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Research Article

Spatio-Temporal Analysis of Wildfire Occurrence Hotspots and Socio-Environmental Predictors in the Atebubu Amantem District, Ghana

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ABSTRACT

The recent surge of fire outbreaks have jeopardized the socioeconomic status of several individuals as well as degraded the biodiversity, specifically in the Atebubu Amantem district and in Ghana in general. However, scientific research effort to assessing and eliciting crucial information for optimized preventive resources allocation and management is limited. This study therefore utilised a 10 year wildfire ignition points data supplied by the Fire Information for Resource Management Systems (FIRMS) to model the fire occurrence and intensity, through the Kernel Density Estimation (KDE) and Getis-Ord G* hotspots analysis. Regression models were also adopted to evaluate the relationship between fire occurrence and certain social, environmental, topographic and climatic variables. Results indicate that, fire occurrence shows a rising trend since 2017 in the district, and the spatial pattern has been fairly consistent over the past 10 years. With respect to factors driving the wildfire occurrence, temperature ($R2=0.1819$, $p=0.0086$), solar radiation ($R2=0.1868$, $p=0.0045$), elevation ($R2= -0.12$, $p=0.0253$) and distance between settlement from wildlands ($R2=0.0691$, $p=0.0412$) were significantly correlated with fire occurrence in the district. It was also discovered that the months of January and December had the highest number of fire occurrence due to the hamattan period. Our study makes ample contribution to management of the wildfire menace through pragmatic measures for institutional collaboration, locally based fire management strategies, public education and stringent law enforcement against arson within the district, amidst the scarce preventive resources available.

Keywords: GIS and Remote sensing; Kernel Density Estimation (KDE); Wildfire; Hotspot analysis; Atebubu-Amantem district

INTRODUCTION

Fires have been used for land management in many countries – especially in facilitating the rate of plant community regeneration [9]. Farmers in developing countries in particular also rely on fire in preparing their croplands, in the slush and burn practice [22]. However, for many geographical regions, the impact of wild and domestic fires has been very damaging [53, 51,35]. It has been estimated that, more than 200 million square kilometres of forest lands have been degraded in less than 200 years due to Wildfires [22]. This has significantly reduced the capacity of the physical environment in generating the needed ecosystem services [42]. The effects of Wildfires globally has straddled both the natural, socioeconomic and cultural aspects including loss of lives, soil erosion, loss of soil nutrients and other threats such as climate change [27,38]. For example, in 2009 alone, About 17,000 people died in Europe as a result of direct impact of Wildfires. In the United States, besides the number of deaths recorded, the economic loss alone is very massive. In 2016, estimated cost of damaged properties in the United States surpassed 70billion dollars [43,44]. Recently, several studies have also been conducted to find the impact of Wildfires on global and local atmospheric chemistry. It has been discovered that, smokes and other aerosols that accompanies wildfire incidence has presented a number of public health challenges [30,49,20] For example 800,000 premature deaths in Africa can be attributed to fine particulate matter such as released during agricultural fires [7]. Also, in developing

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countries where agriculture provides the anchor on which many economies rely, the agricultural impact of Wildfires can be very devastating.

In Sub Saharan Africa, the radical manner of climate change and variabilities coupled with excessive rate of population growth, are likely to increase Wildfires in the near future thereby intensifying the socioeconomic hardships which already characterize the region [48]. It has been noted that, climatic, environmental and socioeconomic variables drive fire frequency and intensity significantly [11,54]. Vegetation stress, increased temperatures, reduced rainfall and other climatic variables such as relative humidity, wind speed and solar radiation have been discovered to have stronger impact on wildfire occurrence [45]. As such, these climatic and environmental variables provide an essential grounds for forecasting seasonal and future weather-fire behaviours across different geographical space. Ghana is ecologically unique country –with rich biodiversity and several forest reserves [13]. However, with population growth, and annual bushfires, several forest lands have been cleared –either to provide space for building, lumbering and indiscriminate burning for hunting purposes [14].

Besides many factors such as indiscriminate cutting down of trees and charcoal production [4]. Wildfires play significant role in destroying a lot of agricultural lands and crops in Ghana especially Atebubu Amantem district within the Bono East region[3,36]. Atebubu Amantem aside its role as a food basket for Ghana, contribute significantly to the GDP of Ghana. Also, agriculture related income provide an important source of revenue for the district assembly to help in the execution of developmental projects. In light of this, the area has received attention, in terms of agricultural development within the district [1]. Therefore, the impact of any external stressor such as Wildfires on agricultural productivity must be curtailed through scientific assessment methodologies. With recent advancement in Remote Sensing (RS), Geographic Information System (GIS) and various Geostatistical techniques, the fusion and integration of large volume of spatial and non-spatial data [6]. for risk modelling and forecasting to aid in decision and policy making – has been used extensively [45,29]. Therefore evaluation of fire statistics and mapping of historical wildfire incidence is important in some of the following ways: (1) to identify areas where fires are likely to start from, (2) to aid in during-fire management such as response, suppression, and identification of evacuation routes (3) to aid in post fire damage assessment and (4) provide appropriate preventive measures to stop its impact on human lives. However, to achieve a realistic risk level estimation, fire frequency, intensity and spatial distribution information must be available to planners [21].

However, it is worth noting that, such research rigor that utilizes the savvy techniques of geospatial tools and efforts – integrating historical fire frequencies, intensities and spatiotemporal patterns mapping and their bioclimatic and social predictors are largely non-existent in Ghana. For example, from the myriad of literatures reviewed on fire outbreaks in Ghana, a large proportion of these omitted the methodology of combining spatiotemporal targeting efforts with their predictors. For instance,[2] analysed the temporal trend of fire outbreaks in Ghana, highlighting personal responsibility in the increased occurrences and severity of fire events across the country, [25]. provided an assessment of temporal variations in annual wildfire occurrences in Ghana and [50]. provided a review of methods for modelling forest fire risk, and [26]. developed a methodology to model the likely spatial coverage of forest fires and applied it to a forested area within southern Ghana. This therefore provide a conspicuous gap within the existing literature, thereby affecting the effectiveness and efficiency of wildfire management and prevention policies in Ghana and within Atebubu Amantem in particular. As part of contributing to achieving multi-scale and layered solution to disasters and effectuate resilience [52]. And in dealing with this knowledge lacuna in Ghana, we modelled spatio-temporal fire occurrence and their socio-environmental dynamics in the Atebubu Amantim district of Ghana in order to guide decision making.

MATERIALS AND METHODS

Study area

Atebubu Amantem district is one of the major districts in Brong East region of Ghana. It lies between latitudes and 22" N and longitudes 30'W and 26'W. As a forest-savannah transitional zone, it receives precipitation of 1400-1800mm per year. It is worth noting that, though the area is wooded, the trees are not as dense and tall as those within the Dry semi Deciduous Forest Zone. Agriculture constitutes the major economic activities among the people –absorbing about 70% of the population within the district. As an agricultural district, both cash and food crops are cultivated. These crops include; the cassava, vegetables, cashew, cotton and tobacco. Most of the people also engage themselves in charcoal production and marketers as secondary economic activity.

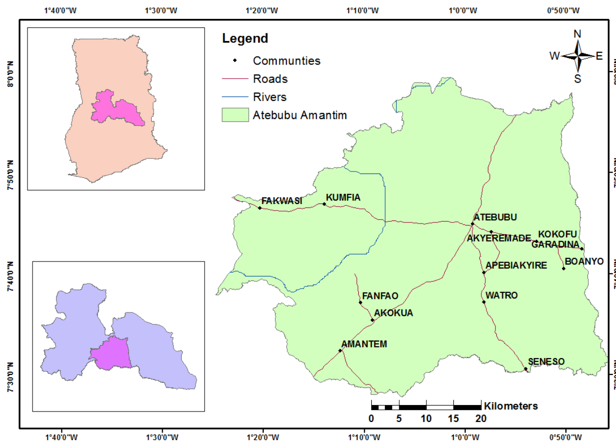

Figure1: A map of Atebubu Amantem district.

Geostatistical methods

The study adopted Kernel Density Estimation (KDE) and Getis-Ord G* hotspots approaches to map historical fire occurrence hotspots. Other techniques including time series analysis and multiple linear regression was adopted to find suitable predictors of wildfire occurrence.

Datasets utilized and their sources

Several datasets were used for the execution of this project. Data used for the historical fire occurrence mapping was obtained from Fire Information for Resource Management System (FIRMS). The on-board Moderate Resolution Imaging Spectroradiometeric sensors (both Aqua and Terra) provide timely and recurrent active data on wildfire occurrences for both day and night. Near real time active wildfire occurrence data available in Shape files and excel (CSV) are delivered upon request by the NASA branch of Fire Information for Resource Management System (FIRMS). This data always come with accompanying attribute information suitable for my study. These information include (1) the x and y coordinates of each fire scanned pixel, (2) brightness temperature (3) time and date of acquisition (4) resolution of the scanned pixels (5) radiative power of the fire representing the fire intensity and (6) the quality assurance data for each scanned pixel value. A decade (10years) data was obtained from https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms. Other datasets such as monthly level rainfall, temperature, wind speed and solar radiation were obtained from https://www.worldclim.org/. Due to geometrical errors, they were re-projected to UTM Zone 30 N and then resampled from 500m to 100m spatial resolution using the bilinear interpolation resampling technique before clipping to my study area (Atebubu Amantem district).Data on population density was acquired from Socioeconomic Data for Application Center (SEDAC) from 2010-2020.

Geospatial methods

The NDVI was extracted from Landsat 8 OLI and Landsat 7 EMT+ (from 2010-2020). Pre-processing using Atmospheric correction due to cloud cover was undertaken, the scanned line errors associated with Landsat 7 data was fixed using the Landsat toolbox in ArcGIS 10.3. Using the expression NDVI =, the NDVI was computed, where the NIR is the Near Infrared band within the electromagnetic spectrum, and the RED is the red band in the visible portion of the electromagnetic spectrum. All topographic variables such as slope, aspect and elevation were extracted from ASTER GDEM at 50m spatial resolution. Software utilized for this study includes ArcGIS 10.3, Statistical Package for Social Sciences (SPSS) and Microsoft suits such as Excel.

Kernel Density Estimation (KDE)

The Kernel Density Function (KDF) is a non-statistical technique that is used to estimate probabilistic densities of points and polylines for hotspots analysis [21, 24]. It has been successfully used for wide range of applications such as wildlife management [34,39]. Wildfire occurrence and frequency mapping[46], crime mapping [19]. and others. This function works efficiently under different data distribution types. For example it is able to estimate the probability densities that is independent of the grid size and any other localization influence. Also, it works well for datasets displaying multi-modals and non-normally distributed datasets [24]. and therefore makes it advantageous for wide range of hotspots data analysis. In this study, both historically annual and monthly level fire occurrence probability density was mapped using the Kernel Density Function. The Kernel Density was estimated using the expression:

$$\mathbf{KDE} = \frac{1}{(R)^2} * \sum_{i=1}^{n} \left[\frac{3}{\pi} * P_i * \left(1 - \left(\frac{D_i}{R}\right)^2\right)^2 \right] \quad (1)$$

Where I is the input points, P is the population field and D is the distance between point I and the (x, y) location. The implementation of this function relies on Quadratic Kernel developed by Silverman (1986) cited in [40]. A search radius or the bandwidth for the computation was chosen using the expression provided below;

$$\mathbf{SR} = 0.9 * min\left(SD, \sqrt{\frac{1}{In(2)}} * D_m\right) * n^{-0.2} \quad (2)$$

Where SR is the search radius, SD is the standard distance. Dm is the median distance and n is the sum of the population field values. The bandwidth calculated for was 1065.4m and that was used for the Kernel density estimation.

Social, environmental and climatic predictors of wildfire risk

One of the key thrust of this study was to ascertain the driving forces of wildfire occurrence within the district – since different factors may influence fire frequency, size and pattern differently across differing geographical settings. In order to implement this, the multiple linear regression model was used to ascertain the relationships between historical fire ignition and socio-environmental and climatic factors such as NDVI, population density, Slope, elevation, distance from roads, distance from human settlement, rainfall, temperature and solar radiation. The expression for the multiple linear regression models is expressed as:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \ldots\ldots \beta_P X_P + \varepsilon; \quad (3)$$

Where, β0 is the y-intercept of the regression line; β1 is the slope and ε is the error term, y is the independent variable and is the independent variable. These predictor variables were all in raster format, for this reason; they were all resampled to equal spatial resolution and then converted into points using the conversion tool in ArcMap 10.3. Further, they were then exported as CSV and then imported to SPSS version 20 for Windows application, for analysis.

Fire intensity mapping

Besides the fire frequency, the intensity of the ignitions hotspots was mapped using the hotspots analysis. The input field utilized for this study was Fire Radiative Power (FRP) which comes as attribute information for the fire ignition points from the FIRMS. The FRP has been used to analyze post fire burned intensity, amount of smoke generated and the fuel load burned [46]. In case where fire ignition points are concentrated on the farmland or forest area, the damaged properties can be examined easily using the amount of energy released during the burning period [41]. In this study, the Hotspot Analysis was utilized to statistically determine significant hotspots and cold spots. Using the Z-score generated from the Hotspot analysis, the points were interpolated using the Inverse Distance Weighing (IDW) to form continuous and smooth surface. The Hotspots can be computed using the expression.

$$Gi* = \frac{\sum_{j=1}^{n} W_{ij} * X_j}{\sum_{j-1}^{n} X_j} \quad (4)$$

Where G* measures the strength of the spatial autocorrelations of event i for n (total events). The xj represents the magnitude of variable x at event j. the win is the weight between events I and j and it signifies the strength of their spatial associations. The G* actually quantifies the magnitude of individual features within the data within the localized environment of its neighbor values. The localized summation of a feature and its neighbors is then compared against the summation of all features. The outcome will be a significant z-score if the difference between the local sum and the expected sum is great. For positive Z-score, the higher the value, the greater the spatial clustering –an indication of hotspots, conversely, for negative z-scores, the higher the number, the intense, the cold spots, and in the context of firefighting efforts, hotspots areas demand more attention than the cold spots zones.

RESULTS AND DISCUSSION

Wildfire frequency

Using the kernel Density Estimation (KDE) interpolation technique, the fire occurrence for 10 years was mapped to identify spatial hotspots in order to provide avenue for optimized manner of resource allocation. The Approach also helped in identifying the sensitive areas in order to prioritize limited resources and intensify law enforcement and public education in these areas. Probabilistic density estimation led to the tracking of spatial changes in the ignition hotspots for individual years–since ignitions are likely to be aggregated or not, depending on the mechanisms of their causality [21,24]. Cumulative fire occurrence for the number of years considered (10 years) correlated variously with certain social and physical environmental variables such as aspects, elevation, slope, NDVI, distance of the ignited points from communities and roads. This ascertained the degree to which the spatial pattern of fire occurrence (as defined by the number of ignition points per square kilometre) is influenced by these factors. Also, the time series analysis revealed the stability and increasing or declining temporal pattern of fire ignitions. The outcome of the time series analysis has been presented in Figure 2 below

Where G* measures the strength of the spatial autocorrelations of event i for n (total events). The xj represents the magnitude of variable x at event j. the wij is the weight between events I and j and it signifies the strength of their spatial associations. The G* actually quantifies the magnitude of individual features within the data within the localized environment of its neighbor values. The localized summation of a feature and its neighbors is then compared against the summation of all features. The outcome will be a significant z-score if the difference between the local sum and the expected sum is great. For positive Z-score, the higher the value, the greater the spatial clustering –an indication of hotspots. Conversely, for negative z-scores, the higher the number, the intense, the cold spots. And in the context of firefighting efforts, hotspots areas demand more attention than the cold spots zones.

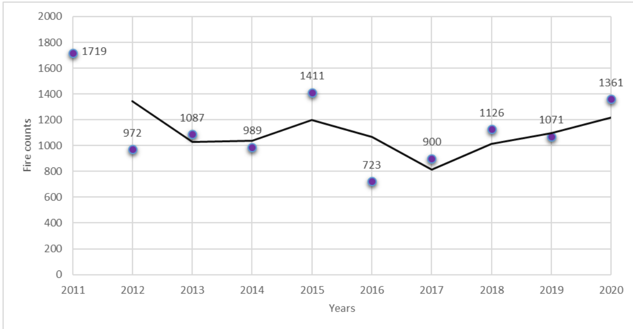

Figure2: Time series chart of fire occurrence from 2011 to 2020.

From Figure 2, it can be seen that, generally, fire occurrence (based on ignition counts) within the district has been fairly persistent. Higher number of ignitions occurred in 2011 (with 1,719 ignition counts) and slightly declined to 989 counts in 2013. The drastic decline was observed for the year 2017 with 900 counts. Unfortunately, from 2017 to present, a rising pattern of wildfire occurrence has been observed as shown in Figure 2. The rising pattern of Wildfires into the future is a worrisome observation and depicts institutional weakness in managing wildfire incidence as discovered by [3]. This therefore calls for more urgent action such as; institutional collaborations, law reinforcement, public education, strategic community wildfire management scheme and natural based fire control.

Furthermore, with respect to seasonality, the trend has been greatly variable. It is crucial to know that Fire outbreaks seems to follow the hamattan period–characterized by low rainfall and greater diurnal temperature ranges, less humidity and higher wind speed. All these may explain why fire outbreaks was higher around December and January where the dry season popularly referred to as Hamattan is at its peak. This also explains why climatological variables have been used in weather-fire occurrence and frequency forecasting. The monthly level occurrence per ignition counts has been presented below (Figure 3). It can be observed that, January and December when Hamattan usually peaks drive the seasonality of wildfire occurrence within the district.

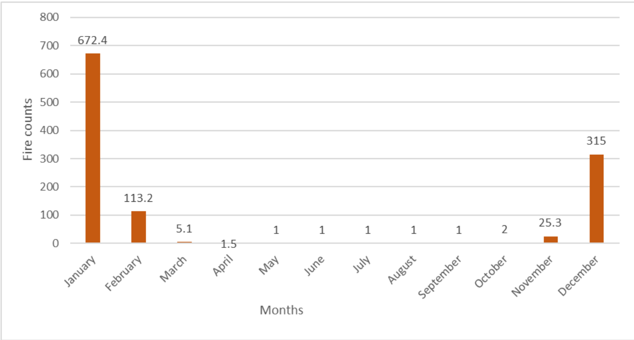

Figure3: Average monthly level fire ignition counts for the 10 years.

However, since locational aggregation or disaggregation of ignitions can help target interventions, the spatial monitoring component is as well very important – as it offers planners and fire fighters an information concerning where fire ignitions will likely start from [21]. As Jsuch, efforts to monitoring spatial changes have been investigated further using Kernel Density Estimation (KDE) as shown in Figure 4(map A to J).

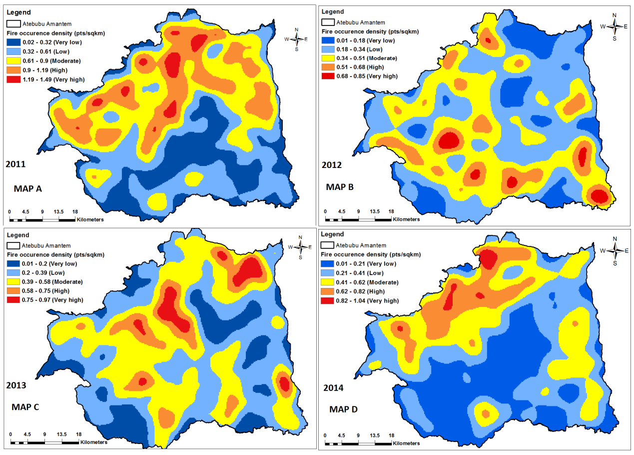

Figure4: map a - d (historical fire occurrence from 2011-2014).

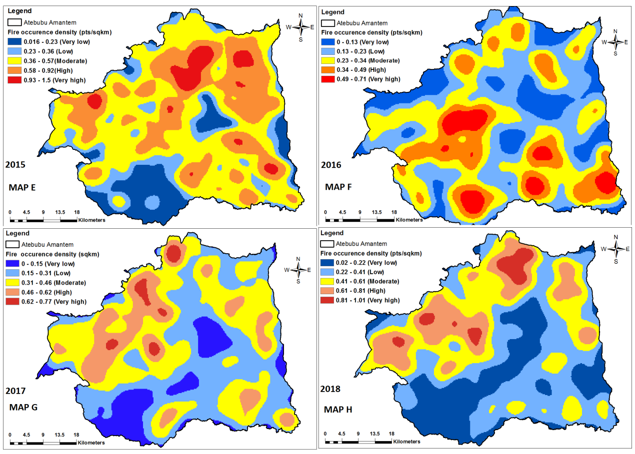

Figure4: map E-H (historical fire occurrence from 2015-2018).

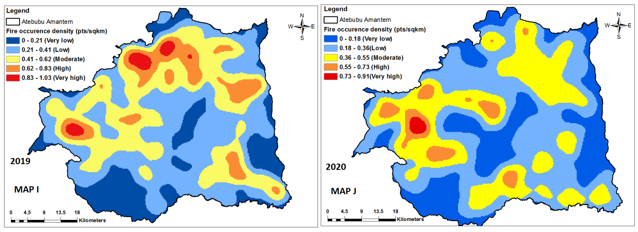

Figure4: map I-J (historical fire occurrence from 2019-2020).

It is apparent that with the exception of years 2012 and 2020 spatial pattern of wildfire occurrence, the rest of the years, fairly show similar spatial pattern (Figure 4). Most of the fire ignition densities classed as "moderate to very high density" fire occurrence happened at the West and North-western quadrant of the district meaning that fire occurrence is not a function of random process. Generally, the central portion, where Atebubu Township is located show less density compared with other areas. This is because in urban areas, fuel load density is relatively less dense, and fuel loads are also less flammable compared to forest and grasslands [47]. Also, fires in the urban areas are mostly domestic in nature and can thus be detected and responded to in a swift manner compared to areas far from urban centers. With careful observation of Figure 4, the extreme south-eastern corner had extremely low ignition, but with subsequent years, this area has recorded significant number of ignitions. This indicates that spatial occurrence of the fire outbreaks is expanding and therefore calls for more intervention. The year 2020, has the moderate to very high hotspots distributed fairly across the area and did not follow selective pattern of the ignition aggregation. The implication is that, if this persists into the future, the associated risk level is going to be more spatially homogenous therefore presenting further challenges in confronting it. Furthermore, the entire decade of ignition counts were temporally aggregated to form a cumulative fire ignitions points for the 10 years. These ignition points were then modelled using the Kernel Density Estimation (KDE). The aim was to identify areas with persistent fire occurrence. Such strategy aids in providing useful information in the optimisation of preventive resources allocation and formulation of robust firefighting strategies [8].

From Figure 5below, it can be seen that, most of the areas are susceptible to fire outbreaks as displayed by the map. However, the pattern shown is spatially selective – it has occurred majorly at the western and north western areas. When analysed with the historical modelling output shown in Figure 4, the pattern has been fairly in phase. Amantim and Atebubu (two major towns in district) experience less fire ignitions. This is due to the fact that, they are urban areas, therefore, with regards to fuel risk, these areas are less [47]. Most of the fires either occurred on grasslands or savannahs where fuel loads are mostly flammable.

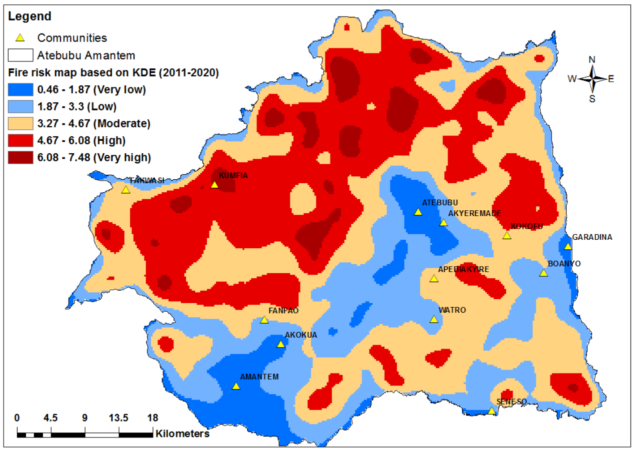

Figure5: Fire risk map showing areas most susceptible to fire ignitions based on modelled 10 year ignition counts data.

Furthermore, in order to investigate historical changes with respect to ignition density classes (Very low, low, moderate, high and very high) according to their areal coverage, the spatiotemporal kernel density of fire occurrence for the 10 years were classified using the equal area classification scheme and then area (in square kilometres) was calculated for each classes. Visually inspecting Figure 6, it can be seen that, generally, the density class pattern for the past 10 years have not change significantly. However, comparing the current time 2020 against the last 10 years (2011),– regardless of the general pattern observed, fire occurrence density especially high to very high classes have decline from 528.8 and 65.4 m2 to 122.8 and 15.7m2 respectively. It can also be observed from Figure 6that, in 2011, the difference between the low and high densities were relatively less, as compared to the relatively sharp slope for 2020. Contrary, with respect to moderate density scenario, wildfire occurrence density has increased slightly from 705.4 in 2011 to 763.2m2 in 2020. This implies that, though the extreme impact may have reduced, yet the likelihood moderate impact of Wildfires has not reduced within the last 10 years. Consequentially, the density level of ignition points has not significantly declined – showing less effort put by the district assemblies and other concern stakeholders in controlling the menace[3]. This less effort may be due to lack of institutional collaborations and a well-defined community level wildfire management strategies.

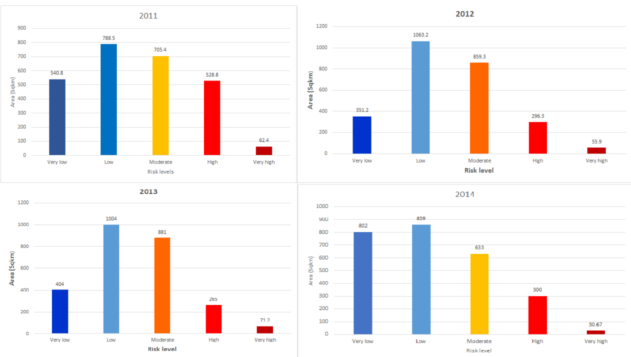

Figure6 (2011-2014): a chart showing the spatiotemporal patterns of fire occurring density areal coverage (Sqkm) estimated from the Kernel Density Estimation.

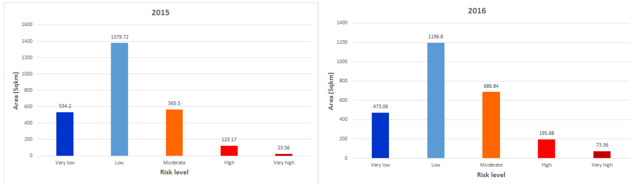

Figure6 (2015-2016): A chart showing the spatiotemporal patterns of fire occurring density areal coverage (Sqkm) estimated from the Kernel Density Estimation.

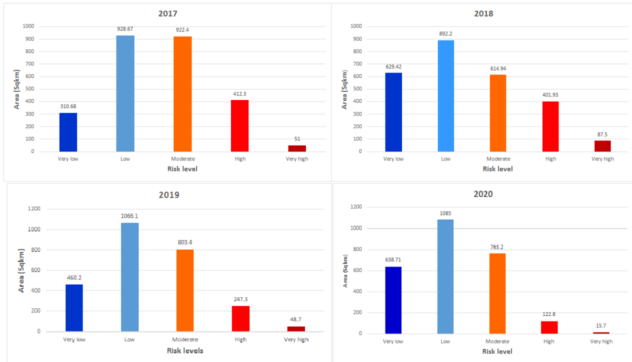

Figure 6: a chart showing the spatiotemporal patterns of fire occurring density areal coverage (Sqkm) estimated from the Kernel Density Estimation.

However, identifying hotspots or densities of ignition frequency do not still give a substantial information as to how intense the burning will likely be. Identifying hotspots of fire intensity can be used to make inference about amount of energy used and released during the burning period [46]. Also, amount of smoke and other particulate matter that was released into the atmosphere during the burning period can be inferred from hotspots analysis of fire intensity [16]. Especially, in such an agrarian district, higher fire intensity –measured by amount of energy used –can be helpful in making a decision of the quantum of crops that might have been burned and thus destroyed, even including amount of biodiversity killed during the ignition period. In this study, results were obtained using the Fire Radiative Power (FRP) of each scanned pixel obtained from the MODIS FIRMS data. The Getis-Ord G* hotspot analysis determined the statistically significant spatial hotspots. Then, the Inverse Distance Weighting (IDW) interpolation technique created a smooth, continuous and predictive surface of wildfire intensity using the Fire Radiative Power (FRP) Z-scores from the hotspot analysis. From the Figure 6, it is apparent that, high to very high fire intensity occur in a uniformly distributed manner within the district. With careful observation, it can be deduced that, less to very less risk can be observed in urban such as Atebubu and Amantem. However, with proximity to these hotspot centres, with the exception Amantem, Atebubu Garadina, Akyeremade and Boanyo, the rest of the communities are situated either close to or within the hotspot zones making human lives and properties very susceptible to destruction. Comparing the intensity map to the frequency density map (Figure 4 and Figure 7), the spatiotemporal pattern has been quite different. This may be attributed to the fact that, an area may have cluster of ignition points but releasing small amount of energy depending on the nature of the available fuel load [10,47]. In contrast, fire ignition points may be less dense, but each ignition point (pixel area, release a great amount energy – depending on the prevailing environmental and climatological conditions as well as fuel load. For example, an area dominated by grasses may be susceptible to fire outbreaks as compared to forested areas. However, an energy released when forest is burning is much greater than on grasslands. This is because; forest lands have denser fuel loads and therefore releases huge amount of energy.

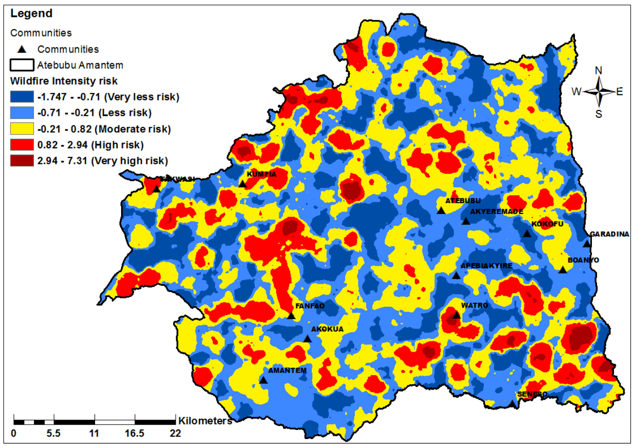

Figure7: A map showing Fire Intensity Hotspots analysis.

This intensity of the fire can have dreadful impact on crops, soil fertility, organic matter content necessary for plants growth as well as human safety [46]. Especially when the intensity hotpots overlaps agricultural lands. It has been discovered that, there exist a stronger relationship between fire intensity and amount of fuel consumed [16]. Per this discovery, when the intensity happens to be within or close to any croplands, the adverse effect on crop loss, loss soil nutrients and soil erosion is very devastative. In this study, attempt has been made to analyses an overlap degree between croplands and fire intensity hotspots – as way of examining the impact of fire occurrence on agricultural productivity in the district. The Figure 8shows a sample overlaps degree between fire intensity hotspots and agricultural lands. Areas with the black rings indicate where cropland(s) lies within or closer to a maximum fire intensity hotspot area. Visual inspection from Figure 8shows that several croplands are laying within or very close to moderate and high fire intensity areas – making it hazardous to crop losses and poverty intensification since most people rely on agricultural activities [1]. Again, it can be seen that towns such as Kumfia, Fakwasi, Watro and Seneso are lying very close to or within the risk zone. This situation presents serious threat to human lives and safety. These areas therefore need a lot of attention to curtail any potential risk to human lives and other infrastructural losses.

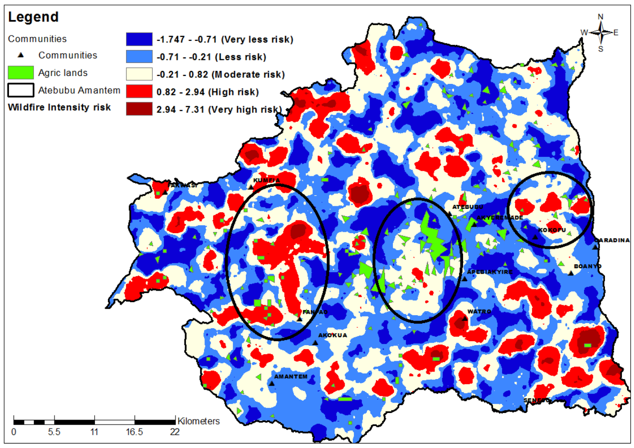

Figure8: Map showing an overlapping degree between agricultural lands and fire intensity hotspot model.

Drivers of wildfire occurrence

Both social, physical environmental, topographic and climatic variables have been analysed with respect to their impact on wildfire incidence within the district. Results have been presented below.

Climate and wildfire occurrence

Several studies have examined the impact of climate dynamics on wildfire frequency, intensity, size and spatial pattern[18,28]. They provide an important information for forecasting wildfire behaviour spatially and temporary. In this study, climatic variables have been examine in their relationship with wildfire frequency (based on ignition counts) and intensity (based on radiative power of the fire). Fire occurrence calculated with the KDE was regressed against the individual variables. This was to determine if spatial distribution of climatic variables such as rainfall intensity influenced the density of the ignitions observed over the past 10 years. A regression tool in SPSS was used to draw the correlation between climatic variables and fire occurrence density.

Results indicate that the wildfire occurrence is strongly correlated with temperature at (= 0.1819; p =0.0086) as discovered by [37], solar radiation was also discovered to have good correlation with fire occurrence density model at (= 0.1868; p=0.0045). Wind speed though depicted an influential relationship as seen by the positive gently rising trend line (see, Figure 9), however, the relationship wasn't statistically significant at (= 0.056; p=0.3112). With respect to rainfall, since it has suppressive impact on Wildfires, it was negatively correlated as shown by the negative direction of the regression trend line in Figure 8. In this current study, rainfall has proven to have an inverse relationship with ignitions with statistical significance at (. Though spatially, rainfall distribution doesn't explain wildfire occurrence to a significant degree, the seasonal variations explained much stronger (than the rest of the climatic variables as discovered by [15]. Although, most of the fire outbreaks are caused by man [51] these climatic features gives information about locally based mechanisms reinforcing the fire frequency, and to also explain why fire occurrence is not spatially random and has therefore been used in predicting wildfire occurrence[12,23]. Other variables such as topographic variables have been considered in later part of the work. Figure 9 shows the regression output between climatic variables and their relationships with wildfire occurrence.

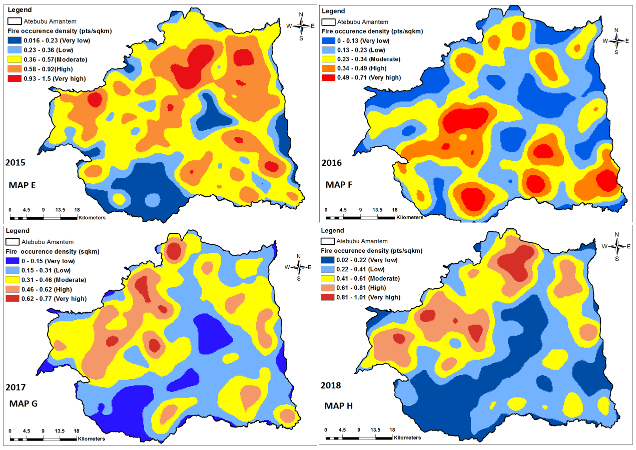

Figure9: The output of regression modelling of the relationship between fire occurrence and Rainfall, temperature, solar radiation and wind speed.

Topography, land cover and Fire occurrence

The topographic configuration of an area also provides a facilitative role –towards wildfire spread and intensity. For example, fire travels faster along steeper slopes than on gentle slopes, therefore aids in expanding perimeter of burned area [9]. On the contrary, on higher elevations, fire spread is mostly subdued because of higher humidity, lower temperatures etc. [22]. Therefore in explaining spatial variation of fire occurrence, topography must be considered. Also, the availability of fuels – arguably most important driver of fire behaviours has been examined by several studies [51]. Different fuel loads as per their moisture content, flammability and density, may influence fire behaviours differently [22]. This current study therefore considered the impact of slope, elevation, fuel types and slope-aspects on fire occurrence. From Figure 10, it can be deduced that maximum fires occurred on grasslands and savannah cover types (refer to Figure 5 and Figure 10map D). These cover types are relatively flammable, and due to their open nature, wind blow relatively faster and therefore may intensify the frequency of ignitions and fire size [33]. Secondly, elevation, per visual inspection has inverse effect on fire occurrence, compare (Figure 10map B and Figure 5). The relationship was in negative direction with statistically significance at (= -0.12; p = 0.0253). This is because on higher elevations, moisture content is high, temperature is low and tree cover is also less. For this reason, fuel load is reduced and temperature to facilitate the drying of fuels is also less making fire ignitions and spread very difficult [5]. With respect to aspect and slope, no significant relationship was discovered, for aspect at (= 0.02; p =0.1421) and slope at (= 0.0006; p =0.583). The study also attempted to evaluate the impact of vegetation health (using NDVI) on spatial distribution of fire occurrence, but found no significant relationships (. This implies that with respect to topographic configuration and land cover impact on fire outbreaks, only elevation and land cover class explained to a moderate extent, the reason behind the non-randomized spatial pattern of the fire occurrence.

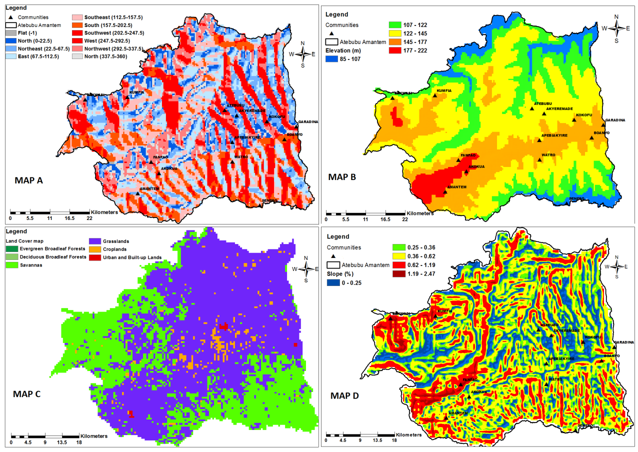

Figure10: Maps showing topographical and Landover information.

Social factors and their impact on fire occurrence

The anthropogenic influence on wildfire occurrence has been a major concern across various geographical settings. Farmers especially in developing world sometimes rely on fire as a land management tool, and in some cases for hunting purposes [27, 51]. Negligence has also been a major cause of Wildfires. Some literatures have even discovered that, criminality has also been a cause of Wildfires [31]. Admittedly, man is spatially and temporally dynamic and therefore quantifying directly how human beings actually start fires have been very challenging [32]. In this current study, attempt was made to quantify – to some extent the impact of man on spatial distribution of fire occurrence based on wildland proximity from communities and roads. Spatial distribution of population density has been excluded from this study. In trying to model spatial relationships between population density and fire occurrence may be quite misleading. This is because, man is spatially non-static due to socioeconomic activities [32]. For example, compare the densities of people in urban centres to say farmlands, it is possible to find that, farmlands are less dense – in terms of population, but these are areas where fires mostly starts –due to slash and burn agricultural practices. In this regard, the relationship will make meaning when analysed in temporal dimension or when the spatial scale of the study is very large – like regional, national or continental level. Results indicates that, proximity to settlement centres explain spatial distribution of Wildfires better (=0.12, p = 0.0412) than proximities to roads (.However, it could not adequately explain the occurrence in all areas across the district as shown in Figure 11below. It is also crucial to note that, agricultural activities are scattered across both the grasslands and savannahs (Figure 1omap D). This may explain the reason for a lot of ignitions occurring on these lands, besides the flammability nature of these fuel types as reported by other researchers [9,27]. Also, looking at how agricultural lands straddle both the moderate and high fire risk zones, the vulnerability of croplands to destruction is very potential and therefore calls for attention in these sensitive zones.

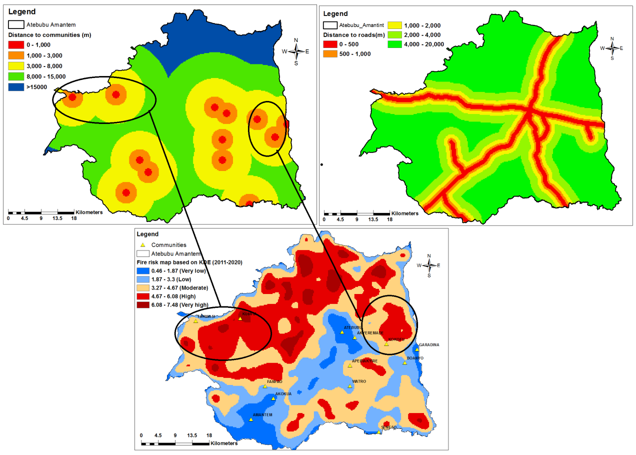

Figure11: Maps showing how social factors such as distance to roads and settlement centres influence wildfire occurrence in the district.

CONCLUSION

Wildfires have been one of the serious challenges confronting several areas in Ghana currently. Atebubu Amantem as an agrarian district over the years has recorded several cases of fire outbreaks. This study investigated this menace in order to identify sensitive zones and mechanisms driving the outbreaks in a bid to optimize allocation of preventive resources. This has a long standing potential to ensuring that limited amount of resources are optimized in its use for wildfire fighting. This study has modeled 10 year wildfire occurrence and intensity using the KDE and Getis-Ord G* hotspots. The general spatiotemporal pattern and trend of wildfire has been consistent. There has also been a rising trend in the number of ignitions recorded since 2017 showing the weakening of institutional systems in fighting the menace. The study revealed that most fires either occurred on savannah vegetation and on grasslands. With respect to climatic variables and mechanisms driving the wildfire behaviors including its intensity, spatial distribution of solar radiation and temperature had stronger impact on fire occurrence as they correlated better with the wildfire occurrence density than with rainfall and wind speed. However, with respect to monthly variation of wildfire ignitions, rainfall explained the variation stronger than all other climatic variables. This trend was attributed to the Hamattan influence characterized by rainfall deficit. With respect to topographic variables, elevation had stronger influence on spatial variation of wildfire occurrence than slope and aspect. With regards to the chances of wildfire being kindled–as a function of anthropogenic influence, proximity between settlements and wild lands influenced fire outbreaks more than proximity between wild lands and roads. It was then discovered that, most agricultural lands intersected with wildfire intensity hotspots, thereby raising the concern of the susceptibility of crops to Wildfires, and subsequently economic downturn.

Holistic and equally sophisticated intervention effort that integrate geospatial techniques are required, to be taken from; institutional collaboration, community participation approach to naturally based fire controls. In this regard, the institutional collaboration and performance levels of the Forestry Commission (FC), African Foresters Brigade Ltd (AFBl), Ministry of Lands and Natural Resources (MLNR), Ghana National Fire Service (GNFS), the ministries, Municipality and District Assemblies (MMDAs) as well as traditional leaders, must be stepped-up to proffer pragmatic measures of containing the upsurge, spread and management of Wildfires in Study district and in Ghana as a whole.

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