Modelling the risk of forest to fire for the Bosomkese Forest Reserve, Ahafo Region, Ghana

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Abstract

Forest fire is a devastating phenomenon in real life, causing huge losses of lives, properties and ecologies. A risk assessment model to identify, classify and map forest fire risk areas is presented in this paper. This model considers four risk models, i.e. ignition model, detection model, response model and fuel model analysis. The first model concentrates on human influence factors in forest fires, including the land use, distance from roads, and distance from settlements and the second model is made up of the possibility of fire visibility from road and settlement viewpoint. The forest fire response included distance from fire stations and motion resistance is the third model. The type of fuel (dry or wet), fuel moisture content, health of the forest vegetation and topography of the area were analysed as the fourth model. The study results indicate that very high-risk zones covered 38.8km^2 representing 25.6% of the total forest area. Findings of the research are helpful in developing forest fire management systems. Fast and appropriate direction could be used by management to stop the spread of fire effectively. It also helps to provide effective means for protecting forests from fires as well as to formulate appropriate methods to control and manage forest fire damages and its spread. Recommendations were made at the end of the work to implement fire towers, break lines and employ the use of modern detection techniques such drones, etc to improve fire detection and response.

Keywords: *Forest, Fire risk, Modelling, Geographic Information Systems, Remote Sensing*

1. Introduction

In today's world, sustainable development should be one of the main topics in every country's agenda. This is as a result of the interaction between human activity and the recent change in climate (Solomon, 2007). However, bridging the gap between economic development and sustainable use of natural resources has been a daunting task. The Forest ecosystem is one of the most important renewable resources which could play an important role in addressing this situation (FC, 2010).

Nevertheless, these forest ecosystems are threatened occasionally with annual depletion and destruction (FAO, 2007).

The notorious agent responsible for forest destruction and reduced productivity is forest fires and it is estimated to have caused an annual loss of 3% of Ghana's GDP during the past years (Agyemang *et al*., 2015). Spatial distribution of forest fire is therefore a key factor in understanding forest fire dynamics. However, several biotic and non-biotic factors are required to determine the forest fire risk of an area. The effects of each factor vary between ecosystems and within spatial and temporal scales (Yang *et al*., 2007).

An integrated analysis approach is required to combine the factors that affect the initiation and spreading of forest fire due to their diversity. A Geographic Information System (GIS) can be used to effectively combine different forest-fire causing factors in order to create a forest fire risk zone map (Erten *et al*., 2004). Spatial analysis of fire danger indices has been developed using several GIS models by different researchers in recent times. For example, Jaya *et al*. (2007) and Kumi-Boateng *et al.* (2016) have described the use of GIS and Remote Sensing technologies for developing forest fires risk model and post fire evaluation which have been of enormous importance in the monitoring of such fires, and could be adapted to help solve the rampant forest fires in Ghana.

Bosomkese Forest Reserve in Ghana provides food, export commodities and serves as habitat for most plant and animal species. Nevertheless, wildfires have reduced productivity and depleted the genetic diversity of the forest which distresses many terrestrial ecosystems in the earth system and leads to economic damage to human (UNDP, 2000). Deprived livelihoods of inhabitants in and around the forest areas due to the annual fires have worsened the forest destruction owing to over-exploitation of the remaining forest cover.

A fire risk and a fire spread simulation model could help inform decisions on interventions and allocation of resources such as fire towers, firefighting equipment to high risk rated areas of the Bosomkese forest reserve. These interventions could help control wildfire spread with its associated destruction thereby protecting forest cover and livelihoods of fringe communities. Protection of forests from fire destruction also improves the quality of human health by providing clean environment and rich ecosystem services (Tavasoli *et al*., 2019). The objective of this study therefore, is to develop a forest fire risk model for the Bosomkese forest reserve for decision making purposes using Remote Sensing and GIS technologies, based on previous fire risk model (Kumi-Boateng *et al.,* 2016), and incorporating the effect of vegetation moisture in the behaviour of the fires (Chuvieco *et al*., 2010). This is because even though the Bosomkese forest is faced with frequent annual fires, rare information exists regarding the hot spots of the fires and their pattern of spread depending on the moisture content of the vegetation/land cover. The adapted model was employed because it was used in the moist semi-deciduous forest in Ghana where the study area is situated.

The occurrence and behavior of forest fires are difficult to predict due to the complex interaction of diverse factors involved. And so to achieve the objective, suggestions of fire risk modelling from various researchers (Chuvieco *et al*., 2010, Kanga *et al*., 2013, Jaiswal *et al*., 2002, Guettouche *et al*.,

2011) were considered and some indicated factors that mostly influence forest fires prediction: elevation, aspect, slope, vegetation cover, fuel moisture and distance to roads and settlements, were analyzed and used in the modelling of the Bosomkese forest fire risk.

2. Study Area Description

Bosomkese forest reserve is geographically located within latitude 6°59'N to 7°10'N and longitude 2°11'W to 2°19'W. It falls within Tano South and Asutifi political districts of the Ahafo region, Ghana (Donkor et al., 2016). The forest reserve was established in 1939 to protect the destruction of important forest species, three years after its demarcation. However, the forest has witnessed rampant and severe fire outbreaks in the past decades, as has been witnessed in other major forests in Ghana (Appiah et al., 2010), thereby losing these protected species. It has a total area of 138.41 square kilometers (13,841 hectares) and managed by Bechem forest district of the Forestry Commission of Ghana. Fig. 1 below shows the map of the study area.

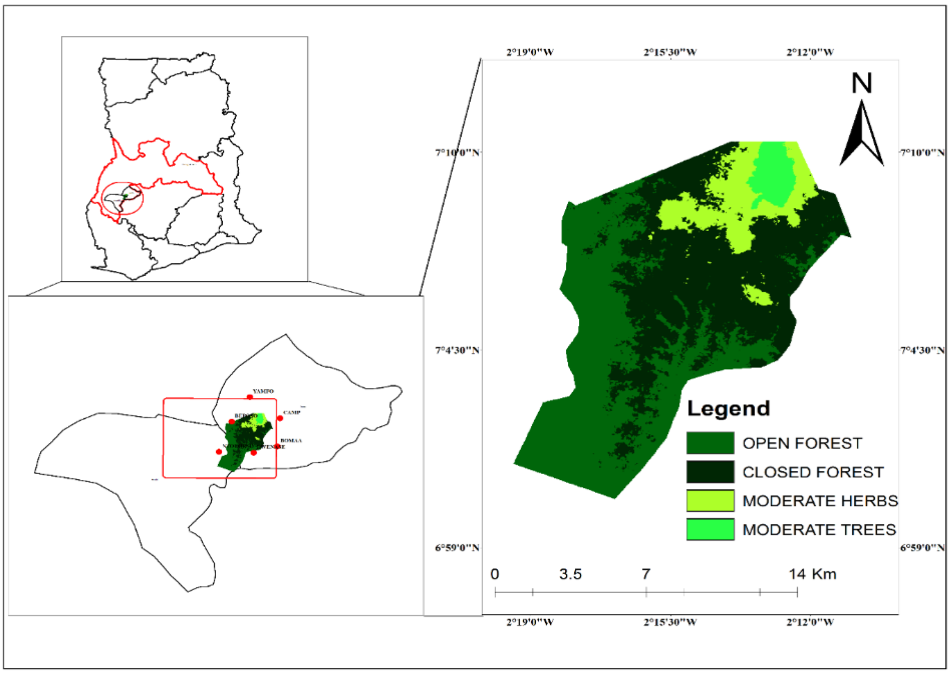


Figure 1: Map of the study area

3. Data Collection and Analysis

Remote Sensing imageries used for the analysis of the Forest Fire Risk Model were obtained from Sentinel archives for the year 2018 acquired from the database of US Geological Survey (USGS). Digital Elevation Model (DEM) was obtained from the Shutter Radar Topographic Mission (SRTM). The digitization of the roads of the study area was performed on the Google earth pro as well as collection of geographic coordinates of the settlements. The location of fire station within the closest proximity of the study area was collected using a Garmin GPS. The Fire management plan of Bosomkese forest reserve was also obtained from the Bechem forestry division office. The satellite image was visually interpreted by validating features on the image as what exists on the ground (forest) through ground truthing. Land use/cover map was then produced through the image classification as input data for the model. All thematic data preparation tasks were carried out using QGIS and ArcGIS software.

3.1. Image pre-processing and classification

This study employed image pre-processing procedures, as described by Lillesand *et al*. (2015), to correct distorted or degraded image data so as to create a more accurate representation of the original scene. The imagery acquired was already geo-referenced from the World Geodetic System (WGS 84).

3.2. Fire risk modelling

Four sub-models namely, ignition risk sub-model, fuel risk sub-model, detection risk sub-model and response risk sub-model were employed to calculate the final forest fire risk model (Fig. 2). Derivation of each of these sub models has been detailed in the following sub sections.

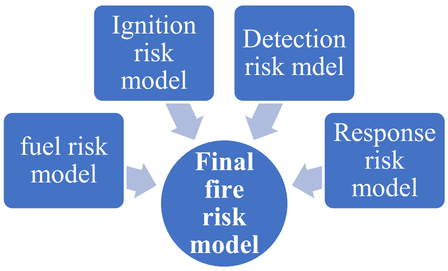


Figure 2: Calculation of the final fire risk model (Source: Adopted and modified from Kumi-Boateng *et al.,* 2016)

3.2.1. Fuel risk sub-model

In order to model the fuel risk, five factors were considered; and they are Elevation, Slope, Aspect, Fuel (vegetation) moisture and Land cover type (which served as the canopy cover) (Fig. 3). These factors were chosen because of their strong influence on fire occurrence and their ability to stimulate the spread of fire. Spatial distribution of various risk levels of the factors was categorized, mapped, indexed and used as input dataset for the fuel risk sub-model. Details of the categorization of the factors have been described in the sub-sections.

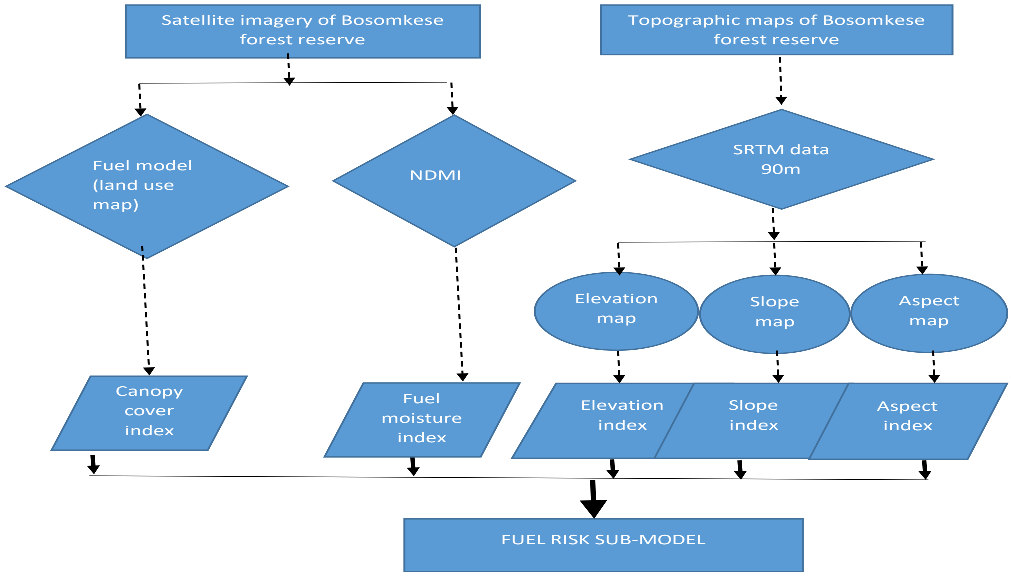


Figure 3: Flowchart of fuel risk sub model. (Source: Adopted and modified from Kumi-Boateng *et al.*, 2016)

Land/canopy cover index

Generation of the fuel class index map considered the inherent characteristics of vegetation and other land cover types. The land cover types were classified into five different classes of fuel risk levels using supervised image classification (Maximum Likelihood). A highly flammable area was assigned a high value, and a low flammable area was given a low value. These values were assigned based on the fact that wetlands are less at risk of burning relative to a natural dry forest. Thus, for the fuel class index, degraded areas were assigned a very low risk index because these areas have less fuel load and cannot sustain fires for long periods; and a closed natural forest a very high- risk index because of their high fuel load that can sustain burning for long periods.

Normalised difference moisture index

The fuel moisture content was generated using the normalized difference moisture index (NDMI) to determine the water content in the vegetation cover of the forest. This new index was introduced into the adopted model in order to analyze the fire model by taking into consideration the role that fuel moisture plays in forests fires. This index was considered because fuel moisture reduces fire heat content as well as the required energy needed for ignition which will advertently cause a reduction in the spread pattern of fires (Rossa, 2017). It was calculated using the Sentinel 2 image (Bands 8 and 11) based on the formula by the US Geological Survey (equation 1)

$$(NIR - SWIR) / (NIR + SWIR) \qquad [1]$$

Where NIR is near infra-red and SWIR is the short-wave infra-red based on the spectral response of the Sentinel image acquired.

The fuel moisture distribution across the Bosomkese forest were classified into five categories ranging from very high moisture content to very low moisture content. Values were assigned to the classes as presented in Table 1.

Slope index

The slope map generated for Bosomkese forest reserve was categorized into five quartiles depicting the different grades of the slopes ranging from 0 to 100 percent. Higher rates were assigned to steepest slopes. The steepness of the slopes was considered in the sub-model due to its contribution to fire spread. The adopted slope rating has been used by majority of researchers in the field of fire risk assessment (Jaiswal et al., 2002, Dong et al., 2005). Following this approach, very high-risk values (5) were given to slopes ranging between 34 and 100 percent of inclination and slopes between 0 percent and 7 percent grades were considered very low risk areas with a value of 1, with the rest of the rating presented in Table 1.

Elevation index

Elevation map shows the study area's altitude in real values depicting the topographical nature of the terrain under investigation. High values were assigned to areas of low altitude since such areas are more prone to fires compared to areas of high altitude. This rating has also been frequently applied in elevation classification. Climatic conditions of the study area was also taken into consideration since areas of high altitude records higher average annual rainfall (Borgaonkar et al., 2011). Hence, the elevation of the study area was reclassified into 5 classes ranging from values of 177m-711m, according to the image pixels displayed. Areas between 177m and 248m above sea level were labeled as very high-risk zones and areas of values of 505m and 711m as very low risk zones (Table 1).

Aspect index

Aspect map for Bosomkese forest reserve were depicted in eight (8) groups representing the 8 different directional coordinate points, namely North (N), Northeast (NE), East (E), Southeast (SE), South (S), Southwest (SW), West (W) and Northwest (NW). Due to the geographic location of the study area, higher rates were given to areas facing South and East. These areas present a greater time period of solar insolation per day than those facing North and West; and this approach has been used by Hernandez-Leal et al. (2006). Hence, very high-risk zones corresponded to S (5) and very low risk zones corresponded to NW (1) and N (1). The other ratings have been presented in Table 1.

Table 1. Classification of risk indices for the fuel risk sub-models

Land cover classes	Vegetation Moisture classes	Slope (%) classes	Elevation (m) classes	Aspect classes	Factor risk Index	Risk rating
Closed forest	Very low moisture content	34-100	177 – 248	South	5	Very high risk
Open forest	Low moisture content	22-34	249 – 298	South-East/ South-West	4	High risk
Plantation	Moderate moisture content	14-22	299 – 378	East	3	Moderate risk
Farmland	High moisture content	7-14	379 – 504	North-East/ West	2	Low risk
Degraded areas/shrubs	Very high moisture content	0-7	505 -711	North-West/ North	1	Very low risk

3.2.2. Detection risk sub-model

To analyse this sub-model, the viewshed analysis (that identified visible and invisible areas from various viewpoints) was carried out using the 3D Analyst (ArcGIS 10.4.1). A viewshed analysis takes into account the DEM information and view point location (Liu *et al*., 2008) (Fig. 4).

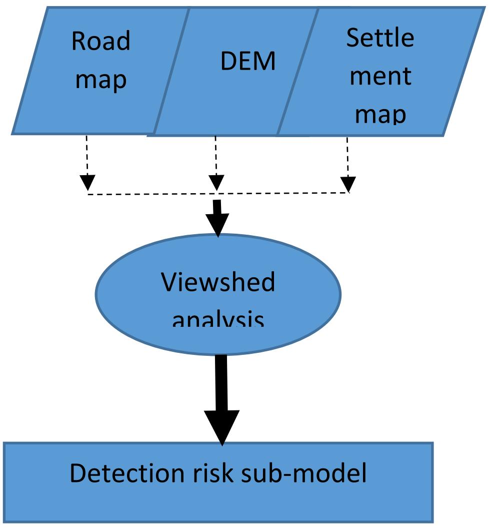


Table 2. Viewshed fire detection risk index

Detection risk class	**Detection risk Index**	**Risk rating**
Not visible	5	Very high risk
Visible	1	Very low risk

Figure 4: Flowchart of the detection risk sub model (Source: Kumi-Boateng *et al.,* 2016)

It determines visibility by considering the offset, azimuth, vertical angle and radius of the viewshed. In this case, the DEM, roads and settlement were used as the input dataset on the basis that people who are likely to detect fires within the Bosomkese forest will be in close proximity within the settlements or on roads within the forest catchment. An overlay analysis which uses the Boolean 'Or' operation was employed for the viewshed analysis. The Boolean math tools interpret the inputs as Boolean values, where non-zero values are considered true, and zero is considered false. The detection risk indices are indicated in Table 2.

3.2.3. Response risk sub-model

Response action to a fire situation within the study area was subjected to two considerations i.e. transport surface and applied friction. In this study, these two factors were calculated as a distance from the nearest fire service department i.e. place of response team dispatch to the Bosomkese forest. Distance and time are the two major factors to consider for a good fire response (Forkuo *et al.,* 2013) and their interrelation is dependent on slope, land cover type, and elevation. A cost distance analysis was performed on the slope, elevation and canopy type maps to generate their friction maps. The friction maps were individually reclassified into maps with response friction values. The three friction maps (slope, elevation and land cover frictions) generated were subsequently combined using the raster calculator operation in ArcGIS to determine the total friction map (Fig. 5).

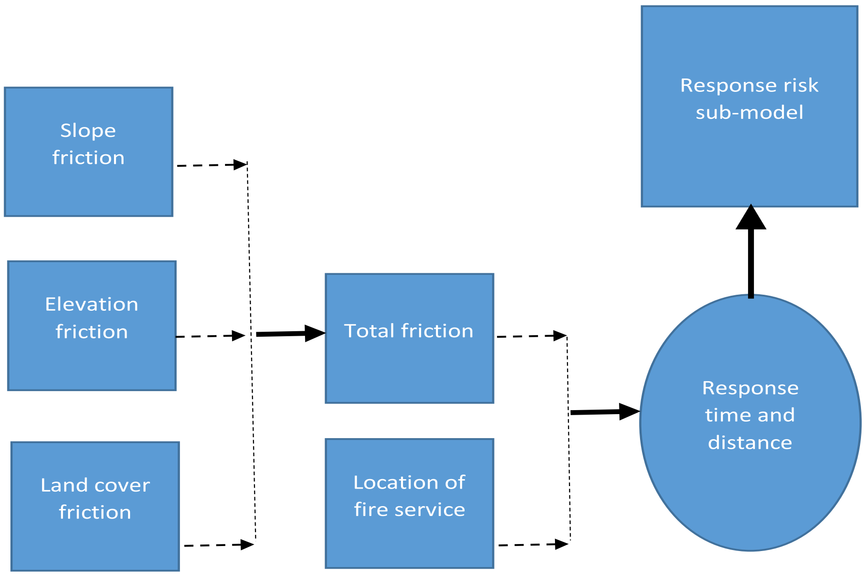


Figure 5: Flowchart of the response risk sub model. (Source: Kumi-Boateng *et al.,* 2016)

3.2.4. Ignition risk sub model

As mentioned earlier, about 90% of forest fires have anthropogenic sources. As such, this model incorporated the human activities that can cause fires in the Bosomkese forest reserve (Fig. 6), as described by (Orozco, 2008). Notable of these activities is farmlands burning. The expansion of fires from these agricultural lands to forested areas is very common within the forest catchment. In addition, the closeness of the forest to roads and settlements could promote fires and so were incorporated in the sub-model. The distance to settlements and roads were generated using the proximity analysis in ArcGIS 10.4.1.

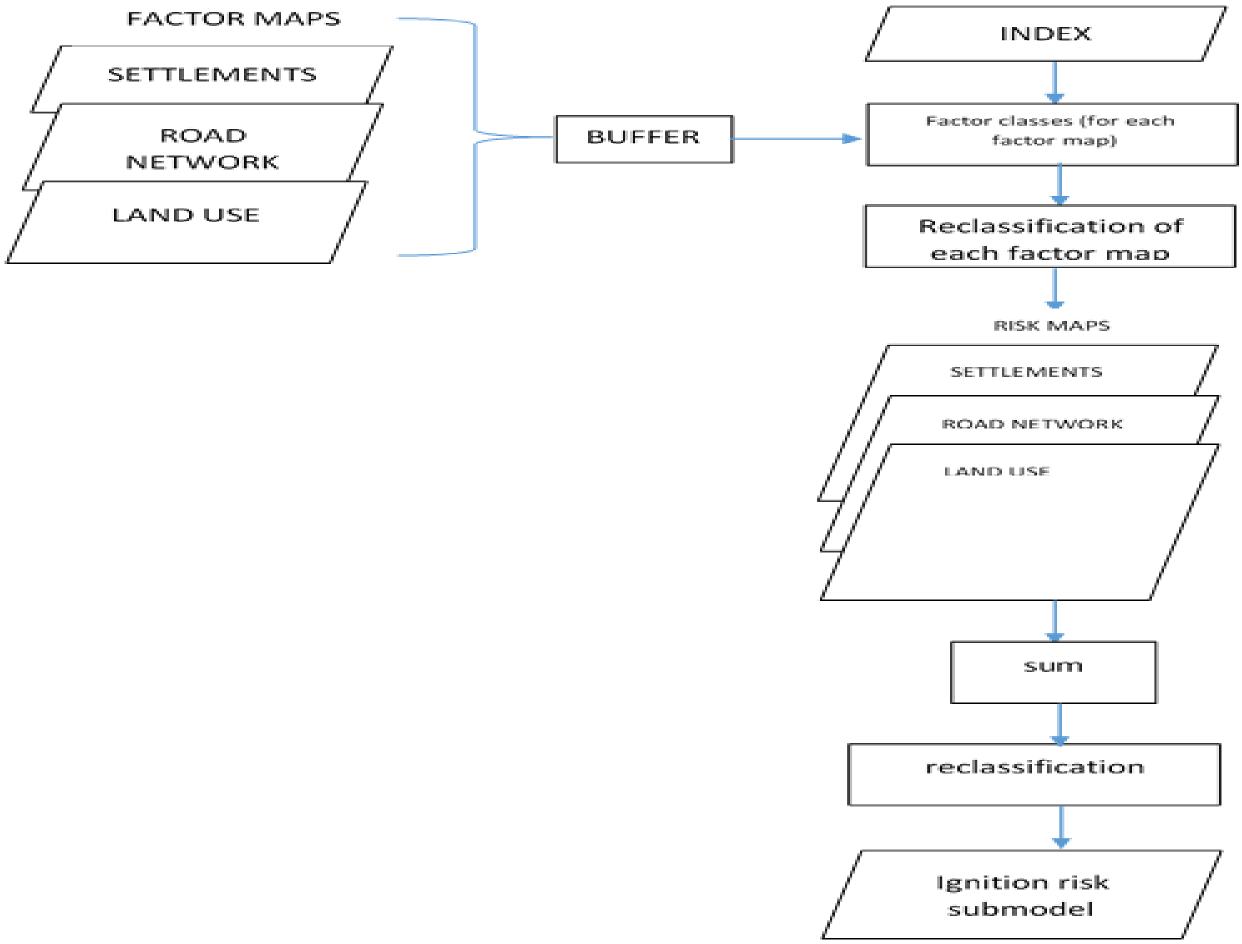


Figure 6: Flowchart of ignition risk sub model (Source: Orozco, 2008)

3.3. Final fire risk model

The logical sequence below (equation 2) was used to develop the final fire risk model. It must be noted that, coefficient of each sub-model was derived based on the number of datasets used for generating each sub-model. Five datasets (land/canopy cover, fuel moisture, elevation, slope and aspect) were used for the FRSM; two datasets (time and distance) were used for RRSM, one dataset (viewshed) was used for the DRSM and finally, three datasets (land cover and proximity to roads and settlements) were used for the IRSM.

$$\mathrm{FFRM} = (5 \times \mathrm{FRSM}) + (2 \times \mathrm{RRSM}) + (\mathrm{DRSM}) + (3 \times \mathrm{IRSM}) \qquad [2]$$

where: FFRM = Final Fire Risk Model, FRSM = Fuel Risk Sub-model, RRSM = Response Risk Sub-model, DRSM = Detection Risk Sub-model, IRSM = Ignition Risk Sub-model.

3.4. Accuracy assessment

Fifty (50) reference points (used for ground truthing) were collected and used for the accuracy assessment of the land cover type classification in February, 2018. This study assessed the accuracy of the classified image using the confusion matrix. Area of each land cover class in square kilometers was generated by the classifier tool (Maximum Likelihood algorithm). Based on the area coverage of each land use class, coordinates of the various land use/cover were collected with the GPS which were used as training samples for the spectral classification of the land cover. Twenty (20) coordinates were collected at locations of plantations, 15 from degraded/ wetland, 10 from open forest, 3 for farmlands and 2 from closed forest (2) based on the vegetation cover of the forest. The overall accuracy of the land cover classification and the kappa coefficient that validated the generated land cover of the forest were then determined.

4. Results and Discussion

4.1. Ignition risk sub-model

The ignition risk map (Fig. 7a) was generated by estimating the slope, elevation and the human risk factors (distance from road, distance from settlement and land use/cover) within the Bosomkese forest reserve. The results obtained indicated that very high- and high-risk zones least dominated the forest (11.8%) (Table 3). This is due to the presence of less roads and human settlements within the forest as a result of the stringent measures put in place by the Bechem forest service division to minimize illegal farming within the forest and its immediate surroundings thereby enhancing monitoring and reducing unauthorized burning.

4.2. Fuel risk sub-model

The fuel risk map generated (Fig. 7b) showed the various areas with the minimum and maximum probability of fire spread with respect to the land cover type. The generated land cover had an accuracy of 76.0% with kappa co-efficient of 0.68 implying that the land cover map was suitable to be used for the fuel risk model generation. The area under high to very high fuel risk covers approximately 50.78km^2 representing 33.3% (Table 3) of the study area. Fuel load is a significant factor in its contribution to the fuel risk zones. A spatial visual analysis between the study area map (Fig. 1) and the Fuel Risk map (Fig. 7b) also support the fact that areas under natural forest correspond to maximum Fuel Risk zones as reported by (Hardy, 2005). Very low to moderate fuel risk areas are mainly found around the farmlands, degraded areas and wetlands since they have least fuel load.

4.3. Response risk sub-model

The response risk map (Fig. 7c) was generated by estimating the total friction from the land cover, slope, elevation and the location of the fire service. A response resistance risk map considers factors such as land cover type, slope and elevation, which would resist movement of fire responders taking into accounts the response distance map thus road distance, settlements and vegetation types which would weigh the risk in terms of distance from the headquarters of the fire service to the point of fire. These maps were then combined using the Raster Calculation facility in ArcGIS spatial analyst (ESRI, 2001) resulting into a fire response risk map. Majority of the area falls under moderate to very low risk also known as moderate to very quick response risk and constitute a total area of 112.02km^2 being 73.8% of the study area (Table 3). These areas are predominately farmland as well as open forest with good demarcated road types. High to very high risk or slow to very slow response risks occupy predominantly closed forest and wetland. This can be attributed to the presence of water bodies, muddy areas, rugged terrain and undulating topography due to which the response time towards fires may be increased (Kumi-Boateng *et al.,* 2016).

Table 3. Area distribution of sub-models' risk zones

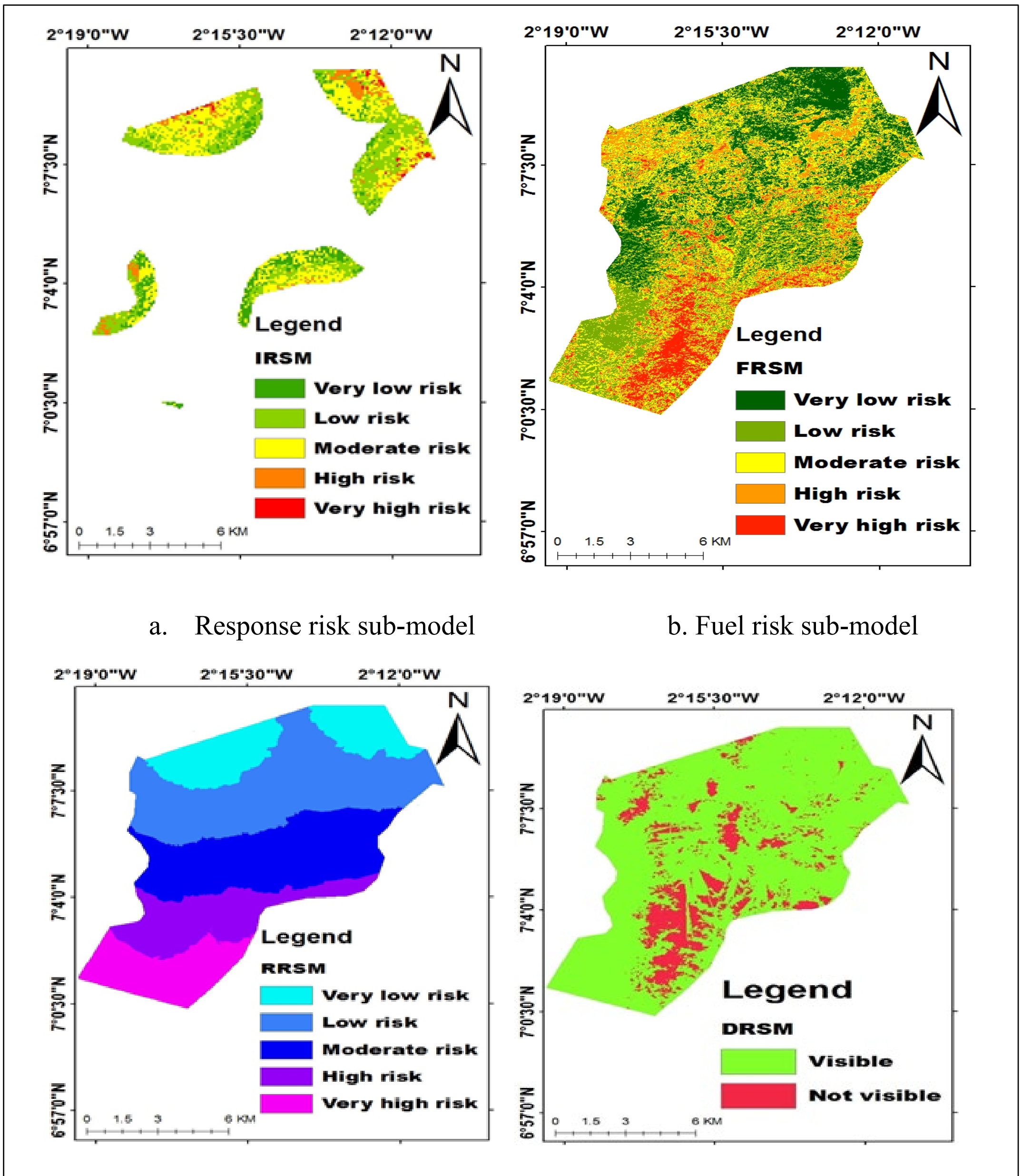
Risk rating	Fuel risk Area Km^2 (%)	Ignition risk area km^2 (%)	Response risk zone km^2 (%)
Very low risk	25.96 (17.1)	32.18 (21.2)	23.37 (15.4)
Low risk	40.68 (26.8)	57.53 (37.9)	49.79 (32.8)
Moderate risk	34.61 (22.8)	44.17 (29.1)	38.86 (25.6)
High risk	34.76 (22.9)	14.12 (9.3)	21.56 (14.2)
Very high risk	15.78 (10.4)	3.80 (2.5)	18.22 (12)

4.4. Detection risk sub-model

With respect to the detection risk map (Fig. 7d), visual (viewshed) analysis helped in the identification of visible and invisible areas from various viewpoints. Findings from Fig. 10 indicated that, the view/visibility gets significantly reduced due to obstructions from forest cover types. Detection risk corresponds to the risk generated due to early or late detection of the fire. Ability to detect fire outbreak in the forest early will result in proper control. Since early detection is also directly correlated to visibility (Orozco, 2008), the visibility was spatially addressed by viewshed analysis. From the analysis, visible areas constitute a total area of 128.55km^2 representing 84.7%, whiles invisible areas occupy the remaining 23.16km^2 representing 15.3% of the total area (Table 4). This could be attributed to the diverse elevations present at the area which are occupied by tall and crowded trees such as teak within the Bosomkese forest reserve (Donkor *et al*., 2016).

Table 4. Area distribution of visibility zones sub-model

Visibility	Area	Percent (%)
Visible	128.55	84.7
Invisible	23.15	15.3



a. Response risk sub-model

b. Fuel risk sub-model

c. Response risk sub-model

d. Detection risk sub-model

Figure 7: Risk sub-models of Bosomkese forest reserve

4.5. Final fire risk map

The resultant map (Fire Risk Hazard Map) was generated from a combination of all the four sub-models (Fuel Risk, Detection Risk, Ignition risk sub model and Response Risk) developed using appropriate ratings depending upon their risk priority (Fig. 2). The moderate to very high fire risk areas are found mostly in the south eastern portion of the study area and constitute a total area of 78.53km^2 representing 51.77%. A careful comparison of the land cover map and the final forest fire risk map (Fig. 8) reveals that the very high fire risk areas and high-risk areas consist mainly of closed forest or natural forest and open forest as discovered in a study conducted by Kumi-Boateng *et al.* (2016) on modelling forest fire risk in the Goaso forest area of Ghana. Their study reported that the vegetation cover of the Goaso forest area was moist semi-deciduous high forest zone and has a high oxygen content which contributed greatly to fire spread, and the Bosomkese forest reserve exhibits similar vegetation characteristics. Forest fires have been the cause of degradation in especially the moist semi-deciduous forest zone and dry semi-deciduous fire zones in recent years (Hawthorne *et al.,* 1995). The very high fire risk areas observed was also due to the differences in elevations as low-lying areas are prone to fire than highlands (Fig.8); the distance from the fire scene to the rescue station which is an important factor in the control and suppression of fire outbreak of the study area.

Another significant reason that could lead to the high-risk levels may be the ability for a fire to be detected. An invisible fire would be difficult to detect. A fire outbreak detected at a great distance (as pertaining to this case) far from a fire station would last longer especially when there are barriers restricting easy accessibility to the fire locations (Orozco, 2008).

On the other hand, very low to moderate fire risk areas dominates the central and northern parts of the study area (Fig. 8) and constitute 73.17km^2 being 48.2% (Table 5) of the total area under study. The minimum fire risk levels were mostly dominated by areas closer to settlements. This is because there are usually people within the settlements to control and stop the fire spread within settlements (Kumi-Boateng *et al.,* 2016).

The moderate fire risks areas observed were predominantly agricultural lands. This could be attributed to the practice by some farmers who believed that better yields are attainable from spots where heaps for stubble are burnt (Parashar *et al.,* 2003). Others also believe that fires drive away wild animals hidden in bushes. Hunting, charcoal production and inefficient logging practices have compounded the problem of making the forest more susceptible especially in drier conditions (Hawthorne *et al.*, 1995). According to Hawthorne *et al.* (1995), the continued exploitation of timber and the reluctance of the Forest Services Division to reduce timber yield in fire prone areas are major challenges in dealing with forest fire in Ghana.

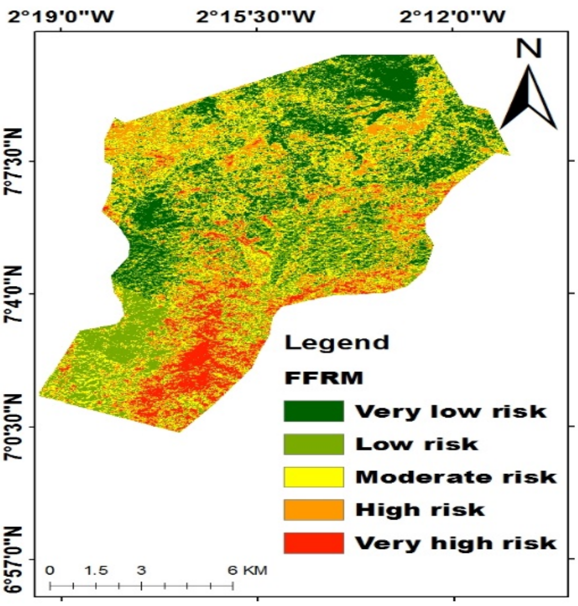


Figure 8: Forest Fire risk map of Bosomkese forest reserve

Table 5. Area distribution of fire risk zones

Risk rating	Area km^2 (%)
Very low risk	29.90 (19.7)
Low risk	43.26 (28.5)
Moderate risk	39.77 (26.2)
High risk	27.17 (17.9)
Very high risk	11.61 (7.7)

5. CONCLUSION

The general objective of this study was to model forest fire risk for the Bosomkese forest reserve in Ghana. The application of remote sensing and GIS analyses have been useful in the fire risk modelling to achieve this objective. The novel forest fire risk methodology developed by Kumi-Boateng *et al.* (2016) was enhanced with NDMI to identify appropriately high, medium and low fire risk zones of the Bosomkese forest reserve. The final fire risk model showed that: 35.81 km^2 (25.6%) of the forest surface is located within the high and very-high risk; 39.72km^2 (26.2%) was found to be moderately at risk to fire and 73.17km^2 (48.2%) was found to be within low to very low risk. The study recommended that additional data such as historical fire data and land surface temperature analysis be included in the model to improve the results of this study. Also, the implementation of fire break lines is highly recommended at areas with high risk of fire. The results and recommendations from the study will be useful for further research on forest fire management.

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