EARTH OBSERVATION STRATEGIES FOR DEGRADATION MONITORING IN SOUTH AFRICA WITH SENTINELS – RESULTS FROM THE SPACES 2 SALDI-PROJECT YEAR 1

C. Schmullius[1], M. Urban[1], A. Hirner[2], C. Berger[1], K. Schellenberg[1], A. Ramoelo[3], I. Smit[4], T. Strydom[4], G. Chirima[5], T. Morgenthal[6], B. Melly[7], U. Gessner[2], N. Mashiyi, A. Mlisa, M. Kganyago and J. Baade[9]

[1]Department for Earth Observation, University of Jena, Löbdergraben 32, 07743 Jena, Germany
[2]Earth Observation Center, German Aerospace Center (DLR), 82234 Wessling, Germany
[3]Geospatial and Environmental Sciences, South African National Parks, P.O.Box 787, Pretoria, S.Africa
[4]Scientific Services, South African National Parks, Private Bag X402, Skukuza 1350, South Africa
[5]ARC-Soil, Climate, Water and Agricultural Enginrg., 600 Belvedere Street, Arcadia 0083, South Africa
[6]DAFF Directorate: Land Use and Soil Management, Delpen Building, Pretoria 0001, South Africa
[7]South African Environmental Observation Network, Fynbos Node, Cape Town, South Africa
[8]South African National Space Agency, Directorate Earth Observation, Pretoria, South Africa
[9]Department of Geography, University of Jena, Löbdergraben 32, 07743 Jena, Germany

ABSTRACT

The overarching goal of SALDi (South African Land Degradation MonItor) is to implement novel, adaptive, and sustainable tools for assessing land degradation in multi-use landscapes in South Africa. This presentation demonstrates results from hyper-temporal Sentinel-1 and -2 timeseries concerning woody cover mapping in complex savanna systems, invasive slangbos bush encroachment in grassland areas and regional soil moisture retrievals. Validation has been performed by cross-comparisons, field trips and permanently installed soil moisture networks.

Index Terms—*Sentinel-1, Sentinel-2, South Africa, land degradation, savanna, vegetation structure, disturbances, soil moisture*

1. INTRODUCTION

The project 'South African Land Degradation Monitor (SALDi)' contributes to the German-South African Science Program SPACES by addressing the dynamics and functioning of multi-use landscapes with respect to land use, land cover change, water fluxes, and implications for habitats and ecosystem services. Particularly, SALDi aims:
i) to develop an automated system for high temporal (bi-weekly) and spatial resolution (10 to 30 m) change detection monitoring of ecosystem service dynamics,
ii) to develop, adapt and apply a Regional Earth System Model (RESM) to South Africa and investigate the feedbacks between land surface properties and the regional climate,
iii) to advance current soil degradation process assessment tools as a limiting factor for ecosystem services.

2. MATERIALS & METHODS

SALDi builds on innovative synergistic methodologies combining biophysical and empirical retrievals from radar remote sensing data [1, 2, 3], complemented by methods providing a basis for recording land use [4, 5], vegetation cover [6, 7] and productivity from optical remote sensing data. The synergistic exploitation of the advantages of optical (vegetation vitality, coverage and types of land use) and radar (vegetation structure, surface moisture) holds high potential for the complex South African landscapes. Corresponding validation work in the field is an essential element [8].

2.1. Study area

Protected areas within our six study regions (Fig. 1) represent benchmark sites, providing a foundation for baseline trend scenarios, against which climate-driven ecosystem service dynamics of multi-used landscape (cropland, rangeland, forests) are evaluated.

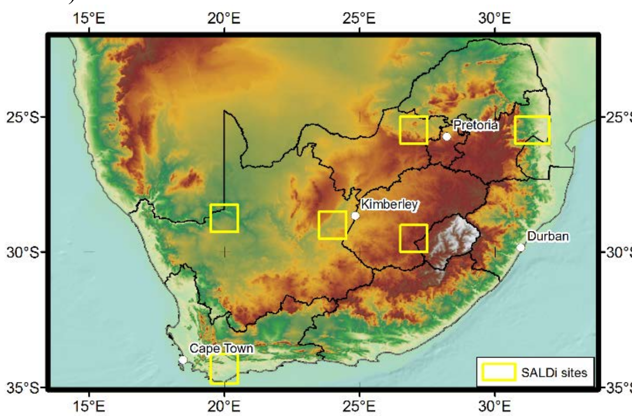

Figure 1. SALDi study sites across South Africa.

2.2. In situ information

In situ soil moisture probes were installed in March 2019 in each of the six SALDi study regions. Three of them are situated in National Parks (Augrabies Falls, Mokala and Kruger National Park). Each soil moisture network consists of a central data logger unit with eight 10 m cables radiating into eight directly opposing directions, each equipped with a SMT-100d soil moisture sensor. The soil moisture as well as soil temperature is measured in a 30 min interval at a depth of 6 to 10 cm. Further in situ information stem from drone campaigns and extensive field data collections during three 6-week site visits.

2.3. Satellite data

We are utilizing Sentinel-1A/B C-Band VV/VH-SAR time series with a 10 m resolution. The revisit time is 12 days in average for South Africa. Pre-processing is done using pyroSAR, a Python framework for large-scale SAR-processing providing processing utilities in ESA's Sentinel Application Platform (SNAP) as well as GAMMA Remote Sensing software [10]. Sentinel-2A/B data were pre-processed to L2A and used to calculate a wide range of vegetation indices (e.g. NDVI, EVI, SAVI, REIP) using DLR's Sen2Cor-processor. The time frame starts with the first Sentinel-1 and -2 acquisitions and continues.

SANSA in collaboration with SARAO (South African Radio Astronomy Observatory), is developing an open data cube, Digital Earth South Africa (DESA) based on SPOT data. Other datasets from different sensors will be ingested at a later stage. The analysis-ready data, that is, harmonized, standardized, interoperable, radiometrically and geometrically consistent data [9], is being ingested in the data cube. Algorithms and models for developing products such as land degradation indicators will be developed using Jypiter notebooks. SALDi's data cubes will be linked for access and exercises.

2.4 Woody Cover Mapping

South African savanna ecosystems are characterized by woody vegetation (shrubs and trees) and grasslands with large seasonal changes and vulnerability to impacts from droughts, fires and herbivory. Hence, structural monitoring is an essential component. Sentinel-1 time series were applied to a random forest machine learning approach [11]. For training, high resolution airborne LiDAR were utilized.

2.5 Disturbances

Land degradation can be triggered by numerous mechanisms that range from slowly operating, low onset processes (e.g. climate change) to abrupt disturbance events like floods or fires. Fires are an important agent because the recovery of vegetation in a system that is already out of equilibrium can result in completely different and often reduced assemblage of plant species. Sentinel-2 vegetation indices (e.g. NDVI, EVI, SAVI, REIP) were used to construct time series for selected areas, in order to describe and quantify vegetation trends before and after fire events.

2.6 Slangbos Monitoring

In the grassy plains of central South Africa (Freestate Province), slangbos (*Seriphium plumosum*, bankrupt bush) communities increasingly encroach into the prevalent open landscapes. The rapid change of the vegetation composition poses great challenges to local ecological dynamics as well as to livestock breeders as it potentially reduces grassland productivity. A national survey by the South African Department of Agriculture, Forestry & Fisheries (DAFF) set the expansion of the bush under scrutiny. Due to the large area infested, remote sensing in conjunction with machine learning models have been tested and led to good results [12].

2.7 Soil Moisture Estimates

Multi-temporal co- and cross-polarized Sentinel-1 C-band data were used to segment vegetation structure followed by a Sentinel-2/Landsat-8 NDVI-based analysis of vegetation dynamics. Thus, pixel values representing soil moisture changes only, and not leaf dynamics, were identified. A hyper-temporal backscatter model was then applied to generate soil moisture maps [13]. Certain regions in South Africa experienced some of the most severe drought conditions on record during the southern summer 2015/16 [14]. Our analysis covers a time span between March 2015 and November 2019. Geographical focus is on Kruger National Park south of 25 degrees latitude (site 6, Fig. 1).

3. RESULTS & DISCUSSION

3.1 Woody Cover Mapping

Sentinel-1A/B VV/VH- data from 2016/2017 were used to map vegetation structure in the Kruger National Park (Figure 2). A high-resolution LiDAR data set [15] was reclassified

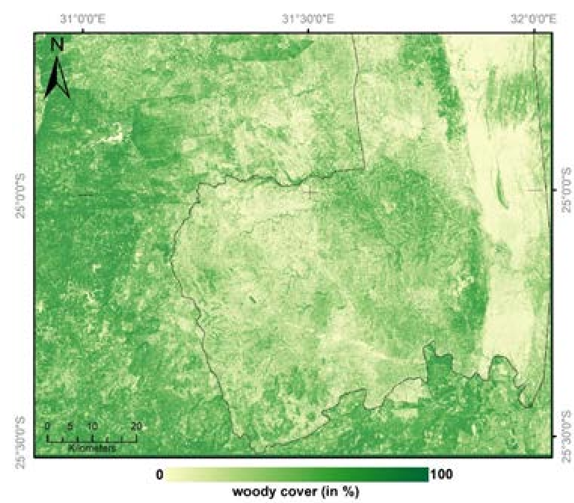

Figure 2. Sentinel-1 derived woody cover map of the southern part of the KNP with a spatial resolution of 10 m for the years 2016/17.

for training. The woody cover estimation is derived from the decision tree classifier random forest [14] using an MLR implementation. Spatial cross-validation resulted in an overall RMSE of approximately 23 %. The final product was validated against a second independent LiDAR derived woody cover data set [16], resulting in a RMSE of 24 % [17].

3.2 Disturbances

The Western and Eastern Cape provinces of South Africa are home to one of only six floral kingdoms in the world. The Cape floristic region is dominated by a natural shrubland or heathland vegetation with an extremely high number of endemic species called fynbos. The fynbos ecoregion is exceptionally prone to fires, with appropriate fire regimes playing an important natural role in system functioning. Fire scars are often visible for multiple years. Invasive species in fynbos often interact with fire by increasing fire frequency and intensity. In addition, some invasive species have faster reproduction rates than the endemic plant types and displace the original vegetation with a low diversity assemblage, whilst concurrently changing the future fire characteristic, and are thus being considered a case of land degradation.

The recovery after wild fires can be observed by time series of vegetation indices like NDVI derived from Sentinel-2 (2016-2018) at different sites. A common pattern (compare Fig. 3) shows no recovery of the index in the year of the fire event and slow recovery during subsequent years. NDVI levels comparable to pre-fire times or neighboring areas not affected by fires are not attained during our observation period of three years. Observations over longer time spans will be able to show natural response rates and eventually help to delineate areas where the recovery is hampered.

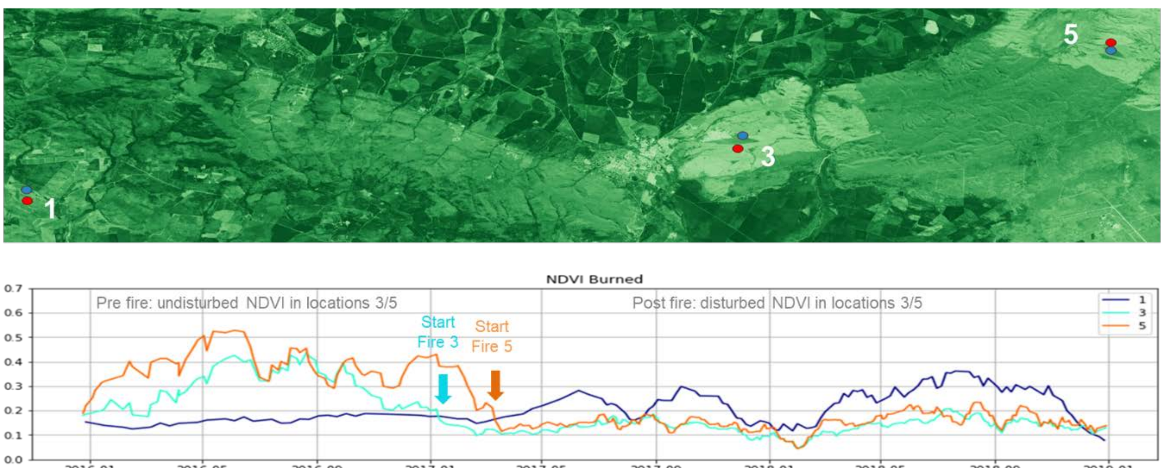

Figure 3. NDVI fire time series based on Sentinel-2 data of Cape Agulhas region: Fires 3 and 5 occurred in 2017 and exhibit a slow recovery. Fire 1 started before 2016 and slowly recovered 2017 and 2018, but NDVI values do not reach pre-fire levels at sites 3 and 5, probably indicating onset of degradation.

3.3 Slangbush Monitoring

A random forest algorithm has been chosen for classification since it has been proven suitable for spatio-temporal applications [12]. The model is trained on the relationship of bush structure and backscatter signals to gain sensitivity for subtle feature discrimination. Training samples were retrieved from aerial imagery and Google Earth. Ground truth information and expert knowledge has been retrieved through field visits and photo documentation

The structural elements of slangbos are likely to be recorded by the C-Band signals. The fraction of bush compartments is roughly of the size where C-Band waves interact mostly. Additionally, the round bush geometry implies to be a strong volume scatterer. First investigations imply stronger VH backscatter with growing bush volume and bush cover density (see Figure 4).

3.4 Soil Moisture Estimates

In situ soil moisture data from the Kruger National Park site near the Lower Sabie Basalt Supersite provide evidence for the strong relation between rainfall events and soil moisture (Figure 5 during March and April 2019) and the very seasonal soil moisture pattern. Rainfall records were collected at the

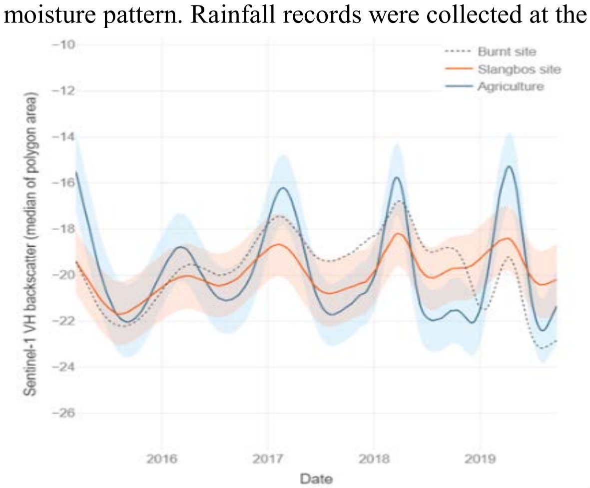

Fig. 4: Median and standard deviation interval of Sentinel-1 VH time series (temporal resolution less than 7d, 354 scenes). Sites associated with slangbos (Seriphium plumosum) return a stronger signal (red, n = 564 pixels). Agricultural sites leave stronger patterns of seasonality without overall slope (blue, n = 1393 pixels). Plots being subject to slangbos control through chemical treatment, burning or manual uprooting or ploughing return significantly less backscatter (black, n = 105 pixels).

two closest climate stations (Lower Sabie and Crocodile Bridge) and used for comparison with the Sentinel-1 derived surface moisture (SurfMI). The agreement and the dynamics between Sentinel-1 derived SurfMI and in situ soil moisture information shows a reasonable performance and indicate, that the suggested synergistic radar-optical approach allows the separation and retrieval of surface moisture conditions in this complex savanna landscape.

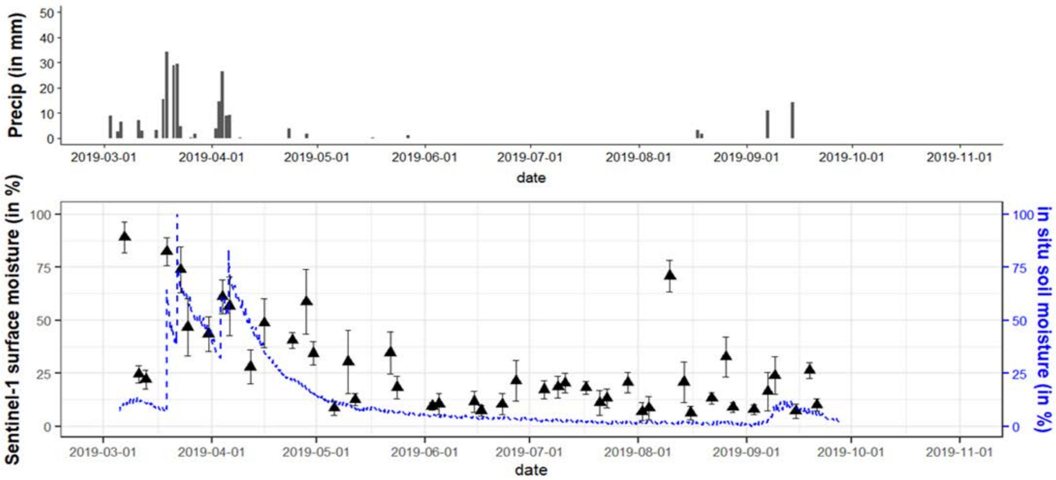

Figure 5. Sentinel-1 SurfMI and in situ soil moisture and precipitation time series for the Kruger National Park (Precipitation Data provided by SANParks Data Repository).

3. ACKNOWLEDGEMENTS

SALDi is funded by the German Federal Ministry of Education and Research (BMBF, grant no. 01LL1701) Substantial support was received through the corresponding SANParks project CO-LD-EMS (ref. no. BAAJ1519).

4. REFERENCES

[1] H. Balzter, B. Cole, C. Thiel and C. Schmullius, “Mapping CORINE Land Cover from Sentinel-1A SAR and SRTM Digital Elevation Model Data using Random Forests,” Remote Sensing, vol. 7, no. 11, pp. 14876-14898, 2015.

[2] C. Schmullius, C. Thiel, C. Pathe and M. Santoro, “Radar Time Series for Land Cover and Forest Mapping,” in: Remote Sensing Time Series, C. Kuenzer, S. Dech and W. Wagner, Eds. Cham: Springer, 2015, pp. 323-356.

[3] M. Urbazaev, C. Thiel, R. Mathieu, L. Naidoo, S. Levick, J. Smit, G. Asner and C. Schmullius, “Assessment of the mapping of fractional woody cover in southern African savannas using multi-temporal and polarimetric ALOS PALSAR L-band images,” Rem. Sens. Env., vol. 166, pp. 138-153, 2015.

[4] K. Knauer, U. Gessner, G. Forkuor, R. Fensholt and C. Kuenzer, “Monitoring Agricultural Expansion in Burkina Faso over 14 Years: The Role of Population Growth and Implications for the Environment,” Remote Sens., vol. 9, #132, 2017.

[5] U. Gessner, M. Machwitz, T. Esch, A. Tillack, V. Naeimi, C. Kuenzer and S. Dech, “Multi-sensor mapping of West African land cover using MODIS, ASAR and TanDEM-X/TerraSAR-X data,” Rem. Sens. Env., vol. 164, pp. 282-297, 2015.

[6] T. Gill, K. Johansen, S. Phinn, R. Trevithick, P. Scarth and J. Armston, “A method for mapping Australian woody vegetation cover by linking continental-scale field data and long-term Landsat time series,” IJRS, vol. 38, pp. 679–705, 2017.

[7] U. Gessner, M. Machwitz, C. Conrad and S. Dech, “Estimating the fractional cover of growth forms and bare surface in savannas. A multi-resolution approach based on regression tree ensembles,” Rem. Sens. Env., vol. 129, pp. 90-102, 2013.

[8] G. Metternicht, J.A. Zinck, P.B. Blanco and H.F. del Valle, “Remote Sensing of Land Degradation: Experiences from Latin America and the Caribbean,” Journal of Environmental Quality, vol. 39, pp. 42-61, 2010.

[9] B. Killough, "The Impact of Analysis Ready Data in the Africa Regional Data Cube," *IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium*, Yokohama, Japan, pp. 5646-5649, 2019.

[10] J. Truckenbrodt, F. Cremer, I. Baris and J. Eberle, J., “PyroSAR: A Framework For Large-Scale SAR Satellite Data Processing,” Proceedings BiDS’19, pp. 197–200, 2019.

[11] L. Breiman, “Random forests,” Machine Learning, vol. 45(1), pp. 5–32, 2001.

[12] M. Ludwig, T. Morgenthal, F. Detsch, T. Higginbottom, M. Lezama Valdes, T. Nauss and H. Meyer, „Machine learning and multi-sensor based modelling of woody vegetation in the Molopo Area, South Africa,” Rem. Sens. Env., vol. 222, pp. 195-203, 2019.

[13] M. Urban, C. Berger, T.E. Mudau, K. Heckel, J. Truckenbrodt, V.O. Odipo, I.P.J. Smit and C. Schmullius, “Surface moisture and vegetation cover analysis for drought monitoring in the southern Kruger National Park using Sentinel-1, -2, and Landsat-8,” Remote Sens., vol. 10, #1482, 2018.

[14] A.M. Swemmer, W.J. Bond, J. Donaldson, G.P. Hempson, J. Malherbe and I.P.J. Smit, “The ecology of drought – a workshop report,” S Afr J Sci., vol. 114-9/10, #5098, 2018.

[15] I.P.J. Smit, G. Asner, N. Govender, N. Vaughn and B. Wilgen, “An examination of the potential efficacy of high-intensity fires for reversing woody encroachment in savannas,” Journal of Applied Ecology, vol. 53, no. 5, pp. 1623–1633, 2016.

[16] D. Milan, G. Heritage and S. Tooth, “Dataset Record: Kruger National Park Rivers LiDAR data (May 2012),” Centre for Environmental Data Analysis, 2018.

[17] M. Urban, K. Heckel, C. Berger, P. Schratz, I.P.J. Smit, T. Strydom, J. Baade and C. Schmullius, “Woody Cover Mapping in the Savanna Ecosystem of the Kruger National Park Using Sentinel-1 Time Series,” Koedoe, vol. 62, in print, 2020.