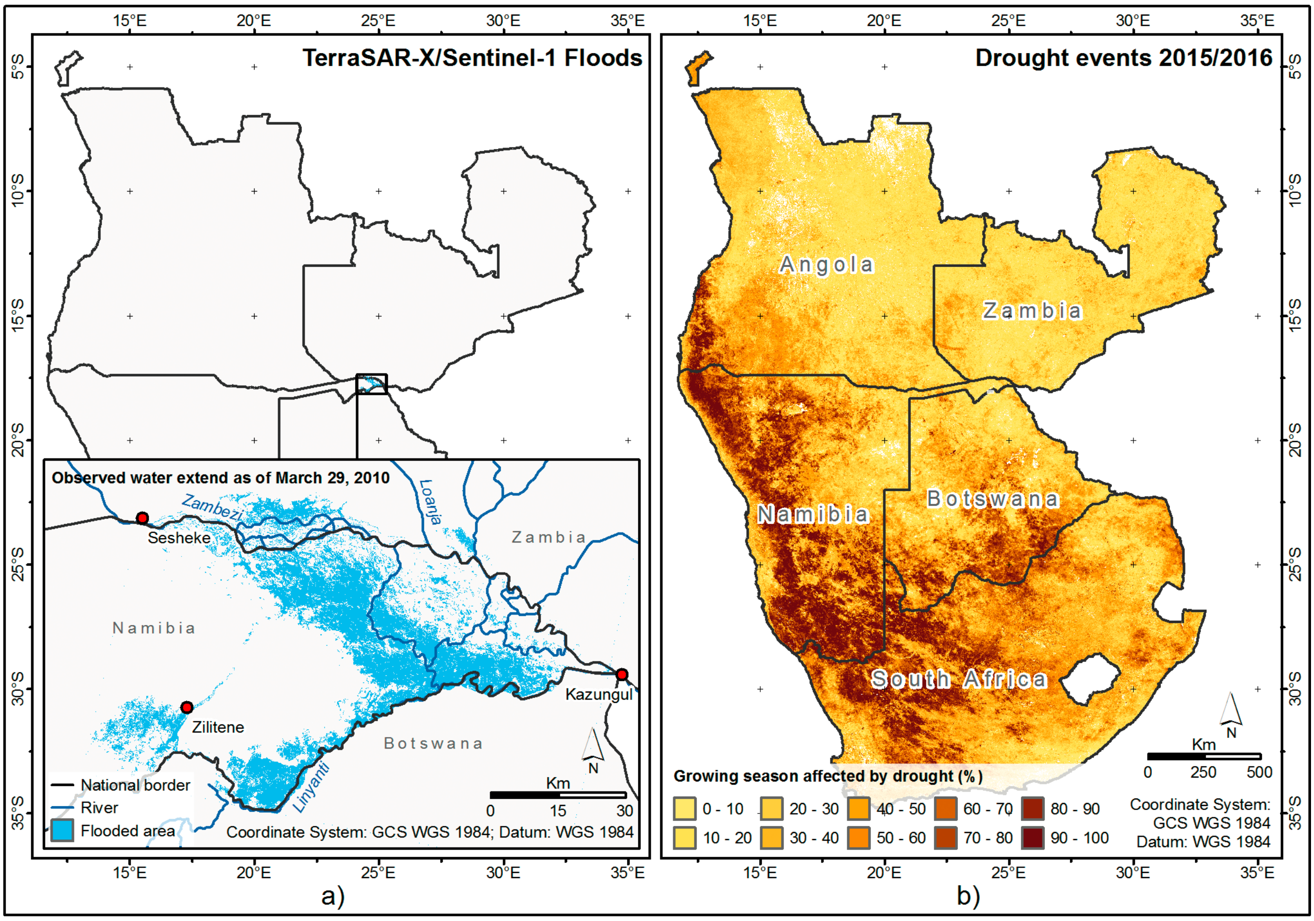

Figure 2: (a) Exemplary extent of water mask processed by TerraSAR-X/Sentinel-1 flood processor and (b) percentage of growing season affected by drought in 2015–2016

in this study was processed by DLR's TerraSAR-X Flood Service (Martinis et al., 2015), which is the previous model of the Sentinel-1 Flood Service. The flood mask displays the extent of the flooded area, including water bodies such as rivers and lakes. To obtain the affected properties and people, the 2011 flood mask, infrastructure data, and population data are intersected for computing geometrically overlapping features. The resulting attribute table is then employed to derive affected properties and number of people.

Droughts

At a national scale we approach the assessment of elements affected by droughts for the countries of South Africa and Botswana. To exemplify the EO-based capabilities, we used 2015/2016 data sets. To define droughts, the observations made from August 2015 to December 2016 were classified into different severity levels. We use four classes (less than 25% of the growing season, 25–50%, 50–75% and more than 75% of the growing season affected by drought events) to assess the severities of droughts. For assessing the exposure of different land cover types to droughts, we compute a spatial overlay analysis localizing the share of different land cover types affected by the drought events.

The population living in areas affected by droughts is derived by a spatial overlay analysis of the percentage of growing season affected by drought and auxiliary population data originating from the WorldPop dataset.

Results

The first section presents the techniques and applications developed to monitor water-related hazards on a continental scale based on multisource earth observation data. Second, datasets generated for exposure assessments in the SASSCAL region are shown. In the last section, the exploitation of the developed methods and generated datasets is presented on the basis of the case studies.

Hazard monitoring in SASSCAL region

Natural hazards feature specific spatial patterns. Figure 2b presents such a specific and distinct pattern for droughts, which occurred between August 2015 and December 2016. A clear spatial grade is illustrated for drought severity across space. Equivalent maps were available for each year between 2000 and 2016, revealing the variability in spatial distributions and extents as well as severities over time. The datasets show the capabilities of multitemporal remote sensing data for monitoring the explicit spatial component of droughts in the SASSCAL region. In the sample year displayed, the western parts of southern Africa are significantly affected during the growing season, while the northern and eastern parts rarely suffer. In addition, Figure 2a illustrates one example of the more than 100 flood events monitored in the area of SASSCAL since 2013. In comparison to droughts, floods are a rather local event. Within the area of SASSCAL, most

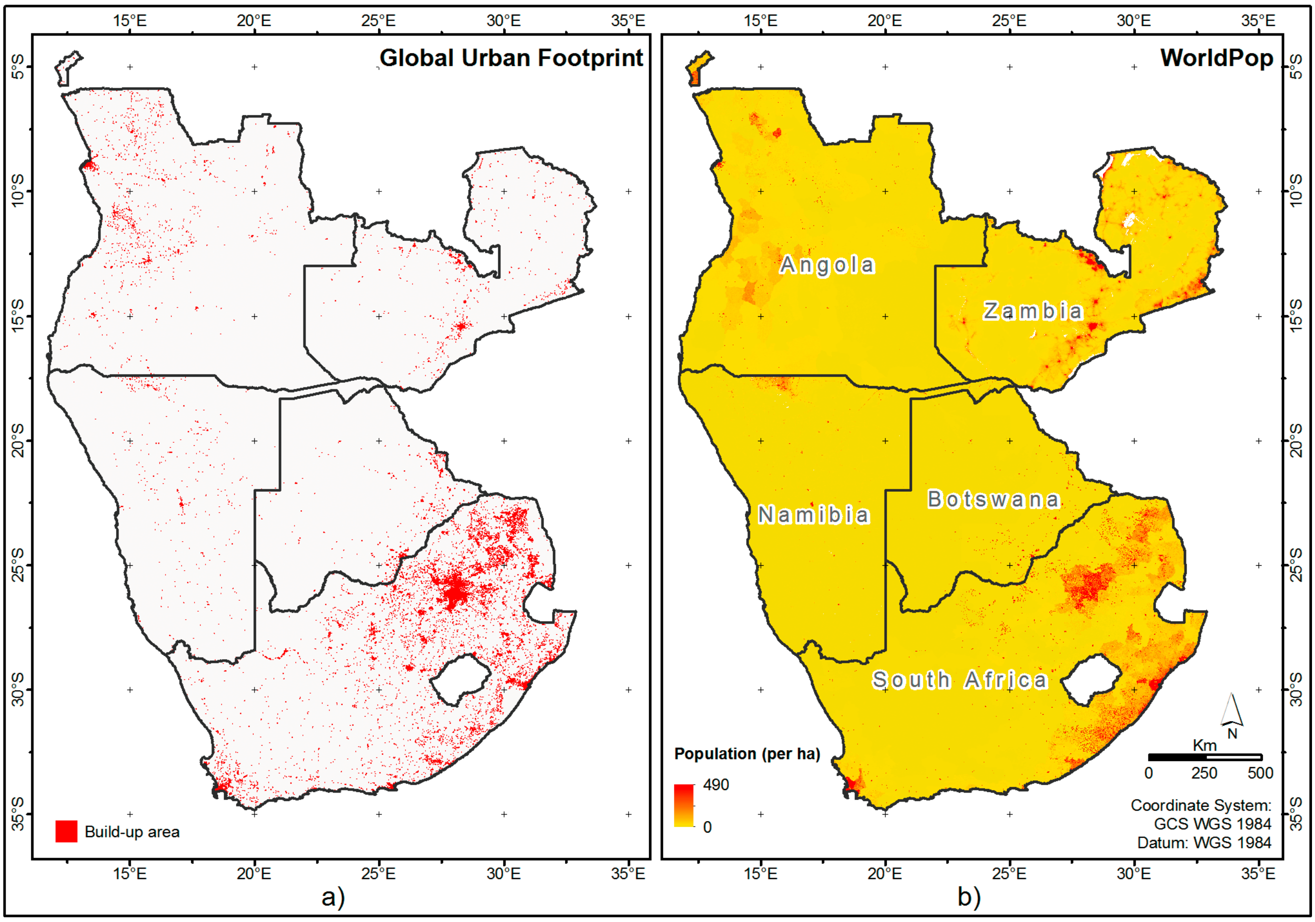

Figure 3: Settlement classification based on (a) the Global Urban Footprint and (b) population density within SASSCAL area based on WorldPop data

observations were made in the Cuvelai-Etosha Basin in the north of Namibia and at the border area between Namibia, Botswana, and Zambia. The floods monitored cover areas ranging from a few square kilometers up to several hectares, such as the one displayed in Figure 2a that stretches over 70 km from north to south and 100 km from east to west.

Exposure assessment in SASSCAL region

As with natural hazards, the exposed elements also feature specific spatial patterns. The classification of settlement distribution (global urban footprint at a spatial resolution of 12 m) is displayed in Figure 3a, indicating the uneven development of human settlements in southern Africa. The clustering of settlements in northeast South Africa with Johannesburg as center reveals this uneven spatial distribution of possibly exposed built environment when compared to, for example, the rural and very low-density settlement areas in Botswana or Namibia.

In addition to the spatial distribution of settlements, the population density is displayed in Figure 3b at a spatial resolution of 1 ha. The comparison of both datasets illustrates similarities and reflects that the spatial clustering of the built environment obviously correlates with population densities; despite the existence of correlation between built-up environment and population densities, however, some differences exist. Overall, these datasets clearly show the capabilities of earth observation data to provide an assessment of exposure on a continental scale.

Local scale analysis: Exposure to water-related hazards

The classifications of hazard- and exposure-related parameters reveal the uneven spatial distribution of each perspective. To assess exposure, we illustrate the capabilities of these geoinformation layers for assessing elements at risk for two examples: a flood event in Namibia in 2011 and drought events in South Africa in 2015.

Flood

Figure 4 presents the distribution of affected properties during the receding stage of the flood, which had peaked two weeks earlier in relation to the April 1, 2011, flood mask. Because Sentinel-1A and Sentinel-1B had been launched in 2014 and 2016, the flood visualized in Figure 4 was processed by the TerraSAR-X flood processor, which is the previous model of the Sentinel-1 flood processor. During that period of the flood on April 1, 2011, Oshakati and its environs had approximately 11,900 properties, of which 270 (2.3%) were still affected by the flood. Almost 90% of the flooded properties were situated in settlement areas, and only 11% were in the countryside. Within the settlement areas, 82% of these properties were in informal settlements, confirming the often proclaimed exposure of the urban poor posited by, for example, Braun and Aßheuer (2011), Davis (2007), and Douglas et al. (2008).

The spatial analysis reveals that 47% of the entire affected building stocks were dwellings. In the period under consideration, the study area had a population of approximately 47,000 residents, out of which 680 (1.5%) were being directly affected. The next most affected (35%) category of properties pertained to demolished structures or vacated dwellings. Commercial properties accounted for 16%, while public services were least affected (less than 1%).

Drought

To assess the impact of droughts, we calculate the share of areas affected by drought of different persistency for four Climate Change Initiative land cover classes (Fig. 5).

In general we found that differences in spatial distributions of droughts and exposed elements led to significant differences in drought hazards in neighboring countries. In Botswana almost 20% of croplands and almost 10% of natural vegetated areas suffered from drought that lasted longer than 75% of the growing season. This is a significantly higher impact than in South Africa, where only 3% of the croplands and 1% of natural vegetated areas suffered this intense drought situation. Nevertheless, the focus should be not on extreme values but on the distribution of the share of the single land cover classes in terms of drought persistency. For example, in Botswana drought persistency above 25% affected more than 20% of cropland (rainfed), while in South Africa less than 5% of the cropland (rainfed) was affected by droughts lasting longer than 75% of the

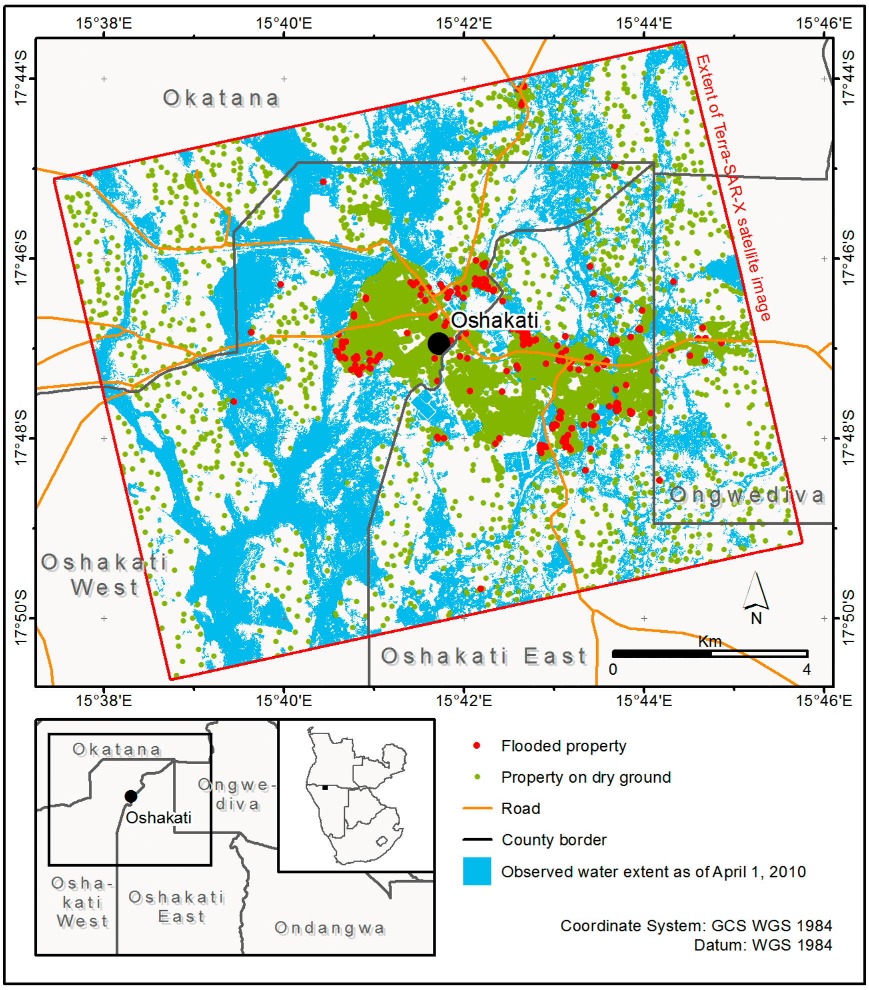

Figure 4: Distribution of flooded properties in and around Oshakati on April 1, 2010, two weeks following the flood peak

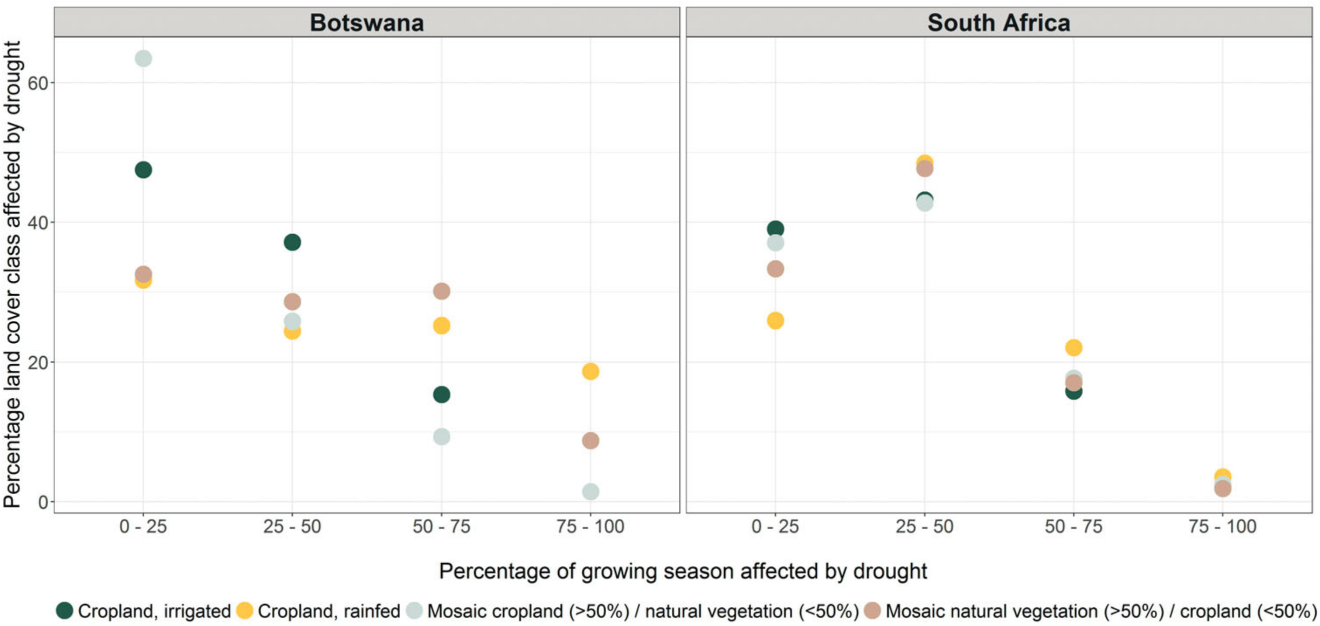

Figure 5: Percentage of land cover classes affected by droughts of different persistency

Table 2: Relative and absolute share of population living in areas affected by droughts of different persistency

Percentage of growing season affected by drought	Botswana		South Africa	
	Population (%)	Population (abs.)	Population (%)	Population (abs.)
0-25%	2.19	46,287	7.1	3,649,307
25-50%	4.74	99,588	11.12	5,710,591
50-75%	7.16	151,402	3.78	1,942,892
75-100%	3.27	69,141	0.5	254,776
Sum	17.33	366,417	22.5	11,557,565

growing season. Additionally to the share of affected land cover, we calculated the share of the population living in affected areas differentiated in accordance with drought persistency (Tab. 2).

In both countries most people living in areas of investigated land covers were affected by droughts that lasted for 25% to 75% of the growing season (Botswana, 11.9% of the total population; South Africa, 14.9% of the total population). Because of the difference in total population numbers, the absolute number of people living in areas affected by droughts during 25% to 75% of the growing season is 30 times greater in South Africa (7.5 million) than in Botswana (about 250,000). Nevertheless, comparing the population living in areas affected by droughts lasting longer than 50% of the growing season, the relative population affected is higher in Botswana (10.4%) than in South Africa (4.3%).

Discussion

Earth observation data in combination with other geodata are capable of detecting and monitoring water-related hazards and identifying exposed elements. The study reveals the immense capability of multisensorial and multitemporal remote sensing applications for identifying and evaluating different components of risk spatially for large areas as well as in high spatial and thematic detail.

In general, remote sensing allows assessment of risk with high accuracy; it must be considered, however, that remote sensing methods do not produce cadastral data sets with respect to accuracy. Also, vegetation parameters used as proxies to assess droughts may not provide a perfect match. Thus, the methods of deriving flood masks, monitoring droughts, and classifying land cover can be optimized using better-calibrated algorithms or different, higher-resolution datasets, or by extending thematic information (e.g., by assessing flood depth in addition to flood extent). For example, studies dealing with flood or settlement detection based on EO data revealed that accuracies are in the range of 80–90% (Klotz et al., 2016; Martinis et al., 2015), which allow assessment with high reliability. The following discussion sheds light on the capabilities of EO data in terms of *hazard management*, the *value of the developed methods* and *derived datasets*. Furthermore, the discussion focuses on the benefits and challenges of applying EO data in managing hazards.

Mapped floods derived from freely available EO data, which are independent of weather condition and daylight, provide information of unique spatial scale and resolution. EO data enable the monitoring of floods on a continental scale and can provide information about the spatial extent of floods within a few hours. Nevertheless, the temporal resolution of Sentinel-1 data in Africa is not as high as stated by the European Space Agency; we observed that the temporal resolution ranges from a few weeks to a couple of days depending of the area of interest in the SASSCAL region. The importance of the timeliness of the data in case of floods is also highlighted in the case study. Because of runoff, high evaporation rates, and permeability, the flood extent captured two weeks after the flood peak inevitably underestimates the impacted infrastructure and number of people. Nevertheless, it reveals the persistence of the flood impact, which is crucial for flood damage assessment. In our study case, people in informal settlements were identified as the most affected, partly as a result of the fact that they often (have to) settle in marginalized areas, including flood-prone zones. The high number of demolished or vacated dwellings in and around Oshakati may be attributed to earlier displacement from the previous floods that took place in the area for two consecutive years, 2009–2010 (Mendelsohn et al., 2013). Even if additional datasets – as in this case study – were not available, the settlement classification based on the Global Urban Footprint and the population data from WorldPop provide sufficient information about hot spots affected by floods.

For people involved in hazard management, the results of the exposure analysis (settlement distribution and population data) can easily be made available, and the case studies show that EO data are capable of providing a unique overview of hazardous situations.

Climate is changing, and to be able to adapt to these changes it is crucial to monitor the changing systems. In contrast to monitoring floods, the aim of monitoring drought is to gain knowledge in order to address the following question: What areas are most affected with respect to spatial extent, persistency, and intensity of droughts? In the case study, the growing seasons of two countries are compared as an example; the long-term data obviously allow much more research on various spatial and temporal scales. In general, one limitation of the drought dataset used in this study is its spatial resolution of 500 meters. As a matter of fact, the spatial resolution of the data used limits the ability to detect droughts on, for example, scattered small-sized fields surrounded by other land cover types (e.g., irrigated fields, natural vegetation). However, medium-resolution data such as MODIS are to date the only available satellite data that provide sufficient and consistent time series to be used to assess anomalies and thus drought. As soon as longer high-resolution time series (e.g., Landsat-8, Sentinel-2) become available within the next few years, there will be new potential for assessing drought at a higher spatial resolution. Although the data do not consist of information about the impact of these droughts on the population, the data are crucial for long-term analysis.

Climate change comes with an increasing frequency and intensity of extreme events. Those require instruments for rapid monitoring to support hazard management and thus well-founded decisions by stakeholders. Climate change also comes with long-term changes. EO data are capable of providing information on both of these temporal scales. Therefore, the methods developed provide data not only in the short term but also in the long-term, which helps us understand changing systems.

Conclusion

In general, earth observation data and techniques feature immense potential for identifying, assessing, and monitoring water-related hazards. The obvious and necessary extension in the future will be the increase in information content. High-resolution digital surface models might allow assessments of flood depth, new missions such as Sentinel will increase the spatial resolution of drought monitoring (He et al., 2016), and very high-resolution optical satellite data increase the thematic resolution of, for example, settlements into structural types such as business districts or slums (Taubenböck & Kraff, 2014). Beyond, in the time of "big data", the combination with other geodata – as exemplified here with population and socioeconomic data – holds immense capabilities for more comprehensive perspectives on hazards, exposure, vulnerability, and ultimately risks. Data sources of relevance include census, open geoinformation, and social media data. In conclusion, the new advent of data offers immense capabilities for better geoinformation for risk management; however, the methodologies and the topic-adpated useful applications still need to be developed.

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