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Developing early warning systems for land degradation around refugee camps: a preliminary approach

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ABSTRACT

The joint research initiative of H2020 EOTiST and ARICA projects aims to better understand the ecosystem conditions around refugee camps and evaluate the capability of Ecosystem Functional Attributes (EFA) as early warning indicators of ecosystem degradation. The analysis is based on Sentinel-2 optical satellite data and derived geospatial products for the period 2016-2022, reference data collected during the field campaign in 2022, and information gathered during interviews with local authorities and NGOs.

The study area is the Mtendeli Refugee Camp (MRC), Kigoma region, Tanzania. The MRC was established over 30 years ago, in close proximity to the 6 000 km2 Moyowosi Game Reserve, an environmentally fragile area. It was reopened in 2015 at a nearby location and closed in December 2021[1]. The proposed approach consists of quantitative and qualitative temporal analysis of the ecosystem for the period 2016-2022 to assess anthropogenic impact on the camp surroundings. Firstly, the temporal trends and spatial heterogeneity in NDVI seasonal dynamics are derived from EFA[2]. Secondly, Ecosystem Functional Types (EFT)[3] are calculated for the same timeframe. Special attention is paid to the disturbances and anomalies in NDVI dynamics.

In addition to the results of the spatio-temporal analysis, the context for the demonstrated changes was presented with reference to field research and expert knowledge. This approach, complemented with changes in land cover/use, may result in a protocol for early warning system, monitoring and evaluation of the refugee camp surroundings, supporting decision-making on mitigation of environment degradation.

Keywords: ecosystem functioning, early warning system, refugee camp, Sentinel-2, remote sensing

1. INTRODUCTION

By the end of 2022, some 108.4 million people worldwide were forcibly displaced as a result of persecution, conflict, violence or human rights violations. Of these, nearly 35.3 million are refugees[4]. These displacements and settlements of large number of people often have significant impacts on the environment[5,6] due to the additional pressure on the natural resources of the people displaced (provision of food, shelter fuel, etc.) but also for their host communities. Indeed, deforestation, soil erosion or pollution of water resources are some of the most significant environmental problems associated with refugee camps. Although on a global scale the impacts of refugees on the environment is not significant, at local scale it can be devastating. For instance, the refugee crisis in Tanzania in 1994-1996 resulted in a total of 570 km^2 of forest affected, 167 km^2 of which was severely deforested[7]. Unfortunately, these impacts in terms of habitat degradation, biodiversity damage and loss of ecosystem functioning are most often irreversible and also result in reduced levels of income or lower quality of life[7]. Understanding that refugees cannot be expected to put environmental considerations before their own safety and well-being, humanitarian organizations such as UNHCR and others help limit the impact of

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refugees to the lowest possible level by assisting host countries in rehabilitation and clean-up operations[8]. Unfortunately, the resources available for such environmental interventions are scarce, and early detection of environmental impacts would be essential to design an effective intervention plan with optimal cost-effectiveness and maximization of net benefit.

Indeed, one of the most widely used approaches to identify and monitor these impacts is remote sensing[9,10]. Earth observation makes data available relatively regularly and with increasing spatial resolution. Land cover change analysis is the most widely used method[5,11,12]. However, the method itself has some limitations in terms of its applicability as an early warning system, since identification of changes strongly depends on the categories defined and, these, hardly collect covers in degradation (e.g. forests or shrubs, but not degraded forests). In other words, once change has been identified using this method, the threshold of ecosystem condition is probably passed (critical point) and irreversible and restoration interventions are too costly to be implemented. Detecting ecosystem transitions leading to a critical point, through an early warning signal, could therefore improve the degradation mitigation actions and their associated economical costs.

Instead, remotely-sensed Ecosystem Functional Attributes (EFAs) have been identified as integrative descriptors of change by offering an early response of vegetation performance to environmental drivers and human pressures[13]. EFAs quantitatively describe the exchanges of matter and energy between the biotic community and the environment including, among others, indicators of productivity, seasonality, and phenology of carbon gains, and also respond more promptly to change than structural or compositional attributes, such as land cover[14]. Additional qualitatively Ecosystem Functional Types (EFTs) derived from EFAs, group ecosystems on basis of shared ecosystem functions without prior knowledge of vegetation types or canopy structure[15], integrating EFAs information into a spatiotemporal heterogeneity variable useful as indicator of changes in ecosystem function, such as landscape degradation processes[16,17].

Geostatistics of remote sensing images can provide parameters for describing and quantifying theses spatial patterns[18–20]. The present work uses geostatistical tools to test the capability and potential use of EFAs and EFTs derived from Sentinel-2 data as early warning systems of landscape degradation in areas surrounding refugees camp using buffer areas. The proposed approach consists of a spatiotemporal quantitative variogram analysis of vegetation maximum productivity and a qualitative spatiotemporal temporal analysis of EFTs for the period 2016-2022. Results are validated with field research and expert knowledge.

2. STUDY SITE AND DATA

2.1 Study site

The study area is the Mtendeli Refugee Camp (MRC), in the Kigoma region of northwestern Tanzania, and its nearest surroundings, which extend to a radius of 10 km. The MRC was established over 30 years ago, in close proximity to the 6 000 km^2 Moyowosi Game Reserve, an environmentally fragile area. It was reopened in 2015 at a nearby location and closed in December 2021[1] (Figure 1).

The region is characterised by two main seasons, the wet season (November to April) and the dry season (May to October). There is a transition period, the post-wet season, which occurs in April and May. In general, the temperature ranges from 12 °C and 29 °C and rarely falls below 9 °C or exceeds 31 °C. The month with the most days of heavy rainfall is December, when it rains at least one millimeter for an average of 19.6 days. The month with the fewest rainy days is July, when rainfall of at least 1 millimeter occurs for an average of 1.0 day[21]. If we define the growing season as the longest continuous period with temperatures above zero during the year, we can conclude that in the considered area the growing season lasts the whole year. For the purposes of our analysis, we define the start of the growing season in August and its end in July.

The most common forest type in the region is miombo woodlands. They provide building material and fuel, essential inputs for the livelihoods of the communities adjacent to the forest. An important feature of these woodlands is that the undergrowth grows at the beginning of the rainy season and is usually burned during the dry season. The reason is most often spontaneous combustion. Other land cover vegetation types are shrubs and grassland. Land use is mainly limited to agriculture and settlements (campsite and nearby villages). Agricultural activity is limited to five main crops: cassava, corn, beans, brown sorghum and sweet potatoes (Figure 2). The above characteristic has been confirmed during the fieldwork performed in July 2022. In addition, the researchers observed ongoing urban development, such as the expansion of the road which connects Lake Tanganyika with Lake Victoria.

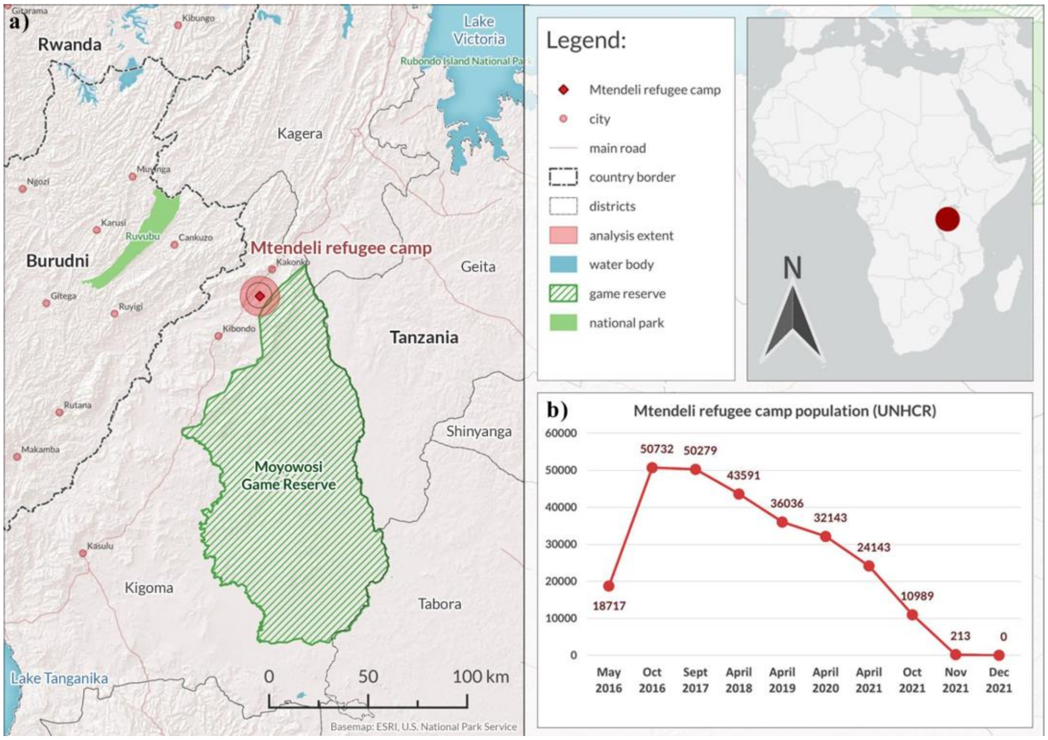


Figure 1. a) Location of Mtendeli Refugee Camp and the surrounding buffer zones; b) distribution of camp population from May 2016 until December 2021 when it was closed.

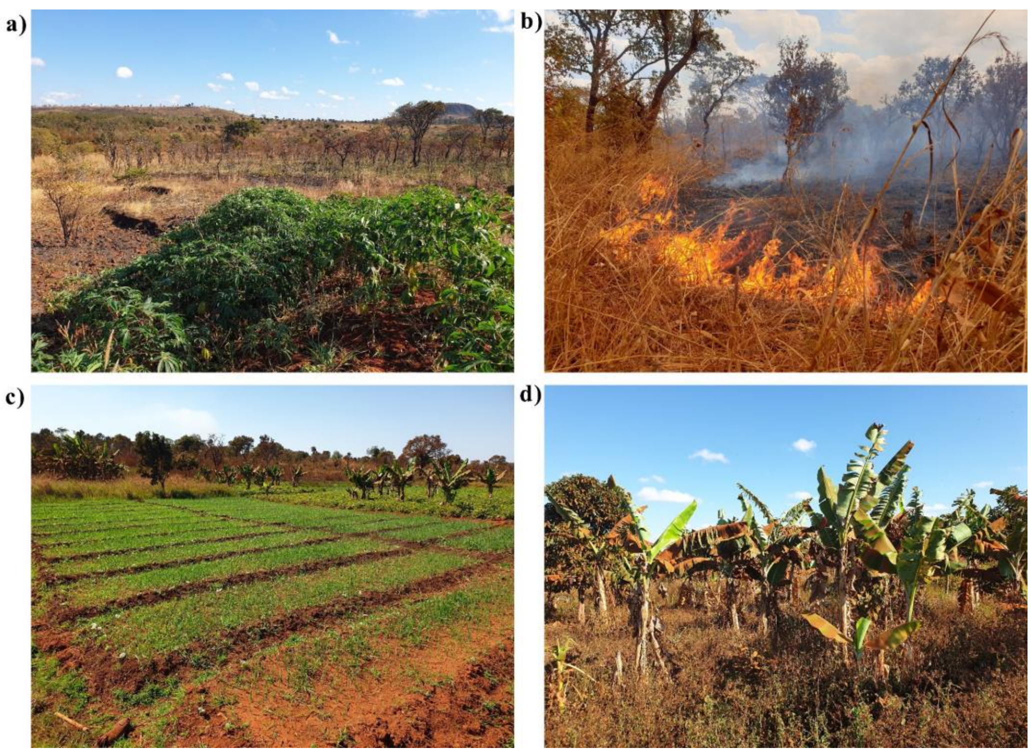


Figure 2. Ground-truth data acquired during the fieldwork in July 2022, a) cassava cultivation in the foreground, and miombo sparse woodland with shrubs and grasslands in background; b) burning undergrowth of miombo woodland; c) agriculture fields: onion and beans cultivation; d) banana trees plantation.

Key information from qualitative interviews with Non-Governmental Organizations (NGOs) representatives and local experts included reflections and explanations of environmental changes in the camp and its immediate surroundings caused by both the host community and refugees. Research on the local context of human impact on the environment in and around the MRC emphasizes the following elements:

1.Before MRC was established, agriculture was not carried out in the area as there was a need to reduce the tsetse flies;

2.Three main causes of deforestation can be distinguished: use of timber to build the camp infrastructure, agriculture activities, demand for charcoal for fuelwood (used for cooking);

3.In the camp area, the largest deforestation occurred between 2016–2017 due to the site clearing. This action removed almost half of the tree cover around the camp;

4.In 2017 the food ration distributed in MRC has been reduced to 62 %[22], the survival mechanism began to operate, and many people exited the camp illegally in search of resources to meet their nutritional needs;

5.In the same time, a series of initiatives, as a push factor for Burundian returns, have been undertaken[23]. The common market on the outskirts of the camp has been closed and the freedom of agricultural activity in the camp has been restricted by prohibiting crops above knee height;

6.As the camp inhabitants are well-known for their farming skills, the host community employed them to do agricultural work, increasing the agricultural activities;

7.Local people confirm that the highest pick of the deforestation in analysed area occurred in the period 2017-2018. This is also the time of the highest increase in cassava prices in the region, which no doubt led to the expansion of the host community's croplands in an area southeast of the camp (near the Moyowosi Game Reserve);

8.To avoid environmental degradation, initial camp rules only allowed camp inhabitants to collect firewood from dead trees. The 10 km buffer zone from the camp boundary has been successively cleared of dead wood. Over the years, the camp inhabitants introduced the so-called debarking of trees. They removed the bark from the tree from under the ground and the tree died, resulting in the legal collecting of firewood;

9.The way fields are cultivated in the region is by rotation. Fields are abandoned, and new cultivation areas are established. The land is burned to improve the soil and eliminate vermin;

10.Fires are seen as a tool for managing the forest, eradicating dangerous animals and creating new pastures for livestock. According to interviewees, bushfires are especially harmful to areas that have been rehabilitated through tree planting;

11.The illegal livestock grazing affects wildlife habitat in Moyowosi Game Reserve[24];

12.After the camp closure, October 2021, the local NGOs started the implementation of the environment restoration programmes in the area, e.g. trees planting[25].

2.2 Data

The time scope of the analysis includes six growing seasons from August 2016 to July 2022. Normalized Difference Vegetation Index (NDVI) time series were calculated using Sentinel-2 (S2) multispectral imagery at 10 m spatial resolution. The number of scenes used depends on the weather conditions and varies according to the growing season considered (Table 1). For the period August 2021 - July 2022, the number of S2 images is 28. In contrast, for the period August 2017 - July 2018, only 10 observations were cloudless, without coverage for the wet season from November 2017 to May 2018. NDVI maximum was the variable selected for the study (NDVIMAX).

3. METHODOLOGY

The analysis is carried out within the area of the camp itself, defined as a 2 km radius circle, and within two buffer zones defined at distances of 2-5 km and 5-10 km from the camp area for the period 2016-2022, on a year basis. The used approach, based on a geostatistical analysis of ecosystem functionalities, analyzes the impact on the landscape due to MRC establishment and activities.

Table 1. Information on data temporal coverage - number of cloudless Sentinel-2 data by seasons

Season	Wet	Post-wet	Dry	Total
2016-2017	1	2	9	12
2017-2018	0	1	9	10
2018-2019	3	0	13	16
2019-2020	4	0	13	17
2020-2021	8	1	8	17
2021-2022	8	4	16	28

3.1 Ecosystem Functioning Attributes

Local heterogeneity in ecosystem functions was characterized by analyzing EFAs seasonal anomalies and trends. Among the 3 metrics (the annual maximum productivity, seasonality and phenology) we focused on maximum productivity since it is one of the most integrative indicators of ecosystem functioning[26]. We used time series of Sentinel-2 Normalized Difference Vegetation Index (NDVI) for the 6 periods. The maximum value of the NDVI (NDVIMAX) in the data series was determined for each pixel representing the land surface. In addition, the standard deviation, mean and the date of the maximum value of NDVI were also computed.

3.2 Ecosystem Functional Types

Ecosystem Functional Types were derived from the 3 metrics of the NDVI seasonal curve, the annual maximum productivity (NDVIMAX), the NDVI seasonal coefficient of variation (sCV) as a descriptor of seasonality (NDVI sCV) and the date of the maximum NDVI as indicator of phenology (NDVIDMAX). The integration of these 3 metrics captures significantly most of the variance in the seasonal dynamics of NDVI, facilitating ecological interpretation[3,27]. In order to establish EFTs based on EFAs, we adopted a classification method that involved dividing the range of values for each EFA into 3 intervals. These intervals were then combined, resulting in a potential total of 27 EFTs. To ensure phenological consistency over the whole time series, fixed boundaries between classes were applied, allowing monitoring of changes in spatial heterogeneity of ecosystem functions on an annual basis. For NDVIMAX and NDVI sCV, first, second and third quartiles were computed for each year. Following, the interannual means of the 6 seasons were extracted and used as thresholds for classifying the data. For the last metric, NDVIDMAX, we used 3 intervals corresponding to the 3 seasons of the year: wet season (November to April), post-wet season (April and May) and dry season (May to October).

For the final classification of EFTs we employed a coding system using 3 letters (H/h - high, *M/m* - medium and *L/l* - low) and a number (1, 2 or 3). The first uppercase letter denotes the level of maximum productivity (NDVIMAX) being *H*, high productivity, *M*, medium and *L*, low productivity. The second lowercase letter corresponds to seasonality (NDVI sCV) being *h* high, *m* medium and *l* low seasonality. Finally, the numerical value corresponds to the phenological indicator of the maximum growing season (NDVIDMAX) where 1 represents wet season, 2 post-wet season and 3 dry season.

3.3 Variogram analysis

In order to verify the spatial heterogeneity of MRC area and its closest surrounding over the defined timeline, a set of variograms[28], one for each season and at different areas of interest, were generated using NDVIMAX. The variogram plots the dependence of the spatial variance so that the spatial pattern can be analyzed. It has been applied using *r* sample point measurements[29] as well as remote sensing images[30]. First, the empirical variogram is computed based on the variance of all pairs of pixels at different intervals (lags) of distances. We defined 20 lags of 100 m, thus the maximum distance between any pair of pixels analyzed is 2 km. In the second step, the sampled variogram is modeled and fitted by a continuous function, which allows identifying three relevant structural parameters that characterize the spatial pattern for any quantitative variable distribution: nugget, sill and range. The nugget is the variance near the X-axis origin (very short distances) and represents the component of the non-spatially correlated error. The sill represents the variance at the variogram saturation, thus the maximum theoretical variance; and the range is the spatial distance at which the variogram reaches saturation and represents the limit distance of the spatial autocorrelation. The MiraMon GIS and Remote Sensing[31] software was the main software used in this part of the analysis.

4. RESULTS AND DISCUSSION

4.1 EFAs and EFTs results

Analysis of EFA NDVIMAX (Figure 3) shows that in the 2017-2018 and 2021-2022 seasons there is a decrease in the mean NDVIMAX value, in each of the analyzed areas (camp area, 5 km and 10 km buffer). From 2018-2019 season to 2020-2021 season, a positive trend of the mean value of NDVIMAX is observed. Results also show that the periodic growth rate decreases with distance to the camp, being 0.0591 at the camp area, 0.0404 at the 5 km buffer and 0.0308 at the 10 km buffer. Additionally, for the 10 km buffer area, a decrease in the minimum value for NDVIMAX is observed for the three subsequent seasons: 2018-2019, 2019-2020 and 2020-2021.

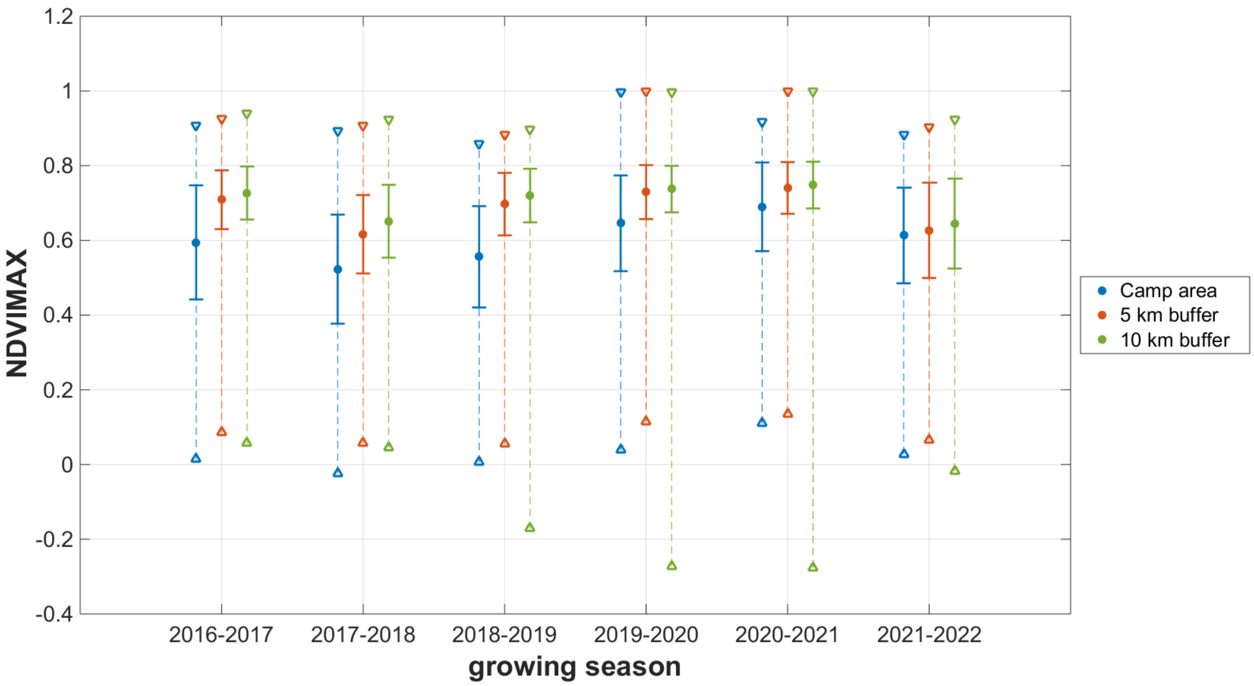


Figure 3. Statistics of the maximum value of the NDVI for three areas considered: camp area (blue), 2-5 km (red) and 5-10 km (green) distances from the camp, for 6 growing seasons between 2016 and 2022.

Calculation of EFA NDVIMAX and derived EFTs resulted in 6 maps of EFA and 6 maps of EFTs representing growing seasons (August - July) from 2016-2022. Figure 4 is presenting the maps of EFTs and EFA of three selected periods, i.e. 2016-2017, 2017-2018 and 2021-2022.

Analyzing the EFA map (Figure 4), we observe a decline in the maximum NDVI value from the time of camp establishment to its closure. As early as the second growing season (2017-2018) of the camp's operation, a significant reduction in the maximum NDVI value becomes evident. This change is particularly pronounced within the camp area, defined as a 2 km radius circle, and extends up to a distance of 2-5 km from the camp. In the region located 5-10 km away from the camp, the most substantial decrease in productivity is observed in the southwest direction. Decrease of NDVIMAX of these areas contrasts with the stable NDVIMAX inside the Moyowosi Game Reserve (southeast), which access is limited by a straight fence and therefore its vegetation is partially protected from human pressure. Still, some productivity loss is detected at the borders of the reserve.

In the period following the camp closure, during the 2021-2022 growing season, we note a positive change in maximum NDVI within the camp area, due to the camp closure and activities related to the environmental restoration programmes. However, negative changes intensify in the southwest direction within the area 2-5 km from the camp, as well as in both the southwest and northeast directions at the distance of 5-10 km. Notably, visible linear structures are evident across the analyzed area, corresponding to the intensified road development connecting Lake Tanganyika with Lake Victoria.

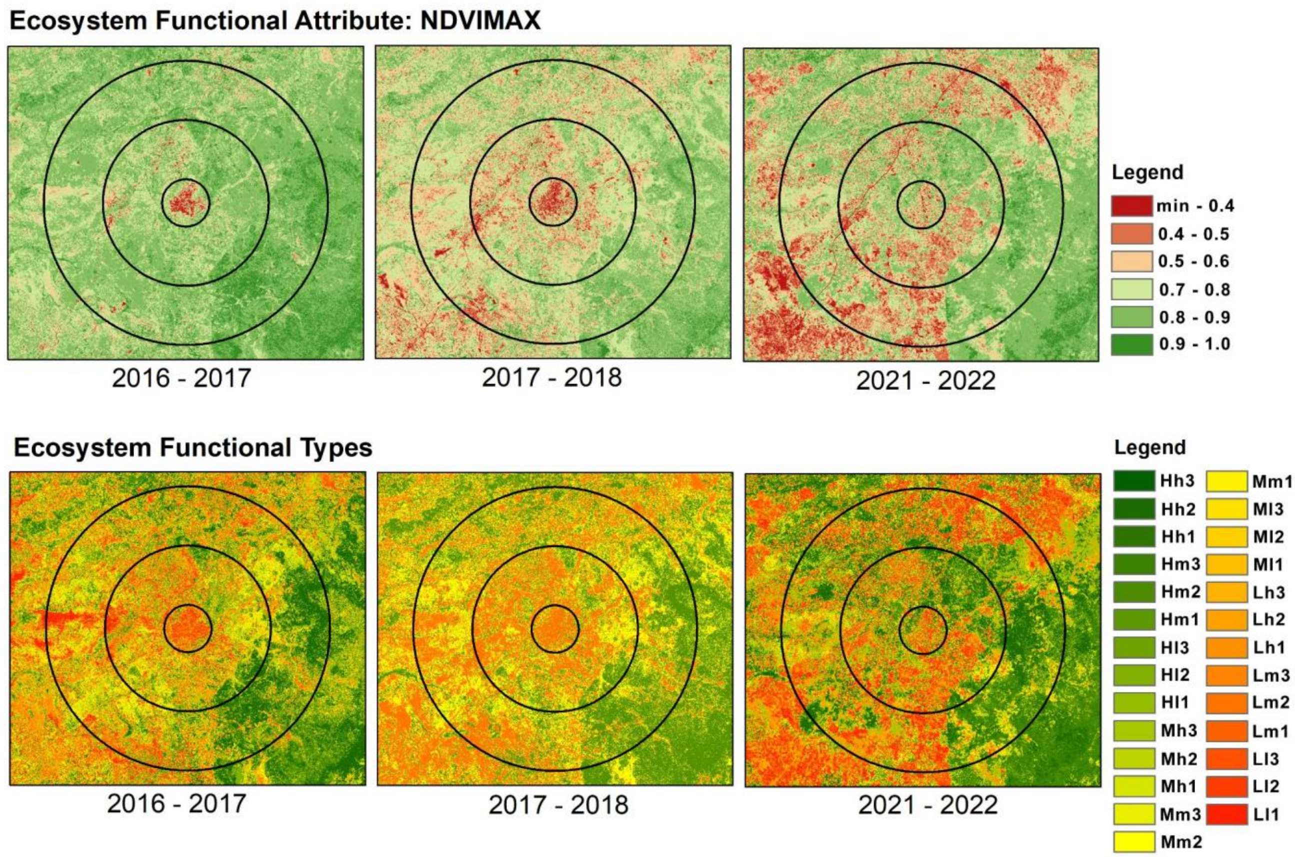


Figure 4. Maps of Ecosystem Functional Attribute (the maximum value of the NDVI) and Ecosystem Functional Types for selected growing seasons. Three areas delineated: camp area, 2-5 km and 5-10 km distances from the camp.

Complementary to EFAs, EFTs maps provide more comprehensive information about changes occurring in the MRC and its surroundings, since it also considers seasonality and phenology. Overall, EFTs suggest that along with the decrease in productivity, there is also a reduction in seasonality, indicating that the new type of vegetation presents a short but quite intense life cycle, commonly found in agricultural landscapes (e.g. croplands vs natural grasslands). Concerning maximum moment of phenology, unfortunately, the 2017-2018 season is marked by limited availability of cloud-free data and marginal temporal coverage during the wet and post-wet seasons, which might affect the accuracy and interpretation of the maximum moment of the phenological cycle trends (NDVIDMAX).

EFTs results confirm trends observed with EFAs, and both, EFAs and EFTs identify changes related to the land cover degradation probably before the land cover change could be identified. According to this, analysis of EFAs seem to be a good candidate to be use as an Early warning system of degradation, especially in the border areas of the Moyowosi Game Reserve.

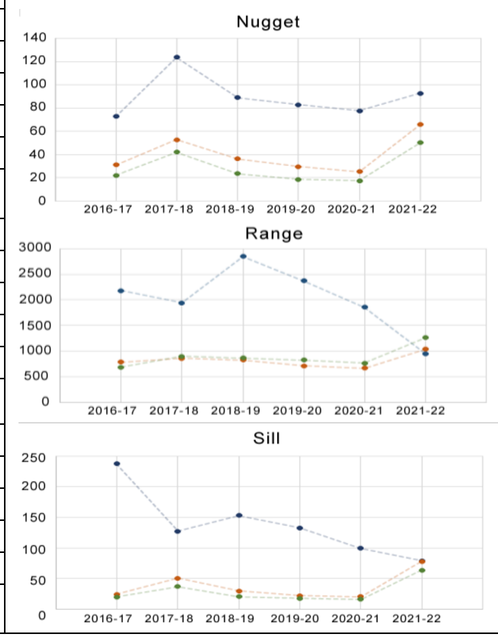
4.2 Variogram analysis results

The more comprehensive examination of spatial heterogeneity of seasonal NDVI dynamics conducted using a geostatistical approach reveals a trend towards a more homogeneous landscape (Table 2). Figure 5 shows a time series of variograms with a consistent shape of fitting functions, except for the first year. Notably, there is a decreasing trend in the variance (Y-axis) of the maximum NDVI values over time (sill) in the camp area. This decline suggests that the landscape exhibits a similar spatial pattern, but it is gradually becoming more homogeneous, both at short distances (represented by low X-axis values) and near the range distances. This change in the sill aligns with the patterns observed in EFAs and EFTs for the same area, indicating a shift towards increased degradation of natural vegetation heterogeneity in favor of more homogeneous agricultural landscapes. These transformed landscapes are characterized by reduced productivity and higher seasonality. The sill trend observed at the 2-5 km and 5-10 km zone is also decreasing except for the period

2021-2022, when sill start increasing significantly again. This is a consequence of refuges leaving the camp, since with this movement, host community is losing manpower for cultivating the area and the abandonment of the agricultural is evident (Figure 6 and Figure 7). The areas furthest away from the refugee camp are the first to be abandoned, as opposed to the areas within the camp itself.

Table 2. Summary of the best fit parameter (exponential function) change in time

Areas	**Seasons**	***Nugget [10^{-2}]***	***Range (m)***	***Sill [10^{-2}]***	**Summary graphs**
Camp area (0-2 km)	2016-17	72.73	2179.41	237.70	
	2017-18	123.67	1944.62	127.46	
	2018-19	88.83	2851.59	153.06	
	2019-20	82.87	2374.53	132.72	
	2020-21	77.52	1855.10	99.08	
	2021-22	92.77	953.46	79.12	
2-5 km buffer zone	2016-17	31.13	787.75	24.14	
	2017-18	52.72	860.41	50.40	
	2018-19	36.11	822.04	29.68	
	2019-20	29.62	711.10	21.70	
	2020-21	25.26	663.94	20.15	
	2021-22	65.74	1036.30	78.04	
5-10 km buffer zone	2016-17	22.03	684.07	19.69	
	2017-18	42.10	895.30	36.72	
	2018-19	23.55	864.20	20.20	
	2019-20	18.58	823.95	17.18	
	2020-21	17.53	765.02	15.96	
	2021-22	50.10	1260.74	63.72	



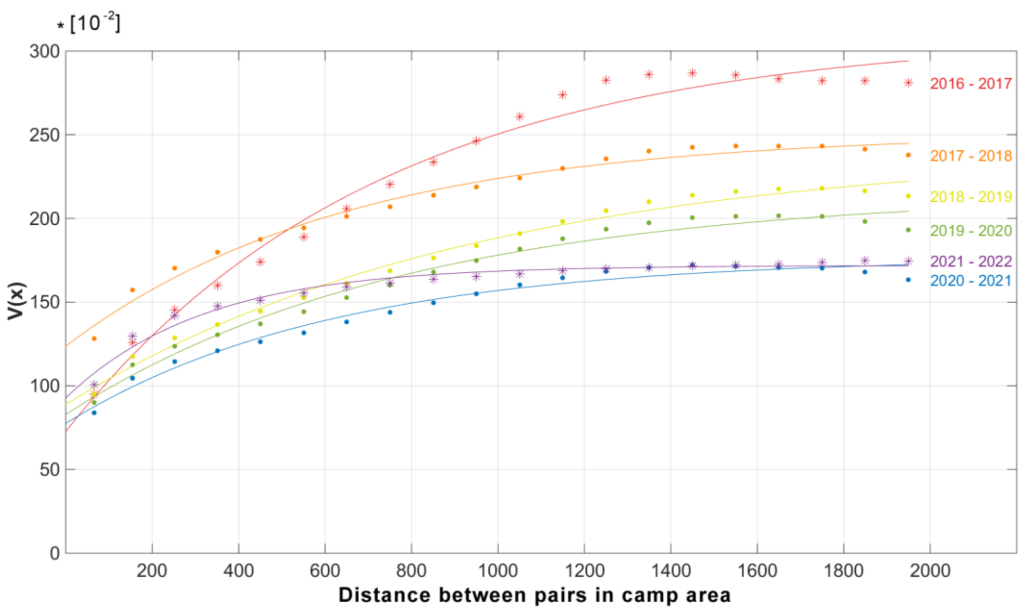


Figure 5. Times series of the variograms for the camp area, defined as a 2 km radius circle. The dots (and asterisks) are the empirical variograms and the lines are the corresponding fitted functions (theoretical variograms of exponential with nugget).

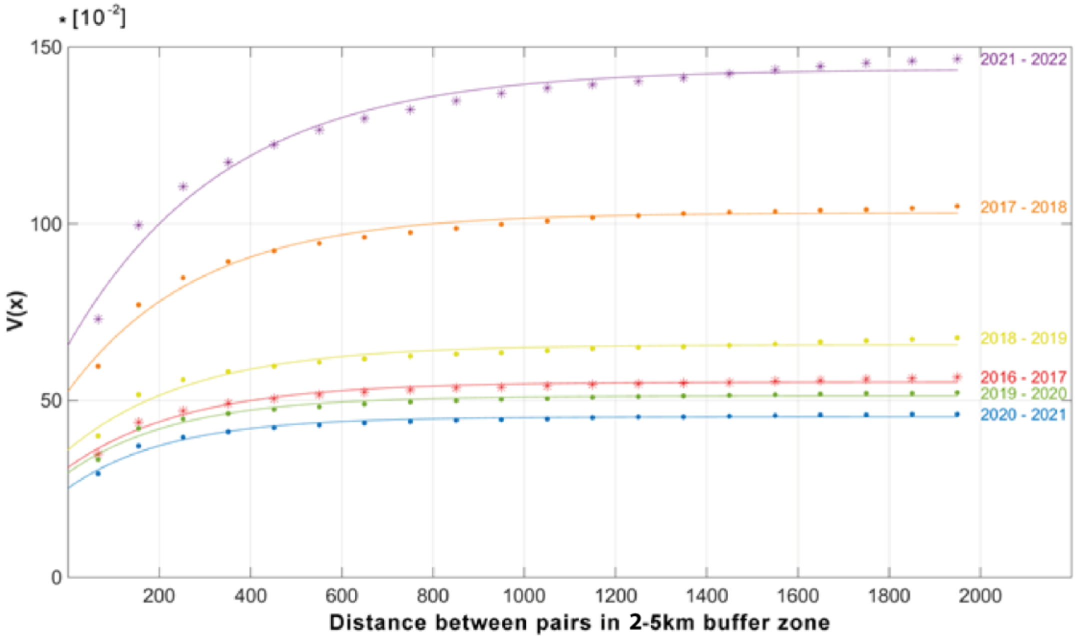


Figure 6. Times series of the variograms for the first buffer zone, 2-5 km distance from the camp. The dots (and asterisks) are the empirical variograms and the lines are the corresponding fitted functions (theoretical variograms of exponential with nugget).

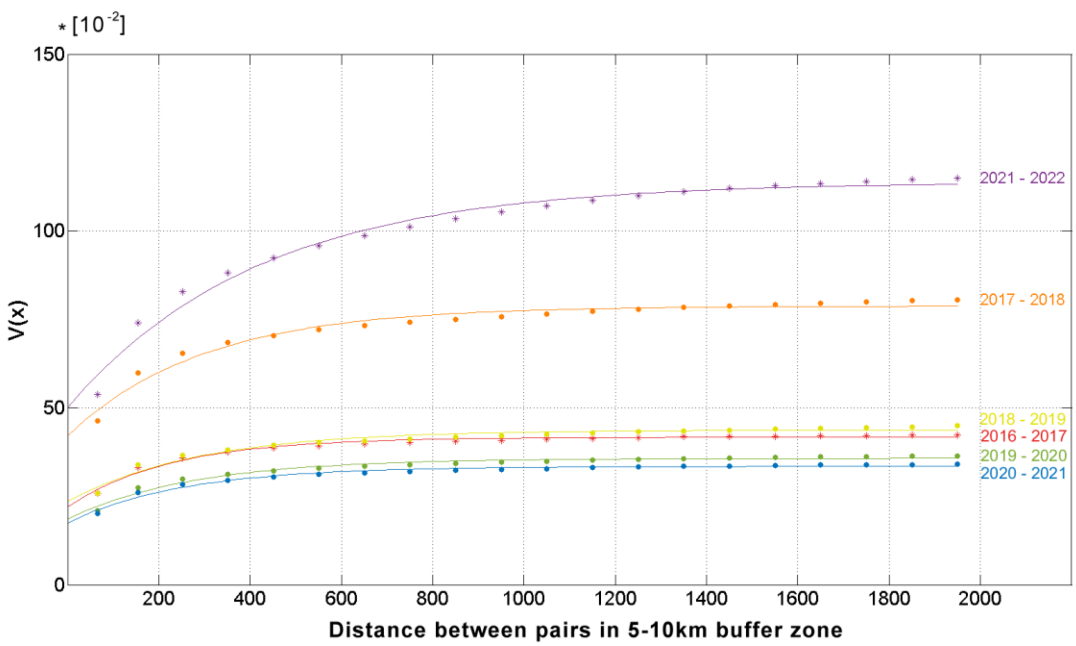


Figure 7. Times series of the variograms for first buffer zone, 5-10 km distance from the camp. The dots (and asterisks) are the empirical variograms and the lines are the corresponding fitted functions (theoretical variograms of exponential with nugget).

5. CONCLUSIONS

The establishment of refugee camps can reinforce existing local environmental transitions. It is crucial to identify the critical moment of transition and, at a later stage, understand its environmental consequences.

The use of remote sensing environmental monitoring technology holds significant potential in enhancing the management of camps and other areas exposed to intensive human activities. Analysis of Ecosystem functional attributes (EFAs) and Ecosystem functional types (EFTs) reveals a change in ecosystem productivity attributed to human activity in the area. This observation is reinforced by assessments conducted in several buffer areas surrounding the camp, confirming both the impact of the refugee camp and the subsequent tipping point of recovery after closure. In addition, analysis of EFTs reveals alterations in the phenological cycle of vegetation attributable to human pressures. Complementing this interpretation, a geostatistical approach based on variogram analysis further highlights changes in the spatial heterogeneity distribution of vegetation in and around the camp.

The insights offered by this methodology can play a pivotal role in decision-making, facilitating the preservation of a healthy environment in both its current state and its anticipated future perspectives trajectory. Additionally, these insights can contribute to nurturing positive hosts-refugees' relations. This approach, complemented with changes in land cover/use, may result in a protocol for early warning system, monitoring and evaluation of the refugee camp surroundings, supporting decision-making on mitigation of environment degradation.

6. ACKNOWLEDGEMENTS

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