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Fire Activity and Their Relationship with the Global Fire Weather Index Database Components in Guinea

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Abstract

The relationships between the Canadian Fire Weather Index (FWI) System components and the monthly burned area as well as the number of active fire which has taken from Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua/TERRA were investigated in 32 Guinean stations between 2003 and 2013. A statistical analysis based on a multi-linear regression model was used to estimate the skills of FWI components on the predictability of burned area and active fire. This statistical analysis gave performances explaining between 16 to 79% of the variance for the burned areas and between 29 and 82% of the variance for the number of fires (P<0.0001) at lag 0. Respectively 16 to 79 % and 29 to 82 % of the variance of the burned areas and variance for the number of fires (P<0.0001) at lag0 can be explained based on the same statistical analysis. All the combinations used gave significant performances to predict the burned areas and active fire on the monthly timescale in all stations excepted Fria and Yomou where the predictability of the burned areas was not obvious. We obtained a significant correlation between the average over all of the stations of burned areas, active fires and FWI composites with percentage of variance between (75 to 84% and 29 to 77%) for active fires and burned areas at lag0 respectively. While for burned area peak (January), the skill of the predictability remains significant only one month in advance, for the active fires, the model remains skilful 1 to 3 months in advance. Results also showed that active fires are more related to fire behavior indices while the burned areas are related to the fine fuel moisture codes. These outcomes have implications for seasonal forecasting of active fire events and burned areas based on FWI components, as significant predictability is found from 1 to 3 months and one month before respectively.

Keywords: Active fire, Burned area, FWI components, Guinea

1. Introduction

The fire has an important role in the structure and functioning of ecosystems (Archibald et al., 2013). It is commonly used by people for various purposes in function of socio-economic activities and geographic areas as a management tool. Fire's satellite observations could be obtained with different time resolutions : daily (Alonso et al.,2003, Lozana et al., 2007, Alberson et al., 2009, Wottan et al., 2010, Padilla et Vega, 2011, Sakr et al., 2011), monthly (Preister et al., 2004, Boulanger et al., 2014), and yearly (Prestemon et Butry, 2005, Hu et Zhou, 2014, Karouni et al., 2014). Some authors consider fire as a planning tool of the savannas (Dupuy, 1968, Jeffrey et Humphrey, 1975), while others particularly point it out as the ecological, economic and social threat (Sheehan et Hewitt, 1969). The long term effects of bush fires on ecosystems have been highlighted by several recent studies (Scholze et al., 2006; *Miller et al., 2013; Reed-Dustin, 2015;* Doerr and Sant ń, 2016; Hagmann et al., 2018; Guiterman et al., 2018; Inoue et al., 2018) which demonstrated their disruptive role on the water cycle, soil absorption capacity, aerosol emission, climate change, vegetation dynamics and soil fertility. The estimation of the danger of fire is a way to quantify the potential or capacity of a fire to start, spread and cause damage (Merrill et Alexander, 1987). In the current context of climate change, it is therefore important to have indicators of risk of bush fires to better define the management policies of ecosystems.

The Fire Weather Index (FWI) has been developed by the Canadian method, involving weather parameters such as wind, relative humidity, surface temperature, and rain to characterize the level of bush fire risk. The evaluation system of the dangers of fires (Stocks et al., 1989) includes two subsystems currently used: the Canadian fire weather index (Van Wagenr, 1987) system and the Canadian system of fire forecasting (PBF) (Group Fire Danger of Forests Canada 1992). This system uses a method so-called Canadian method of the fire weather index (Turner and Lawson, 1978, Van and Pickett, 1985). This method was widely applied over North America and Europe where observation stations are very dense and the results were very conclusive. This index is derived from different indices characterizing the state of fuel or the weather conditions on a specific point of the globe. These indices are:

- The Fine Fuel Moisture Code (FFMC) is a numeric rating of the moisture content of litter and other cured fine fuels. This code is an indicator of the relative ease of ignition and the flammability of fine fuel.
- The Drought Code (DC) is a numeric rating of the average moisture content of deep, compact organic layers. This code is a useful indicator of seasonal drought effects on forest fuels and the amount of smoldering in deep duff layers and large logs.
- The Duff Moisture Code (DMC) is a numeric rating of the average moisture content of loosely compacted organic layers of moderate depth. This code gives an indication of fuel consumption in moderate duff layers and medium-size woody material.
- The Initial Spread Index (ISI) is a numeric rating of the expected rate of fire spread. It combines the effects of wind and the FFMC on a rate of spread without the influence of variable quantities of fuel.
- The Buildup Index (BUI) is a numeric rating of the total amount of fuel available for combustion. It combines the DMC and DC.
- The Fire Weather Index (FWI) is a numeric rating of fire intensity. It combines the Initial Spread Index and the Buildup Index. It is suitable as a general index of fire danger throughout the forested areas of Canada.

In West Africa, many types of research were conducted on the spatial and temporal distribution of the fires activities (Millimono et al., 2017, Mbow, 2000, Sow, 2012, Valea, 2010, Barry et al., 2018). For better management, it is important to have preventive measures of bush fire with early warning systems through on fire's occurrences. In this study, FWI's products from the National Aeronautics and Space Administration (NASA) through the Goddard Institute for Space Studies (GISS) are used. All details of these products are described in (Field et al., 2015). The FWI components have been widely used to characterize bush fires in many countries (Carvalho et al., 2008, Davies et Legg, 2016, De Groot et al., 2007) and the results are very interesting for saving the environment. Figure1 shows the structure of the fire weather index‘s calculation.

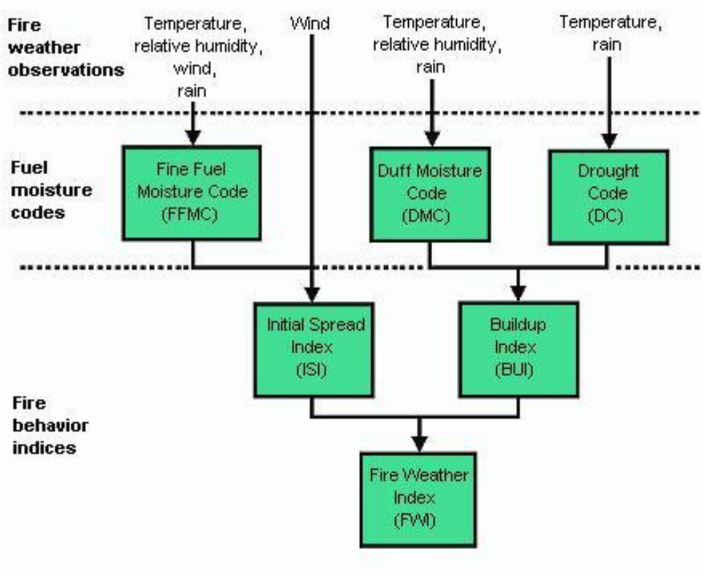

Figure 1. Basic structure of the fire weather index 's calculation (Van Wagner, 1987)

The most active world fire areas (Africa and Latin America) still require modeling efforts (Costefreda-Aumedes et al., 2018) and few studies are devoted to fires in these areas of high forest fire activities (Chuevieco et al., 2008, Krawchuk et al., 2009 , Knorr et al., 2014, Bedia et al., 2015). For this purpose, this study seeks the relationship between FWI components, burned areas and active fires on a monthly time scale based on the combinations of FWI components as predictors. A statistical analysis using a linear prediction model is used to define the performance of the two indices to predict bush fire on the different sites selected for this study at the national level.

The main contributions of this study are outlined as follows:

- The predictability of active fires and burned areas in Guinea at the whole scale and in 32 specific sites was highlighted.
- For each site, the FWI components that most characterize active fires and burned areas are identified and ranked in order of importance.
- The dependence of the predictability with the nature of the vegetation cover is highlighted.

The paper is organized as follows. In Section 2, data and methodology (including the presentation of the study area) used in this study are described. Section 3 is accorded to results highlights and discussion. Finally, section 4 presents the conclusion.

2. Data and Methods

2.1 Study Area

The vegetation of Guinea, according to the annual report of 2015 of the Ministry of Environment, Water, and Forests (MEEF), consists of 1.02% of mangroves, 2.85 of humid forests, 6.51% of dense forests, 43.26% wooded savannah, 6.9% cropland and 30.5% fallow.

According to the Tropical-Guinea Forestry Action Plan (TFAP, 1988) and the Report on Forest Policy and National Forest Action Plan of 2010, the forest patrimony would amount to about 13 186 000 hectares (53,64 % of the national territory). The vast Savannah encountered in Guinea, 43.26% of the national territory, combined with slash-and-burn activities in most of the country, offers a very exposed environment to the negatives effects of bush fires on the ecosystems. These savannas are mainly found in the areas of upper and middle Guinea and part of Forest Guinea.

According to the 2015 annual report of the National Directorate of Water and Forests, the average annual deforestation rate is 30 000 ha per year against an annual reforestation rate of 1043 ha. That means a negative difference of 19850 ha each year over the period from 2004 to 2013. In the same report, the average area of forests devastated by bush fires between 2004 and 2013 has been estimated to 205.318 ha, although the trend has been declining since 2009. Statistics on the annual afforestation rate, the deforestation rate and the area under bush fire damage according to the National Directorate of Water and Forests (DNEF) are shown in Table 1.

Table 1. Statistics of vegetation cover in Guinea from 2003 to 2014 (see DNEF report, 2015)

Years	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Reforested areas per year (ha)	1070,29	2500	2828,54	337,35	511,89	404,36	908,22	938,51	618,25	317,72
Deforestation rate (ha/ year)	30 000	30 000	30 000	30 000	30 000	30 000	30 000	30 000	30 000	30 000
Total area of forest burned (ha/year)	333001	332950	333153,5	332972,5	332 960	377,5	100402	98384,5	95455,84	93 532

32 sites were selected for this study in order to specify in detail, the level of risk across the country. These sites are shown in Figure 2 and the main characteristics of each site are described in Table 2.

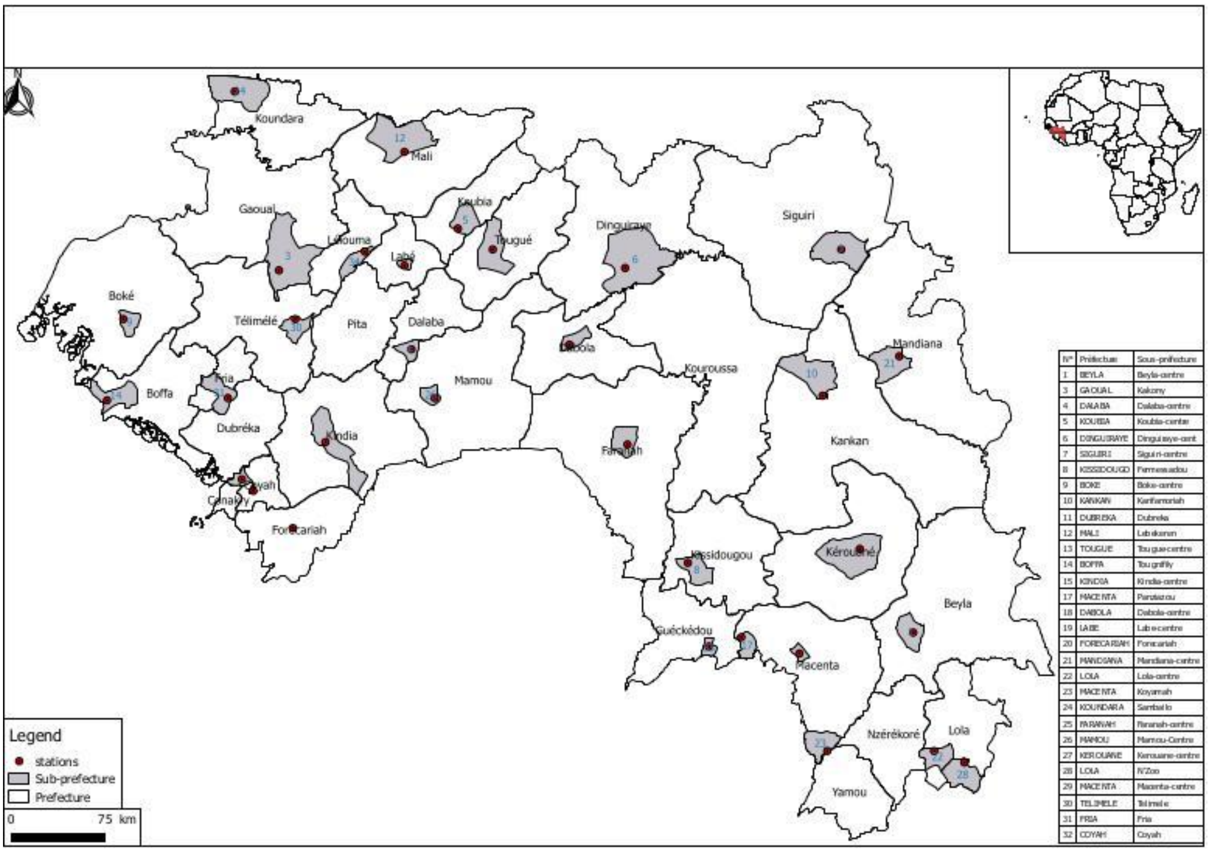

Figure 2. Location of Guinea on the African map and sites of interest identification

Table 2. Main characteristics of the stations considered in the present study (cf National Directorate of Water and Forests (DNEF))

Station	Longitude (°W)	Latitude (°N)	Altitude	Beginning data	End date	Number of years
Coyah	13.23	09.42	20	January 2003	December 2013	11
Dubréka	13.28	09.47	15	January 2003	December 2013	11
Kindia	12.52	10.03	458	January 2003	December 2013	11
Forécariah	13.06	09.26	47	January 2003	December 2013	11
Fria	13.34	10.22	160	January 2003	December 2013	11
Boffa	14.26	10.21	30	January 2003	December 2013	11
Boké	14.19	10.56	69	January 2003	December 2013	11
Télíminè	13.05	10.56	650	January 2003	December 2013	11
Labé	12.18	11.19	1050	January 2003	December 2013	11
Dalaba	12.15	10.43	1202	January 2003	December 2013	11
Mamou	12.05	10.20	782	January 2003	December 2013	11

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Mali	12.18	12.08	1464	January 2003	December 2013	11
Tougué	11.40	11.26	868	January 2003	December 2013	11
Gaoual	13.12	11.17	100	January 2003	December 2013	11
Lélouma	12.35	11.25	892.35	January 2003	December 2013	11
Koubia	11.55	11.35	722	January 2003	December 2013	11
Koundara	13.31	12.34	90	January 2003	December 2013	11
Kankan	09.18	10.23	376	January 2003	December 2013	11
Faranah	10.42	10.02	358	January 2003	December 2013	11
Kouroussa	09.53	08.39	372	January 2003	December 2013	11
Dinguiraye	10.43	11.18	490	January 2003	December 2013	11
Kérouané	09.02	09.17	510	January 2003	December 2013	11
Siguiri	09.10	11.26	361	January 2003	December 2013	11
Dabola	11.07	10.45	438	January 2003	December 2013	11
Mandiana	08.45	10.40	388	January 2003	December 2013	11
N’Zérékoré	08°17	07.45	467	January 2003	December 2013	11
Macenta	09°28	08.32	542	January 2003	December 2013	11
Kissidougou	10°16	09.11	524	January 2003	December 2013	11
Guéckédou	10°07	08.35	425	January 2003	December 2013	11
Beyla	08°39	08.41	695	January 2003	December 2013	11
Lola	08°30	07.50	501	January 2003	December 2013	11
Yomou	09°16	07.50	48	January 2003	December 2013	11

2.2 The Burned Areas

As described in burned area products User Guide Version 3.0.1 of MODIS (Boschetti, 2018), the burned areas are characterized by deposits of charcoal and ash, removal of vegetation, and alteration of the vegetation structure (Roy et al., 1999). To map the burned areas, the MODIS algorithm takes advantage of these spectral, temporal, and structural changes. The algorithm detects the approximate date of burning at 500 m resolution by locating the occurrence of rapid changes in daily surface reflectance. A bidirectional reflectance model is used to deal with angular variations found in the satellite. The bidirectional reflectance model-based change detection algorithm developed for the MCD45 product is a generic change detection method that is applied independently to geolocated pixels over a long time series (weeks to months) of reflectance observations (Roy et al., 2002, Roy et al., 2005). Reflectance sensed within a temporal window of a fixed number of days is used to predict the reflectance on a subsequent day. A statistical measure is used to determine if the difference between the predicted and observed reflectance has a significant change of interest. Rather than attempting to minimize the directional information present in a wide field of view satellite data by compositing, or by the use of spectral indices, this information is used to model the directional dependence of reflectance. This provides a semi-physically based method to predict change in reflectance from the previous state. However, it allows MODIS to map only the spatial extent of recent fires and excludes fires that occur- red in previous seasons or years.

2.3 The Active Fire

As described by Giglio et al., (2003); Giglio, (2010); Giglio, (2015) and Giglo et al., (2016), the detection algorithm of active fire uses native (i.e., unprojected swath) 4-, 11-, and 12-µm brightness temperatures derived from the corresponding 1-km MODIS channels, denoted by $T4$, $T11$, and $T12$, respectively. And, for daytime observations, 0.65-, 0.86-, and 2.1-µm reflectance (denoted by $\rho0.65$, $\rho0.86$, and $\rho2.1$, respectively), aggregated to 1-km spatial resolution are used. Table 3. provides a summary of all MODIS bands used in the algorithm.

Table 3. Summary of MODIS channels used in the detection algorithm and ingested from the Collection 6 MODIS Level-1B radiance product (MOD021KM/MYD021KM). Details regarding the blending of bands 21 and 22 may be found in (Giglo et al., 2003)

Channel number	Central Wavelength (μm)	Purpose
1	0.65	Sunglint and coastal false alarm rejection; cloud masking.
2	0.86	Bright surface, sun glint, and coastal false alarm rejection; cloud masking.
7	2.1	Sunglint and coastal false alarm rejection.
21	4.0	High-range channel for active fire detection.
22	4.0	Low-range channel for active fire detection.
31	11.0	Active fire detection, cloud masking, forest clearing rejection.
32	12.0	Cloud masking.

The goal of the detection algorithm is to identify "fire pixels" that contain one or more active burning fires at the time of the satellite overpass. To this end, the algorithm ultimately classifies each pixel of the MODIS swath as *missing data*, *cloud*, *non-fire*, *fire*, or *unknown*. For the sake of backward compatibility, the collection 6 fire products actually use a slightly larger set of classes that can be uniquely mapped into the five classes defined here. Framing the algorithm output in terms of these five classes, however, greatly simplifies the subsequent description of the collection 6 algorithm. Full details may be found in the product User's Guide (Giglo, 2015).

The MODIS active fire products have been evaluated in different studies (e.g.,Csiszar et al., 2006; Hawbaker et al., 2008; Schroeder et al., 2008; Tanpipat et al., 2009; Freeborn et al., 2014; He and Li, 2011; De Klerk et al., 2008; Hantson et al., 2013; Maier et al., 2013), and in the context of optimizing the global MODIS algorithm for use within a specific region (e.g. Cheng et al., 2013; Ressl et al., 2009; Wang et al., 2007).

2.4 The Fire Weather Index database

The FWI components used are the Global FWI v1p5 of the fire weather index and they are available online at ftp.nccs.nasa.gov or on the website of the Center for research in climate and society at the University of Colombia (http://iridl.ldeo.columbia.edu/SOURCES/.GISS/.GlobalFWI/). With 0.5 latitudes and 0.66 longitude grid resolution and a daily temporal resolution. The development and testing of the Global Fire WEather Database (GFWED) details can be found in Field et al., 2015). Applications of the FWI system can be found in Taylor and Alexander (2006), and the technical descriptions are provided by Field et al., 2015 and Dowdy et al., 2009. The GFWED can be used for analyzing historical relationships between fire weather and fire activity at continental and global scales, in identifying large-scale atmosphere-ocean controls on fire weather, and calibration of FWI-based fire prediction models (Field et al., 2015). The severity of the risk thresholds defined by the Canadian method described in Table 4.

Table 4. Interpretation of the values of the components of the FWI (Van Wagner CE, 1987)

Indices	Low	Moderate	High	Very High	Extreme
FFMC	0-81	81-88	88-90.5	90.56-92.4	92.5+
DMC	0-13	13-28	28-42	42-63	63+
DC	0-80	80-210	210-274	274-360	360+
ISI	0-4	4-8	8-11	11-19	19+
BUI	0-19	19-34	34-54	54-77	77+
FWI	0-5	5-14	14-21	21-33	33+

The values of the different components of the FWI were extracted from the 32 sites using the nearest neighbor method. A statistical analysis using a linear prediction model is used to define the performance of the two indices (components of FWI) to predict the burned areas calculated from the MODIS burned area products (Boschetti et al., 2009) and active fire (Giglo et al., 2016). The predictors are used to perform a leave-one-out cross-validated hindcast at lag 0 (predictors/predictands based on the same period). Then, the linear regression model is built for each month to be predicted, calculating the coefficients of the model with all the months in our database except the one that is predicted (ter Braak and Juggins, 1993; Birks, 1981). This method consists to take, for each month, all the values of the combined indices and that of the burned area, with the exception of the month that we wish to predict, and this for all months of our time series, and to compare the observed signal with that predicted by the linear model that combines regressions and their coefficients. The hind-cast is performed and correlated with the omitted observations. The FWI components (table 4) are then introduced in the multi-linear regression model as predictors and the terms were selected only if they reach the 0.05 significance level. Lagged correlations and model skills from lag-1 (one month before) to lag-5 (five months before) are evaluated and the results and discussions are explained in the next section. All statistical analysis and processing are performed as our own Matlab codes.

3. Results and Discussion

3.1 Month-to-month Variability of Fire Activity

The monthly MODIS active fire and burned area are calculated for the 32 sites across Guinean, over the period 2003-2013 to investigate the fire spatial and temporal activity. Results show very remarkable differences regarding the variability of observed fire activity of each site without considering the human activity. Figure 3 presents the distribution over the 2003-2013 period of monthly bush fire activities and burned areas of the 32 sites. Many extra box-plot values are observed for almost all of the sites, meaning the local monthly temporal distribution of both bush fire and burned areas present strong local variability, with many extreme and unusual situations. This feature is more marked with the number of active fire than with the burned areas.

Figure 3a also reveals that the highest number of fire cases are observed in Kankan with a maximum of 1500 fire cases per month and within 25% of values higher than 750 cases, Beyla and Kouroussa with a maximum of 1100 cases per month for both sites, and within 25% of the values higher than 400 and 600 cases respectively and finally Kérouané and Dubreka with a maximum of 1000 cases per month for both sites, with 25% of the recorded values higher than 400 cases of fire. The lowest values were recorded in Labé, Koubia, Touhgué, Lélouma, Siguiri, Fria, Dabola and Forécariah with a maximum less than 70 cases of fires per month. Regarding the burned areas, the highest values are noted over Siguiri and Kankan with a maximum of 8.10^4 ha per month and within 25% of values higher than 5.10^4 ha, Beyla, Tougué, Mali and Kérouané with a maximum of 5.10^4 ha per month and within 25% of values higher than 2.10^4 ha (Figure 3b). And for the lowest values of burned areas over the period, 2003 to 2013 are recorded in the N'Zérékoré, Koubia, Tougué, Lélouma, Macenta, Boffa, Kindia, Coyah, Labé, Fria, Dabola and Forécariah sites with maxima values less than $1,5.10^3$ ha per month. These results show that the Northern sites such as Kankan, Kérouané, kouroussa, Dinguiraye, are the most vulnerable to bushfires. A finding that is in agreement with the results of Barry et al., (2015). These sites are characterized by high temperatures recorded during the dry season (season of wildfires) that can reach more than 42℃, with minimum rainfall, low relative humidity and a strong wind compared to the Southern sites.

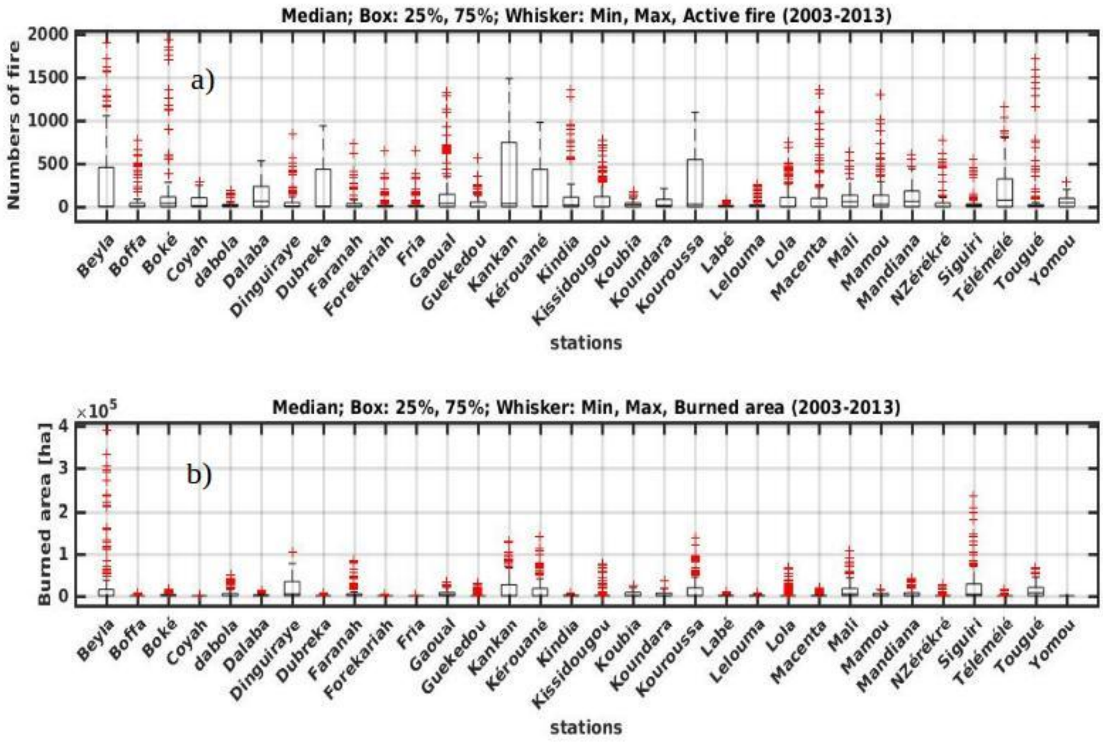

Figure 3. Number of active fires (a) and area burned (b) by site in Guinea, for the period of 2003– to 2013

3.2 Seasonal Cycle of Fire Activity

Figure 4 presents the seasonal cycle of the number of actives fire as well as the burned areas based on the monthly climatology over the period 2003-2013 when data overall 32 sites have been averaged. As expected, no fired case is recorded by MODIS Aqua/TERRA combination during the monsoon period extending June to October (Figure 4a). In contrast, the highest numbers of fire are observed from January to April, with a monthly mean higher than 200 cases. The strongest peak is noted in April, with a maximum of 310 fire cases, within 25% of these cases higher than 300 cases. Also, a moderate number of cases are observed during May and November-December. These periods correspond to early fires corresponding to early dry season and late fires (late dry season respectively. Regarding the seasonal cycle of burned areas, likewise the number of active fire, zero surfaces is recorded (Figure 4b). Observed burned area increases from November to January and decrease from January to March. January is indexed as the month in which the burned area is strongest according to the high value of the burned areas median in this month. The maximum observed is around $3.9.10^4$ ha, with 25% of values higher than 3.10^4 ha.

One can see that seasonal cycles of the number of active fire and burned area are not correlated. The peak of the number of fire is noted in April (figure 4a) while that of the burned area in January (figure 4b). Indeed, November to January period is the beginning of the dry season, there are several burned areas even if the number of active fire is low. In April, the number of active fire is higher because at this period there is no humidity and the vegetation is dry according to the opinions of water and forest officers and field observations during this period. But this does not lead to a maximum of the burned area because there is no surface to be burned anymore due to the early burning by a small number of active fire in January for instance. Also, this dis-proportionality could also result from the fact that active fires are samples that correspond to the fires recorded during the passage of the satellite in contrast to the burned areas that are not dynamic over time.

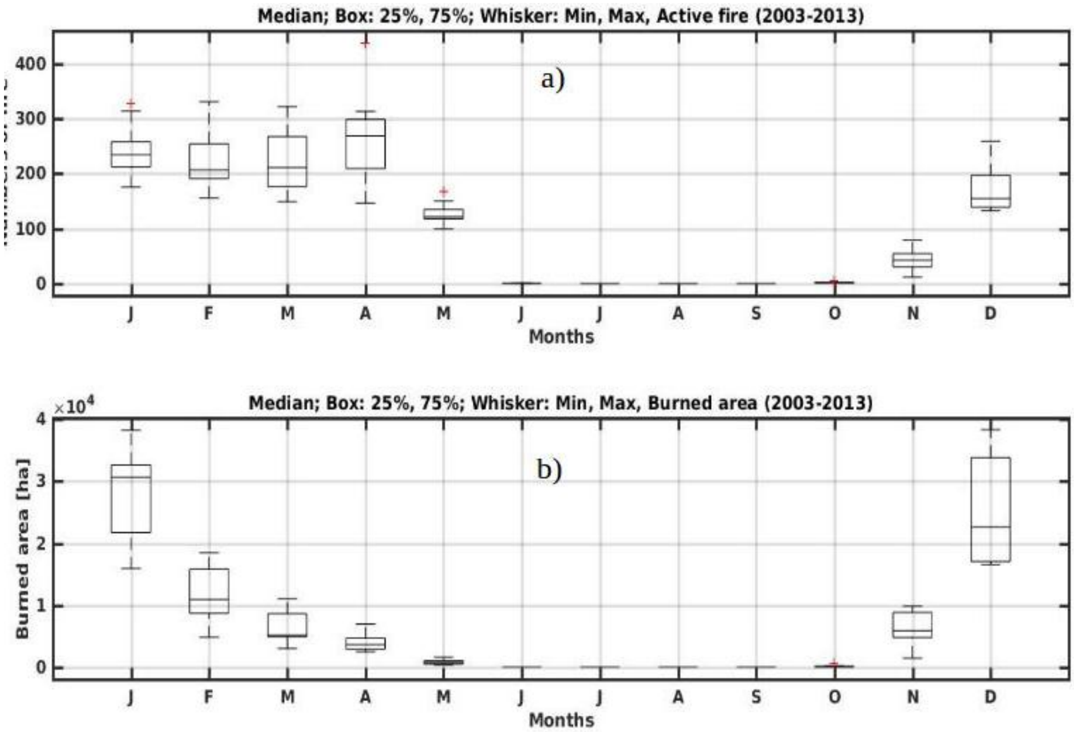

Figure 4. Number of active fires (a) and Area burned (b) by month in Guinea, for the 2003–2013 period

The spatial and temporal variabilities of observed fire activities (Figure 3 and Figure 4) demonstrate the importance of the implementation of forest fire warning systems in Guinea. Several studies on the variability of bush fires activity and fire emission show the ability of FWI components to characterize bush fire activity in some other areas (Amiro et al., 2005, Flannigan et al., 2005, Carvaillo et al., 2008, Giuseppe et al., 2018, Jain et al., 2018, Erickson et al., 2018). According to these authors, it is possible to investigate the predictability of active fires and burnt areas using the FWI components as predictors in addition.

Therefore, based on these findings, we have tried to assess the predictability of fire activity in Guinea using cross-validation multi-linear regression model and results are presented and discussed in the following section.

3.3 Predictability of Fire Activity

The predictability of fire activity is investigated using a multilinear regression model using combinations of a couple of FWI components as predictors and the number of active fire as well as burned areas as predictands. This analysis is applied to monthly time series using values from the 32 sites for each parameter. Tables 5 and 6 summarize the explained variance of the monthly burned area and monthly active fire respectively for 32 sites considered in this study. All components of the FWI (Figure 1) have been combined and combinations that lead to significant skills have been selected. These skills are ranked in Table 5 and 6 in increasing order of importance (percent explained variance). Concerned sites (Tables 5 and 6) are classified by alphabetic order. Two by two combinations: (FWI-FFMC, ISI-FFMC, BUI-FFMC, DMC-FFMC, DC-FFMC, DC-DMC, DMC-FWI, DMC-BUI, ISI-BUI, ISI-DC, FWI-DC, BUI-DC, BUI-FWI, ISI-FWI) have been used. And combinations with significant skill are selected through the multi-regression stepwise, for each site.

The explained variance ranges of the number of active fire, from 29% (at Siguiri) to 98% (at Kankan) (Table4) and for the burned area from 28% (at Télémelé) to 79% (at Kankan) (Table 6) are all highly significant ($P < 0.0001$). The results obtained for the burned area are higher than those from the statistics given by the 2015 report of the DNEF. This is due to the fact that these statistics on the burned area do not concern all the regions of Guinea, in contrast to our analysis where the missing data are here taken into account. Also, the method used by DNEF to estimate areas burned is not mentioned in the report and the differences could come out from the methodology as well.

In the northern and central region, 15 out of the 32 sites involved in this research, cover 60.51% of the areas burned and 46.12% of the cases of active fire during the period from 2003 to 2013 with a very heterogeneous distribution. The largest cumulative area burned has been recorded at Beyla (15% of burned area) while for the number of active fire, Kankan records the most important cases (9.58% of the total number of fire cases).

The percentages of variances explained for the burned areas and for the number of active fire are more significant with combinations of DC, DMC, and FFMC (Fuel Moisture Codes) and ISI (Fire Behavior Code). For instance, the DMC-BUI combination in Kouroussa explains 82% of the variance of the active fires and that of ISI-FWI explains 79% of the variance of burned area in the same location.

The results show strong performances of the linear model in the sites with a homogeneous distribution of the vegetation cover like the case of the regions of Upper Guinea where one finds vast expanses of Savannah. However, in areas with a heterogeneous vegetation cover (Savannah with trees), like Middle Guinea and Lower Guinea predictability gives significant values of performance but with lower skills. This could be explained by the fact that the code of fuel is not variable inside the $0.5° * 0.5°$ grid of the GFWED, and could reduce the precision in case that, inside the grid, the plant cover is non-homogeneous.

Tables 5 and 6 show that from one site to another, the combination of predictors with significant skills and strong explained variance of area burned and the number of active fire, differ significantly. Although most of the significant variables are found in all districts except Yomou, Labé, and Fria. For these sites, the burned areas could not be predicted with good skills. The results show the ability of the FWI components to predict active fire and burned areas across Guinea with highly significant performance and with several possible combinations for 90% of sites considered. In Faranah, Forékariah, Tougué, Télémelé, Labé, and Lélouma, the percentages of the variance of areas burned and the number of active fires is the lowest. This can be due to the fuel characteristics and the physical conditions surely different from the fuel characteristics and the physical conditions related to the rest of the country (Carvaillo et al., 2008) and the homogeneity of vegetation cover.

Table 5. District monthly number of active fire explained variance (r^2) and variables selected, in order of importance, by stepwise regression

Sites	Significant selected combinations	Explained variance range (%)	N	P
Beyla	ISI-DC, FWI-DC, ISI-FWI, DMC-BUI, DMC-FWI	75 to 79	132	<0.0001
Boffa	ISI-BUI,, DMC-FWI, DMC-FFMC, ISI-DC, FWI-FFMC	60 to 77	132	<0.0001
Boké	FWI-DC, ISI-DC, DC-DMC	38 to 43	132	<0.0001
Coyah	ISI-FFMC, FWI-FFMC, DMC-FFMC, ISI-DC, DC-FFMC	50 to 59	132	<0.0001
Dabola	BUI-DC, FWI-DC, ISI-DC	37 to 41	132	<0.0001
Dalaba	DMC-FFMC, ISI,-FFMC, FWI-FFMC, BUI-FFMC	67 to 78	132	<0.0001
Dinguiraye	DMC-FFMC, DC-DMC, DMC-BUI	34 to 50	132	<0.0001
Dubréka	ISI-FWI, ISI-FFMC, BUI-DC, DC-DMC, FWI-FFMC, BUI-FFMC	74 to 77	132	<0.0001
Faranah	BUI-DC, FWI-DC, DC-DMC, ISI-DC	31 to 36	132	<0.0001
Forécariah	BUI-DC, DC-DMC, BUI-FWI	31 to 37	132	<0.0001
Fria	DC-DMC, BUI-DC, FWI-DC, ISI-DC	33 to 41	132	<0.0001
Gaoual	BUI-DC, FWI-DC, ISI-DC, DC-DMC, DC-FFMC	39 to 59	132	<0.0001
Guékédou	BUI-DC, FWI-DC, ISI-DC, DC-DMC, DC-FFMC	56 to 77	132	<0.0001
Kankan	DMC-BUI, FWI-DC, FWI-FFMC, ISI-FWI, DMC-FWI	70 to 79	132	<0.0001
Kérouané	ISI-DC, FWI-DC, BUI-DMC, BUI-DC, DC-DMC	72 to 81	132	<0.0001
Kindia	BUI-DC, FWI-DC, DC-DMC, DC-FFMC	37 to 46	132	<0.0001
Kissidougou	BUI-DC, FWI-DC, ISI-DC, DC-DMC, DC-FFMC	73	132	<0.0001
Koubia	DMC-BUI, FWI-DC, DC-FFMC, ISI-DC, DMC-FWI, FWI-FFMC, ISI-FWI	41 to 60	132	<0.0001
Koundara	ISI-DC, FWI-DC, ISI-BUI, ISI-FWI, ISI-FFMC	79 to 82	132	<0.0001
Kouroussa	ISI-DC, FWI-DC, BUI-DC, DC-FFMC, DC-DMC	77 to 81	132	<0.0001
Labé	BUI-DC, DC-DMC, ISI-DC, FWI-DC, DC-FFMC	39 to 47	132	<0.0001
Lélouma	DC-DMC, BUI-DC, ISI-DC, FWI-DC	42 to 46	132	<0.0001
Lola	BUI-DC, DC-FFMC, DC-ISI, DC-FWI, DC-DMC	72 to 73	132	<0.0001
Macenta	BUI-DC, DC-DMC, ISI-DC, FWI-DC, DC-FFMC	50 to 60	132	<0.0001
Mali	DMC-BUI, DMC-FWI, ISI-FWI	36 to 41	132	<0.0001
Mamou	BUI-DC, FWI-DC, DC-DMC, ISI-DC, DC-FFMC	41 to 51	132	<0.0001
Mandiana	BUI-FWI, DMC-FWI, FWI-FFMC, ISI-FFMC, ISI-BUI, FWI-DC, ISI-FWI	53 to 57	132	<0.0001
N'Zérékoré	BUI-DC, ISI-DC, FWI-DC, DC-DMC	45 to 49	132	<0.0001
Siguiri	DMC-BUI, DC-DMC	25 to 29	132	<0.0001
Télimélé	DC-FFMC, BUI-FFMC, DMC-FFMC, FWI-FFMC	37 to 70	132	<0.0001
Tougué	DMC-BUI, DC-DMC, BUI-DC, ISI-DC	30 to 37	132	<0.0001
Yomou	ISI-FFMC, FWI-FFMC, DMC-FFMC, BUI-FFMC	29 to 34	132	<0.0001

Table 6. District monthly area burned explained variance (r^2) and variables selected, in order of importance, by stepwise regression

Sites	Significant selected combinations	Explained variance range (%)	N	P
Beyla	FWI-DC, BUI-FWI, DMC-FWI, FWI-FFMC, ISI-FWI	75 to 77	132	<0.0001
Boffa	ISI-DC, DC-FFMC, FWI-DC	39 to 40	132	<0.0001
Boké	BUI-FFMC, FWI-FFMC, DMC-FFMC	33 to 37	132	<0.0001
Coyah	DC-FFMC	19	132	<0.0001
Dabola	ISI-DC, DC-FFMC, FWI-DC	42 to 43	132	<0.0001

Dalaba	DC-FFMC, FWI-FFMC, BUI-FFMC	24 to 32	132	<0.0001
Dinguiraye	FWI-DC, ISI-FWI, BUI-FWI-FWI-FFMC, DC-DMC	54 to 65	132	<0.0001
Dubréka	ISI-FWI, ISI-BUI, FWI-DMC	20 to 22	132	<0.0001
Faranah	BUI-FWI, FWI-DC, ISI-DC, FWI-FFMC	42 to 49	132	<0.0001
Forécariah	DC-FFMC, ISI-FWI	22 to 25	132	<0.0001
Fria			132	<0.0001
Gaoual	DC-FFMC, DC-DMC, ISI-DC, FWI-DC, BUI-DC	46 to 47	132	<0.0001
Guékédou	FWI-DC, BUI-DC, BUI-FFMC, FWI-FFMC, DC-DMC, ISI-BUI, BUI-FWI	54 to 57	132	<0.0001
Kankan	ISI-FWI, FWI-DC, FWI-FFMC, DMC-FWI, BUI-FWI	74 to 79	132	<0.0001
Kérouané	DMC-FWI, BUI-FWI, ISI-FFMC, ISI-DC, ISI-FWI, ISI-BUI	69 to 74	132	<0.0001
Kindia	ISI-FWI, ISI-FFMC, DMC-FFMC, Fwi-FFMC, BUI-FFMC	23 to 25	132	<0.0001
Kissidougou	BUI-FFMC, ISI-FWI, DMC-FFMC, DC-FFMC, FWI-FFMC	59 to 61	132	<0.0001
Koubia	DC-FFMC, ISI-DC, FWI-DC, FWI-FFMC, ISI-FFMC, ISI-BUI	28 to 41	132	<0.0001
Koundara	ISI-DC, FWI-DC, ISI-BUI, BUI-FWI, ISI-FWI, DMC-FWI, ISI-FFMC	56 to 67	132	<0.0001
Kouroussa	ISI-FWI, ISI-DC, ISI-FFMC, ISI-BUI, FWI-FFMC, DMC-FWI, DMC-BUI	65 to 70	132	<0.0001
Labé	DC-FFMC	16	132	<0.0001
Lélouma	DMC-FFMC, BUI-FFMC	22 to 25	132	<0.0001
Lola	ISI-DC, ISI-FFMC, ISI-FWI, FWI-FFMC, ISI-BUI, DMC-FWI	62 to 65	132	<0.0001
Macenta	ISI-FFMC, ISI-DC, ISI-BUI, ISI-FWI, DMC-FWI, DMC-BUI, FWI-FFMC	56 to 61	132	<0.0001
Mali	DC-FFMC, BUI-FWI, ISI-BUI, FWI-DC	32 to 42	132	<0.0001
Mamou	ISI-FWI, ISI-BUI, ISI-FFMC, DC-FFMC, ISI-DC, DMC-FFMC, FWI-FFMC	47 to 53	132	<0.0001
Mandiana	BUI-FWI, FWI-DC, ISI-BUI, FWI-FFMC, ISI-FFMC, DMC-FWI, ISI-DC	52 to 54	132	<0.0001
N'Zérékoré	ISI-FFMC, ISI-DC, DMC-FWI, ISI-BUI, ISI-FWI, FWI-FFMC, FWI-DC	56 to 59	132	<0.0001
Siguiri	ISI-BUI, BUI-FWI, FWI-DC, ISI-DC	37 to 41	132	<0.0001
Télémelé	ISI-DC, FWI-DC, DMC-DC	26 to 28	132	<0.0001
Tougué	DC-FFMC, ISI-DC, FWI-DC, ISI-FWI, ISI-FFMC	24 to 36	132	<0.0001
Yomou			132	<0.0001

Based on the average monthly values of the number of active fire cases (table 5) and areas burned (table 6) for the 32 sites, all combinations of FWI components present very significant skill, with explained percentages of variance range between 75 and 84% and between 29 and 77% respectively. Figures 5a and 5b show results from the best combinations of predictors for active fire (FWI-DC) and burned area (FWI-BUI).

However, the analysis of simple correlations between the FWI components and the burned and active fires shows that the FWI (better correlated) alone explains 82% of the variance of the active fires whereas the FFMC (better correlated) explains 50% of the variance of burned areas. This shows that active fires are easier to characterize with the fuel moisture codes and as are the burned areas with the fire behavior indices.

A qualitative analysis of the relationship between best-selected combinations and both active fire and burned areas (figure 5) shows that the multi-linear regression model is able to predict fire in Guinea on monthly timescale with highly significance skills at lag 0. The predicted and observed plots (figure 5a and figure 5b) show the same evolution with often underestimation of the burned area and active fire at the beginning of the year during the whole period 2003 to 2013 except the year 2005 where both have been over-estimated and 2011, when burned area alone are overestimated. The underestimates and overestimates bias of active fire and area burned in Guinea seen in Figure 5, can be explained by human activities. For periods of over-estimation of burned areas and active fire, the risk of starting and spreading fires has been high, but the human activities were less intense and conversely when we have an under-estimation.

The percentages of unexplained variances can be attributed to the homogeneity of the vegetation cover. In sites where vegetation cover is homogeneous, the percentages of variances explained are the most important. The spatial resolution of the FWI data could also smooth the small scales details. The prevention and sensitization campaigns that the National Directorate of Water and Forests (DEF), and the Center for Observation, Monitoring and Environmental Information (COSIE) and their local authorities implemented at the beginning of fire period is also another aspect that can influence the forest fires statistics and bush fire ignition according to Carvailho et al. (2008).

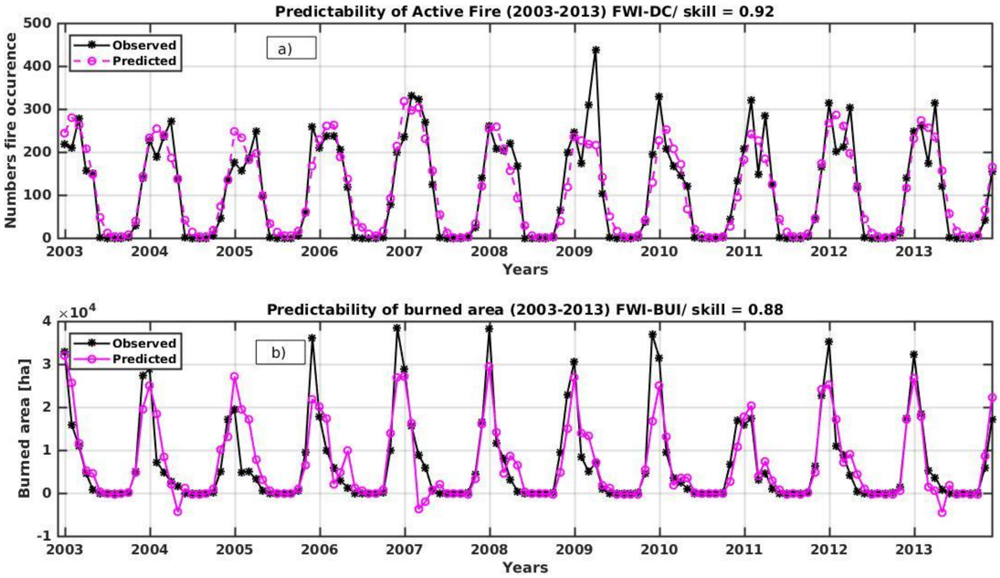

Figure 5. Observed (black line) and predicted (pink line) monthly active fire (a) and burned area (b) between 2003 and 2013, over Guinea

In figure. 6, the same model is extended to take into account the pairs of selected predictors, FWI-DC and FWI-BUI, for the active fires and the burned areas respectively, at lag0 (January), then at lag-1 (December of last year) until-5 (June of last year) successively. In figure 6, the shifted correlations between predictands (active fire and burned areas) and predictors (selected FWI components) are provided with bars, while the skill scores of the multi-regression model are represented with stars. For December, active fire events, appear significant predictable by FWI and DC predictors down to 3 months in advance (Figure. 6a, 95% confidence level). The model is then able to predict in, October the situation in

December, based on FWI and DC as predictors. This result is also in agreement with the shifted correlation values, which are statistically significant (same confidence interval) for both DC (thin bars) up to lag-1 (one month before) and FWI (wide bars) until lag-2 (two months before). Figure 6a also shows that where we have positive correlations between the active fires and the two predictors, model performance is significant.

For burned areas, the skill of the predictability of the situation in January (based on the FWI and BUI predictors) remains significant just on 1 month in advance (November) (Fig. 6b). There is also a rapid decrease in the correlations between burned areas and the two predictors (FWI and BUI). As with active fires, we note that significant performance is observed when we have significant correlations between area burned and predictors. The difficulty of predicting areas burned more than a month in advance can be attributed to the fact that they are not dynamic over time (these are not the events but rather the consequences of active fires). These results are therefore extremely important given the fact that the model has the ability to predict active fire events (cause of burned areas observed) down to 3 months in advance, thus providing the opportunity to take fire prevention measures.

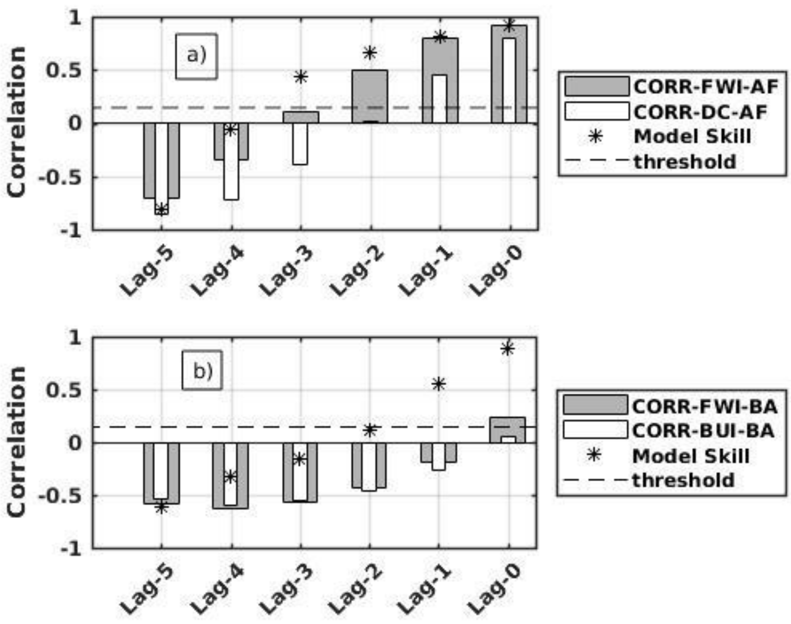

Figure 6. Lagged correlation and cross-validation hindcast of Bush fire: (a) Active fire, (b) Burned area for January. Bars denote lagged correlations on a monthly basis between January active fire and burned area (predictands) and preceding monthly FWI, DC, and BUI (predictors). The dashed horizontal line delimits the statistical significance (95% confidence level) for correlation. Markers are the multi-linear regression model skill

4. Conclusion

This study investigates the relationship between Global Fire WEather Index Database components and monthly burned area and active fire recorded by MODIS Aqua/TERRA combination overall Guinea considering 32 sites. Statistical analysis through a multiple linear regression model evaluated the predictability of active fires and burned areas in these stations and across the country using two-by-two combinations of Fire Weather Index (FWI) components of predictors. The combinations of Drought Code (DC), Initial Spread Index (ISI), Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), The Buildup Index (BUI) and FWI components have been selected by the linear multi-regression stepwise model based on the skill of the model to predict the fire activity. All two-by-two combinations of these components show very significant skill at lag 0 for both active fires and burned areas, with a percentage of variances between 75 and 84% and between 29 and 77% respectively. Results also showed that active fires are more related to fire behavior indices while the burned areas are related to the fine fuel moisture codes.

In the latest way, the application of lagged correlations and the evaluation of the stepwise multi-linear regression model skills from lag0 (same month) to lag-5 (five months before) has been computed based on the month of January for active fire and burned areas. Monthly FWI and DC and monthly FWI and BUI for the active fire and burned areas respectively have been considered as predictors. Results show that the active fire events can be predicted several months in advice using FWI and DC as predictors and the burned areas can be predicted just one month in advice using FWI and BUI as predictors. These may have implications on seasonal forecasting of active fire events specially. These are also a stepping stone in supporting Guinea's water and forest services in protecting ecosystems and biodiversity against the impacts of bush fires. These results also open up perspectives on the possibility of using forecasting models to project future and past events in order to better understand the long-term effects of bush fire on ecosystems, biodiversity and on the pollution of the environment.

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