Evaluating Satellite and Climate Data-Derived Indices as Fire Risk Indicators in Savanna Ecosystems

Jan Verbesselt, Per Jönsson, Stefaan Lhermitte, Jan van Aardt, and Pol Coppin, *Member, IEEE*

***Abstract*—The repeated occurrence of severe wildfires has highlighted the need for development of effective vegetation monitoring tools. We compared the performance of indices derived from satellite and climate data as a first step toward an operational tool for fire risk assessment in savanna ecosystems. Field collected fire activity data were used to evaluate the potential of the normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and the meteorological Keetch–Byram drought idex (KBDI) to assess fire risk. Performance measures extracted from the binary logistic regression model fit were used to quantitatively rank indices in terms of their effectiveness as fire risk indicators. NDWI performed better when compared to NDVI and KBDI based on the results from the ranking method. The c-index, a measure of predictive ability, indicated that the NDWI can be used to predict seasonal fire activity ($c = 0.78$). The time lag at the start of the fire season between time-series of fire activity data and the selected indices also was studied to evaluate the ability to predict the start of the fire season. The results showed that NDVI, NDWI, and KBDI can be used to predict the start of the fire season. NDWI consequently had the highest capacity to monitor fire activity and was able to detect the start of the fire season in savanna ecosystems. It is shown that the evaluation of satellite- and meteorological fire risk indices is essential before the indices are used for operational purposes to obtain more accurate maps of fire risk for the temporal and spatial allocation of fire prevention or fire management.**

***Index Terms*—Fire risk evaluation, Keetch–Byram drought idex (KBDI), logistic regression, normalized difference vegetation index (NDVI), normalized difference water index (NDWI), SPOT VEGETATION, vegetation moisture dynamics.**

I. Introduction

THE LACK of information on the vegetation status and fire risk prior to the use of fire as a management tool in savanna ecosystems leads to a significant deterioration of the natural vegetation and biodiversity [1], [2]. Assessment of the fire risk therefore constitutes the basis of effective fire management. Traditional methods of fire risk assessment rely on meteorological danger indices (MDI) that take the critical variables of fire ignition (e.g., vegetation water status) into account [3], [4]. Besides the uncertainty inherent in the derivation of a MDI, the application of such indices also presents certain operational challenges. These challenges are related to the lack of meteorological data for specific areas, as well as spatial interpolation techniques that are not always suitable for use in areas with complex terrain features [5]. Satellite data have the potential for providing sound alternatives to meteorological indices in this context. Remotely sensed data possess significant potential for monitoring fire risk at regional to global scale, given the synoptic coverage and repeated temporal sampling of satellite observations [6], [7]. The use of spectral indices also has been considered as ideally suited for use in savanna ecosystems, because, unlike closed canopies systems, spectral saturation of vegetation indices does not pose a problem [1], [8].

Relationships between fire risk indices derived from satellite and climate data have been studied for different vegetation types [3], [5], [9]. However, no studies have been undertaken to compare the fire risk assessment performance of these indices. The aim of this study therefore was to evaluate the performance of remote sensing indices and a MDI, related to vegetation water status, for fire risk assessment.

At ground level vegetation water status is mainly measured as fuel moisture content (FMC). FMC is defined as the ratio between the quantity of water in live vegetation and either the fresh or dry weight of vegetation [10]. FMC alone does not provide a comprehensive assessment of fire risk. Other factors related to fire ignition (e.g., lightning, human factors) or propagation (e.g., wind, slope) also need to be taken into account. FMC, however, is widely regarded as one of the most important variables in fire risk modeling and therefore is incorporated in most fire danger rating systems worldwide (e.g., U.S. National Fire Danger Rating System) [4], [11]–[13]. The concept of fire risk in this study therefore was restricted to the likelihood of fire occurrence, given a particular vegetation water status (i.e., FMC).

The MDI considered was the Keetch–Byram drought index (KBDI). KBDI is a cumulative algorithm for estimating fire potential from meteorological information, including daily maximum temperature, daily total precipitation, and mean annual precipitation [14]. The algorithm for the derivation of KBDI can be found in Dimitrakopoulos and Bemmerzouk [15]. Several studies have shown that KBDI is related to vegetation water status dynamics, especially for shrub species [3], [11]. KBDI was designed to incorporate soil water content in the root zone of vegetation and assesses the seasonal trend of fire risk for a wide range of climatic conditions [3], [15]. KBDI therefore is strongly related to FMC, since most cases of moisture stress in plants (grass and shrub species) are caused by soil moisture deficiencies [5]. Additionally, KBDI has been recommended for operational use in South Africa [16].

Several authors have proposed the use of indices derived from satellite data as a method to monitor FMC for fire risk assess-

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ment [3], [7]–[12], [17]. The proposed indices are subdivided into two classes.

A. Chlorophyll-Related Indices

Chlorophyll-related indices are related to FMC based on the hypothesis that when vegetation dries out, the chlorophyll content of leaves decreases proportional to the moisture content [7], [9]. This assumption has been confirmed for selected species with a shallow rooting system (e.g., grasslands and understory forest vegetation) [17], [18], but cannot be generalized to all ecosystems [7]. Therefore chlorophyll-related indices, such as the normalized difference vegetation index (NDVI), can only be used in regions where the relation between chlorophyll content, degree of curing, and water content has been established.

B. Vegetation Water Status-Related Indices

NDVI does not exhibit an immediate and direct response to changes in vegetation water status [7]. Indices directly related to vegetation water status such as the normalized difference water index (NDWI), a variation of NDVI, use the SWIR spectral region rather than the red region [19]

$$\mathrm{NDWI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{SWIR}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{SWIR}}} \tag{1}$$

where ρ_{NIR} and ρ_{SWIR} are the reflectances of the near-infrared (NIR, 0.78–0.89 μm) and shortwave-infrared (SWIR, 1.58–1.75 μm) regions, respectively. Several studies have demonstrated that NDWI is strongly related to the quantity of water per unit area but not related to the quantity of water per unit of dry vegetation weight [7], [10]. Consequently, NDWI is not directly related to FMC but to the quantity of water per unit area [7], [20], [21]. It is reasonable, however, to suppose that such a wavelength combination will be useful for fire risk assessment [3], [7], [10].

The specific objective of this work was to evaluate the ability of the selected indices (NDVI, NDWI, and KBDI), related to vegetation water status, to assess fire risk in savanna ecosystems. Index performance was evaluated using fire activity data. Satellite images can be used to obtain more accurate maps of fire danger once the fire risk performance of a satellite index is known. Performance measures (AIC, c-index, and probability range) extracted from the binary logistic regression model were used to evaluate the relationship between the selected indices and fire activity data. The time lag at the start of the fire season between time-series of fire activity data and selected indices (KBDI, NDVI, and NDWI) also was studied to verify the capacity of the indices to predict the start of the fire season.

II. Evaluation of Indices for Fire Risk Assessment

Fire risk indicators yield dissimilar results when applied to different biomes or geographic regions, a fact which creates confusion concerning their effectiveness [22], [23]. In particular, the main unresolved problem is the performance evaluation of fire risk indices based on satellite or meteorological data. Evaluation of fire risk indices furthermore is challenging because it is a somewhat nebulous concept, as opposed to better defined fire behavior prediction which is used to calculate observable fire characteristics (e.g., rate of spread). A fire risk index consequently is not meant to describe the characteristics of a specific fire, but rather to serve as an indication of fire risk for a management area [24]. Three well-established methods generally are used to evaluate such indices [3], [22]. These methods consist of correlating indices with: 1) fire activity data; 2) meteorological data; or 3) FMC data. In this study fire activity data were used to evaluate the ability of the selected indices to assess fire risk, the reasons being threefold. The first reason is that an operational fire risk application only becomes feasible once the relationship between the index and fire activity data is known [22]. The second reason pertains to fire activity data being a direct way of evaluating the potential for fire risk assessment of an index, compared to the indirect methods such as using MDI's and FMC data. Fire activity data also can be retained as an indication of the stress that is exerted on vegetation by seasonal meteorological dynamics, based on the assumption that nonmeteorological factors do not change drastically in the period of analysis [23].

The relationship between indices and fire activity data has been evaluated successfully in several studies using logistic regression [24]. The use of logistic regression for fire risk evaluation does not depend on predefined index intervals, nor does it require rescaling of indices for comparison. In addition to the statistics associated with logistic regression models, the temporal behavior of an index also should be evaluated before it can be used as an early warning tool for fire risk assessment [10], [24], [25]. The ability to predict the start of the fire season (i.e., temporal behavior) is an important factor in the evaluation of the prediction power of an index and often is studied using time-series function fits [26]. The TIMESAT program was selected to extract seasonal parameters (i.e., start of the fire season) and quantify the temporal behavior of the fire risk indices [26], [27]. The program is based on an iterative and adaptive Savitzky–Golay filtering method that has been shown to be effective in obtaining a high quality time-series from which seasonal parameters can be extracted [27]. The extracted seasonal parameter (i.e., fire season start) can be used to quantify the ability to predict the start of the fire season, by evaluating the time lag between the extracted metric from time-series of fire risk indices and fire activity [28], [29].

III. Study Area and Data

A. Study Area

The study area was the Kruger National Park (KNP), located between latitudes 23°S and 26°S and longitudes 30°E and 32°E in the low-lying savanna of the northeastern part of South Africa (Fig. 1). Elevations range from 260–839 m above sea level, and mean annual rainfall varies between 350 mm in the north and 750 mm in the south. The rainfall regime within the annual climatic season can be confined to the summer months (November to April), and over a longer period can be defined by extended wet and dry seasons [2]. The KNP is characterized by an arid savanna dominated by thorny, fine-leafed trees of the families *Mimosaceae* and *Burseraceae*. An exception is the northern part of the KNP where the Mopane, a broad-leafed tree belonging to the *Ceasalpinaceae*, almost completely dominates the tree layer.

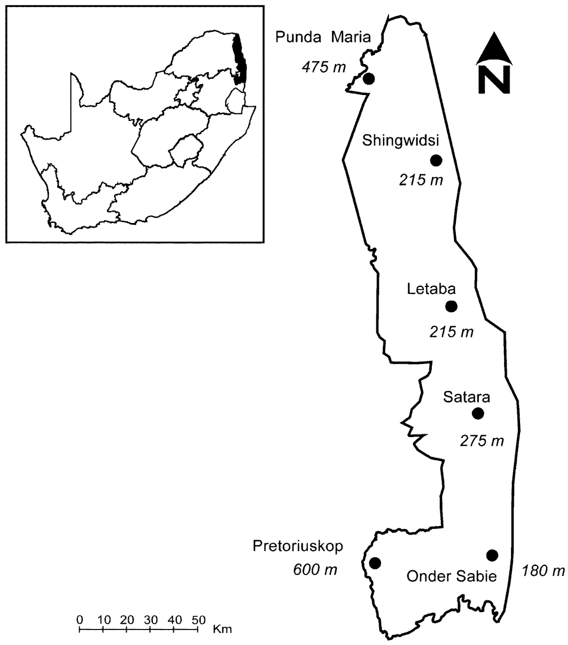

Fig. 1. Kruger National Park study area with the weather stations used in the analyses (right). The elevation of each weather station also is indicated. South Africa is shown with the borders of the provinces and the study area (top left).

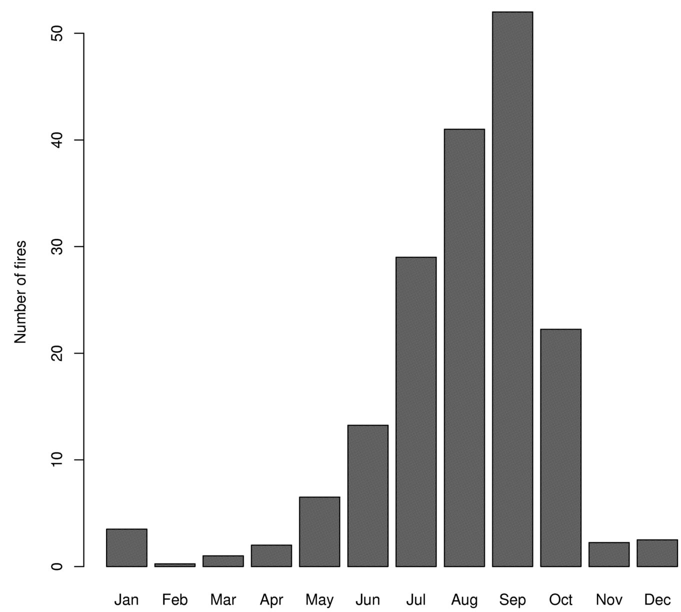

Fig. 2. Average number of arson fires per month in the Kruger National Park during the study period (1998–2002). The fire season starts approximately in May and ends at approximately the end of October.

B. Satellite Data

The dataset is composed of ten-day SPOT VEGETATION (SPOT VGT) composites (S10 NDVI maximum value syntheses) acquired over the study area for the period April 1998 to December 2002. SPOT VGT can provide local to global coverage on a regular basis (e.g., daily for SPOT VGT). The syntheses result in surface reflectance in the blue (0.43–0.47 μm), red (0.61–0.68 μm), NIR (0.78–0.89 μm), and SWIR (1.58–1.75 μm) spectral bands. Images were atmospherically corrected using the simplified method for atmospheric correction (SMAC) [30]. The geometrically and radiometrically corrected S10 images have a spatial resolution of 1 km. NDVI and NDWI indices were derived from the corrected SPOT VGT S10 data.

The S10 SPOT VGT time-series were preprocessed to detect data that may erroneously influence the function fit of TIMESAT (e.g., spectral anomalies caused by clouds). Several masks developed by Stroppiana *et al.* [31] therefore were used to set weights of indices to zero such that data errors do not influence the function fit to the correct time-series. The specific masks used to remove data anomalies were the following.

1) SWIR Mask: The occurrence of lost detectors in the SWIR SPOT VGT channel was flagged by the status mask of the S10 synthesis, provided by the data suppliers. The weights of these data points were set to zero based on the status mask.

2) Satellite Viewing Zenith Angle (VZA) Mask: Pixels located at the very edge of the image $(\mathrm{VZA} > 50.5^\circ)$ swath are nonlinearly affected by resampling methods that yield erroneous spectral values [32], [33]. The weights of data points with a VZA above 50° therefore were set to zero such that such pixels would not erroneously influence the function fit of TIMESAT.

3) Cloud Mask: A threshold approach, based on a method developed by Kempeneers *et al.* [34] and Stroppiana *et al.* [31] and specifically derived for SPOT VGT S10, was applied to identify cloud-free pixels data for the study area. A pixel was classified as cloud-free if the blue reflectance was less than 0.07. The weights of pixels with cloud contamination were set to zero.

C. Fire Activity Data

A comprehensive fire activity database of the KNP was used in this study to evaluate the selected indices. The park was subdivided into over 400 management blocks when prescribed burning was introduced in 1957 [2], and records were kept of all fires in each block. The date of each fire, its cause, and position were extracted from the database for the study period from 1998 to 2002. The causes of fires were recorded in several categories such as prescribed fires, lighting fires, arson fires, and fires of unknown origin [35].

In this study only arson fires were selected. Arson fires are anthropogenic fires lit by immigrants, poachers, or tourists. These fires are influenced by seasonal variation of vegetation water status and are spatially and temporally random in nature as opposed to lightning and management fires [36]. Lightning fires, on the other hand are dependent on thunderstorms and occur at the start of rain seasons when vegetation starts regreening. Management fires, dependent on fire managers, are lit when vegetation is not completely cured such that fires are not excessively intensive and destructive. Arson fires and the selected indices are both related to vegetation water status. Arson fires consequently were selected to evaluate the performance of indices to identify sites that have a higher fire risk, thereby enabling managers to prevent this type of destructive fire on these sites. (Personal communication Govender N. scientific services KNP). Fig. 2 illustrates the monthly fire activity of arson fires in the Kruger National Park during the study period (1998–2002).

An absolute calibration of each of the considered methods was not attempted, since this would require a much larger dataset in order to include all temporal climatic changes in the study area [2], [23]. Fires that burned for several days were considered as single events in tallying the number of fires. The daily fire series were transformed into ten-day fire series. This was done in order to match fire data and the SPOT VGT dekades (i.e., ten-day period) by taking the sum of the number of fires per ten days.

D. Climate Data

Climate data from six weather stations in the KNP with similar vegetation types were used to derive the daily KBDI (Fig. 1). KBDI was derived from daily precipitation and maximum temperature data to estimate the net effect of daily precipitation and evapotranspiration on the soil water balance [12]. Assumptions in the derivation of KBDI include a soil water capacity of approximately 20 cm and an exponential moisture loss from the soil reservoir. KBDI was initialized during periods of rainfall events (e.g., rain season) that bring soils to field capacity and KBDI to zero [15]. The preprocessing of KBDI was done using the method developed by Janis *et al.* [37]. Missing daily maximum temperatures were replaced with interpolated values of daily maximum temperature, based on a linear interpolation function [38]. Missing daily precipitation, on the other hand, was assumed to be zero. A series of error logs were automatically generated to indicate missing precipitation values and associated estimated daily KBDI values. This was done since zeroing missing precipitation may lead to an increased fire potential bias in KBDI. The total percentage of missing data gaps in rainfall and temperature series was maximally 5% during the study period for each of the six weather stations. The influence of the missing data gaps was reduced by two procedures. First, the influence of missing data was minimized through interpolation and transformation to ten-day time-series. The daily KBDI time-series were transformed into ten-day KBDI series, similar to the SPOT VGT S10 dekades (i.e., ten-day periods), by taking the maximum of each dekad. Second, the generated error logs were used to approximate the ideal upper-envelope of the negative of the KBDI series (i.e., -KBDI) by the iterative fitting method of TIMESAT, thereby minimizing the influence of missing data. The -KBDI was analyzed in TIMESAT because the fit to the upper envelope of the time-series corrected for the dips in the -KBDI series caused by assuming that missing daily precipitation values were zero. The -KBDI, NDVI, and NDWI therefore were used throughout this paper to evaluate their performance as fire risk indices.

IV. METHODS

Care was taken in the selection of the spatial extent of the sampling area around each weather station to be able to evaluate time-series of fire activity data and selected indices. This was done in order to achieve a balance between the need for a statistically adequate amount of fire activity data and the demand for homogeneity within sampling areas. Nonmeteorological factors were assumed to remain relatively constant in the sampling area, such that fire activity data can be used as an indication of the stress that is exerted on vegetation by seasonal meteorological dynamics.

Time-series of satellite indices were derived by selecting savanna pixels, based on the land cover map of South Africa [39], in a 3×3 pixel window centered at each of the meteorological stations to reduce the effect of potential misregistration [5]. Median values of the nine-pixel windows were retained instead of single pixel values. The median was preferred to average values since it is less affected by extreme values, and therefore is less sensitive to potentially undetected data errors.

Fires were selected within a radius of 30 km around each weather station in order to extract time-series of fire activity data. The selected indices were assumed to be valid for the 30-km radius around each weather station, since the fire risk indices (e.g., -KBDI, NDVI, or NDWI) are intended as an indication of fire potential for a management area, and not of specific fire characteristics [24], [25]. Furthermore, the sample areas around weather stations did not overlap, resulting in fires being selected only once per weather station. As mentioned before, the study focused on index-based fire risk evaluation, as well as assessment of the potential to predict the start of the fire season.

A. Fire Risk Evaluation

Binary logistic regression successfully has been used in several studies to evaluate the performance of indices by analyzing the relationship between the index and fire events [23], [24]. A binary logistic regression model therefore was used to define the probability of a fire-dekade (Y), a dekade (i.e., ten-day period) with one or more fires, as a function of an explanatory variable (X), i.e., fire risk index

$$\begin{aligned}\text{logit}\{Y = 1 \mid X\} &= \text{logit}(P) = \log[P/(1-P)] \\ &= \log[\text{odds that } Y = 1 \text{ occurs}] \\ &= X\beta \end{aligned} \tag{2}$$

where $X\beta = \beta_0 + X_1\beta_1 + \cdots + X_k\beta_k$ and P is the probability that $Y = 1$ for a given X. The regression parameters (β) were estimated using the maximum likelihood method [40]. $\text{Logit}(P)$ is the logistic function of $P/(1-P)$. The logit model is a linear regression model, since $\text{logit}(P)$ is a weighted sum of the Xs. Fire-dekades can be retained as an appropriate indication of fire activity and the associated vegetation stress due to seasonal meteorological dynamics, based on the assumption that nonmeteorological factors do not change drastically in the period of analysis [23]. Binary data (e.g., fire-dekades and no fire-dekades) and not the amount of fires therefore were used in current study. This was done because the objective of the study was related to prediction of fire-dekade probability as measure of fire activity and not the amount of fires [24]. Accurate burnt area data were not directly available in this study and therefore were not used in the analysis.

All available fire activity data selected per weather station were used in a binary logistic regression model with fire activity data as response variable and a categorical station variable and an index (-KBDI, NDVI, or NDWI) as explanatory variables. The station variable was included in the model to determine if the probability of a fire-dekade was statistically different for the various weather stations and station related factors (e.g., soil type). The Wald test statistic was used to verify if explanatory variables used in the model were significant to warrant inclusion in the final model [40]. The Wald test statistic also was used to verify the assumptions of linearity. The X-values were expanded into restricted cubic spline (RCS) functions, with the number of knots specified according to the estimated "power" of each predictor. We assumed that the most complex relationship could be fitted using a RCS function with five knots, similar to Harrell [40]. Five knots therefore were used in all the models to be able to compare results, while accounting for similar amounts of nonlinearity [40].

Common measures to assess model performance include overall performance measures to assess the model fit and discrimination measures to evaluate the ability of the model for distinguishing between fire-dekades and no fire-dekades. The modified Akaike's information criterion (AIC) and the model probability range were used in this study to assess the overall performance, while the c-index was used to evaluate the discrimination power of the fire risk indices [24], [40]. The "le Cessie-van Houwelingen" unweigted sum of squares test for goodness-of-fit furthermore was used to examine the difference between the actual probability and the predicted probability. This statistic was used to determine if the model is well-calibrated and provides a significant fit for the data [40].

The AIC was used in adjusted "chi-square" form

$$\mathrm{AIC} = LR\chi^2 - 2df \tag{3}$$

where $LR\chi^2$ is the model likelihood ratio chi-squared statistic and df is the degree of freedom of the model. The AIC was used to rate the model fit and penalize for complexity, i.e., the number of parameters used in the model. The higher the AIC, the better the model fit and overall performance of the model [40]. However, the value of AIC only provides information about the relative performance of the model, since the value itself has no other specific meaning.

The c-index therefore was included since it provides interpretable information on the discrimination of the logistic regression model and also can be used as a parameter to rank the different fire risk indices. This statistic is identical to the area under the receiver operating characteristic curve, given that the outcome variable is binary. A c-index value lower than 0.5 indicates random predictions, whereas a value of 1 indicates a perfect prediction. A model having a c-index of roughly 0.8 has utility in predicting the responses of individual subjects [40].

The range of probability values also is an important indication of the effectiveness of an index since it corresponds to a wider range of vegetation conditions [24]. Andrews *et al.* [24] stipulated that a model with a wide range of probability values is preferred to a model with a small range of probability values.

The comparison technique of Andrews *et al.* [24] that quantifies the performance of indices in assessing fire risk was used in this study. The selected measures (AIC, c-index, the model probability range) were used to rank the selected fire risk indices. The three measures were ranked, with the lowest rank (i.e., 1) being the measure that performed "best" when estimating fire risk assessment performance of an index (-KBDI, NDVI, and NDWI). The ranks were summed and an overall rank was assigned to each index.

B. Ability to Predict the Start of the Fire Season

The TIMESAT program was optimized for this study to process individual time-series of different origin (e.g., fire activity, climate, and remote sensing data) and to extract a specific metric. The "start of the fire season" metric was used to evaluate the time lag between fire activity data and selected satellite and meteorological indices. This method made investigation of the time lag at a defined instant in time possible, as opposed to regression or cross-correlation analysis, by which only the general time lag between time-series can be studied [38].

The TIMESAT program implements a number of possible processing algorithms. The method used was based on local polynomials that were iteratively fitted to the upper envelope of the time-series, described as an adaptive Savitzky–Golay filter [27]. The function was fitted to the upper envelope since most noise in the selected indices was negatively biased (e.g., noise associated with clouds and atmospheric contamination in NDWI and NDVI) [26]. The ancillary metadata from the preprocessing of the SPOT VGT S10 data and the climate data furthermore were used in the iterative least-squares fitting to the upper envelope of the time-series (-KBDI, NDVI, and NDWI). Consequently, the Savitzky–Golay filter efficiently reduced contamination in the time-series [27].

One of the critical issues in using satellite data to detect the start of the fire season, is identifying the offset threshold (i.e., the start of the decrease) of the satellite-based indices [28], [41]. The definition was different for the fire activity data and the indices (-KBDI, NDVI, and NDWI), because the indices decrease when fire activity increases (number of fires) (Fig. 3). Figs. 4 and 5 illustrate the defined metric for fire activity data and selected indices, respectively. The start of the fire season for fire activity data was defined as the point in time for which the function fit value was 20% (to the left side of the fire season midpoint) of the maximum (Fig. 4). Fire activity (number of fires per dekade) served as a valid definition of the fire season, which therefore was approximated correctly by fitting a function through the upper envelope [24]. The start of the fire season for the selected indices was defined from the function fit as the point in time for which the function fit value was 80% (to the right of the fire season midpoint) of the maximum (Fig. 5).

This method is similar to the method of Kang *et al.* [41] where different thresholds (e.g., 10% and 20%) were used to define the onset of greenness in the MODIS leaf area index. The 20% and 80% values were used for this study because smaller factors are vulnerable to potential contamination by clouds and misregistration [41]. The purpose of the metric was not to define the start of the fire season, but to serve as a sampling technique for comparison of time-series at a point in time.

V. Results

A. Fire Risk Evaluation

The factor plot in Fig. 6 illustrates the relationship between binary fire activity data and the selected indices and demonstrates the difference between fire-dekades and no fire-dekades for -KBDI, NDVI, and NDWI. It is clear that the overlap between fire-dekades and no fire-dekades was smaller for NDWI compared to NDVI and -KBDI. Logistic regression models were fitted to quantify the ability to discriminate fire-dekades from no fire-dekades.

Results of the Wald statistic for the fitted logistic regression models that included the index and categorical station as explanatory variables, demonstrate that the indices and the nonlinearity in the model were significant ($p < 0.05$) at a 95%

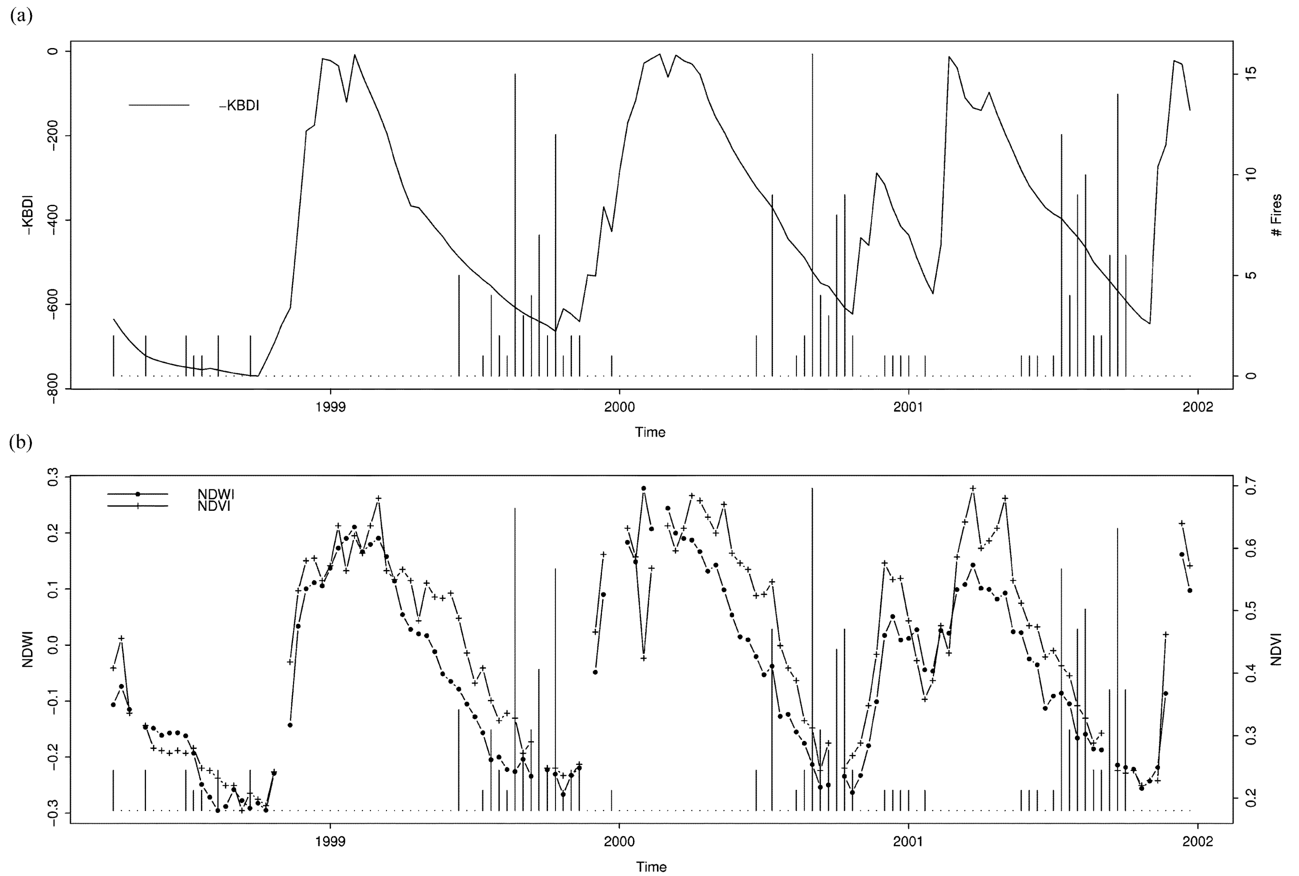

Fig. 3. Temporal dynamics of fire activity and vegetation water status around the Letaba weather station are illustrated by the number of recorded fires (number of fires) along with (a) -KBDI, and (b) the relationship between NDVI and NDWI. The axis of the fire histogram in (a) and (b) is shown at the right-hand side of plot (a).

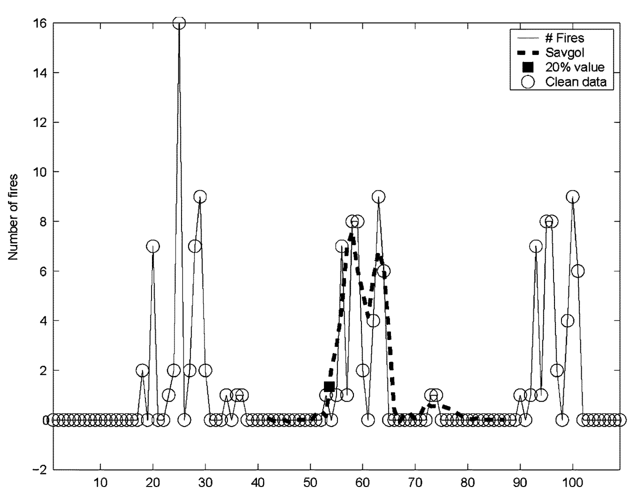

Fig. 4. Final fit of the Savitzky–Golay (SAVGOL) function to the fire activity data series, with the start of fire season metric (20% value) overlaid on the graph. The start of the fire season was defined as the time at which the number of fires had risen to 20% of the peak index value of the final SAVGOL fit where a dekade is defined as a ten-day period. The fire activity data contained no data errors (clean data) when the SAVGOL function was fitted.

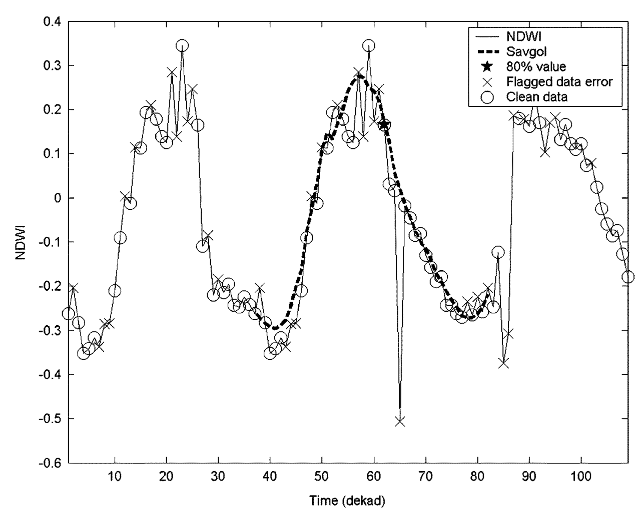

Fig. 5. Final fit of the Savitzky–Golay (SAVGOL) function to the NDWI series (clean data), with the start of fire season metric (80% value) overlaid on the graph. Points with flagged data errors were assigned weights of zero and did not influence the fit. The start of the fire season was defined as the time for which NDWI had decreased to 80% of the peak index value of the final SAVGOL fit where a dekade is defined as a ten-day period.

confidence level. It therefore was decided to account for the nonlinearity when comparing different logistic regression models. Results of the Wald statistic also illustrate that the categorical station variable was not significant $(p > 0.1)$ at a 95% confidence level. This means that after the index variable was taken into account, the probability of observing a fire was not statistically different for the various weather stations. It also indicated

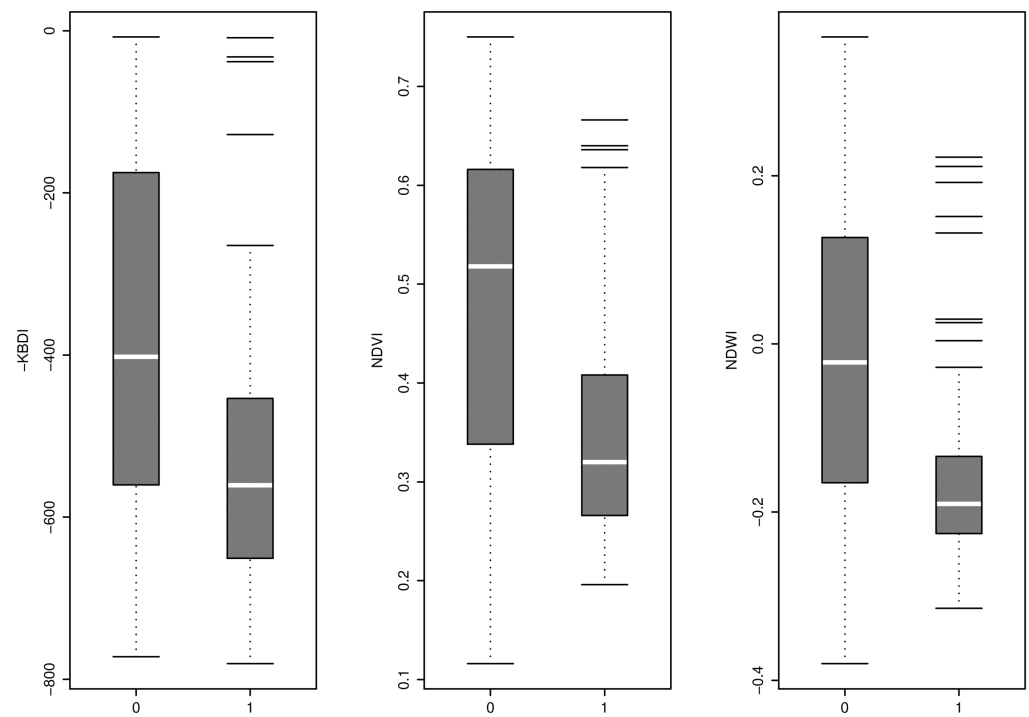

Fig. 6. Factor plots of the fire-dekades as binary data ($0 =$ no fire-dekad; $1 =$ fire-dekad) against the selected indices (-KBDI, NDVI, and NDWI). The fire activity data included 586 no fire-dekades and 115 fire-dekades. The upper and lower boundaries of the box indicate upper and lower quartiles. The median is indicated by the solid white line within each box. The whiskers connect the extremes of the data which were defined as 1.5 times the interquartile range of the box. Outliers are represented by (—).

TABLE I
MEASURES AND RANKING FOR THE LOGISTIC REGRESSION MODEL OF FIRE DEKADES AND -KBDI, NDVI, AND NDWI THE THREE BINARY LOGISTIC REGRESSION MODELS (DEGREES OF FREEDOM= 4) WERE ALL SIGNIFICANT ($P < 0.05$) WITH SIGNIFICANT EXPLANATORY VARIABLES (-KBDI, NDVI, AND NDWI) ($P < 0.05$) AND A SIGNIFICANT NONLINEAR COMPONENT ($P < 0.05$). THE RESPONSE VARIABLE INCLUDED 586 NO FIRE-DEKADES AND 115 FIRE-DEKADES. THE VALUES IN THE PARENTHESES ARE THE RANK VALUES

Index	AIC	c-index	Model probability range	Rank Sum	Final Rank
-KBDI	56.2 (3)	0.72 (3)	0.252 (3)	9	3
NDVI	76.5 (2)	0.75 (2)	0.328 (2)	6	2
NDWI	91.9 (1)	0.78 (1)	0.332 (1)	3	1

that station related factors (e.g., nonmeteorological factors such as soil type) did not influence the relationship between the selected indices and fire activity. Consequently, the categorical station variable was excluded as a variable in the logistic regression models.

The selected indices (-KBDI, NDVI, and NDWI) and the nonlinearity of the indices were found to be significant by the Wald test statistic ($p < 0.05$) at a 95% confidence level. The "le Cessie-van Houwelingen" goodness-of-fit statistic confirmed that the three models fitted the data well at a 95% confidence level. Table I shows the results of the statistical measures that were used to rank the fire risk assessment performance of the indices extracted from the final model fit for each index. It is evident from the final ranking that NDWI performed better than NDVI and -KBDI. The results from Table I confirm the conclusions related to the factor plot (Fig. 6), where NDWI best separated the fire-dekades from the no fire-dekades.

Fig. 7 demonstrates the increased probability for a fire-dekade as the value of the index decreased, which conformed to expectations illustrated in Fig. 3. The logit proportions of fire activity by deciles of -KBDI, NDVI, and NDWI illustrate the goodness-of-fit of the logistic regression model. The logit proportions confirm that the model adequately fits the data since more than approximately 95% of the logit proportions fall inside the confidence intervals [40]. Fig. 7 also shows that probabilities of -KBDI, NDVI, and NDWI started to decrease when the values of -KBDI, NDVI, and NDWI were at their lowest level. This was attributed to the significant nonlinear behavior of the data.

B. Ability to Predict the Start of the Fire Season

The SPOT VGT S10 time-series consisted of four fire seasons (1998–2002) from which four values for the fire season metric (the start of fire season) could be extracted. Twenty-four metric values ultimately were available for analysis per index, since six weather stations were used. Fig. 8 summarizes the time lag data between the fire activity data and the selected indices. It should be noted that adequate fire activity data were unavailable to estimate the fire season and extract the metric for specific years. These metrics were filtered out which resulted in 20 time lags per index.

P-values from the t-test were adjusted with the Bonferroni method for multiple comparisons to evaluate the differences shown in Fig. 8 [38]. The p-values illustrate that time lags for -KBDI, NDVI, and NDWI were significantly positive at a 95% confidence level ($p < 0.01$). The results show that these fire risk indices related to vegetation water status start decreasing before the fire activity increases.

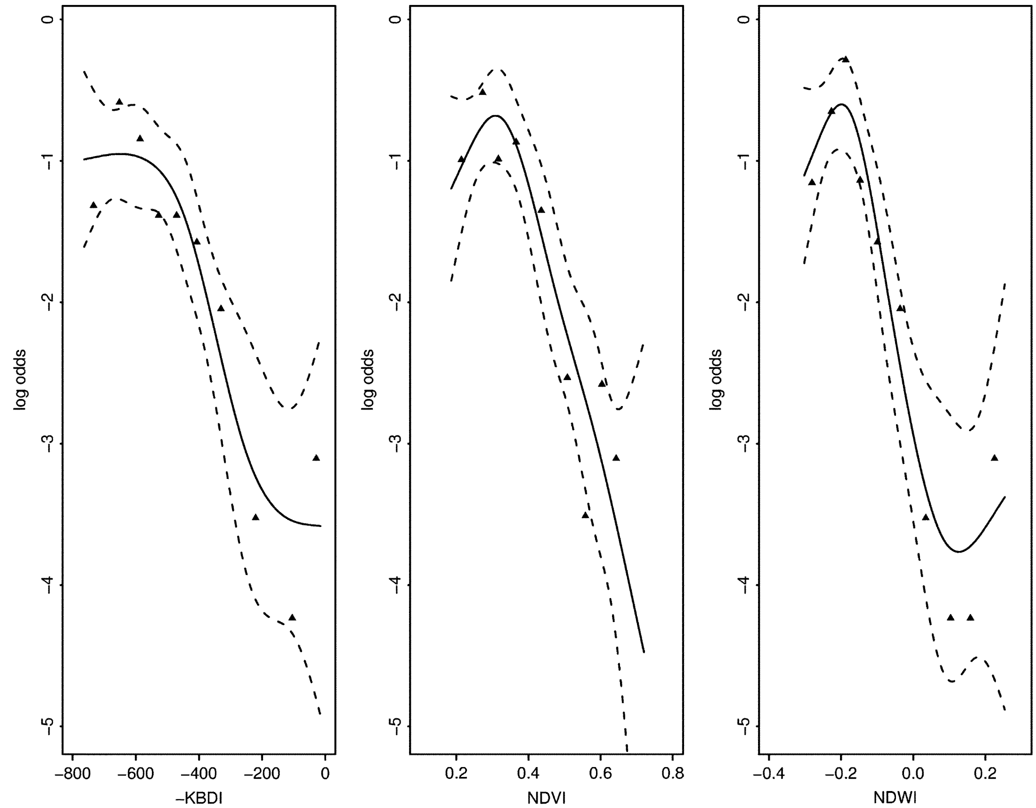

Fig. 7. Logistic regression curves (—) for log odds (i.e., $\log[P/1-P]$, where P is the probability of a fire-dekade) of a fire-dekade to occur versus -KBDI, NDVI, and NDWI. The dashed lines (- - -) indicate the upper and lower borders of the 95% confidence interval. The logit proportions of fire activity by deciles of -KBDI, NDVI, and NDWI (586 no fire-dekades and 115 fire-dekades) are shown by the ▲ to illustrate the model fit.

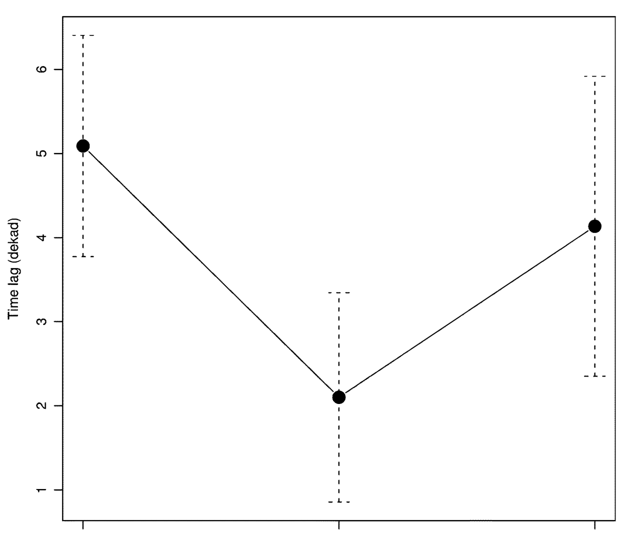

Fig. 8. Plot of the time lag means expressed in dekades (i.e., ten-day periods) for -KBDI ($n = 20$), NDVI ($n = 20$), and NDWI ($n = 20$) with fire activity at the start of the fire season. The error bars indicate the 95% confidence interval around each mean.

The analysis of variance model fit (ANOVA) indicated that the means of the time lags for -KBDI, NDVI, and NDWI were significantly different ($p = 0.01$). This result was confirmed by the Tukey multiple comparisons of means test which showed that time lags of -KBDI and NDVI differed significantly at a 95% confidence level ($p < 0.01$). The Tukey test also indicated that time lags of NDWI and NDVI ($p = 0.1$), and NDWI and -KBDI ($p > 0.3$) did not differ significantly at a 95% confidence level. The Levene's test for homogeneity of variance indicated that the variances of time lags of -KBDI, NDVI, and NDWI did not differ significantly at a 95% confidence level ($p = 0.2$).

VI. Discussion

A. Fire Risk Evaluation

In this study we focused on relating time-series of selected indices (-KBDI, NDVI, and NDWI) to field collected fire activity data. Satellite and meteorological indices, related to vegetation water status, were evaluated with a comparison technique based on ranking of logistic performance measures. Fire-dekades (i.e., 1), a ten-day period with one or more fires, and no fire-dekades (i.e., 0) were used as a binary measure of fire activity related to vegetation stress in a logistic regression model.

Multiple-fire-dekades, defined as a dekade with more than five fires were used in a preliminary phase of the research to better describe the fire activity. The use of multiple fire-dekades resulted in similar conclusions concerning the performance of the indices with fire-dekades. It therefore was decided to use a fire-dekade as an appropriate indicator to represent fire activity since the number of fires per decade did not influence the ranking of the selected fire risk indices. The use of fire-dekades and no fire-dekades as a binary predictor variable in a binary logistic regression model also was justified to make results comparable to other evaluation studies of meteorological fire risk indices [23], [24]. "Large fire-dekades" (e.g., a ten-day period were the burn area is larger than 10 ha) could be defined as another indicator of fire activity in the future when accurate burnt area data becomes available.

It is clear from Table I that the satellite-derived NDWI exhibited an improved performance over NDVI when studying the relation of each index with fire activity. The selected indices are directly (NDWI) or indirectly (NDVI) related to vegetation water status [10]. These findings showed that NDWI, related to the amount of water per unit area, is a superior indicator of seasonal fire activity during 1998–2002 for savanna vegetation of the KNP. A c-index of 0.78 was achieved for the logistic regression model with the NDWI as explanatory variable which means that the model has utility in predicting fire activity [40] (Table I). NDWI therefore could be used to monitor seasonal fire activity in savanna ecosystems.

The integration of satellite variables with meteorological variables such as wind speed, relative humidity, and socio-economic parameters, is however necessary to account for all the fire activity variation during a fire season. The logistic regression model with one index (e.g., NDWI) alone therefore should not be used as a reliable predictor of fire behavior. However, the remotely sensed index could be used to monitor the seasonal trend of fire potential and to determine the spatial allocation for management fires.

The distinct nonlinearity in the model indicated that the selected indices did not account for all the variation in fire activity. The nonlinearity demonstrated by Fig. 7 was attributed to the low fire activity at low index values (Fig. 3). Fig. 3 shows that fire activity started to decrease at the end of the fire season when indices (-KBDI, NDVI, and NDWI) were still low. This phenomenon was identified as the origin of the decrease in probability (i.e., log odds) of a fire-dekade when the index was at its lowest level (e.g., NDVI < 0.25), shown in Fig. 7. The phenomenon itself was explained by the fact that the fire management of the Kruger National Park was on high alert during the period of extreme weather conditions (e.g., no rain and high temperatures). Fire activity possibly decreased during this period because potential ignition sources were removed and occurring fires were immediately extinguished.

Another factor that influenced the illustrated index nonlinearity (Fig. 7) could have been the small fire activity dataset (115 fire-dekades occurred during 1998–2002). This can be explained by the rule that as vegetation dries, so does the probability of a fire occurrence increase [42]. The influence of exceptions, i.e., fires that occur when vegetation is still wet or lack of fires when vegetation is dry, increases for a smaller fire activity dataset. However, datasets of comparable sizes were used by Viegas *et al.* [23] to assess the performance of meteorological indices. The behavior of the indices could be explained by taking the nonlinear trends into account, as shown in Fig. 7. It would have been impossible, assuming linearity, to reveal the decrease in probability at the time period when indices were low.

B. Ability to Predict the Start of the Fire Season

The ability of the selected indices to predict the start of the fire season was studied by extracting the "start of fire season" metric from time-series of selected indices and fire activity data with TIMESAT and evaluating the time lag between these metrics. TIMESAT, a simple but robust method based on the Savitzky–Golay filter, also was used to remove noise (e.g., clouds and atmospheric conditions) in the time-series. The possibility exists that short-duration index anomalies caused by insufficient/abundant rain were suppressed by smoothing. TIMESAT, however, was developed to make the fit of the upper envelope approach the time-series and to reflect significant anomalies through an iterative process [27]. Chen *et al.* [43] concluded that this approach is more flexible and effective in obtaining high-quality time-series when compared to the existing Best Index Slope Extraction (BISE) algorithm and Fourier-based fitting methods.

The start of the fire season was defined as a metric to evaluate the effectiveness of the index time-series to serve as early warning indicators, based on the time lag between time-series of fire activity data and the selected indices (Fig. 8). Results corroborated the findings of Anyamba *et al.* [13], which showed that the fire season started at least halfway through the senescent phase of the NDVI curve, following the end of the rain season (Fig. 3). The results from Anyamba *et al.* [13] furthermore were confirmed by the finding that the selected indices detected change in vegetation condition before the fire season started (Fig. 8). The initiation of the decrease of the indices (-KBDI, NDVI, and NDWI) occurred before the fire activity increased, as illustrated by Figs. 3 and 8. This indicated that the indices detected change in vegetation water status before the start of the fire season and could be used to predict the start of the fire season.

It was shown that the NDWI time lags did not differ significantly from the NDVI and -KBDI time lags (Tukey test, $p > 0.1$) and that variances of NDWI, NDVI, and -KBDI were not significantly different (Levene's test, $p = 0.2$). Figs. 8 and 3 however show that NDWI tended to detect fire activity earlier than NDVI. This accentuated the direct relationship between NDWI and the amount of water content per unit area [10]. The water content per unit area, related to NDWI, first will decrease whereupon the vegetation will start drying out as meteorological conditions change (high temperatures and no rain). Consequently, the drying out of the vegetation will cause a decrease in NDVI. This phenomenon is highlighted by Fig. 3, which shows that NDWI started to decrease before NDVI during the fire part of the fire season. The difference between NDWI and NDVI time lags however was not significant (Tukey test, $p = 0.1$) because NDVI also is related to vegetation water status (i.e., FMC) for selected species with a shallow rooting system (i.e., grass species in savanna) [7].

Fig. 8 showed that -KBDI detected the start of the fire season earlier (approximately 4–6 dekades) than the NDVI (approximately 1–3 dekades). This also underlined the expected relationship between meteorological condition changes and vegetation drying out. The -KBDI, determined by the meteorological conditions, therefore will decrease after which the drying of vegetation will cause a decrease in NDVI.

The results demonstrated that analysis of time lags between time-series of fire activity and fire risk indices is an important consideration when evaluating performance of fire risk indices. Results of the ability of fire risk indices to detect the start of the fire season can be used as an indication of the difference in temporal properties. More research however is needed to study time lag at other specific moments in time (e.g., end of the fire season).

VII. Conclusion

The performance of satellite indices and meteorological indices for fire risk assessment in savanna ecosystems was evaluated. We focused on the relation of the time-series of selected indices (KBDI, NDVI, and NDWI) with fire activity data. The aim was to compare the performance of indices derived from climate and satellite data toward an operational implementation of an early warning tool for fire risk assessment.

We used binary logistic regression to rank indices in order to evaluate their performance as fire risk variables. Fire-dekades were used as an appropriate indicator of fire activity related to vegetation water status. RCS functions were applied to account for significant nonlinearity, thereby making the study of the nonlinear relationship between the indices and fire activity feasible. NDWI demonstrated higher overall performance and discrimination power when compared to NDVI and KBDI. The logistic performance measures showed an improved performance for the satellite-derived indices (NDVI, NDWI) when compared to the meteorological variables (KBDI) which could enable fire managers to obtain more accurate large area maps of fire risk for the allocation of fire management. The c-index, a measure of predictive ability, indicated that the NDWI can be used to predict fire activity ($c = 0.78$). NDWI therefore by extension could be used to monitor the seasonal trend of fire activity. This spatial and temporal information source on vegetation water status should be integrated with climate parameters (e.g., wind speed) for operational and accurate fire risk assessment.

The time lag between time-series of fire activity data and time-series of the selected indices at the start of the fire season also was studied to evaluate the ability of index time-series to predict the fire season start. Results showed that KBDI, NDVI, and NDWI can be used to predict the start of the fire season. This indicates that the temporal behavior analysis at specific points in time is important for the evaluation of performance of fire risk indices and that further research is required to study the time lag at other specific moments in time (e.g., end of the fire season). Binary logistic regression and temporal analysis have shown to be important tools to evaluate fire risk indices. The NDWI had the highest capacity to monitor fire activity dynamics and is able predict the start of the fire season. Further research also is needed to investigate the performance of meteorological and satellite-derived fire risk indices for other vegetation types (e.g., forest and shrubland).

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