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Monitoring herbaceous fuel moisture content with SPOT VEGETATION time-series for fire risk prediction in savanna ecosystems

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Abstract

This paper evaluated the capacity of SPOT VEGETATION time-series to monitor herbaceous fuel moisture content (FMC) in order to improve fire risk assessment in the savanna ecosystem of Kruger National Park in South Africa. In situ herbaceous FMC data were used to assess the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Vegetation Dryness Index (VDI), Improved VDI (IVDI), and Accumulated Relative NDVI Decrement (ARND) during the dry season. The effect of increasing amounts of dead vegetation on the monitoring capacity of derived indices was studied by sampling mixed live and dead FMC. The IVDI was proposed as an improvement of the VDI to monitor herbaceous FMC during the dry season. The IVDI is derived by replacing NDVI with the integrated Relative Vegetation Index (iRVI), as an approximation of yearly herbaceous biomass, when analyzing the 2-dimensional space with NDWI. It was shown that the iRVI offered more information than the NDVI in combination with NDWI to monitor FMC. The VDI and IVDI exhibited a significant relation to FMC with R^2 of 0.25 and 0.73, respectively. The NDWI, however, correlated best with FMC ($R^2 = 0.75$), while the correlation of ARND and FMC was weaker ($R^2 = 0.60$) than that found for NDVI, NDWI, and IVDI. The use of in situ herbaceous FMC consequently indicated that NDWI is appropriate as spatio-temporal information source of herbaceous FMC variation which can be used to optimize fire risk and behavior assessment for fire management in savanna ecosystems.

Keywords: Fuel moisture content; Live and dead fuel; Improved Vegetation Dryness Index (IVDI); Fire risk; SPOT VEGETATION

1. Introduction

This paper is the second in a two-part study to investigate the potential of the SPOT VEGETATION (SPOT VGT) satellite data for fire risk assessment in the savanna ecosystem of Kruger National Park, South Africa. In the first part, the most optimal method to estimate herbaceous biomass was selected through correlation analysis with in situ biomass measurements. In situ fire activity data were used to validate the hypothesis that fire risk assessment was enhanced by the monitoring of biomass and vegetation water content (VWC) with the SPOT VGT sensor (Verbesselt et al., 2006a). The correlation of VWC related satellite indices with in situ VWC measurements, however, still required evaluation in order to improve fire risk models. The moisture content of fuel is one of the most important variables in fire ignition and behavior modeling and is included in most fire risk models worldwide (Chuvieco et al., 2004a). The concept of fire risk therefore is restricted in this study to the likelihood of fire occurrence, given a particular fuel moisture content (FMC). The physical definitions of VWC used in literature vary from water volume per leaf or ground area (equivalent water thickness, i.e. EWT) to water mass per mass of vegetation dry matter (i.e. FMC) (Jackson et al., 2004). The quantity of water per dry mass (FMC) is a more important variable for monitoring fire risk when compared to the amount of water per area (EWT), since it affects fire ignition and propagation (Agee et al., 2002). Additionally, EWT is difficult to operationally measure in the field, because it requires the calculation of leaf area (Chuvieco et al., 2003).

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FMC is defined as the ratio of the water quantity in vegetation and the dry weight of vegetation for both the dead and live vegetation (i.e., fuel):

$$\mathrm{FMC} = \frac{\mathrm{FW} - \mathrm{DW}}{\mathrm{DW}} \times 100\ [\%] \tag{1}$$

where FW is the fresh weight and DW is the dry weight of the same vegetation sample. Dead fuels are fuels in which moisture content is exclusively controlled by environmental conditions (e.g., dormant or dead grasses, litter, twigs, branches), whereas live fuels are influenced by soil moisture and plant physiology (e.g., length of the root system). Live fuels can be divided in two categories, namely herbaceous and woody. Herbaceous fuels include grasses, forbs, and ferns, while woody fuels include the leaves and twigs of small woody shrubs (Carlson & Burgan, 2003). Live herbaceous fuels are modeled in the 1978 National Fire Danger Rating system as dead fuels when the live FMC dips below 30% (Carlson & Burgan, 2003). Dead fuels are the most dangerous because they are drier than live fuels and more dependent on atmospheric variables (e.g., relative humidity, solar insolation). The moisture content of live fuels has a marginal role in fire ignition, but it is critical in fire propagation modeling because the amount of water in live vegetation is directly related to the rate of fire spread (Carlson & Burgan, 2003).

Traditional methods for FMC measurement are based on field sampling or approximation by meteorological fire risk indices (Camia et al., 1999). Dead FMC can be estimated with meteorological danger indices, which attempt to account for the adsorption–evaporation relationship in inert materials (Camia et al., 2003). Applying meteorological indices to live FMC trends is complex because live plants are much less dependent on atmospheric conditions than dead materials (Chuvieco et al., 2004b). Additionally, meteorological data are frequently not available for fire prone areas, whereas satellite data have the potential to provide spatial and temporal measurements of live FMC given the large areas affected by wildland fires. Several remote sensing studies, however, included dead fuels when measuring live FMC of herbaceous vegetation since dead grasses are also observed by satellite sensors (e.g., Chuvieco et al., 2003; Ceccato et al., 2002; Hardy & Burgan, 1999). Herbaceous FMC, instead of strictly live or dead FMC, is defined in this study as the FMC of a mixture of actual proportions of live and dead herbaceous vegetation. On the one hand, the inclusion of dead fuels in FMC samples increases the correlation with satellite vegetation indices since the overall FMC variation will increase. On the other hand, the estimation of FMC for dead fuels from remotely sensed data is more complex since dead fuels do not show changes in chlorophyll content of leaves due to weather related water variations.

The estimation of live FMC from satellite data has been attempted with both high and low resolution sensors. The former reduces noise in quantitative correlation with field data, since they provide a higher spatial accuracy (Chuvieco et al., 2002). The latter offers a higher temporal resolution and are more likely to be used operationally since fire managers require frequent updates of FMC (Chuvieco et al., 2004b). Several studies have examined relationships between satellite vegetation indices and live FMC. Good correlations between FMC and multi-temporal series of NOAA-AVHRR have been found for herbaceous species using the normalized difference vegetation index (NDVI), but low correlations coefficients were found for shrubs and trees (Chuvieco et al., 2002; Hardy & Burgan, 1999; Illera et al., 1996). These studies assumed that the chlorophyll content of leaves or the degree of curing was proportional to the moisture content. This assumption may be correct for some species but cannot be generalized to all ecosystems. Water absorption measures, such as the Normalized Difference Water Index (NDWI), may prove to be more appropriate for monitoring live FMC than measures of chlorophyll absorption since the NDWI is directly related to plant water content (Chuvieco et al., 2002; Dennison et al., 2005). The NDWI, first proposed by Hunt et al. (1987) who named it the Normalized Difference Infrared Index, is derived by combining NIR and SWIR spectral domain to derive leaf water content:

$$\mathrm{NDWI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{SWIR}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{SWIR}}} \tag{2}$$

where ρ_{NIR} and ρ_{SWIR} are the reflectances of the NIR and SWIR regions, respectively. Gao (1996) used the SWIR band centered at 1.24 μm, now available on MODIS, for NDWI because this band has similar atmospheric transmittance as the NIR band whereas other studies used the SWIR band in the 1.58–1.75 μm spectral domain to derive the NDWI from SPOT VEGETATION or LANDSAT TM/ETM+imagery (e.g., Jackson et al., 2004; Maki et al., 2004; Xiao et al., 2002).

Additional efforts are required for vegetation canopies where the influence of soil and plant species mixing complicates the estimation of FMC from satellite data. The total leaf area quantity per unit area, namely the leaf area index (LAI), must be known in addition to NDWI in order to estimate FMC at canopy level (Maki et al., 2004). Previous studies have investigated the relationship between LAI and remotely sensed data and reported findings suggesting that LAI was related to NDVI (Carlson & Ripley, 1997; Myneni et al., 1997). Maki et al. (2004) accordingly used the NDVI to estimate the total leaf area quantity and derived the vegetation dryness index (VDI) by combining NDVI and NDWI. Ceccato et al. (2002), however, demonstrated that NDVI is highly linearly related with NDWI in savanna ecosystems. It is therefore likely that the combination of NDVI and NDWI will not be able to improve the monitoring of herbaceous FMC in savanna ecosystems. On the other hand, the sum of the Ratio Vegetation Index values (RVI), the ratio of NIR and red wavelength ranges, during the previous rain season (November to April) is significantly related to the yearly herbaceous biomass during dry season (Verbesselt et al., 2006a):

$$i\mathrm{RVI} = \sum_{i=1}^{n} \mathrm{RVI}_i \tag{3}$$

where RVI_i is the RVI value at time i. It consequently was hypothesized that iRVI, in combination with NDWI, could improve the VDI (i.e. IVDI) and optimize the monitoring of herbaceous FMC for fire risk assessment.

This study evaluated the capacity of selected satellite vegetation indices to monitor herbaceous FMC data during dry season in order to improve fire risk assessment. The herbaceous FMC sampled during the dry season included the actual proportions of live and dead vegetation in the study area in order to represent the moisture contents that wild land fires would encounter when burning through the herbaceous layer. The effect of increasing amounts of dead herbaceous vegetation as the dry season progresses is studied, since fire risk assessment is particularly important in that period due to the high fire activity. The selected vegetation indices derived from the SPOT VGT sensor were NDVI, NDWI, VDI, IVDI, and the accumulated relative NDVI decrement (ARND).

2. Study area and data

2.1. Study area

The Kruger National Park (KNP), located between latitudes 23°S and 26°S and longitudes 30°E and 32°E in the low-lying savannas of the north-eastern part of South Africa, was selected as study area (Fig. 1). The KNP was chosen because of the existing facilities to measure biomass and FMC in the field and an established fire research program to improve fire management based on fire risk and behavior assessment. Elevations range from 260 to 839 m above sea level, and mean annual rainfall varies between 350 mm in the north and 750 mm in the south. Most of the rain falls during a 5 month rain season in the summer months (November to April) (van Wilgen et al., 2004).

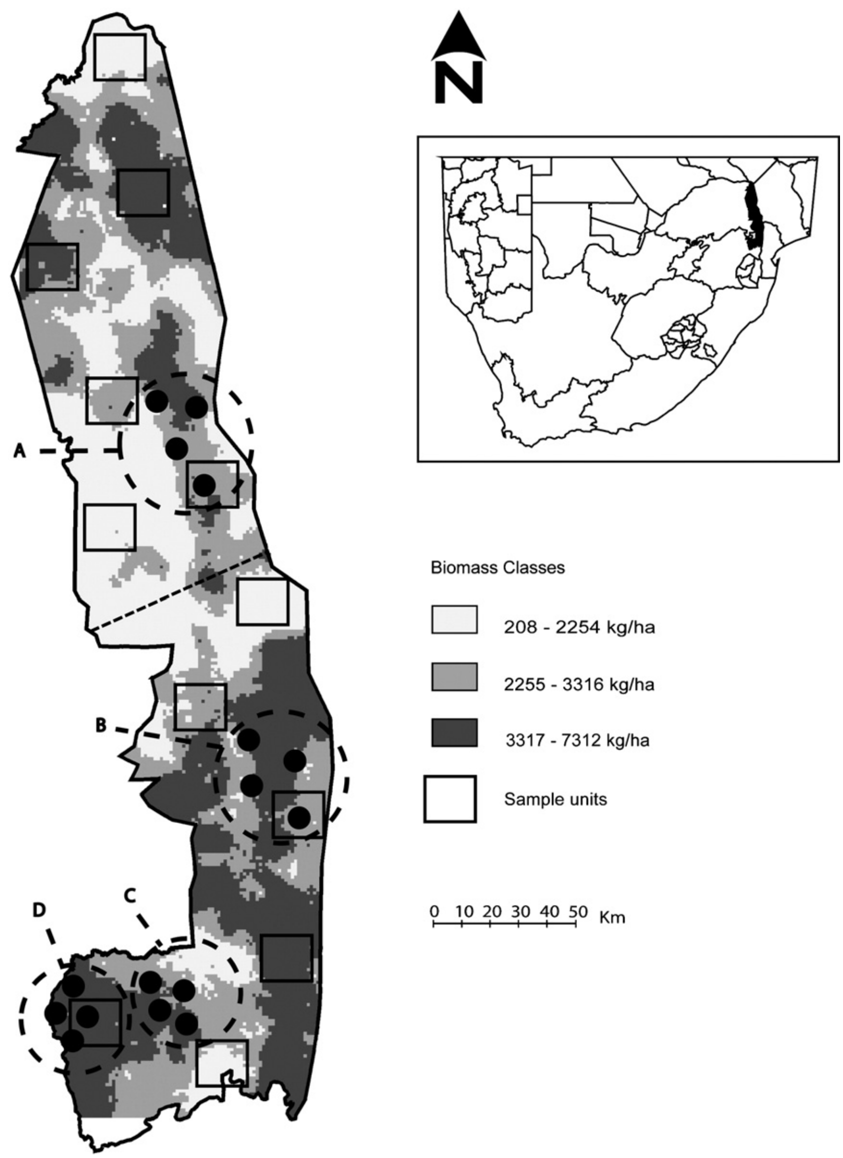

Fig. 1. Sampling design and experimental burn plots (EBP) in the Kruger National Park, South Africa. The EBP's consist of four replicates (●) in each of the four major savanna woodland landscapes in the park; (A) Mopani, (B) Knob Thorn, (C) Combretum, and (D) Sourveld plots. A two-stage stratification approach was used to divide the study area in 6 strata (2 vegetation type strata separated by (- - -) and three biomass classes) to select the 12 sample units (Verbesselt et al., 2006a). The legend illustrates the range in herbaceous biomass (kg/ha) per class. Southern Africa is shown with the borders of the provinces and the study area (black) (top right).

The KNP comprises mainly tropical grassland with scattered thorny, fine-leafed trees of the families Mimosaceae and Burseraceas. An exception is the northern part of the KNP where the Mopane, a broad-leafed tree belonging to the Ceasalpinacea, almost completely dominates the tree layer.

2.2. Satellite data and pre-processing

The potential for fire risk assessment of the S10 ten daily composites of SPOT VGT data, acquired over the study area for the period April 1998 to September 2003, was evaluated. The S10 syntheses provide surface reflectance in the blue (0.43–0.47 μm), red (0.61–0.68 μm), near-infrared (NIR, 0.78–0.89 μm), and shortwave-infrared (SWIR, 1.58–1.75 μm) spectral bands. The SPOT VGT images were acquired daily by the SPOT VGT satellite around 10h30 local solar time, which is the best acquisition time to obtain a minimal cloud cover. This acquisition time, however, is not most appropriate time to monitor maximum vegetation dryness since minimum FMC for grasslands occurs around 14h00, but offers a good approximation (Chuvieco et al., 1999). The atmospherically, geometrically, and radiometrically corrected S10 images have a spatial resolution of approximately 1 km^2. Images were atmospherically corrected using the simplified method for atmospheric correction (SMAC) (Rahman & Dedieu, 1994).

The S10 data were computed from all the overpasses above the study area during 10 daily periods. The synthesis between different passes is performed by selecting the measurement that corresponds to the maximum NDVI value to reduce the influence of the atmosphere, aerosols, and clouds (Holben & Fraser, 1984). This Maximum Value Compositing (MVC) technique minimizes data gaps due to cloud interference or missing data and overcomes systematic errors that reduce the satellite index value. The disadvantage of the compositing technique is that the temporal resolution is reduced from daily to 10 daily resolutions and it has a tendency to select pixels with lower vegetation dryness (Chuvieco et al., 2005). The 10-day revisit cycle of the SPOT VGT satellite might not be amenable to operational fire risk assessment, but is sufficient for evaluation of the fire risk assessment ability of satellite data (Maki et al., 2004; Verbesselt et al., 2006b). Daily satellite data from SPOT VGT, MODIS, AVHRR, and other satellite sensors that offer a high temporal resolution can be used for operational purposes once the performance of satellite time-series for assessing fire risk has been fully evaluated. The SPOT VGT pre-processing is described in detail in Verbesselt et al. (2006a).

2.3. In situ herbaceous FMC data

The herbaceous FMC data were measured on experimental burn plots (EBP's), established for optimization of fire management in the Kruger National Park (Biggs et al., 2003). The EBP trial initiated in 1954 is one of few ongoing long-term fire ecology research projects in Africa and aims to assess the impact of different fire regimes (Govender et al., 2006). The trial consists of 16 replicates, made up of four replicates in each of the four major savanna woodland landscapes (Gertenbach, 1983): *Colophospermum* mopane shrubveld (Mopani), *Sclerocarya birrea/Acacia nigrescens* savanna (Knob Thorn), *Combretum collinum/Combretum zeyheri* woodland (Combretum), and Lowveld Sour Bushveld (Sourveld) (Fig. 1). Each replicate consists of 12 to 14 full plots with each plot covering approximately 7 ha (i.e. 370 × 180 m). The trial is described in detail by Biggs et al. (2003). Prior to each experimental fire on an EBP, the FMC of the grass sward was estimated according to Eq. (1). The method for sampling herbaceous FMC combined live plus dead fuels, and also combined different grass species in order to represent the moisture contents that wild land fires would encounter. Four spatially random samples of the grass sward (approximately 100 g each) were placed in air-tight bottles, weighed, and dried at 65 °C for four days to determine dry and wet weight. Grass fuel loads are dominant on the EBP's and contribute 70–98% of the total fuel (Shea et al., 1996). The majority of fires occurring in tropical grasslands, savannas, and woodlands are primarily supported by herbaceous fuel load, whereas the living trees typically do not burn (Govender et al., 2006; van Wilgen et al., 2000). The herbaceous FMC data were selected to evaluate satellite indices since monitoring the FMC of the most flammable fuel was considered most important for this study.

The in situ herbaceous FMC data, collected around midday (10h00–14h00 local time) and available from 1999 to 2002, were selected during the period with the highest fire activity (i.e. May to October). The daily variations in herbaceous FMC for the study area are small when compared to the seasonal variation of FMC (wet to dry season) where vegetation transforms from live to dead vegetation (Personal Communication, Govender N., scientific services KNP). Daily variations increase when vegetation senesces, since dead vegetation is more dependent on dynamic atmospheric conditions (e.g., relative humidity) but remain smaller than the seasonal FMC variation (Agee et al., 2002). Furthermore, FMC conditions measured on the field plots would still be comparable to those at satellite acquisition time since measurement around midday minimizes daily FMC variation.

The sampling strategy of FMC data was similar to the nested sampling strategy used by Chuvieco et al. (2004b) to relate FMC data with coarse spatial resolution images. Nested sampling is a common strategy for the scaling-up of field measurements (Atkinson et al., 2000). The sampling involves collecting data from plots at different levels of details, e.g. plot and replicates stratified per major landscape type, while acknowledging the convenience of working with homogeneous areas for calibration purposes (Fig. 1). Firstly, the KNP is covered mainly by savanna woodland on very gentle slopes (Scholes et al., 1996). No agricultural practices are carried out since it is a protected area, and temporal changes of 10-daily imagery therefore are associated with seasonal vegetation trends rather than crop variations. Secondly, field measurements of EBP's could be considered as representative of the temporal variation of FMC for large plots, since no abrupt spatial changes in climatic variables (e.g. temperature, rainfall) occurred in the study area (van Wilgen et al., 2000). The FMC measurements consequently can be coupled to coarse spatial resolution satellite images (Chuvieco et al., 2004b). An average FMC value per replicate and date was derived since FMC data from the EBP trial were available for one to three plots (4 to 12 random FMC samples) per each replicate and date.

Satellite indices were derived for each 10-daily period of available S10 SPOT VGT data and concurrent FMC data by selecting pixels in 3 × 3 pixel windows centered at each of the replicates (Fig. 1). The median satellite index value of the 9 pixel-window was retained instead of single pixel index values since it is less affected by extreme values, and therefore is less sensitive to potentially undetected data errors. It was assumed that the effect of the experimental burns after each FMC measurement was reduced as a result of the maximum NDVI compositing (MVC) technique and the sampling strategy. Firstly, pixels do not have a maximum NDVI after an EBP burn due to the burning of biomass and therefore are not selected by the MVC technique (van Leeuwen et al., 1999). The reduced biomass due to a previous fire also could not produce a lower NDVI value since FMC samples on a specific EBP were never repeated within a year. Secondly, the influence of the burn on the biomass and vegetation moisture condition measured by the satellite sensor is minimal since the size of an actual EBP (i.e. 370 × 180 m) is small compared to the 1 × 1 km sample size of the selected median value used for derivation of remotely sensed vegetation indices.

3. Methodology

In this section the methods to derive the VDI, IVDI, and ARND firstly are explained. Secondly, the methodology to analyze the correlation of selected satellite indices (NDVI, NDWI, VDI, IVDI, and ARND) with in situ herbaceous FMC is described.

3.1. Vegetation indices related to FMC

3.1.1. VDI

Information on the quantity of water and leaf material per unit area is necessary to estimate FMC or vegetation dryness at canopy level (Maki et al., 2004). Ceccato et al. (2002) have shown that NDWI is related to EWT or the quantity of water per unit area in savanna ecosystems. Carlson and Ripley (1997), on the other hand, reported findings that LAI, as an approximation of leaf quantity per unit area (Maki et al., 2004), was related to NDVI. Fig. 2 illustrates the scatter plot of NDVI and NDWI values (a) during the dry season periods (May–September) and (b) for the whole period from 1998 to 2003. The scatter plots indicate that maximum and minimum water contents per unit area (NDWI) are associated with leaf quantity per unit area approximated by NDVI. Maki et al. (2004) illustrated that this feature is similar to the water deficit index (WDI) (Moran et al., 1994; Vidal & Devaux-Ros, 1995). The WDI is an index that indirectly estimates FMC per leaf quantity with the surface minus air temperature difference ($T_s - T_a$). A simplified WDI, based on an empirical parameterization of the relationship between T_s and NDVI, was suggested by Sandholt et al. (2002) to estimate surface moisture status of a savanna ecosystem in Senegal. The VDI, in contrast, directly estimates FMC per NDVI using NDWI (Maki et al., 2004). Fig. 3a illustrates the theoretical trapezoidal shape and the definition of the limits, i.e. dry and wet edge, used to derive the VDI:

$$\mathrm{VDI} = 1 - \frac{\mathrm{AC}}{\mathrm{AB}} \tag{4}$$

where AC and AB are the distances represented on Fig. 3a, between the left (dry conditions) and right (wet conditions) limits of the trapezoid. Vertices n ($n = 1, 2, 3, 4$) in Fig. 3a are

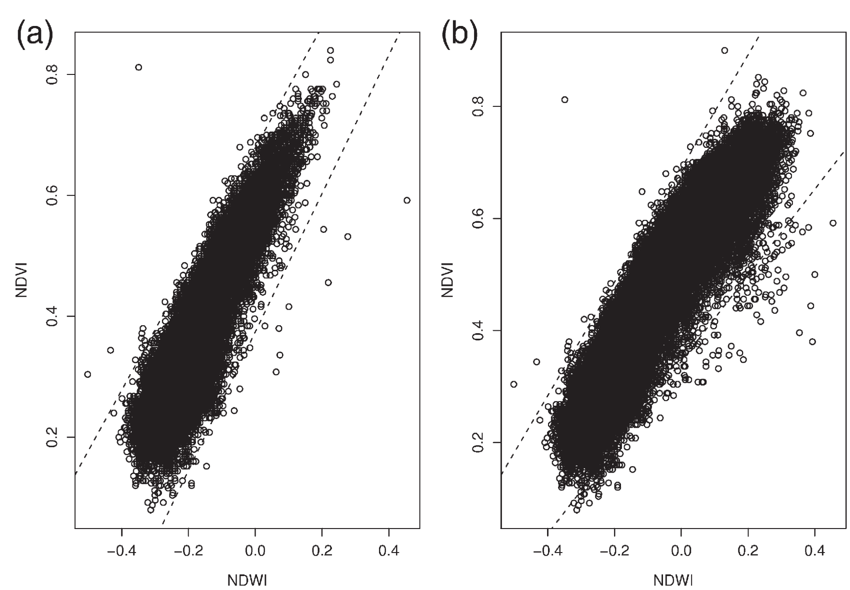

Fig. 2. Stable dry and wet edges (- - -) representing the spatial and temporal range in NDVI/NDWI 2-dimensional space. Thirty random pixels per sample unit (Fig. 1) were used to select data during the dry season (May–September) (a) or the whole year (b) from 1998 to 2003. The dry and wet edges (- - -) are visualized on the left and right hand side of the data, respectively.

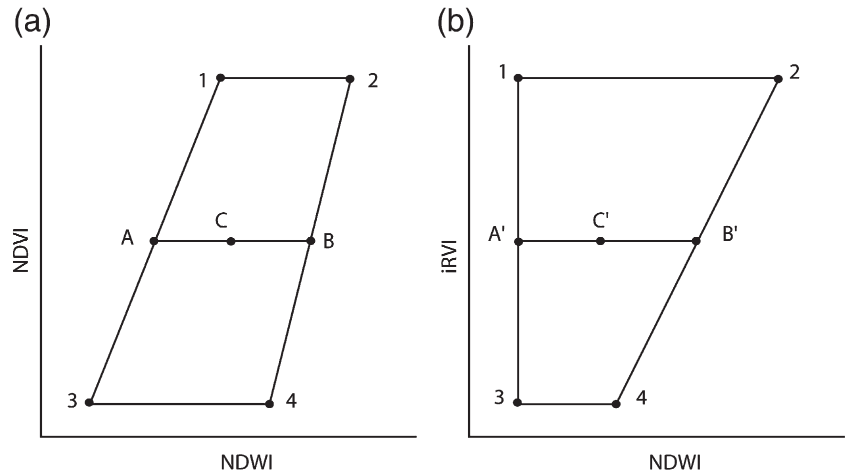

Fig. 3. The theoretical trapezoidal and triangular shape resulting from (a) the NDVI and NDWI and (b) the iRVI and NDWI continuum to derive VDI and improved VDI (IVDI), respectively. The VDI of point C is given by 1-AC/AB as shown in Eq. (4) and the IVDI of point C′ is given by 1-A′C′/A′B′, as shown in Eq. (5), where (1) indicates rich vegetation and poor water, (2) rich vegetation and rich water, (3) poor vegetation and poor water, and (4) poor vegetation and rich water.

rich vegetation and poor water, rich vegetation and rich water, poor vegetation and rich water, and poor vegetation and poor water, respectively. The slope and intercept of the dry and wet edge were obtained using least squares linear regression of the minimum and maximum NDWI values, respectively, for small intervals of NDVI extracted in the NDVI/NDWI space (Sandholt et al., 2002). Verstraeten et al. (2005) illustrated that this method performed best after comparison of several sorting and selection methods to estimate the boundaries of the 'T_s/Surface Albedo' space, which is similar in shape to the NDVI/NDWI feature space.

Additionally, care must be taken when deciding on the temporal and spatial selection of satellite data to derive the dry and wet limits of the NDVI/NDWI space. Firstly, 30 random pixels per sample unit were selected in this study to represent the spatial variation in NDVI and NDWI in the study area from 1998 to 2003 (Fig. 1) (Verbesselt et al., 2006a). Distinctly more outliers were present when all pixels in the study area were used, which made the accurate estimation of upper and lower boundary unreliable. Similarly, Sandholt et al. (2002) illustrated that estimation of the dry and wet edges in the Ts/NDVI space was difficult due to atmospheric effects and cloud screening. Secondly, Fig. 2a illustrates that when only data during dry seasons from 1998 to 2003 were selected, the maximum water content line was underestimated when compared to Fig. 2b where all the data from 1998 to 2003 were used. This could cause an underestimation of derived VDI values and therefore all NDVI and NDWI values from 1998 to 2003 were selected in order to obtain a stable maximum water content line.

3.1.2. IVDI

The improved VDI (IVDI) was proposed in order to enhance herbaceous FMC monitoring in savanna ecosystems by analyzing the iRVI/NDWI instead of the NDVI/NDWI feature space. Fig. 4a and b illustrate the iRVI/NDWI scatter plot, which indicates that maximum and minimum water contents per unit area (NDWI) were associated with the yearly herbaceous biomass amount (iRVI). 30 random pixels per sample unit were used to select data during the dry seasons (May–September) (Fig. 4a) and the whole period (Fig. 4b) from 1998 to 2003, similar to the methodology for derivation of the VDI. Fig. 4a illustrates that when only data during dry seasons from 1998 to 2003 were selected, the maximum water content line was underestimated when compared to Fig. 4b where all the data from 1998 to 2003 were used, similar to the VDI method. This could cause an underestimation of derived IVDI values and therefore all iRVI and NDWI values from 1998 to 2003 were selected in order to obtain a stable maximum water content line.

A more triangular shape was observed in the case of the iRVI/NDWI feature space as opposed to the trapezoidal shape in the NDVI/NDWI feature space (Fig. 4b). Other studies also observed a triangular shape when a full range of leaf quantities and vegetation moisture contents was represented in the data (e.g. Carlson et al. (1995), Gillies et al. (1997), and Vidal and Devaux-Ros (1995)). The iRVI/NDWI feature space shown in Fig. 4b subsequently can be interpreted as the space representing the range in water content (NDWI) for each yearly amount of herbaceous biomass (iRVI) per unit area (per pixel). The wet edge in Fig. 4b illustrates that the water content increased with the available herbaceous biomass per unit area. Conversely, Fig. 4b shows that a constant NDWI value represented the dry edge for iRVI values from approximately 40 to 100. A full range of NDWI values for iRVI values lower than 40 and higher than 100 was not available in this savanna ecosystem during the analysis period. However, Fig. 4b illustrates that a minimum NDWI value of approximately −0.4 was obtained for the majority of iRVI values in the savanna ecosystem of the study area.

Feature space parameters were estimated on the basis of pixels representing the entire range of surface moisture contents, from wet to dry vegetated surfaces. The slope and intercept of the dry and wet edges, similar to the VDI method, were obtained using least squares linear regression of the minimum and maximum NDWI values, respectively, for small intervals of iRVI extracted in the iRVI/NDWI space. Fig. 3b

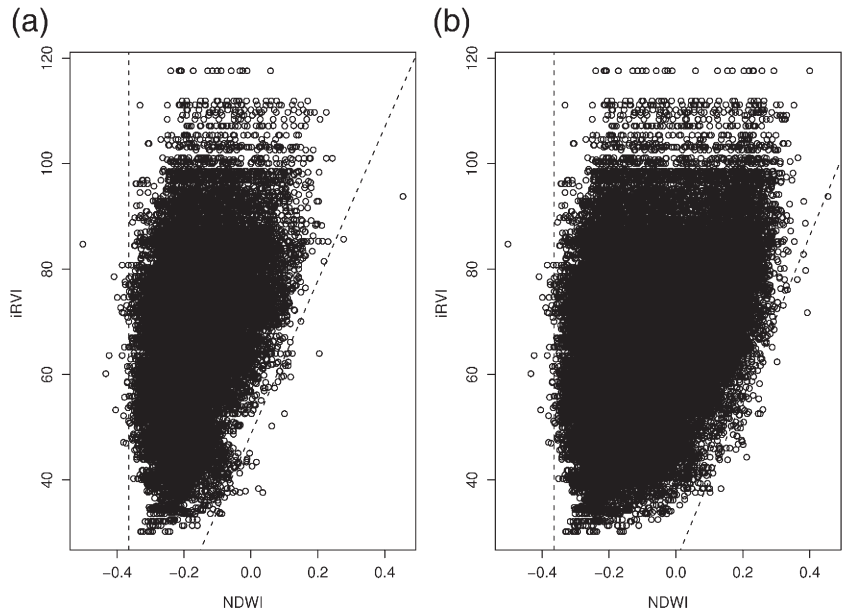

Fig. 4. Stable dry and wet edges (- - -) representing the spatial and temporal range in iRVI/NDWI 2-dimensional space. Thirty random pixels per sample unit (Fig. 1) were used to select data during the dry season (May–September) (a) or the whole year (b) from 1998 to 2003. The dry and wet edges (- - -) are visualized on the left and right hand side of the data, correspondingly.

illustrates the theoretical shape and the definition of the limits, i.e. dry and wet edges, used to derive the IVDI:

$$\mathrm{IVDI} = 1 - \frac{A'C'}{A'B'} \tag{5}$$

where $A'C'$ and $A'B'$ are the distances represented on Fig. 3b, between the left (dry conditions) and right (wet conditions) limits of the shape.

3.1.3. ARND

The ARND was selected in order to compare its capability for monitoring in situ FMC with the vegetation indices (NDVI, NDWI, VDI, and IVDI), since the ARND has been shown to perform best as an index to predict local fire activity in the study area (Verbesselt et al., 2006a). The ARND is a fire risk-related index, based on the NDVI, specifically designed for and applied to forested areas in the Mediterranean climate zone (Illera et al., 1996; Sebastian-Lopez et al., 1991). The ARND is derived as:

$$\mathrm{ARND} = \sum_{i=1}^{n} \frac{\mathrm{NDVI}_{(i+1)} - \mathrm{NDVI}_{(i)}}{\mathrm{NDVI}_{(i)}} \tag{6}$$

where $\mathrm{NDVI}_{(i)}$ is the NDVI value at time i. The temporal evolution of the NDVI can be used to monitor fire risk because a decrease in the NDVI is related to an increase in vegetation stress and fire risk of herbaceous vegetation (Chuvieco et al., 2003). Vegetation stress can be defined as any disturbance that adversely influences growth (Jackson, 1986). This stress can be due to many factors, one of which is a lack of water that restricts transpiration, inducing closure of stomata and resulting in less water evaporating from the leaf surface.

3.2. Correlation analysis with in situ herbaceous FMC

Ordinary least squares analysis (OLS) was used to analyze the correlation between explanatory variables (NDVI, NDWI, VDI, IVDI, and ARND) and in situ herbaceous FMC data. Physical interpretation of index behavior became feasible by taking non-linear behavior of the explanatory variables into account (Verbesselt et al., 2006b). The explanatory variables therefore were expanded into restricted cubic spline functions (RCS), with a specific number of knots (Harrell, 2001). The coefficient of determination (R^2) was derived between extracted satellite indices and in situ FMC data. The satellite vegetation index with the highest R^2-value was considered most suitable to monitor FMC during the study period. The different correlation coefficients (r) were transformed into a normalized distribution using a Fischer z-transform to test whether the correlation coefficient of the best method represented a significant improvement over correlation coefficients of the other methods (Dennison et al., 2005):

$$Z_f = 0.5\ln[(1+r)/(1-r)] \tag{7}$$

where r is the correlation coefficient. The difference between Z_f for two indices was calculated as:

$$Z = \frac{Z_{f1} - Z_{f2}}{\sqrt{(1/(n_1-3) + 1/(n_2-3))}} \tag{8}$$

where n is the number of samples and Z_{f1} and Z_{f2} are the transformed values of index 1 and 2, respectively. The Z_f-values were compared against the Z_f-value of the index with the highest R^2 in order to verify whether the correlation coefficients were significantly different (Verbesselt et al., 2006a). A one-

Table 1
Results of correlation analysis between in situ herbaceous FMC data and remote sensing vegetation indices (NDVI, NDWI, VDI, IVDI, and ARND)

FMC ~ Index	R^2	SE_{model}	$P_{variable}$	$P_{non\text{-}linearity}$	$Z_{fNDWI}-Z_f$	p
NDVI	0.73	0.15	<0.01	0.59	0.04	0.43
NDWI	0.75	0.14	<0.01	0.03	/	/
VDI	0.25	0.25	0.01	0.66	0.77	<0.01
IVDI	0.73	0.15	<0.01	0.05	0.04	0.43
ARND	0.60	0.18	<0.01	<0.01	0.29	0.12

where R^2 is the coefficient of determination, SE_{model} is the residual standard error of the model, $P_{variable}$ the significance of the variable in the model, $P_{non\text{-}linearity}$ the significance of non-linearity in the model, Z_f the Fisher z-transformation score, and p the significance of the one tailed t-test (n=37).

tailed t-test was used to determine whether Z was significantly positive. A significant Z-value indicated a significantly stronger correlation for the index with the highest correlation coefficient.

4. Results

The results of the correlation analysis of the selected indices with in situ herbaceous FMC are presented in Table 1. The explanatory variables were expanded into restricted cubic spline functions (RCS), with three knots to account for the non-linear behavior between indices and FMC data. Three knots were used in order to prevent over-fitting of the data, since only 37 measurements were available. This approach was used in all the fitted OLS regression models to facilitate comparison of results, while accounting for similar amounts of non-linearity (Harrell, 2001).

Table 1 shows that the selected index variables were significantly related to FMC at a 95% confidence interval. The correlation coefficient-values (r) of IVDI, NDVI, ARND did not differ significantly ($p>0.10$) from the r-value of NDWI, whereas the VDI value did differ significantly from NDWI ($p<0.01$) (Table 1). Harrell (2001) stated that the use of plots is the best way to present results from fitted RCS functions. Fig. 5 illustrates the results of the OLS regression model between FMC and selected indices as explanatory variables. An approximately bi-modal distribution is shown in the scatter plots (a, b, d, and e), where values are clustered in low (<0.5) and high (>0.6) FMC groupings (Fig. 5). Furthermore, the NDWI (p=0.03), IVDI (p=0.05), and ARND ($p<0.01$) in Fig. 5b, d, and e illustrate a significant non-linear behavior. Table 1 and Fig. 5a, c contrarily show that the NDVI and VDI were linearly related to the herbaceous FMC at a 95% confidence interval (p=0.59 and 0.66, respectively). Additionally, the VDI demonstrated a weak but positive correlation, whereas the IVDI showed a negative and strong correlation with in situ herbaceous FMC (Fig. 5c and d).

5. Discussion

The discussion was divided into two main sections, namely (1) correlation analysis of the selected indices with in situ herbaceous FMC data, and (2) the use of these indices for fire risk assessment.

5.1. Correlation analysis with in situ herbaceous FMC

The transition from wet to dry savanna vegetation occurs fast (approximately 1–2 months), which explains the approximately bi-modal distribution, along with the fact that FMC measurements were not exported continuously during the dry season. The data of low and high FMC groups were not analyzed separately, since the objective of this study was to evaluate the potential of remote sensing to assess herbaceous FMC during the complete dry season. The significant coefficients of determination in Table 1 ($p<0.05$) indicate that remote sensing can be used to monitor herbaceous FMC of vegetation samples with increasing proportion of dead/dormant versus live vegetation towards the end of the dry season. These results corroborated the findings of Dilley et al. (2004) who obtained accurate FMC estimations with the NDVI derived from the NOAA-AVHRR sensor over the complete curing duration of three grassland sites in Australia.

Table 1 indicates that the IVDI, derived from the iRVI/NDWI feature space, was correlated stronger than VDI with the herbaceous FMC (R^2=0.73 versus 0.25) (Table 1). Furthermore, Fig. 5c illustrates a positive correlation between VDI and FMC, which is against expectations since the VDI is a measurement of vegetation dryness and should exhibit an inverse relationship with FMC. An accurate FMC-VDI model fit was negated by the low sensitivity of VDI to FMC (R^2=0.25). These findings corroborated the hypothesis that the iRVI/NDWI feature space, used to derive the IVDI, was more appropriate for monitoring vegetation moisture dynamics than the NDVI/NDWI space. The NDVI and NDWI values were highly correlated (Fig. 2a, b) and confirmed the earlier findings of Ceccato et al. (2002). NDVI is indirectly related to the herbaceous FMC since NDVI is related to chlorophyll content of leaves or LAI (Chuvieco et al., 2004b), which can be assumed proportional to moisture content or degree of curing (Hardy & Burgan, 1999). It can be concluded that NDVI does not contain extra information, which is needed to optimize FMC monitoring with NDWI in savanna ecosystems dominated by an herbaceous layer.

The IVDI needs to demonstrate a distinct improvement for monitoring FMC when compared to NDVI or NDWI, since the derivation of NDWI or NDVI is less complex than the derivation of IVDI. Maki et al. (2004) did not compare the abilities of VDI and NDVI or NDWI to monitor FMC. This study illustrated that the IVDI exhibited significant potential to monitor herbaceous FMC, although the IVDI did not offer an improvement when compared to NDWI or NDVI in savanna ecosystems (Table 1). The use of one index to estimate FMC, however, can be regarded as an inflexible approach, since it assumes that only one variable is required for estimation, which is rarely the case (Verstraete & Pinty, 1996). For example, FMC also can be estimated by inversion of radiative transfer models which simulate EWT and dry matter content (DMC) and can be expressed as the ratio of EWT and DMC (Riaño et al., 2005). Further research is necessary to evaluate and improve the monitoring of leaf quantity using satellite-derived indices towards optimization of the VDI-concept. The VDI could be improved by derivation of an iRVI that accounts for the influence of biomass decay during

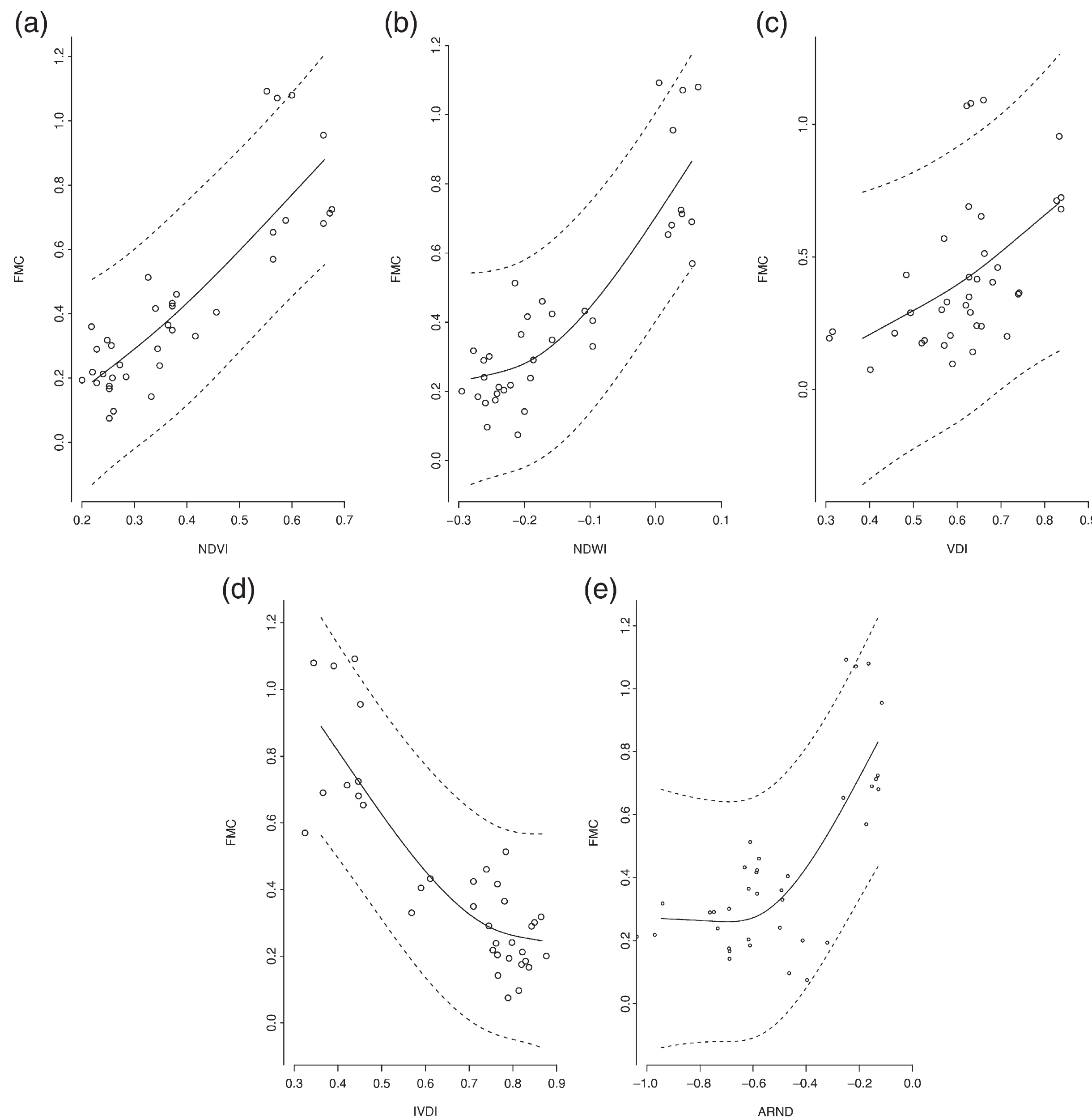

Fig. 5. The OLS regression curves (—) between FMC as dependent variable and (a) NDVI, (b) NDWI, (c) VDI, (d) IVDI, and (e) ARND as explanatory variables. The dotted lines (- - -) indicate the upper and lower borders of the 95% confidence interval (n=37).

dry season such that the link with FMC is optimized, since a decrease in herbaceous biomass is expected during the drought period (Scholes et al., 1996).

The NDWI and IVDI in Fig. 5b and d illustrate a significant non-linear behavior at low FMC values (Table 1). Table 1 and Fig. 5a contrarily show that the NDVI was linearly related to the herbaceous FMC at a 95% confidence interval (p=0.59). Stow et al. (2005) indicated that the visible atmospherically resistant index (VARI) (Gitelson et al., 2002), which is based on green, red, and blue spectral regions of the MODIS sensor, may be less sensitive than NDWI to spatial variation in vegetation cover fractions and background reflectance. Dennison et al. (2005) compared the ability of NDVI and NDWI to monitor FMC in a shrubland ecosystem and indicated that NDWI is less sensitive than NDVI to moisture changes in vegetation containing small amounts of water. Herbaceous fuels can be considered as dead fuels when the FMC is below 30% (Carlson & Burgan, 2003). The higher degree of scatter for NDWI and IVDI at low FMC values when compared to NDVI, consequently, could be explained by the fact that the SWIR spectral region is (1) more sensitive to background reflectance or (2) less sensitive to FMC variation when vegetation is dead, when compared to the red spectral region. Additional research efforts are needed to verify this hypothesis for vegetation canopies where the influence of soil and dead fuels complicate the estimation of FMC from satellite data. These findings also indicated that the evaluation of the influence of dead fuels in FMC samples became feasible by taking non-linear behavior of the explanatory variables into account. The use of thermal satellite measurements (e.g., surface temperature) furthermore could improve the monitoring of FMC during a dry season because surface temperature is indirectly related to weather parameters relevant to dead FMC variations (e.g., air temperature) (Camia et al., 2003). However, the ability of remotely sensed indices to monitor FMC dynamics at low FMC values only is required for specific fire behavior models, whereas the ability to monitor seasonal FMC variation is essential for regional fire risk models (Pyne et al., 1996). The ability to monitor FMC variation during the dry season was higher for NDWI than NDVI with R^2-values of 0.75 and 0.73, respectively (Table 1). These results corroborated the findings of Dennison et al. (2005) and Chuvieco et al. (2002) who illustrated that NDWI had higher R^2-values than NDVI for grass- and shrublands. The r-values of NDVI and NDWI, however, did not differ significantly, which can be explained by the fact that NDVI in grassland ecosystems is related to FMC (Hardy and Burgan, 1999; Paltridge & Barber, 1988). Dilley et al. (2004) furthermore illustrated that FMC estimates based on NDVI in grassland ecosystems are site dependent and vegetation specific. The NDWI consequently is more appropriate for integration in fire risk or fire behavior (e.g., fire intensity) models, because NDWI is not vegetation specific and has been shown to exhibit higher correlations with in situ FMC data (Table 1).

The ARND also was significantly non-linearly related to the herbaceous FMC ($R^2=0.6$) and the r-value did not differ significantly from the r-values of NDVI, NDWI, and IVDI, as shown by the Fisher z-transformation scores (Table 1). Fig. 5e shows that the ARND was not related strongly to low FMC values, i.e. FMC <40%. This explains the decreased ability of ARND compared to NDWI, NDVI, and IVDI ($R^2>0.7$) to monitor FMC. The poorer performance of ARND for low FMC values was attributed to the fact that ARND is related to vegetation stress and not FMC (Illera et al., 1996). Vegetation stress is proportional to the decrease in FMC at the start of the dry season. However, the decrease in FMC stagnates due to water shortage and the protection mechanisms of vegetation, while ARND and vegetation stress continues to increase as the dry season progresses.

5.2. Fire risk assessment performance

Results in previous study indicated that ARND, although not best suited for in situ FMC estimation (Table 1), performed best in conjunction with iRVI (i.e. ARND+iRVI model) when correlation to fire activity data was considered (Verbesselt et al., 2006a). The ARND is an index related to vegetation stress and has a different temporal behavior than NDVI, NDWI, and IVDI (Chuvieco et al., 2003; Sebastian-Lopez et al., 1991). The superior fire risk assessment performance of the ARND was attributed to the temporal behavior of the index and its ability to account for a decrease in fire activity at the end of the dry season. It should be noted that remotely sensed indices with a researched biophysical background are preferred for integration in fire risk models (Carlson & Burgan, 2003). It has been shown in this study that the NDWI was best correlated with in situ FMC data, while Verbesselt et al. (2006a) have demonstrated that the iRVI was best related to herbaceous biomass amount at the end of the rain season. Govender et al. (2006) have shown that fire intensity varies with fuel moisture content as well as with fuel load in the savanna ecosystem of the Kruger National Park. The combination of NDWI and iRVI, compared to the ARND and iRVI, consequently is more suited for integration in fire risk and behavior models since NDWI and iRVI correlated best with in-situ data of FMC and biomass.

6. Conclusion

The ability of vegetation indices derived from SPOT VGT data to monitor herbaceous FMC was evaluated in this study using in situ herbaceous FMC for the savanna ecosystem of the Kruger National Park, South Africa. The selected satellite vegetation indices under evaluation were NDVI, NDWI, VDI, IVDI, and ARND. The improved VDI (IVDI) was proposed to enhance the monitoring of FMC dynamics in savanna ecosystems by analysis of the iRVI/NDWI feature space instead of the NDVI/NDWI 2-dimensional space. The major conclusions of this research were:

1. The use of iRVI, as an approximation of yearly herbaceous biomass, improved the VDI (i.e., IVDI) by providing information on total leaf quantity per unit area such that the monitoring of FMC became feasible in savanna ecosystems dominated by grasslands. However, further research to improve FMC monitoring is necessary, since it was illustrated that the VDI ($R^2=0.25$) and IVDI ($R^2=0.73$) did not offer improvement when compared to the NDWI or NDVI with R^2-values of 0.75 and 0.73, respectively. The IVDI could be improved by an iRVI that accounts for biomass decay such that the link with total leaf material per unit area is optimized.
2. The use of in situ herbaceous FMC data illustrated that the ARND was not strongly related to FMC values ($R^2=0.6$) when compared to NDWI ($R^2=0.75$). In the previous study the ARND, however, demonstrated the highest ability to assess fire activity in the study area which was attributed to the temporal behavior of the index (Verbesselt et al., 2006a). This study has shown that the NDWI can be used to monitor FMC variations in savanna ecosystems during dry season when dead fuels complicate the FMC estimation from satellite data. The NDWI provides a spatial and temporal information source of seasonal herbaceous FMC variations which can be used to optimize fire risk and fire behavior models.
3. Further research is necessary in order to calibrate regression models when monitoring FMC with satellite data for specific study areas (e.g., Africa, Australia, America). Managers of savanna or grassland areas consequently can manipulate fire intensity by choosing the FMC based on maps derived from satellite data, and by subsequent burns in areas with higher or lower fuel loads.

Ongoing research is focusing on optimization of fire risk assessment with satellite data in forest ecosystems.

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