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Spatial and temporal pattern of wildfires in the MasitoUgalla Ecosystem (2008-2019), Tanzania

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Abstract
Background: *Wildfire is the most common natural disturbance on the planet, posing a social and environmental risk. Studying wildfires' spatial and temporal distribution provides a scientific basis for effective management strategies.*
Materials and Methods*: Using moderate-resolution imaging spectroradiometer fire anomalies data, we analyzed the spatial and temporal patterns of wildfires within the MasitoUgalla Ecosystem from 2008 to 2019. Descriptive statistics tool from IBM SPSS 26 was used to examine the temporal patterns, while by using kernel density and Hot Spot Getis-Ord Gi* tools of Arc GIS, we determined the magnitude (density) and identified hot and cold spot zones throughout the Masito-Ugalla Ecosystem.*
Results*:Results showed that 12,925 wildfires occurred in the area over the 12 years, resulting in the burning of 18,676.10 km^2. Wildfires in the area usually started in May and continued through October, with July being the most common burn time of the year. There was a negative trend in wildfire incidence over the study duration, although the results varied. Wildfire density had the lowest and highest density values of occurrence of 0.2 to 1.4 (13%) and 2.5-3.7 (19%) active fires per 1 km^2, respectively, throughout the study period. In addition, we found high clustering of fires (1.7<14.9) and low (-2.2<0.7) of fire radiative power GIZscore values across the study area, with a coverage of 448 km2 (8%) and 3364 km2 (56%) This indicate that massive space in the MUE is experiencing wildfire with low fire radiative power, which might not be posing substantial detrimental effect on the existing vegetation.*
Conclusion: *These results provide a scientific basis for zoning wildfire risk areas based on a specific conservation target in the MasitoUgalla Ecosystem.*
Keywords: *Hot Spot Getis-Ord Gi*, Kernel Density; Masito-Ugalla Ecosystem, Spatio-temporal pattern.*

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I. INTRODUCTION

Wildfire is a natural process with significant negative impacts on global terrestrial and aquatic ecosystems[1]. The extent and effects of wildfire depend on factors such as time since the last burn, vegetation type, topography, climate, frequency, intensity, or severity [2]. While fires can contribute to climate change that poses threats such as species extinction at the global level [3], wildfires can facilitate the regeneration of an ecosystem at the local level [4].

Globally, wildfires burn over 350 million hectares of world vegetation each year [5]. Africa is the leading continent for both the number of wildfire occurrences, and the size of the area burned [6]. Most of the occurred fire incidences on the continent are believed to be because of human activities under controlled or uncontrolled conditions [5]. Though each type of fire has both positive and negative effects, the literature suggests that wildfire in Tanzania has a significant adverse impact on natural ecosystems [7].

The need to understand the nature of wildfire regimes is increasing due to climate change threats to nature conservation [6]. Novel approaches have already been developed and used to monitor wildfire issues, including the use of field surveys, geographical information systems (GIS), and remote sensing (RS) techniques [8]. Various aspects of wildfires that can be monitored using remotely sensed data (RSD) include identifying active fire, burning time, date, location, rate of spread, intensity, and severity [6]. Wildfire RSD is also used to study the characteristics of a particular fire by facilitating the mapping of the spatial extent of the fire, post-fire vegetation response, and identification of areas where the naturally recovering process fails as a response to burning [9].

The challenge to understanding fire behavior is the availability of data on such a pervasive and vast entity fire occurrence event. A detailed understanding of wildfire spatiotemporal patterns is essential for creating sustainable management plans for the area's threatened biodiversity and other socio-economic activities that are directly affected by wildfire occurrences in a particular site. Apart from that, the knowledge of various behavior of wildfires like the burning season, spread rate, and severity is helpful to all stakeholders whose goals are affected in one way or another by the occurrence of wildfire incidence in a particular area of concern.

This study was conducted to investigate the nature of wildfire Spatio-temporal patterns in the MasitoUgalla Ecosystem (MUE), Western Tanzania, using wildfire RSD and GIS techniques. It offers the applicability of several tools and data sets that can be used to assess wildfire characteristics (frequency, the extent of burn, season, and behavior (density, and hotspot area) of wildfires that occurred in a particular location within a specific period, with a list minimum cost and time, while providing complete results.

II. MATERIAL AND METHODS

Study Location: This study was conducted in MUE, located in the Uvinza and Tanganyika districts of the Kigoma and Katavi regions, respectively, in western Tanzania. The study area elevation ranges from 900 to about 1800masl, and its landscape is composed of steep hillsides combined with several valleys, cliffs, and flat-topped hills, intermixed with enormous areas of intact forest and woodland [10-12]. The area's drainage system comprises permanent and seasonal rivers found almost on every side of the region[13]. The wet season rainfall starts from November to April, while the dry one is from May to October [14]. The MUE annual temperature ranges from 11°C to 35°C, and the annual rainfall is from 900 to 1400mm [10]. MUE is an ecologically rich area that serves as a refuge for several species identified by the IUCN as subjects of conservation concern like African Elephants, Eastern chimpanzees, Ground Pangolins, Lion, and African Wild dogs[15-17]. The area's vegetation is composed of miombo woodland, grassland, evergreen, and riverine forests [10, 13, 18]. The main socio-economic activities include farming, pastoralism, fishing, beekeeping, and charcoal making [19].

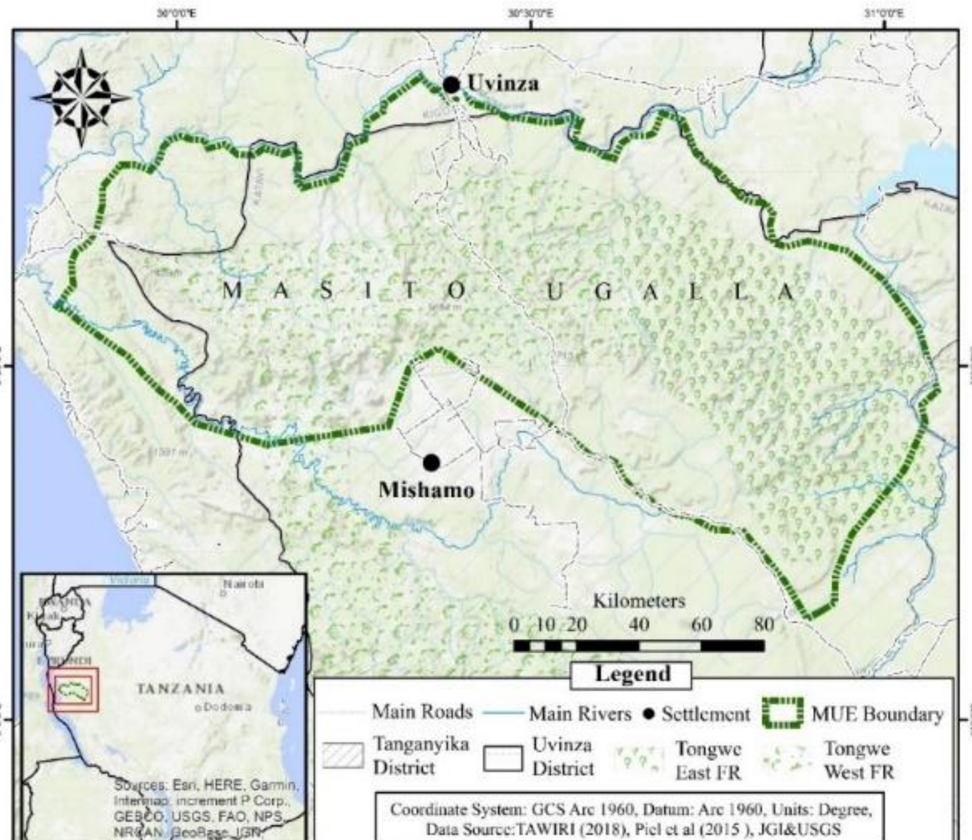

Figure 2: Study Area location (Data source: Piel et al. l 2015, TAWIRI 2018, JGI and USGS)

Data collection: Wildfire data were collected from MODIS Collection 6 Global Monthly Active Fire Location (MCD14ML) and burned area (MCD64A1) from January 2008 to December 2018. The MODIS MCD14ML data contains information for understanding timing, spatial distribution (location), and characteristics (date, time, fire radiative power) of active fire within 1 km2, and MCD64A1 offers data about a burned area like the extent of the burn, burn date, and the first and last day of the burn, in a particular landscape. Data from these products provide helpful information for monitoring the spatial and temporal distribution of fires, estimating the extent of burns, detecting changes in fire distribution, identifying fire hotspots and cold spots, and calculating the frequencies of fires in the study area. Both products were downloaded from the University of Maryland server [20].

Data Processing: MCD14ML and MCD64A1 were clipped to the MUE boundary using ArcGIS 10.8 and registered to the Universal Transverse Mercator (UTM) coordinate system of UTM Zone 36 South Spheroid Clarke 1880, and Datum Arc 1960.

Data analysis: This objective aimed to determine the characteristics (season, frequency, and burning extent) of wildfire and spatial behavior (clustering pattern) in the study area from 2008 to 2019. To determine the spatial-temporal pattern of fire events in MUE, fire and burned area time series (2008-2019) were analyzed using ArcMap 10.8 and descriptive statistics. To determine the characteristics, descriptive analyses (frequency, season, trend, and size of the area burned) were conducted in IBM SPSS 23, while spatial characteristics, kernel density, and Hot Spot Analysis (Getis-Ord Gi*) techniques were employed. The spatial methods were selected becausethey are widely used to generalize or smooth discrete point data into a continuous surface [21] and identify areas with a statistically significant concentration of points with similar characters [22, 23].

III. RESULTS

Temporal patterns

MODIS MCD14ML recorded 12,925 active fires (AF) within the MUE between 2008 and 2019, with an average and standard deviation of 1077.08 and 210.28 AF per year. The highest number of fires (1368) was recorded in 2010, while the lowest (661) was in 2015 (figure XX). The linear trendline in the figure below shows a moderate decrease in the number of AF in the MUE over the study period. Figure two below presents the number and trend of AF recorded in MUE at a confidence level of 50% to 100% from 2008 to 2019.

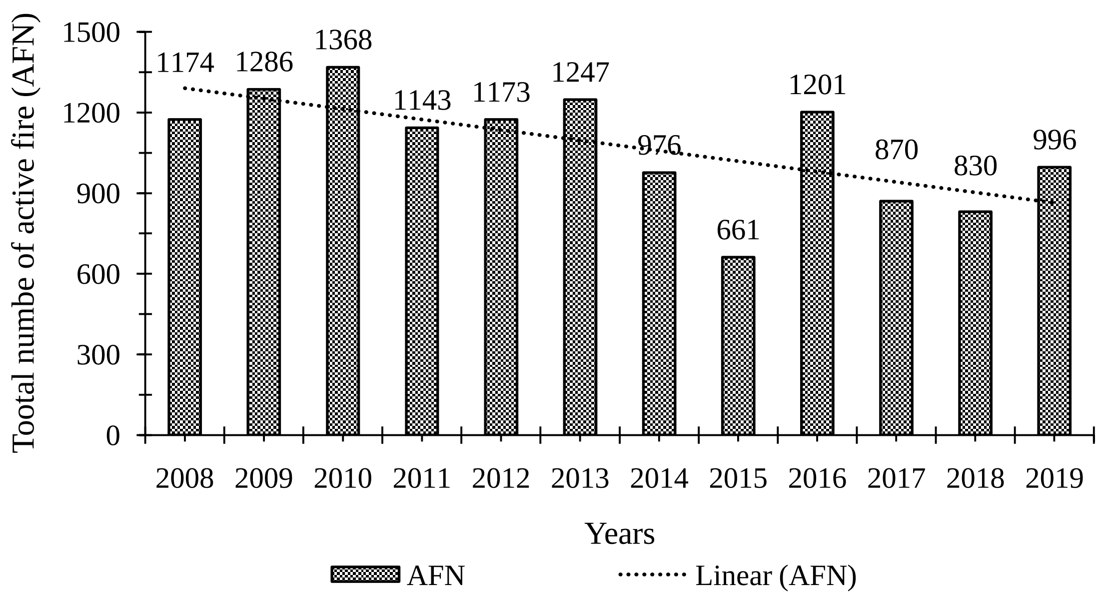

Figure 2: The total number of active fires that occurred in the MUE from 2008 to 2019.

Size of the burnt area

From 2008 through 2019, 18676.10 km2 were burned with the highest level (2171) and lowest (1095) values in 2010 and 2014, respectively (Figure XX). The linear trend line on the figure below shows a moderate decrease in burnt area (BA) size over the study period. Figure XX below presents the size of BA and unburnt area (UBA) during the study period.

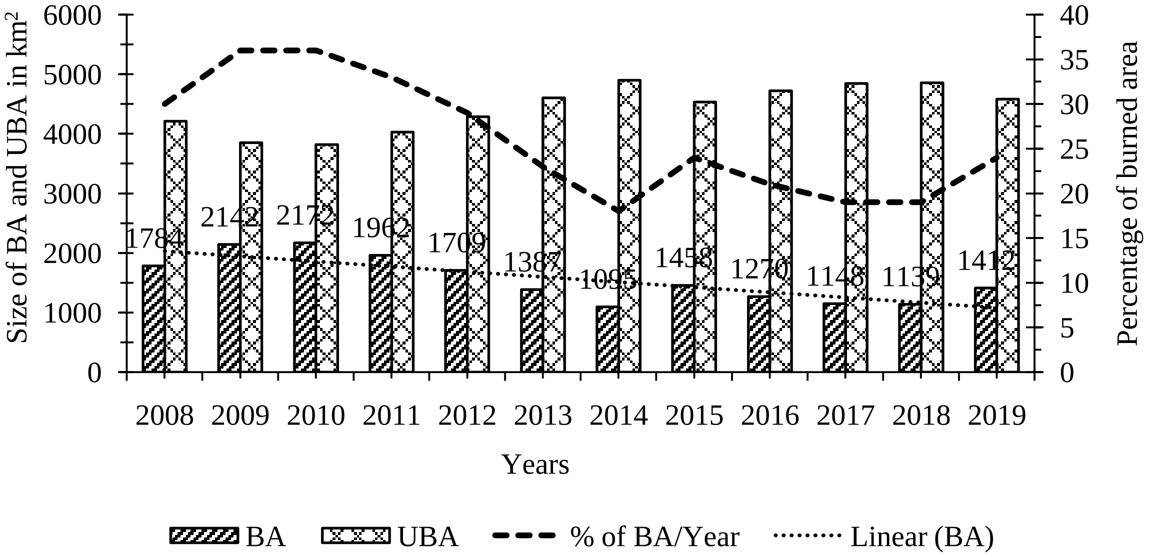

Figure 3: Size of the areas burned in the MUE from 2008 to 2019.

Wildfire season

For all combined years, 41.59% (N=12,925, n=5,375) of active fires occurred in July, and May and October experienced fewer minor fires (Figure XX). The typical pattern of all wildfires is increasing from May to July and increasing from May to July, and decreasing from August to October.

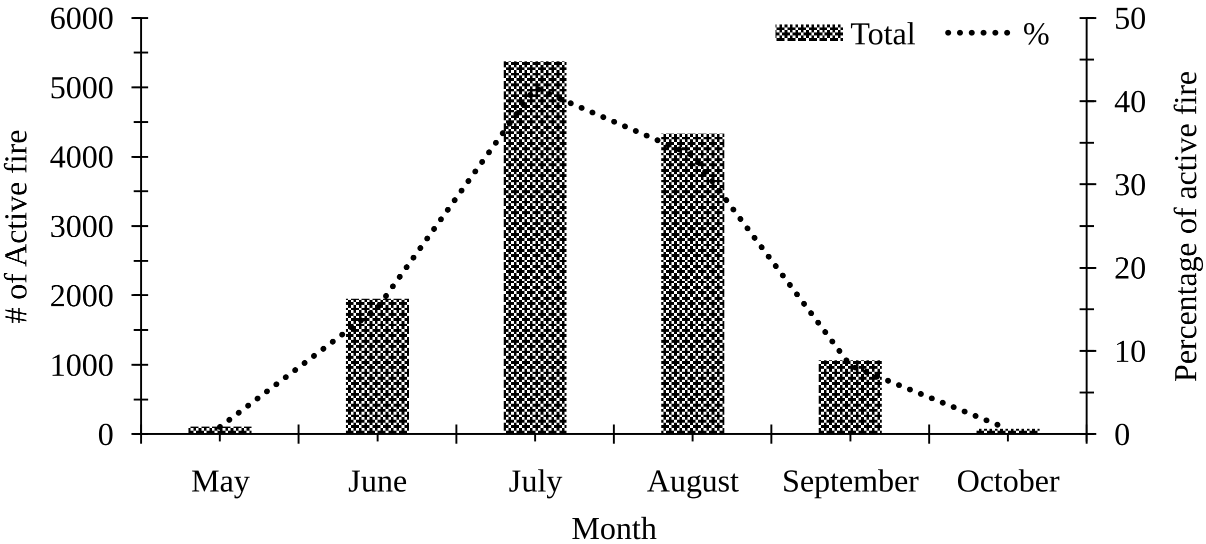

Figure 4: Size of the areas burned in the MUE from 2008 to 2019.

Spatial arrangement

The density of active wildfire in MUE

The kernel density maps below (Fig. 5) show that the density of active fire (AF) distribution in the MUE ranged from 0.2 to 3.7 per 1 km2 from 2008 to 2019. However, the distribution was not uniform throughout the area as two distinct areas with high (2.2 to 3.7) numbers of active wildfires are noted to be located mainly in the

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western and eastern parts of the area, while those areas with lower values are found primarily on the middle part of the area.

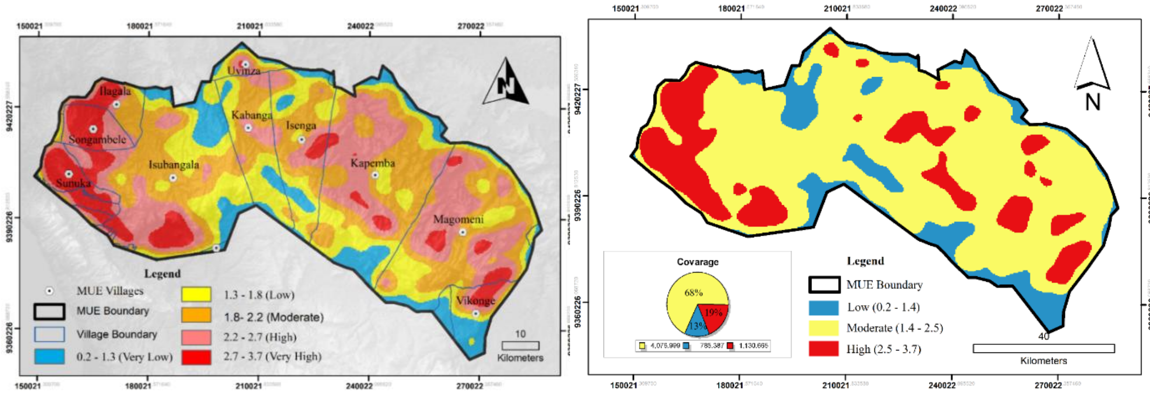

Figure 5: Density of active fire in the MUE from 2008 to 2019.

Hotspot areas

Figure 5 above presented the density of active wildfires in the MUE from 2008 to 2019 before identifying areas with statistically significant clustering based on FRP. This study applied the Getis-Ord Gi* tool to identify the site with statistical significance clustering of high and low FRP. The figure below presents the average FRP values of all active fires that occurred in different months from 2008 to 2019, while figure 7 presents the results of the Getis-Ord Gi* tool.

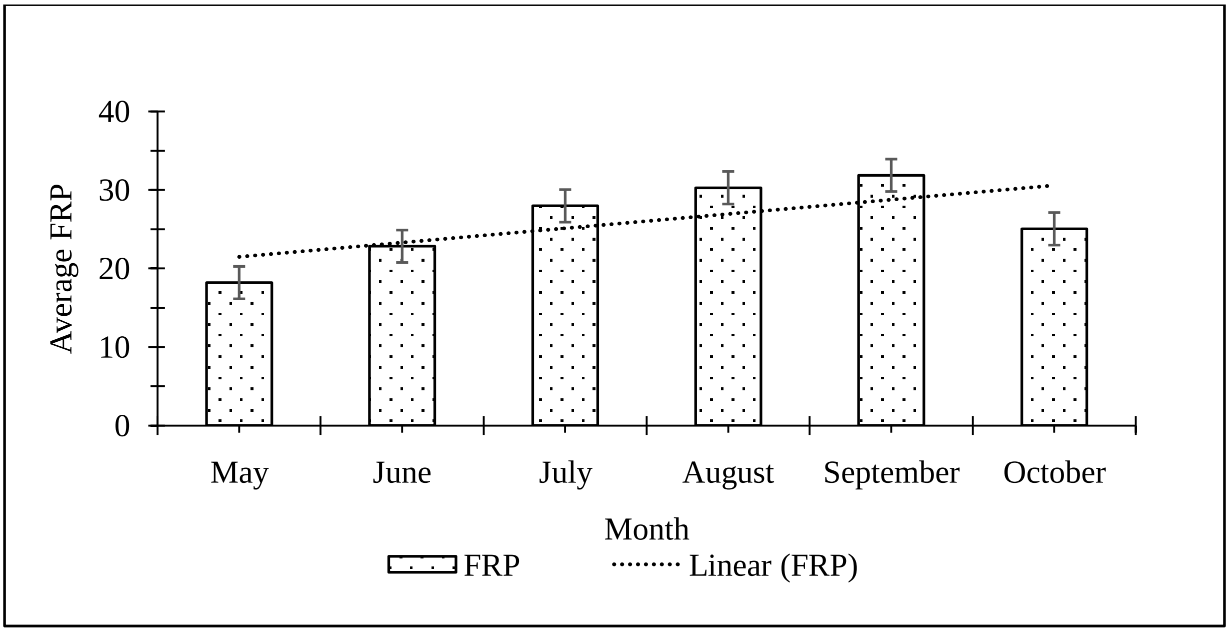

Figure 6: Average FRP recorded from all AF occurred in the MUE from 2008 to 2019.

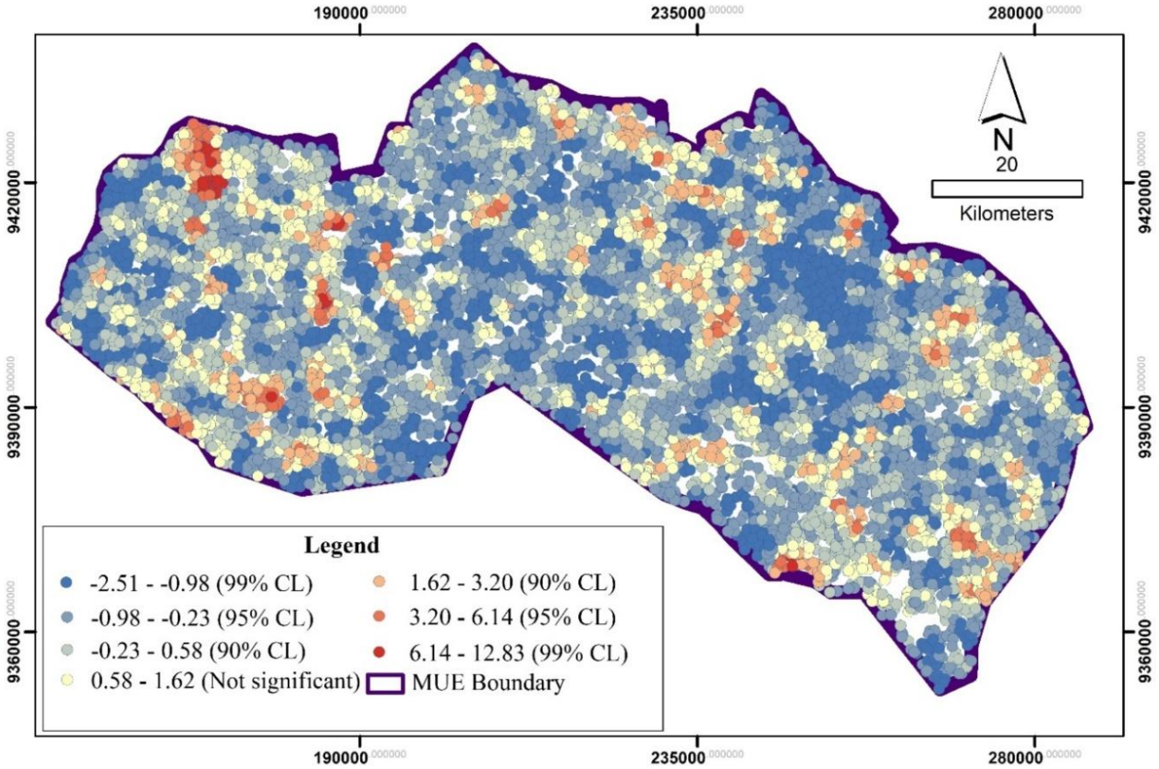

Figure 7: Hot spot areas in the MUE based on the interpolated values of GIZScore.

Figure 7 above shows hotspots and cold spots presented by points where the values were 1.6>12.83 (red) and -2.5 < 0.58 (blue), respectively. In addition, Fig. (XX) shows that features with high positive value of z score are specified as the hotspots, whereas attributes with low values are defined as the cold spots (blue). Nevertheless, the map also shows the hot spot and cold spot zones and discloses that the clustering pattern of hot spot areas is lower than cold spot areas at a statistical confidence level of 90 to 99%.

Figure 8 below presents the results of interpolated values of GIZScore, which were produced after applying the Inverse Distance Weighted (IDW). IDW was applied to the hotspot map generated by using Getis-Ord Gi* analysis to visualize hotspots' smoothed continuous surface in the study area. The continuous smooth surface is classified into three different classes of hotspots. The Very High (red) areas reflect the areas that require more attention from the local management based on the effect of FRP on a particular site. In contrast, the very low areas (blue) show a statistically significant clustering pattern of negative z-score; hence the indicated area requires the least attention as they are considered cold spots.

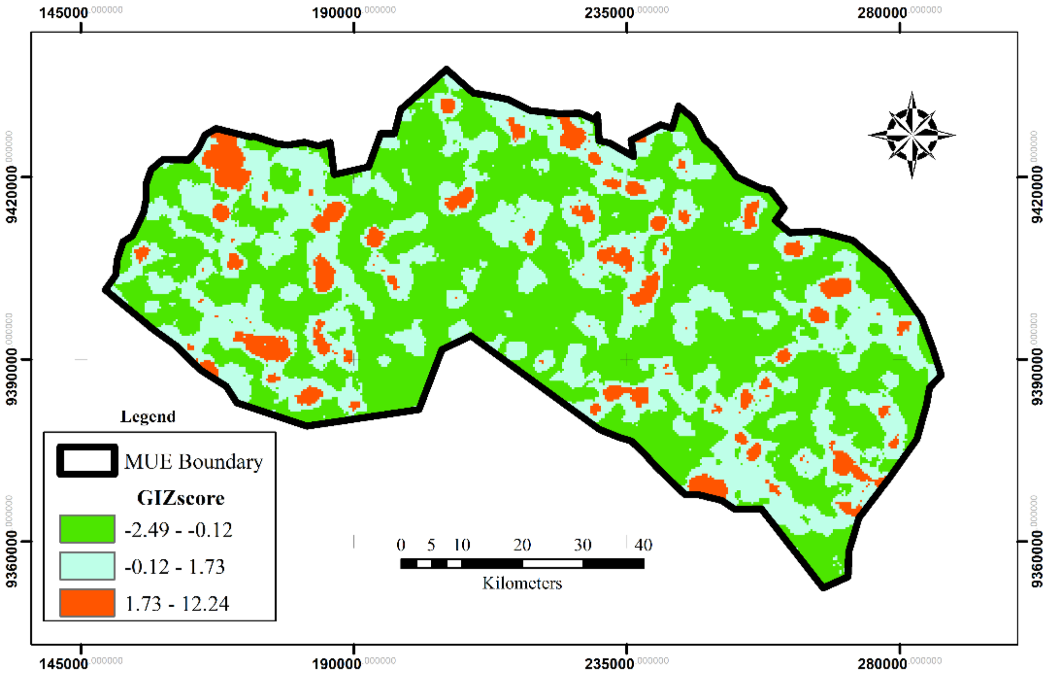

Figure 8: Hot spot areas in the MUE based on the interpolated values of GIZScore.

IV. DISCUSSION

Temporal Pattern

This study investigated wildfires in the Masito-Ugalla Ecosystem and found that they occur within a different spatial and temporal framework. The number of active fires and the size of the destroyed area peaked in 2010 (1,368 and 2,172 km2) and decreased in 2015 (661 and 1095 km2). According to the monthly variation of fire disturbance in MUE, the peak of the wildfire disturbance is in July, while the low value is in October. The burning season begins in May and ends in October, which coincides with senescence and the wet season. According to studies conducted in the wildlands of Tanzania's western region, these results possess consistency.

Spatial distribution

The density map of active fires (AF) showed that AF locations varied across the MUE during the study period. The density was divided into five categories: very-low, low, moderate, high, and very high. In the Western Part, high and very high densities are in Ilagala, Songambele, Sunuka, and Isubangala, whereas in the Eastern Part, they occur primarily in Vikonge, Magomeni, and Kapemba. With the Getis-Ord Gi*, the z score shows statistically significant clustering of the hotspot and cold spot areas, which indicates that spatial processes are at play. Literature suggests that vegetation type, topography, bioclimatic conditions, social economy, or other factors in a particular area may impact the observed patterns in this study.

V. CONCLUSION

This study analyzed spatial and temporal patterns of wildfires in the MUE using MODIS active fire data (MCD14ML) and burned surface data (MCD64A1). It was found that a spatial-temporal pattern of active fires and burned areas existed in the study area. Fire season runs from May to October, while the most significant number of fires and the most extensive area burned are from July to September, averaging a peak in July.

Based on the results of these geographic analyses, insights are offered into the locations where fire occurrences are concentrated spatially, based on a given FRP and frequency of fires from 2008 to 2019, and reveal which areas have been most affected during this period. Among the 1,185.14 km^2 included in this study, 18% occurred in areas of high AF density, 34% moderate density, and 47% low density. In terms of the amount of heat produced during the burning period (FRP), September appears to have the highest average.

The MODIS-derived data have proven to be influential in determining the extent and distribution of fires. However, due to the limitations of MODIS active fire detection in 1-km resolution data, these products may also underestimate the number of fire occurrences in ecosystems that might be prone to tiny, low-intensity fires. Even though these products occasionally encounter commission errors, their high temporal fidelity makes them the ideal tools to monitor wildfire impacts daily. Knowing fire concentrations will allow us to identify areas prone to fire and assess their ecological and socio-economic effects throughout history.

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