Using the Soil Brightness Indicator to inform Participatory Community Planning for SDG2 Projects – a case study in Dodoma, Tanzania

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Abstract

Soil is a crucial component of the ecosystem, affected by climate change, and is often overlooked by remote sensing experts and insufficiently considered while discussing sustainable development projects. To enhance the use of soil related datasets based on earth observation during the planning phase of participatory processes, a specific analysis workflow was piloted during community consultations in Dodoma, Central Tanzania. In order to enhance the integration of the soil conditions during the design of a new community development plan Landsat 8 data from 2023 and 2024 was processed and prepared to make soil information more accessible to non-technical staff and the local communities in Chamwino district. Results confirm the suitability of the SBI as soil indicator thanks to its high resolution, easy interpretability, and context specificity. Preprocessing through experts was identified as viable solution for preparing the data. In addition, field truthing exercises and conversations with the local community members further confirm the accuracy of this dataset for highlighting areas affected by soil salinity or fertility loss and for the final use during participatory planning processes.

1. Introduction

The United Nations World Food Programme (WFP)[1] extends its efforts beyond humanitarian relief operations by developing resilience projects under its Food Assistance for Assets (FFA) program (United Nations World Food Programme, 2024). The implementations range from the rehabilitation of farmland, over the construction of water points to the reforestation of forests. As Planning and programming follow the Three-Pronged Approach (3PA) (United Nations World Food Programme, 2024) that encourages technical experts, NGOs and communities to work together, FFA puts the community at the centre and empowers them to take the lead on the project. Meanwhile analysis on land degradation food insecurity levels and gender are conducted at the national or regional level, community level information is solely drawn from local consultations. Including the community in the planning and development process is key to sustainable maintenance of the assets, following examples from development theory including Mishra & Singh (2023) and Gonsalves et al. (2005). The importance of soil science cannot be emphasized enough when regarding ecosystem services (Breure et al., 2012). Soil is the basis for agricultural production. While scientists have overlooked the crucial role of soils in the past, soil coverage was lost faster than it builds up (Banwart, 2011). Identified pressures on soil include wrong land use management, the decline of organic matter, erosion, flood, landslides, and salinization processes (Bünemann et al., 2018). It is evident that sustainable soil management practices are essential to achieve SDG 2 (zero hunger), SDG 6 (clean water), SDG 7 (clean energy), SDG 13 (climate action) and SDG 15 (life on land) (Ussiri & Lal, 2018; Lal et al., 2021). Among these, SDG 2 is central to WFP’s goals and has led to an emphasis of the integration of soil science into daily efforts of the organization. There is a high potential for effective communication about soil formation, the relationship to ecology and economy, and what this means for local communities and their agriculture, forestry, and conservation practices (Lal et al., 2021). Soil is also the largest terrestrial carbon sink, a unique chance for adaptation and mitigation of climate change through climate-resilient agriculture (Lal, 2016). Land management practices that comprise principles of regenerative or conservation agriculture lead to increase of soil organic carbon (SOC) (De Oliveira Ferreira et al., 2024), which results in overall improvement of the soil conditions. Promoting the right management is key to avoid the loss of nutrients, crop productivity, water and nutrients storage and carbon itself (Marques et al., 2020). These efforts can be supported by remote sensing (Lal et al., 2021). Analysing satellite images has become a standard method for evaluation of vegetation changes. Further the use of remote sensing products for land monitoring, deforestation, or wildfire analysis (Ariza et al., 2021) or the description of anthropogenic dynamics (Nguyen et al., 2012) are commonly recognized. In the sphere of soil science, remote sensing equally is overshadowing traditional methods like sampling and lab analysis (Ding et al., 2008 & Zlinszky et al., 2015). Applications range from soil mapping (Mulder et al., 2011), to SOC estimations (Mondal et al., 2016 & Croft et al., 2012), to the use of multispectral or hyperspectral data in correlation with soil sampling (Shibendu et al., 2004). Earth Observation has become a crucial tool for hazard analysis and mapping in research (Tiede et al., 2013, Lang et al., 2020 or Quinn et al., 2018) and operations[2]. Instead, development actors just recently started to operationalize the use of satellite analysis for the development planning process with the focus of these efforts in urban planning (Xi et al., 2023, Prasad et al., 2022), even if the potential of using remote sensing for the sustainable development goals is evident (Holloway et al., 2018). While at WFP satellite data is already key to identify regions being

[1]https://www.wfp.org/who-we-are

[2]https://storymaps.arcgis.com/stories/8f2396e762154841b16d264e5b3008be

affected by land degradation (Borelli et al., 2021), to monitor conflicts and climate conditions, a more localized approach was vacant. This paper illustrates a first pilot study that aims to create a new analysis workstream that tailors remote sensing for participatory planning processes of sustainable development projects related to SDG2 and climate resilience.
The overall research questions of this paper are: Can the Soil Brightness indicator be used to complement the local community consultation process with regard to landscape characteristics and increase the consideration of soil conditions in the development planning process? How should this information be provided and communicated to colleagues and the local community? It will examine these questions based on a case study conducted using soil brightness maps in three departments in Tanzania in 2024, highlighting one specific case from Dodoma district.

2. Theoretical Framework

A major obstacle in WFP's operational context is the availability of local soil data. Whereas open access datasets cover the Global North into detail, there are major limitations in availability and resolution of soil datasets (Liu et al., 2008). In-field testing is not only affected by major challenges in terms of cost and logistics, but also political reasons can constrain any in-field testing. For this study both high resolution data and open-access rights were needed, to perform the analysis successfully. Given that the local data availability was quite limited, Remote Sensing based observations were considered the most suitable approach. Soil Reflectance is a key variable as soil properties such as organic matter, moisture, mineral oxide contents, texture and surface roughness influence the reflectance at unique wavelengths (McGuirk et al., 2024). One of the more straightforward valuable remote sensing indicators to describe soil features is the Soil Brightness Indicator (SBI) (Hordiienko et al., 2022). According to Mathieu et al., (1998) the SBI according to Mathieu et al. 1998 is defined by the square root of the squared visible channels (R, G, B) divided by 2 (Equation1).

$$SBI = \sqrt{(R^2 + G^2 + B^2)/3} \qquad (1)$$

The SBI expresses the reflectance of topsoil, which is influenced by three main factors: Soil Moisture, Salt presence and Organic matter content (Escadafal, 1989). Soil Moisture plays a vital role for crop growth as it enables nutrient uptake, microbial activity and prevents soil erosion. General wet soils appear darker as they absorb more light, which results in a high usefulness of the SBI for irrigated land monitoring. Salt presence on the soil surface or saline soils in general will result in higher SBI values (Flypard, 2024). Excess salt prevents plant growth and SBI values greater than 0.3 have been identified as indicator of soil problems and reduced tree growth (Marques et al., 2020). Soil Organic matter was found to be significantly negative correlated with the SBI (r = -0.408) (Mandal, 2016), highlighting that dark hummus rich soil result in low SBI values. Soil Brightness has become one of the key variables for SOC modelling (Mandal, 2016). Also crusted soil surfaces give higher reflectance values, which can be critical to identify depleted topsoil (Baumgardner et al., 1985). The SBI was chosen for this study over several other indicators and data products due to the high spatial resolution it offers. Since the activities of WFP concern mostly small-holder farmers, a higher resolution is necessary to distinguish different plots and owners. It generally works best with soils with very little vegetation at the time of the observation from the satellite (Hordiienko et al., 2022). The advantages of the SBI are the high spatial and temporal resolution and the possibility to calculate it with open-access satellite data. Shortcomings of these indicators lie in the interpretability, as the thresholds vary across landscapes and soil types. It is therefore crucial to compare values in the local context to identify hotspots or Points of Interest (POI) of poor soil conditions. Further, the indicator does not discriminate water or urban surfaces, for which it is important to either filter the map with a land use dataset or manually outline the study area. Cloud or plant cover are further aspects to considers, as the SBI works best on dry and bare lands.

3. Data and methods

Our investigation looks at how remote sensing indices like the SBI can aid and enhance participatory community planning initiatives. In support of field activities in 2024, we used remotely sensed data from the 2023 and 2024 dry season to provide a supportive evidence base to guide operations on the ground. As we discuss in this section, remotely sensed data, provided primarily in the form of annotated maps, helped the community sample locations for in-situ inspection, helped the team navigate the area, and informed the choice of remedial interventions.

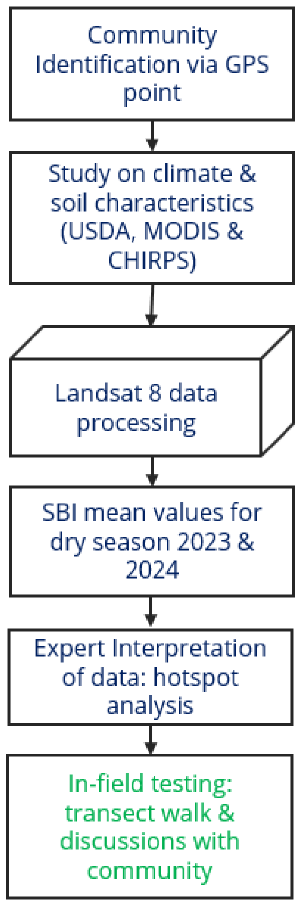

Figure 1. Workflow showing the steps from data processing steps in blue to join discussions in green.

3.1 Study Area

Meanwhile the analysis was provided for 20 villages across Tanzania, the in-field testing could only be realized for one village in Dodoma region. For this reason, this paper focuses on this specific example. The Study Area is in Chamwino District council in Dodoma region (see Fig. 2 & 3) where a Bsh, hot arid steppe is prevalent. The district experiences a semi-arid climate with a long dry season from May to October and short uni-modal rainy season from November to April. Temperatures range from 20°C to 30°C and the annual rainfall sum is between 500 and 700 mm (WFP & TASAF, 2024). According to the USDA soil database the districts has predominantly Alfisols and Inceptisols. Meanwhile Alfisols are soils from warmer temperatures, typically found under forested cover being natively rich in clay and in fertility. The typical vegetation is savanna or grasslands, that are used as cropland or for grazing. The Alfisols in this region are usually strongly weathered. Inceptisols instead occur in relative active landscapes, e.g. mountain slopes or riverbeds and are under strong weathering effects. This soil class usually has very minor development of soil horizons, being under genesis. They have little to no accumulation of clay, iron or aluminium, though an initial umbric horizon is visible (USDA Soil Taxonomy, 1999).

Figure 2. Locator Map of the Study Site.

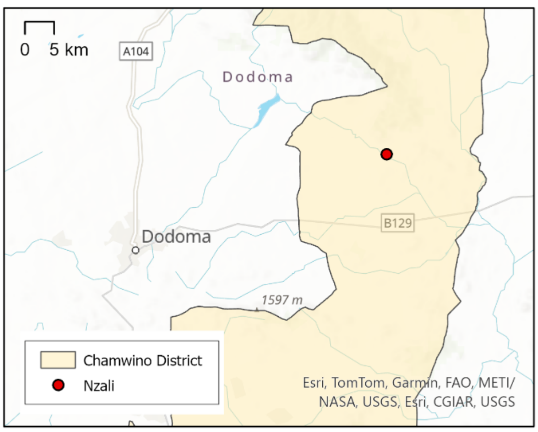

Figure 3. Map of Nzali in Chamwino District.

The primary economic driver in Chamwino district is agriculture. The community concerned in this case study is Nzali and has approximately 7000 inhabitants. There are around 2000 households and nearly all of them are engaged in agricultural activities, with 65% working with livestock, 25% in agricultural businesses, and 5% in beekeeping. The main crops produced are maize, sunflowers, sorghum, sesame, groundnuts, legumes, and vegetables. Livestock is composed by mainly cattle, goats, sheep, donkeys, pigs, and chicken. A significant challenge is the securement of adequate water for irrigation during the dry season, soil erosion, loss of soil fertility, increase in salinity, and excessive grazing. The environmental constraints led to harmful and unsustainable practices that strain communal resources. Further, harmful events such as outbreaks of pestilent insects, droughts and heavy rainfall accompanied by strong winds have led to severe crop damage and decreased harvest yields. Around 30% of the households are currently in a degrading economic situation, which includes making less than 40USD a year, eating one meal per day, relying on day labour, having less than one acre of farmland and not owing livestock. Approximately 60% of the household have reported that their status has remained similar in recent years, which means they have a land ownership of 2-10 acres and have small business activities, as well as owning up to 10 cattle and eating 2-3 balanced meals daily. Their yearly income is between 65 and 75 USD. The remaining 10% of the household reported improving conditions of being able to afford more than three meals per day, owning a tractor and more than 10 acres of farmland and being able to employ other people. Their yearly income is higher than 80 USD. Efforts to advance community development focus on improving infrastructure and services through partnerships between the government, NGOs, and the community (WFP & TASAF, 2024).

3.2 Data

The satellite imagery used for this study was taken from the USGS (United States Geological Survey) Landsat Collection 2 Level-2 atmospherically corrected surface reflectance series[3]. The bands accessed through the Planetary Computer STAC API were the red, green and blue bands. Landsat's satellites high resolution (30m) imagery combined with a long-term data record make it an effective source of multi-spectral imagery to assess changes in the landscape.

3.3 Data Processing

The imagery was processed in the Jupyter Hub service within WFP's Humanitarian Data Cube (HDC)[4] and underwent several pre-processing steps to ensure data quality. The steps include cloud and cloud shadow masking using the Landsat Quality Assessment bitmask band, as well as surface reflectance outliers' removal. Given the substantial cloud cover over the study area, the mean Soil Brightness information was retrieved from for the dry season in 2023 prior to the field visit and for 2024 as mean values over the months of June to September. Since the analysis of this case study focused on rainfed agriculture, the imagery was therefore analysed for the dry season only. By filtering the time-series a focus on the salinity and organic matter of the study area is possible.
A SBI map was generated for each village (see Fig. 4), which were then inspected and interpreted, comparing results with land cover information visible from the VHR imagery. This enables the analyst to understand whether the SBI is reliable or not, since landcover is an important factor for soil conditions.

[3] https://www.usgs.gov/landsat-missions/landsat-satellite-missions
[4] https://api.earthobservation.vam.wfp.org/ows/

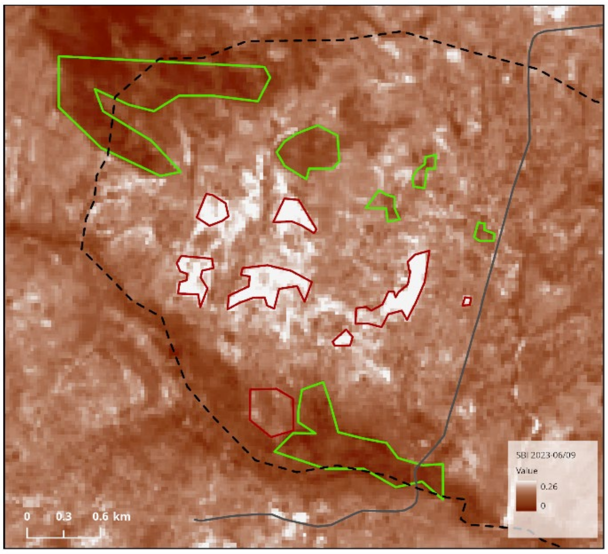

Figure 4. Interim status: The SBI based on Landsat during the dry season 2023 with the hotspots outlined through polygons.

Lower Soil brightness is expected in higher fertile areas, such as forests or areas with tree cover. Higher Soil Brightness is rather expected for areas with high soil brightness or visible signs of land degradation. Using the VHR imagery, the experts outlined areas of very high and very low brightness values excluding areas with buildings, waterbodies, or ambiguous signals. This approach was taken to reduce the information load for the non-technical staff and to increase the information quality at the same instance.

3.4 Data Visualization

The SBI hotspots were outlined as polygons for better visualization. Areas with higher soil brightness were marked on the maps as areas with “Poor soil conditions”, meanwhile the areas with lower soil brightness were marked as areas with “Better soil conditions” to facilitate the interpretation (see Figure 1). Since the SBI values are context-specific, no

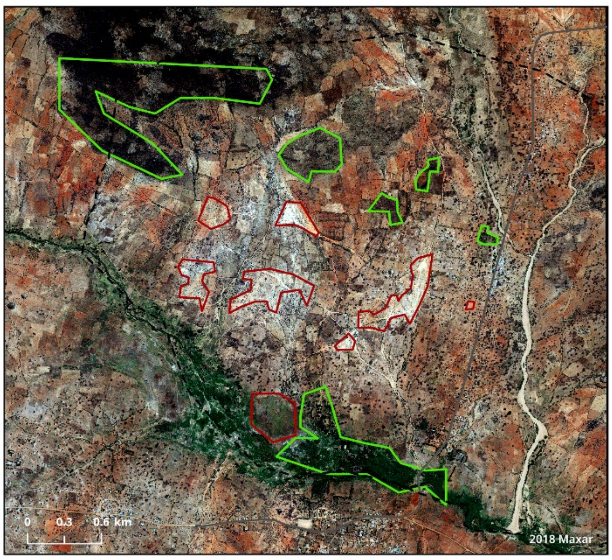

Figure 5. The SBI based polygons on the VHR map (Maxar 2019).

thresholding took place. The analysis intended to highlight the hotspots of fertility and degradation, for which only the highest and the lowest SBI values were mapped out. Further, POI were selected based on the presence of clusters of polygons highlighting the different SBI hotspots. The final visualization was composed of a commercial very-high resolution image as basemap with key annotations (Fig. 5). This was done to enable WFP staff in the field to orient themselves with less difficulty.

3.5 In-field testing

The field activities in three districts in Tanzania were performed during the months of May and June 2024, following the 3PA process set within WFP. For each participatory planning exercise, a printed village map was provided highlighting areas of interest regarding soil brightness. A training session on BSI map interpretation was conducted to the field staff by a remote sensing expert. This also allowed for a better understanding and integration of the index values in relation with the ground conditions and landscapes. For this training the interpretation schema from Table 1 was presented.

Observation	**Interpretation**	**Possible field observations**	**Possible reasons**
High Soil Brightness	High Soil salinity	Salt crusted on the soil surface	water drainage is malfunctioning
	Low Soil fertility	Sandy soils very little organic matter very little vegetation cover farming was abandoned or is unproductive herbaceous litter, leaves are not decomposing no tree cover land degradation visible	given local conditions or deterioration of these conditions previous tree cutting leading to soil erosion unsustainable farming practices
Low Soil Brightness	Low Soil salinity	No salt crust	Water drainage is working
	High Soil fertility	Darker topsoil with a lot of organic matter good vegetation cover tree presence, farming is conducted with success, if litter is present, it is decomposing, proper land management	given local conditions or good land management practices e.g. regenerative practices

Table 1. Interpretation schema

During the village consultations the maps were used to create Transect Walks, that pass different POI of the community. By looking at the printed maps, WFP staff was able to give background information according to the schema. The maps were further consulted during group discussions among the community. The study in Nzali was realized in April and May 2024 considering Soil Brightness data from June to September 2023. WFP staff stayed in the community for three days to discuss current shortcomings, threats through climate change and identified needs. Figure 6 was presented during the field stay.

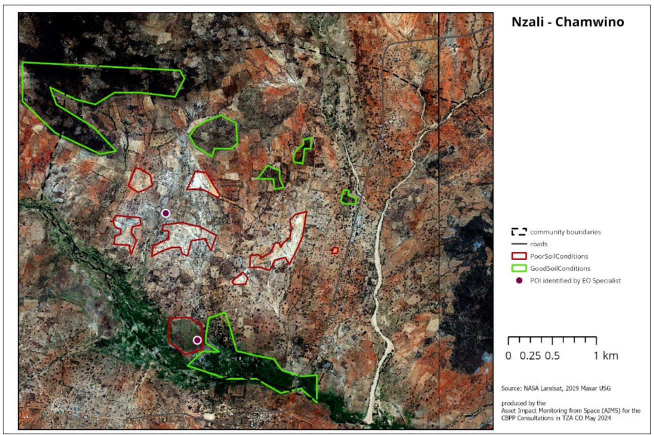

Figure 6. The final village map showing the SBI polygons & POIs on the Very-high resolution map (Maxar 2019). This map was used for the in-field testing

4. Results

After concluding the field activities, overall, the SBI emerged as a suitable and informative index for use in participatory planning. There is a clear correspondence between the map and the ground conditions. The expected shortcomings of the SBI

Figure 7. Hotspot of soil salinity

Indicator could be overcome by the pre-selection of hotspots or POIs through an Earth Observation Expert and by visualizing the results on a VHR map that shows landscape features for orientation.
Figure 7 depicts a map showing an area that showed several

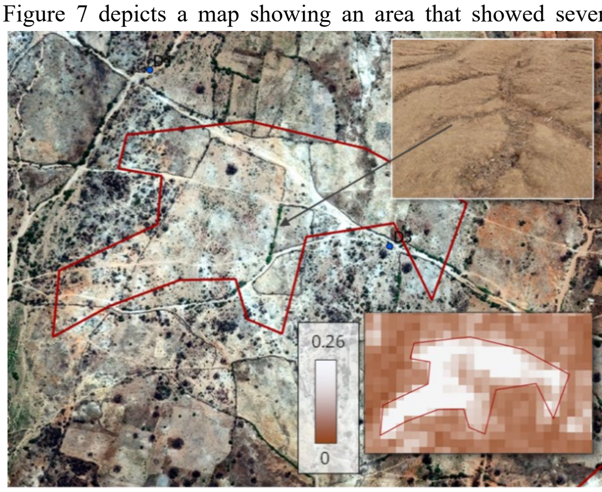

Figure 8. Abandoned farmland

signs of increased soil salinity. Ongoing degradation processes were identified. The grassland was abandoned and salt production for commercial use was started by the community. Tree growth of species associated with salt presence is present. The SBI was 0.15 in 2024 during the time of the field visit. Figure 8 shows abandoned farmland with high sand presence and ongoing land degradation. SBI values in 2024 were 0.2. Figure 9 shows an area affected by crusty topsoil with little to no vegetation and gully formation. SBI was 0.19 in 2024.
Figure 10 shows an example of tree covered plot with agroforestry activities showing that sustainable land management results in SBI values of 0.08 in 2024.

SBI threshold	Dominant landcover	Soil observations
<=0.1	Forest, agro-forestry activities	Darker, more soil organic matter
>0.1 – <=0.16	Agricultural activities	Medium dark soils, first signs of degradation, e.g. salination
> 0.16	Barren land, cropland with poor vegetation cover	Bright and sandy soils, clearly visible land degradation, poor topsoil

Table 2. Localized thresholds

Figure 9. Degraded land

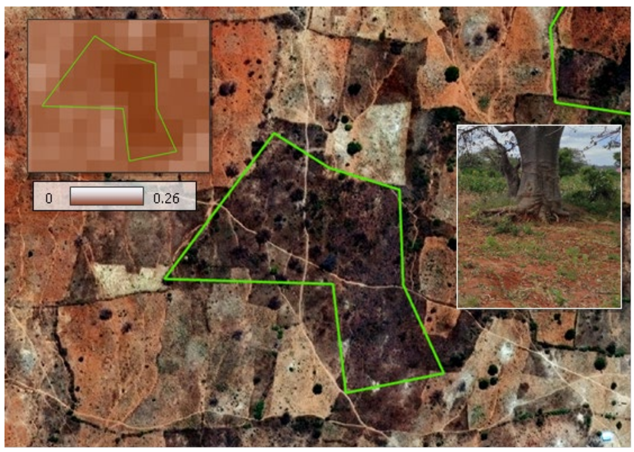

Figure 10. Agroforestry plot.

Figure 11 shows a forested area with clearly better soil conditions according to the SBI. In 2024 the SBI was 0.09. Areas with SBI values greater than 0.15 were visibly and through communications with the community identified to be under degradation processes. This threshold is clearly below the value 0.3 indicated by literature, (Marques et al., 2020) which means that the value interpretation indeed is very context specific (see Fig 12). The number of environmental aspects identified through a single satellite indicator brought the degradation processes to the conscience of the community. In previous discussion most of the attention of the community focused on a bridge rehabilitation. Understanding the underlying land degradation processes was helpful for the community in order to connect soil erosion and siltation as contributors to the poor status of the bridge. Instead of the foreseen bridge rehabilitation, the community opted for a gully rehabilitation, which means the root causes of the degradation processes of the land and the bridge are treated.

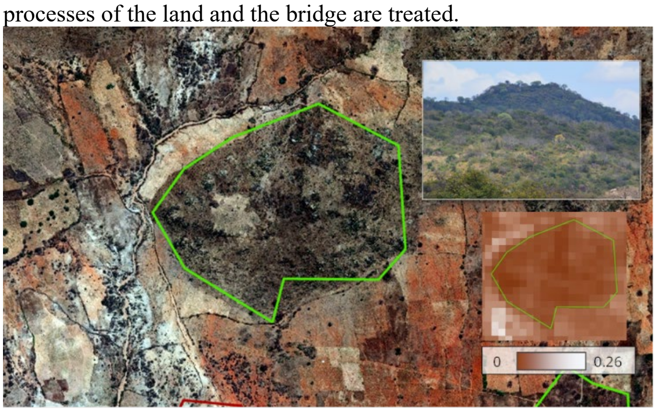

Figure 11. Forested area

The expected outcome of the gully rehabilitation is the stabilization of the topsoil, the retention of water and the overall increase of vegetation and recovery of soil functions. This rehabilitation was implemented in 2024, and results from internal monitoring of the outcomes is outstanding. Since the

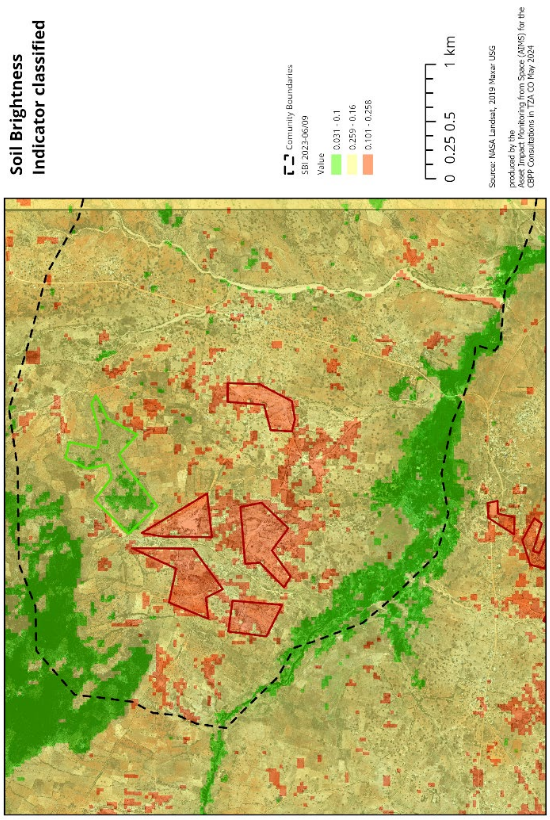

Figure 12. Map with SBI classification based on Table 2 thresholds.

positive effects of such interventions take several years to unfold, first positive outcomes can be expected for 2025. In the long-term an increased resilience of the community against climate change impacts and pressure on the food production is expected.

5. Discussion

Using a single indicator to enhance community planning resulted in positive outcomes. Given the plethora of soil related indicators in remote sensing, this list should clearly be expanded to consider further ecological aspects. A more in-depth study regarding the soil texture and taxonomy could be added to reinforce the findings. Integration of Bare Soil Frequency could deliver an increased understanding of the land management practices and possible reasons for land degradation, further NDVI trends can reveal long-term vegetation loss and using historic VHR images can explain reasons for such changes. The identified workflow is operational and lightweight for the analyst, the interpretation of the data before the mapping according to the authors obligatory. Another suggestion for improvement is to integrate a multi-level approach, that regards the underlying conditions on a regional level and a watershed analysis. Given that villages are not only influenced by the local management, but also by global, regional or neighbouring effects, analysing on several levels is a necessary step. For informing the villages on their development planning it is not sufficient to look at the current state of the ecosystem but to enhance the analysis with historic VHR and the consideration of climate change models to understand possible future scenarios for the local agricultural production. Receiving a full picture on soil quality is rather complex (Bünemann et al., 2018), for which further remote and on-the-ground assessment should be conducted. This assessment could include the considerations of further remote sensing data such as temperature and vegetation indices (e.g. Normalized Difference Vegetation Index, Soil Adjusted Vegetation Index). More field validation in different climatic and cultural contexts is needed to set further thresholds considering the soil texture, climate, land use and soil taxonomy. The presence of a remote sensing and environmental scientist is highly recommended to provide further details of the results during the discussions themselves.

6. Conclusion

Using the SBI to increase the consideration of soils during participatory planning processes resulted in positive outcomes. Having a map highlighting areas of concern was useful during the field visits, as it gives reference to the community local knowledge. Conducting an expert-guided preparation of the indicator data and selecting the areas of concern excluding ambiguous information can be considered a useful and straightforward practice. It is needed to ensure maps and information are rightfully interpret and properly conveyed during group discussions, at the same time ensuring quality and reliability. Providing a table for the results interpretation was further helpful. Considering the future scenarios and further discussed improvements, the use of soil data for sustainable development projects is highly encouraged.

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