Variability and predictability of bush fire in Guinea on inter-annual and multi-year timescales based on NDVI-MODIS datasets analysis

M. B. Barry¹,², D. Badiane¹, M. Diakhaté¹, S. M. Sall¹, H. Senghor¹ and T. N. Millimono¹,²

¹Laboratoire de Physique de l’Atmosphère et de l’Océan Siméon Fongang (LPAO-SF), Université Cheikh Anta Diop, Senegal.
²Laboratoire de Physique, Institut Supérieure des Sciences de l’Education de Guinée (ISSEG), Guinea.

This study investigates the variability and the predictability of bush fire on inter-annual and multi-year timescales in Guinea (latitudes 7° 05 and 12° 51 N and longitudes 7° 30 and 15° 10 W). Using Moderate Resolution Imaging Spectroradiometer (MODIS) with a spatial resolution of 231 m × 231 m and 16 days composite temporal resolution between 2001 and 2016, two brush fire hazard indices are calculated based on the NDVI variability. Results show that both indices could be considered as good indicators of NDVI deficiency corresponding to the drought of vegetation. Multiple linear regression model using these risk indices as predictors and burned areas as predictands has shown a non-significant model skill of 0.33 (lower than the significant threshold equals to 0.42), at the inter-annual scale, while at the multi-year timescale (>5 years), the model's skill rise up to 0.89. These indices can therefore be used as predictors of Guinea burned areas on multi-year timescale. This novel finding improved our understanding on the forecasting of burned area in Guinea, and could therefore help for successful adaptation strategies.

Key words: Bush fire, Guinea, index of risk, NDVI-MODIS, variability and predictability.

INTRODUCTION

Bush fires are a critical factor in savannas areas where pressure from human activities is low, and fire frequency is high. It is considered as a major factor in explaining vegetation dynamics (Jacquin, 2010). Their effects on ecosystems and hydrology are considerable, notably on the loss of vegetation and on the transformation of the soil, which greatly disrupts the flow patterns and hydrological behavior expected during years after fire (Cydzik and Hogue, 2009; Debano, 2000; Huete et al., 2002; Jung et al., 2009; McMichael et al., 2009; Pierson et al., 2008). This could promote erosion, accelerate surface runoff, sediment deposition, transport and impact soil moisture. Nowadays, satellite observation is an essential tool used by researchers in environmental field.
It is accurate and provides information in regions where human access is very difficult. Archiving of satellite data provides an objective view of plant activity by measuring surface reflectance at regular and frequent time intervals. Time series analysis of satellite data can provide information on trends in multi-factor vegetation dynamics including climate change (Reed 2006), entropic activities, and changes in the land use. Drought events are normal and recurring climatic events that often have negative effects on many sectors of society, including agriculture, energy, recreation, tourism, transportation (Rosenberg et al., 1978; Wilhite, 2000). Among these effects, bush fire is the most important, with disastrous consequences in places, unfortunately leading to losses in human life.

The risk assessment of bush fires is of paramount importance in the prevention and management of the damage they cause each year in the savanna countries. Its importance lies above all in the ability to anticipate decision-making by raising awareness of the risks and consequences for the environment. This would facilitate the establishment of a program to rehabilitate the areas affected by fires and the conservation of spared areas. Fires produce different types of signals that are easily observed in space (Robinson, 1991) by infrared and thermal infrared satellite channels.

The effects of fire on vegetation are the subject of an adversarial debate (Mbow, 2000). Indeed, some authors consider fires as tools for savannah management (Dupuy, 1968; Jeffrey and Humphrey, 1975) while others (Trabaud, 1987; Whelan, 1995; Scholze et al., 2006; Doerr and Santín, 2016; Hagmann et al., 2018; Guiterman et al., 2018; Inoue et al., 2018) pointed out the bad impact of bush fire on vegetation and biodiversity. This contradiction really proves that our knowledge of the exact effects of fires is very limited and that research must be conducted in this context for their good management. The fire risk assessment should be considered as the most relevant components associated with the occurrence of fire. To estimate when and where the fire will produce adverse effects, we need to model both the ignition and spread potential of fire and the vulnerability of ecosystems (Chuvieco et al., 2014).

Many studies have been recently conducted on bush fires in West Africa (Mbow, 2000; Millimono, 2009; Valea, 2010; Sow, 2012; Millimono et al., 2017) and results from these studies provide important information on fire regimes and environmental consequences. For instance in Guinea, like other savanna countries under the recurring threat of bush fires, a fire management policy organizing awareness campaigns on their harmful effects through rural radios has been implemented since 2009. However, despite efforts made by researchers to understand some aspects of active fires, many questions remain about their actual impacts. The methods of active fire discrimination, fire traces with remote sensing tools and Geographic Information System (GIS) allow us now to have an approach analysis of the management of these fires. Such approaches based on satellite data, have been recently used over Guinea using MODIS data to investigate the spatial and temporal distribution of active fires (Millimono, 2009) and the estimation of areas burned (Barry et al., 2015).

Regarding the lack of information on bush fires in Guinea emphasized by National Directorate of Water and Forests (DNEF), and the Center for Observation, Monitoring and Environmental Information (COSIE), this work aims to develop indices from vegetation index variables and to evaluate their ability to predict bush fire events. In addition, the previous studies cited above have addressed aspects generally related to the climatology, and therefore using a prediction model in the present work, we investigate the predictability of bush fires at inter-annual and multi-year (above 5 years) timescales over Guinea for the first time. This study overcomes the limitations of information on bush fires and could enrich the literature whose deficiency is very notorious in this geographical area.

MATERIALS AND METHODS

Burned area MODIS datasets

The MODIS burned area is derived from combination of TERRA and AQUA satellites acquisitions described in the MODIS Collection 5 Burned Area user’s guide by Boschetti et al. (2009). This report gives detailed information about mapping burned area and algorithms based on the Bidirectional Reflectance Model-based Expectation Approach, Temporal Implementation and the Iterative Procedure for Identification of Burned Pixel Candidates. Burned areas are characterized by deposits of charcoal and ash, removal of vegetation and alteration of the vegetation structure (Roy et al., 2002). The Moderate-Resolution Imaging Spectroradiometer (MODIS) algorithm to map burned areas takes advantage of these spectral, temporal, and structural changes. The applications for the MODIS products to characterize the fire patterns in the savanna's zone give very interesting results with climate data and Fire Weather Index components (Mataveli et al., 2018; Bedia et al., 2015). The algorithm used detects the approximate date of burning at 500 m by locating the occurrence of rapid changes in daily surface reflectance time series data. It is an improvement of previous methods through the use of a bidirectional reflectance model to deal with angular variations found in satellite data and the use of a statistical measure to detect change probability from a previously observed state (Roy et al., 2005).

The bidirectional reflectance model-based change detection algorithm developed for the MCD45 product is a generic change detection method 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. Rather than attempting to minimize the directional information present in 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 (Boschetti et al., 2009). All burned area images processing and area burned calculations were performed using the ArcGIS Geographic Information System (GIS)
software and have been cumulated for each year.

**NDVI-MODIS datasets**

The data used are provided by TERRA MODIS sensor with a spatial resolution of 231 m in longitude over 231 m in latitude and a 16-day temporal resolution (MOD13Q1) (Justice et al., 1998; Huete et al., 2002) between 2001 and 2016. These data are available on the following link: http://lsv-info.boku.ac.at/index.php/eo-data-processing/dataprocess-global?chronoform=dataprocess-global-evolution& event=submit. The choice of NDVI is motivated by its very wide use in various fields according to Huete et al. (2002). The Quality 1 (Q1) collection of MODIS data is justified by its better spatial resolution compared to former NDVI products offered by MODIS.

Two indices are extracted from the NDVI: The first index corresponds to the interannual standard deviation of greenery during the NDVI growth period Equation 1.

\[ \text{dSG} = \frac{\text{SG}_i - \text{SG}_{\text{avg}}}{\text{SG}_{\text{avg}}} \tag{1} \]

where SG is the sum of NDVI during the growth period of year i and SGavg is the average of the entire time series. It gives the value of the risk of bush fire at the beginning of the dry season. The second index is obtained by combining the maximum NDVI at the end of the rainy season, its value at the driest period of the season and its value before the start of the rainy season Equation 2.

\[ \text{AnnualRGRE} = \frac{\text{NDVI}_{\text{maxPhase}} - \text{NDVI}_{\text{minPhase1}}}{\text{NDVI}_{\text{minPhase1}}} \tag{2} \]

\( \text{NDVI}_{\text{maxPhase}} - \text{NDVI}_{\text{minPhase1}} \) indicates for each pixel, the amount of living biomass produced during the growing season, while \( \text{NDVI}_{\text{minPhase2}} - \text{NDVI}_{\text{minPhase}} \) gives the amount of biomass that is still green during the driest period of the season. The ratio between the two (RGREannual) corresponds to the proportion of the remaining green biomass (produced along the year) at the end of the dry season. The lower the annual RGRE is, the more dead is the biomass and the greater is the fire susceptibility. These indices are obtained from a synthesis of two methods of analyzing bushfire risk through time series of NDVI-MODIS (BROWN et al., 2008; Chéret and Denux, 2007; Chéret and Denux, 2011). For the first time, dSG has been applied and tested for sensitivities in the West African region. dSG inverted values below 0 better characterize the risk of bush fire in this region. These two indices (dSG and RGRE) used to characterize the risk of bush fires are complementary. dSG gives the risk of fire at the beginning of the dry season and allows sensitization through maps of the spatial distribution of occurrences and the Annual RGRE. It evaluates the intensity of the dryness of vegetation at the end of the dry season. dSG, which is not commonly used, has been adapted to the study area through tests of significance (dSG < 0 is proved significant for the prediction of burned areas) and the results have been found very realistic.

The linear multi-regression model

A statistical analysis using a linear prediction model is used to define the performance of the two indices (dSG and RGRE) to predict the burned areas calculated from the MODIS burned area products (Boschetti et al., 2009), already validated in this field of study for the same period. The predictors are utilized to perform a leave-one-out cross-validated hindcast at lag 0 (predictors/ predictands based on the same period). In this way, the linear regression model is built for each year to be predicted, calculating the coefficients of the model with all the years in our database except the one that is predicted (ter Braak and Juggins, 1993; Birks, 1981). The hindcast is performed and correlated with the omitted observations.

**RESULTS**

The phenomenological cycle of NDVI

Figure 1 presents temporal evolution of spatial monthly average of NDVI from 2001 to 2017. A strong growth of NDVI is shown in Figure 1, probably due to the intense rainfall for at least six months out of twelve. The NDVI profile shows a clear annual cycle with a growth phase between February and October and a decay phase between October and December. A moderate decrease of NDVI variation is also observed each year between July and August. This situation could be, due to the intense monsoon activity during summer season and could then affect the visibility and reflectance measured by the sensors. The intensity of this NDVI decreasing is also shown to vary from year to year depending probably on the intensity of the rainfall recorded each season. This confirms the work of various authors on plant phenology and ecophysiology cycle over the year (De Lillis and Fontanella, 1992).

Spatiotemporal distribution of indices of fire risk

The dSG threshold values are categorized as follows: Values below -20% correspond to extreme risks; that between -20 and -5% to high risk; that between -5 and 5% to medium risk; and that above 5%, low risk (Chéret and Denux, 2011). Figure 2 shows a strong inter-annual variability of dSG that can be attributed to various origins including human activities (agriculture, livestock, mining, etc.), climate variability due to large-scale forcing like El Niño (Wooster et al., 2012). During the years 2007, 2012, 2015 and 2016, the index displays significant values below the extreme risk threshold of -20%. According to the dSG evolution, the year 2007 recorded the highest risk on average (Figure 2) whereas the RGRE (Figure 3) indicates the year 2006 as the year of the critical risk. To better understand the differences in risk estimation by the two indicators, an analysis of the spatial distribution of these indices is necessary. Figure 4 shows the distribution of the risk level of bush fires for the year 2007.

Both indices agree well on the high level of risk in the northern zone in agreement with the previous studies (Millimono, 2009, 2017; Barry et al., 2015) highlighting the drastic consequences of bush fires in North part of Guinea. Whereas, in the southern zone, the risk is not clearly represented within the RGRE, while with the dSG, one can estimate it throughout the area. Indeed, over the southern zone, the West Africa monsoon starts in April, and since the RGRE assesses risk at the end of the dry season, generally estimated in June in Guinea, leading...
therefore to an unrealistic estimation of the risk within RGRE in this region during this period. Figure 4 also clearly highlights the heterogeneity of the spatial distribution of the risk of bush fires in Guinea, which could be explained by the diversity of socio-economic activities, types of vegetation and relief, rainfall and climate among others.

**Variability of the burned areas**

Figure 5 presents the inter-annual evolution of burned areas and its 4-years moving average from 2001 to 2016. No absolute trend of increasing of burned area has been observed during this period of study. However during the periods, 2003-2009 and of 2013-2016, MODIS shows clear increased burned areas. This ongoing increasing shows the urgency to act in the face of this drastic phenomenon.

The year 2016 has been found as the most alarming one. Recorded burned area for this year is twice compared to those observed in 2004, 2010 and 2011 for example. 2007 and 2006 that respectively appeared as the most critical ones regarding dSG and RGRE respectively (Figures 2 and 3) appear quasi normal regarding the recorded burned areas. Therefore taking into account separately risk indices, no clear link between them and the recorded burned areas is noted. This
situation therefore lead us to the multi-linear regression approach in order to see whether by combining both risk indices effects, one can reproduce the temporal variability of burned areas over Guinea.

Predictability of burned areas based on the indices of risk of bush fire

As seen above, the linear multi-regression model is used
to combine effects of both indices of risk on predicting the burned areas. Therefore dSG and RGRE indices are used as predictors and the burned areas as predictand. The statistical multi-regression model has been first run using interannual time series (Figure 6a). Results show that predicted burned areas fit sometimes well with observation (example 2006, 2009, and 2013). But the correlation between predicted time series and the observation is weak (0.33) and non-significant (significant threshold equals to 0.42); meaning that even by combining effects of both indices of risk, no linear evidence of predictability is found at interannual timescale. Moreover, Figure 6a also reveals that temporary trends (from 2003 to 2009 and from 2011 to 2016), previously discussed within the observed burned areas (cf. Figure 5) are more or less reproduced by the predicted time series. At a more smoothed timescale, skill of the linear regression model could be significant. In order to handle this, the linear multi-regression model is run again using this time, the 4-years mobile averaged indices (Figure 6b). By applying 4-years mobile averaged, we remove all fluctuations below 5 years, and keep only variability above, called multi-year variability (Sheen et al., 2017). As expected, the skill of the model rose up to 0.89 (Figure 6b) despite the model seemed to overestimate (underestimate) burned areas from 2001 to 2013 (from 2014 to 2016).

The statistical analysis therefore reveals that dSG and RGRE indices are useful benchmarks for the predictability of bush fires in Guinea. Indeed, even the performance of the model at the inter-annual timescales is very weak at inter-annual variability, at multi-year timescale the dSG, adapted to the study area, appears strongly correlated with the burned areas extracted from the already validated MODIS Burned Area data; its combination with the RGRE gives a very significant performance in the prediction of fire traces. Risk index maps have been broadly consistent with the realities observed each year in the area. For all years, the maps of the dSG show a strong capacity to reproduce the areas burned by indicating the high risk of wildfires especially in the northern zone which borders the Sahel (very dry zone). The RGRE is unable to reproduce the areas burned in the southern zone, which is very humid, with an average of 7 to 8 months of rain per year.

**DISCUSSION**

In this paper, we have investigated the variability of the NDVI, indices (dSG and RGRE) of bush fire risk and that of burned areas over Guinea as well as the predictability of bush fire based on the risk indices. Risk indices have been performed using NDVI-MODIS datasets and bush fires are assumed by observed burned areas. For the predictability of bush fire, a linear multi regression model with burned areas considered as the predictand and risk indices of predictors is used. This statistical model was
Figure 6. Predictability of burned area based from linear multi-regression model using dSG and RGRE as predictors at inter-annual (a) and at multi-year (b) timescales. Black lines represent the observed burned areas and the pink ones correspond to predicted burned area by the linear multi-regression model.

Results show that over NDVI is associated with a clear annual cycle, with a growth phase between February and October and a decay phase between October and December, in agreement with previous works on plant phenology and ecophysiology cycle over the year (De Lillis and Fontanella, 1992). The NDVI and the derived risk indices present also a strong inter-annual variability but no absolute trend is noted during the period of the study. However analysis made on NDVI index maps is qualitative and therefore not necessarily exhaustive. 32 maps produced from these RGRE and dSG for the period 2001-2016 have been used to understand the evolution of bush fires in Guinea independently of the weather conditions. During the wet years, distribution of the level of risk is found almost homogeneous in zones with similar ecosystems whereas during dry years, the values contrast strongly (specially in the south). We also note that for a dry year, dSG gives very high values of the fire risk level while within the RGRE index, we note a minimal risk in the same meteorological conditions. Regarding the predictability, there is a very high and significant performance of dSG and RGRE in predicting fire traces at multi-year scales (> 5 years). However, at this interannual timescale no clear evidence of predictability is found.

Results demonstrate the usefulness of the indicators proposed in this research, first by establishing the interannual variability of the state of the vegetation linked to local weather conditions (at the beginning of the dry seeding with the dSG and at the end of dry season with the annual RGRE) and secondly by showing the possibility of using these two indices as predictors to make predictions at the multi-annual scale of the areas burned in Guinea. The geographical details of local variability maps of the risk of bush fires at the beginning and end of the dry season (conducive to bush fires) provide particularly valuable information for ecosystem planners and managers. A very important additional benefit of dSG is its ability to map burned areas in the previous year across the study area.
Conclusion

It would be important in the future to specify the areas of interest in order to classify the risk according to the ecosystems and the activities of the people. It is also necessary to use the Forest Weather Index (IFM), which can give fire risk values at daily time steps if there are stations that provide daily records of weather conditions. We plan to put in place clues that could produce bush fire risk prediction maps from MODIS-NDVI at 16-day and one-month time scales in the interest of early warnings of wildfire for an effective management for a successful protection of the Guinean environment and ecosystems. We also plan to use a new gridded burned area products provided by European Space Agency, (Chuvieco et al. 2018) combined by the MODIS active fire products (Giglio et al., 2003; Giglio, 2010; Giglio, 2015) to study the spatial-temporal relationship between burned area and dSG and RGRE.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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