



# Fire danger and wildfire occurrence in Botswana's savannas: evaluating fire-danger indices and early-warning thresholds using 2001–2024 observations

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10 **Abstract.** Fire danger indices are important tools for operational fire management, yet their performance in African savannas remains poorly evaluated. We assessed eight widely used indices, Fine Fuel Moisture Code (FFMC), Forest Fire Weather Index (FWI), McArthur Forest Fire Danger Index (FFDI), Initial Spread Index (ISI), Drought Moisture Code (DMC), Buildup Index (BUI), Drought Code (DC), and Keetch–Byram Drought Index (KBDI) against 24 years (2001–2024) of Moderate Resolution Imaging Spectroradiometer (MODIS) derived fire occurrence data across Botswana. Index values were  
15 calculated from ERA5 Land reanalysis data and evaluated using Spearman rank correlation, logistic regression with cross-validated area under the receiver operating characteristic curve (AUC) and percentile-based odds ratios across annual, dry-season, and wet-season periods. Fine fuel moisture indices consistently outperformed deep drought codes. FFMC showed the strongest discrimination (AUC = 0.821; P90 OR = 9.08), followed by FFDI, FWI, and ISI, whereas DC and KBDI ranked lowest. Fire occurrence odds were approximately seven to nine times higher at or above the 90th percentile than below the  
20 threshold, with the steepest increases occurring above approximately the 70th–75th percentile range. No index was significantly correlated with seasonal fire totals ( $p < 0.22$ ,  $p > 0.05$ ), indicating that these indices are better suited to assessing daily fire danger than cumulative seasonal activity. The findings support a fire danger monitoring framework for Botswana in which FFMC serves as the primary daily indicator, supported by FFDI and FWI, with alert thresholds anchored to the 75<sup>th</sup> and 90<sup>th</sup> percentiles of a locally derived climatology.

## 25 1 Introduction

### 1.1 Fire danger in Botswana

Fire is a recurrent feature of Botswana's savanna landscapes. Each year large areas of savanna, grassland, and woodland burn across the country especially during the dry season when grasses cure and atmospheric conditions favour fire spread. Botswana lies within sub-Saharan Africa, the most fire-active region globally which accounts for more than half of the



30 world's burned area each year (Giglio et al., 2013; van der Werf et al., 2010). Southern Africa including Botswana, Mozambique, Zambia, and Zimbabwe contributes a large portion to this global fire activity.

Fire danger conditions remain poorly characterized in Botswana despite the frequent occurrence of fires. Subsistence farming communities often have limited capacity to suppress or recover from large fires, while protected areas and wildlife corridors may experience ecological impacts associated with uncontrolled burning (Dube, 2013; Cassidy et al., 2022; Russell-Smith et al., 2021). These challenges may become more severe under climate change as rising temperatures, increasing atmospheric dryness and changes in rainfall patterns are expected to lengthen periods conducive to fire and increase the frequency of extreme fire weather conditions across southern Africa (Matt Jolly et al., 2015; de Groot et al., 2013). Effective fire danger management therefore depends on reliable and operationally accessible tools for assessing daily fire danger and supporting early warning systems and informed land management decisions.

40 Botswana's fire environment is largely determined by its climate and vegetation. Most of the country lies within the Kalahari Basin, a broad and relatively flat savanna dominated by C4 grasses and scattered trees that serve as the primary fuels for fire across much of southern Africa (Scholes and Walker, 1993). During the rainy season these grasses grow rapidly in response to available moisture. Once the rainy season comes to an end the vegetation dries progressively through the dry season leading to an accumulation of highly flammable fine fuels. This creates conditions where fire can ignite and spread widely.

45 Fire activity is particularly common in the wetter northern regions, including the Okavango Delta and Chobe where higher rainfall supports greater biomass production, whereas the more arid south and southwest burn less frequently (Dube, 2013).

## 1.2 Fire danger indices and their relevance in savanna systems

Fire danger indices use meteorological observations to estimate how likely a fire is to start and spread on a given day. They typically integrate temperature, relative humidity, wind speed, and rainfall to characterize fuel flammability and potential fire behaviour (Dimitrakopoulos et al., 2011). These indices are used operationally in many countries to guide decisions about firefighter deployment, prescribed burning, park closures, and public warnings (Andrews et al., 2003). The McArthur Forest Fire Danger Index (FFDI) has been the foundation of fire danger rating in Australia since the 1960s (McArthur, 1966; Noble et al., 1980), while the Canadian Forest Fire Weather Index (FWI) system (Van Wagner, 1987) has been adopted or evaluated in numerous countries worldwide. The Keetch-Byram Drought Index (KBDI) is widely used in parts of the United States, particularly in the southeast (Keetch and Byram, 1968).

Each of these indices was developed under specific climatic and ecological conditions. The FWI system was originally designed for Canadian forest environments, where fire behaviour is strongly influenced by the moisture content of deep organic layers that can sustain combustion for extended periods (Van Wagner, 1987; Turetsky et al., 2011). Indices such as Drought Code (DC) and KBDI, which track longer-term moisture deficits are therefore well suited to those systems. In contrast, the dominant fuels in African savannas are fine grasses that can dry within hours to days following rainfall (Scholes and Walker, 1993). Consequently, daily fire danger is likely to be influenced more strongly by short-term atmospheric conditions particularly humidity and wind speed than by cumulative drought over many weeks. This suggests that indices



responsive to short-term changes in atmospheric conditions, such as Fine Fuel Moisture Code (FFMC) and FFDI, may perform better in Botswana than deeper drought codes. However, this has not been formally tested using a long record of  
65 observed fire data.

### 1.3 Knowledge gaps in African fire danger assessment

Research evaluating fire danger indices has expanded considerably over recent decades, yet Africa remains poorly represented in this literature. Most published assessments have been conducted in Australia (Dowdy et al., 2010), North America (Andrews et al., 2003; Flannigan et al., 2009), and Europe (Dimitrakopoulos et al., 2011; Sirca et al., 2018), where  
70 well established fire management systems are supported by extensive fire occurrence records. A recent global review of fire vulnerability assessment methodologies found Africa to be the least represented region in the peer-reviewed literature reflecting broader limitations in fire risk research capacity across the continent (Mihajlovski and Zhiyanski, 2025). Existing studies involving Africa have largely relied on global fire weather products that include the continent as part of broader assessments (Field et al., 2015; Matt Jolly et al., 2015), rather than evaluating multiple indices against observed fire  
75 occurrence at national scales.

This gap is important because African savannas behave differently from the forest environments where most of these fire danger indices were developed. At seasonal and interannual timescales, African savannas are generally characterized as fuel-limited systems in which landscape-scale fire activity is influenced more strongly by grass biomass availability than by atmospheric drying conditions (Archibald et al., 2010; Krawchuk and Moritz, 2011). On the other hand, at daily timescales,  
80 atmospheric factors particularly fine fuel moisture and wind speed play an important role in determining whether individual fires ignite and spread. These contrasting relationships suggest that the relative importance of fuel and weather controls depends on the temporal scale under consideration. Fire dynamics also vary substantially by biome and land-use context within Africa itself (Archibald et al., 2010), meaning that results obtained elsewhere provide limited guidance for Botswana's semi-arid savannas.

85 To our knowledge, no published study has systematically compared multiple fire danger indices for Botswana using long-term satellite fire observations or evaluated their performance using multiple statistical approaches. Therefore, there remains little empirical evidence to guide the selection of indices for operational fire danger rating in the country.

### 1.4 Study objectives

This study addresses these knowledge gaps by evaluating eight fire danger indices, Drought Moisture Code (DMC), Initial Spread Index (ISI), Buildup Index (BUI), KBDI, FFDI, FWI, DC, and FFMC, against fire occurrence data derived from the  
90 Moderate Resolution Imaging Spectroradiometer (MODIS) active fire product (Giglio et al., 2016) across Botswana over a 24-year period (2001–2024). The study was guided by three specific objectives. First, to evaluate the relationship between fire danger index values and fire occurrence at both landscape and daily scales across Botswana, and to assess how this relationship varies annually and seasonally. Second, to determine which of the eight indices most effectively discriminates



95 between fire and non-fire days under Botswana's savanna conditions. Third, to identify the index thresholds associated with substantially higher odds of fire occurrence, with the aim of establishing evidence-based benchmarks for a tiered fire danger warning system. Together, these objectives support the development of a national fire-danger monitoring framework tailored to Botswana's fire environment.

## 2 Study Area and Data

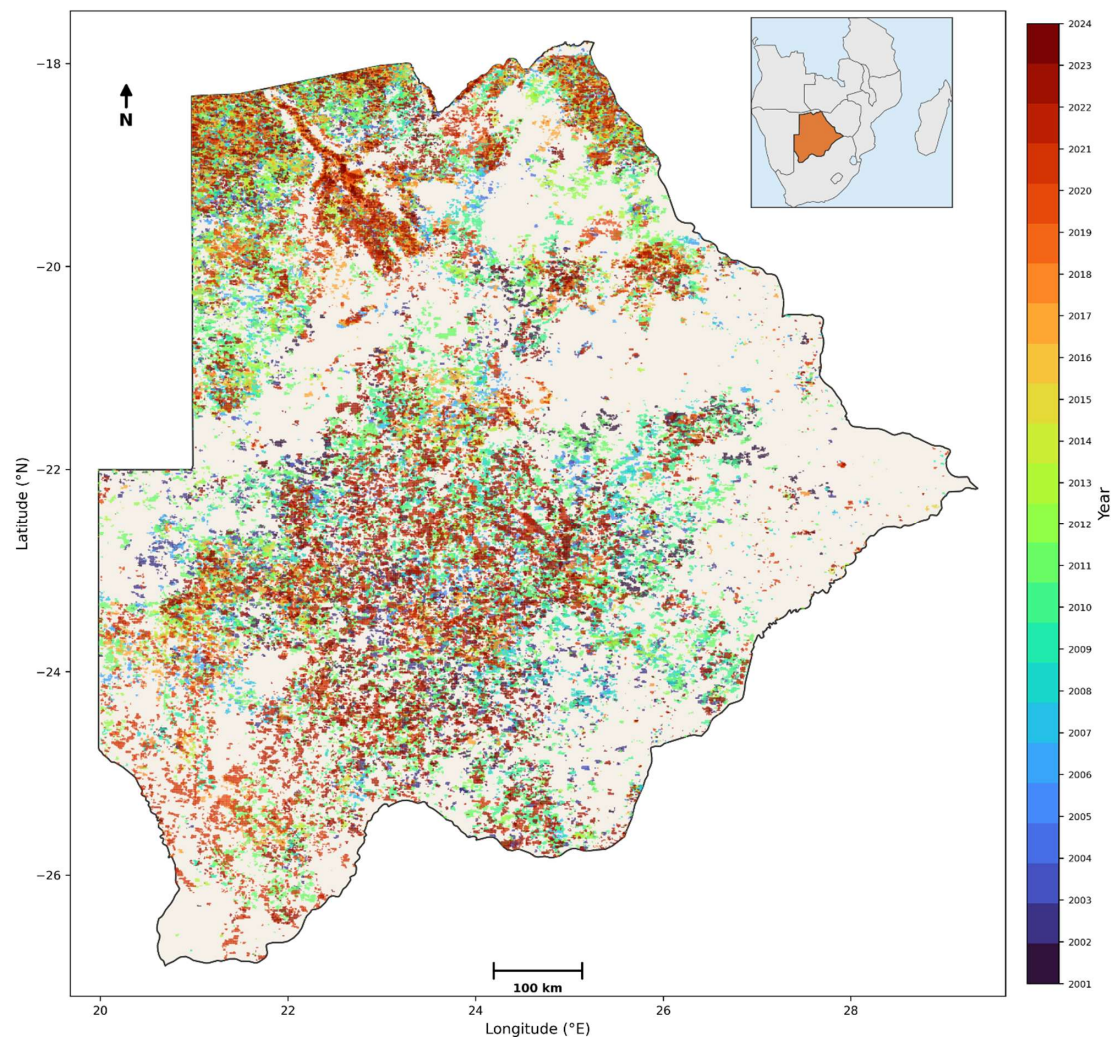
### 2.1 Study Area

100 Botswana is a landlocked country in southern Africa lying between 18 and 27° S, and between 20 and 29° E (Fig. 1), with a total land area of approximately 582,000 km<sup>2</sup>. The landscape is mostly flat to gently undulating with a mean elevation of around 1,000 m above sea level, rising to nearly 1,500 m along the rocky hills of the southeastern border. The Kalahari Basin dominates the landscape extending across the central, western, and southwestern regions. The southwestern portion of the basin is the driest in the country recording a mean annual precipitation of approximately 278 mm and is characterized by semi-arid sandy savanna with sparse, erratic rainfall (Nkoni et al., 2024).

105 Botswana has a semi-arid to sub-tropical climate characterized by a pronounced seasonal contrast between a warm, wet summer and a cool, dry winter. The wet season spans November to April, during which more than 70 % of total annual precipitation falls predominantly as convective thunderstorms (Scanlon et al., 2005). Annual precipitation in Botswana spans a pronounced north-to-south gradient, from above 650 mm in the northeast to below 250 mm in the southwest, with a national mean of 475 mm (World Bank Group, 2021). Daytime temperatures during the summer season can occasionally reach 45 °C while winter nights are often much colder, with sub-zero temperatures and frost events occurring during June and July (Jain et al., 2006).

115 Most of the vegetation is savanna, spanning a continuum of structural forms along the rainfall gradient. Over 60% of the country is covered by sparse savanna woodland and scrub formations. In the drier western parts of the country, low rainfall supports succulents, coarse grasses, and semi-arid tree species. In contrast, the wetter north is characterized by open hardwood woodlands, mainly *Baikiaea plurijuga* and *Pterocarpus angolensis*, much of which falls within designated Forest Reserves (Central Statistics Office, 2004).

120



**Figure 1.** Spatial distribution of active fire ignition points across Botswana (2001–2024), colour-coded by year of detection

Botswana is one of the most fire-prone countries in sub-Saharan Africa, situated within a region that accounts for more than 60 % of global annual burned area (Russell-Smith et al., 2021). Wildfire activity follows a strong seasonal pattern driven by the dry season. Fires typically begin in May and intensify markedly from August through October as vegetation dries, fuel loads accumulate, and hot, dry, and windy conditions prevail (Cassidy et al., 2022; Hansen, 2022). Fire activity reaches its peak in September, several weeks before the onset of the rainy season. At this time, fuel loads are at their maximum and fire-



weather conditions are most severe. The woodland savannas of northern Botswana are particularly susceptible with some  
130 areas having burned in 14 to 16 of the 20 years between 2001 and 2020 (Cassidy et al., 2022). Fires originate from both  
lightning and human ignitions with the latter arising from agricultural clearing, livestock management and hunting. This  
contributes substantially to fire frequency beyond what natural ignition alone would produce (Russell-Smith et al., 2021).  
The combination of extensive fire-prone savanna vegetation, a pronounced dry season, and the recurrent occurrence of  
wildfires make Botswana a relevant setting for evaluating fire-danger rating systems across contrasting environmental  
135 conditions.

## 2.2 Data Acquisition

The data used in this study consist of two satellite derived and reanalysis datasets covering Botswana over 24 complete years  
(January 2001–December 2024). Fire occurrence records were obtained from the MODIS active fire product and  
meteorological inputs required to compute the eight fire danger indices were derived from the fifth-generation European  
140 Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis for the Land surface. Together these datasets provide  
spatially consistent coverage at national scale across the full study period.

### 2.2.1 Fire Occurrence Data

Fire occurrence data was obtained from the MODIS Terra Active Fire product MOD14A2 version 6.1. This dataset provides  
global, gridded fire-mask composites at a spatial resolution of 1 km and a temporal resolution of 8 days. The FireMask layer  
145 encodes the confidence of fire detection using an ordinal classification scheme, where pixel values of 7, 8, and 9 correspond  
to low, nominal, and high confidence fire detections, respectively, while values 6 and below denotes non-fire pixels (Giglio  
et al., 2016). In our case, a pixel was classified as fire-affected ( $Y = 1$ ) if its 8-day composite FireMask value was  $\geq 7$ ,  
thereby retaining all confidence levels of detected fire. Pixels with values below this threshold were treated as non-fire  
observations ( $Y = 0$ ).

### 2.2.2 Meteorological Data and Fire-Danger Indices

The daily weather variables needed to compute the fire-danger indices were sourced from the ERA5 Land hourly reanalysis  
dataset, produced by the ECMWF and made available through the Copernicus Climate Change Service (C3S) Climate Data  
Store (Muñoz-Sabater et al., 2021). ERA5 Land provides a physically consistent, spatially complete reconstruction of land  
surface variables at a native horizontal resolution of approximately 9 km ( $0.1^\circ \times 0.1^\circ$ ). Hourly data for 2 m air temperature, 2  
155 m dewpoint temperature, 10 m eastward (u) and northward (v) wind components and accumulated precipitation were  
extracted from the dataset. Scalar wind speed was subsequently calculated from the u and v wind components. Relative  
humidity was derived from air and dewpoint temperatures using the Magnus approximation (Lawrence, 2005). These  
variables served as inputs to three distinct computational pathways as described below.



The six components of the FWI System (FFMC, DMC, DC, ISI, BUI, and FWI) were computed using daily noon values of  
160 air temperature, relative humidity, wind speed, and accumulated precipitation. Daily KBDI was computed following the  
standard Keetch and Byram (1968) approach using daily maximum air temperature and daily accumulated precipitation  
derived from ERA5 Land hourly data. A national mean annual precipitation value of 475 mm was adopted for Botswana  
(World Bank Group, 2021). Daily FFDI was subsequently calculated following Noble et al. (1980) using KBDI-derived  
165 drought factor values and ERA5 Land estimates of air temperature, relative humidity, and wind speed. The drought factor  
was derived from KBDI using the Griffiths (1999) conversion, an approach widely adopted in gridded FFDI applications  
(Finkele et al., 2006).

### 2.3 Data Preprocessing and Spatial Harmonization

Fire danger indices were computed at the daily timestep from ERA5 Land hourly inputs and subsequently aggregated to 8-  
day means to match the temporal resolution of the MOD14A2 compositing period (Giglio et al., 2016). Since ERA5 Land  
170 and MOD14A2 differ in spatial resolution, approximately 9 km and 1 km respectively, all index fields were regridded to the  
1 km MODIS grid using nearest-neighbour interpolation. This approach was chosen instead of bilinear methods to avoid  
artificial smoothing of index values across grid cell boundaries especially at land cover transitions. It is acknowledged that  
this regridding does not introduce genuine sub-9 km spatial variability, index values remain spatially uniform within each  
ERA5 Land source cell. All data processing, spatial harmonization and statistical analyses were performed in Python.

## 175 3 Statistical Methods

Three statistical frameworks were used to evaluate the fire-danger index performance across different timescales and  
dimensions of the index–fire relationship: Spearman rank correlation, logistic regression with cross-validated AUC and a  
percentile-based odds ratio framework.

### 3.1 Spearman rank correlation

180 Spearman rank correlation was used to evaluate the monotonic association between fire danger index values and fire  
occurrence at the landscape scale. Spearman's rank correlation coefficient was selected because it is a non-parametric, rank-  
based measure that does not require normally distributed data and is suitable for skewed ecological datasets (Potvin and  
Roff, 1993; Bishara and Hittner, 2015), including datasets containing numerous zero observations. Correlations were  
computed between 8-day mean index values and corresponding 8-day fire occurrence records for each grid cell. Pixels with  
185 fewer than three valid observations were excluded. Statistical significance was assessed at  $p < 0.05$ .

To assess seasonal variation in index performance, analyses were conducted separately for the dry season (May–October),  
wet season (November–April), and the complete annual record. For each index and season, correlation coefficients were



spatially averaged across all valid pixels to provide a broad assessment of whether fire danger indices track landscape scale variability in fire activity across Botswana.

### 190 3.2 Logistic regression

Logistic regression was used to evaluate the ability of individual fire danger indices to discriminate between fire and non-fire conditions at the pixel level. Fire occurrence was treated as a binary response variable with each pixel classified according to whether a MODIS fire detection occurred during a given 8-day period. Separate univariate models were fitted for each index. Predictor variables were standardized prior to analysis to facilitate comparison among indices. Fire pixels make up only a small fraction of the spatial domain in any given 8-day period leading to a strong class imbalance, therefore inverse-frequency class weighting was applied to address this. Model performance was assessed using the area under the receiver operating characteristic curve (AUC), which quantifies the probability that a model assigns higher fire probabilities to fire observations than to non-fire observations (Fawcett, 2006). In this study a higher AUC indicates that the model more consistently assigns higher fire probabilities to fire pixels than to non-fire pixels. AUC = 0.5 indicates no discriminative skill, while AUC = 1.0 represents perfect separation. A five-fold stratified cross-validation was used to obtain reliable estimates of predictive performance while preserving the proportion of fire and non-fire cases within each fold.

The odds ratio derived from the fitted logistic model coefficient (OR-L) measures how the odds of fire occurrence change with a one standard deviation increase in the fire-danger index. Values greater than one indicate increasing fire likelihood with increasing index values whereas values close to one indicate weak or negligible associations.

### 205 3.3 Percentile-based odds ratio framework

A percentile-based odds ratio framework was used to identify threshold-dependent changes in fire occurrence. This approach was motivated by evidence that fire occurrence often increases nonlinearly under extreme fire weather conditions rather than responding linearly across the full range of index values (Andrews et al., 2003; Bradstock, 2010).

Observations were partitioned using percentile thresholds from the 10<sup>th</sup> to the 90<sup>th</sup> percentile for each fire danger index. At each threshold, the odds of fire occurrence above the threshold were compared with those below it to estimate odds ratios. Analyses were conducted at the pixel level prior to aggregation to retain spatial variability across Botswana's pronounced climatic gradient.

This framework provides an empirical basis for identifying index values associated with elevated fire occurrence because it directly relates threshold exceedance to observed fire occurrence. Percentile-based thresholds are widely used to define operational fire danger categories in fire climatology and warning systems (Andrews et al., 2003; San-Miguel-Ayanz et al., 2018).



### 3.4 Complementarity of the three approaches

The three analytical approaches address complementary aspects of the index–fire relationship. Spearman correlation assesses whether indices track variability in aggregated fire activity at the landscape scale, indicating the extent to which meteorological conditions explain interannual and seasonal patterns. Logistic regression with cross-validated AUC evaluates pixel-level discrimination between fire and non-fire conditions within individual 8-day periods. The percentile-based odds ratio framework then examines how the odds of fire occurrence change as index values move into the upper part of their distribution, providing an empirical basis for identifying candidate fire-danger thresholds. Together, the three methods provide a more comprehensive assessment of index performance than any single approach could achieve in isolation.

## 4 Results and Discussion

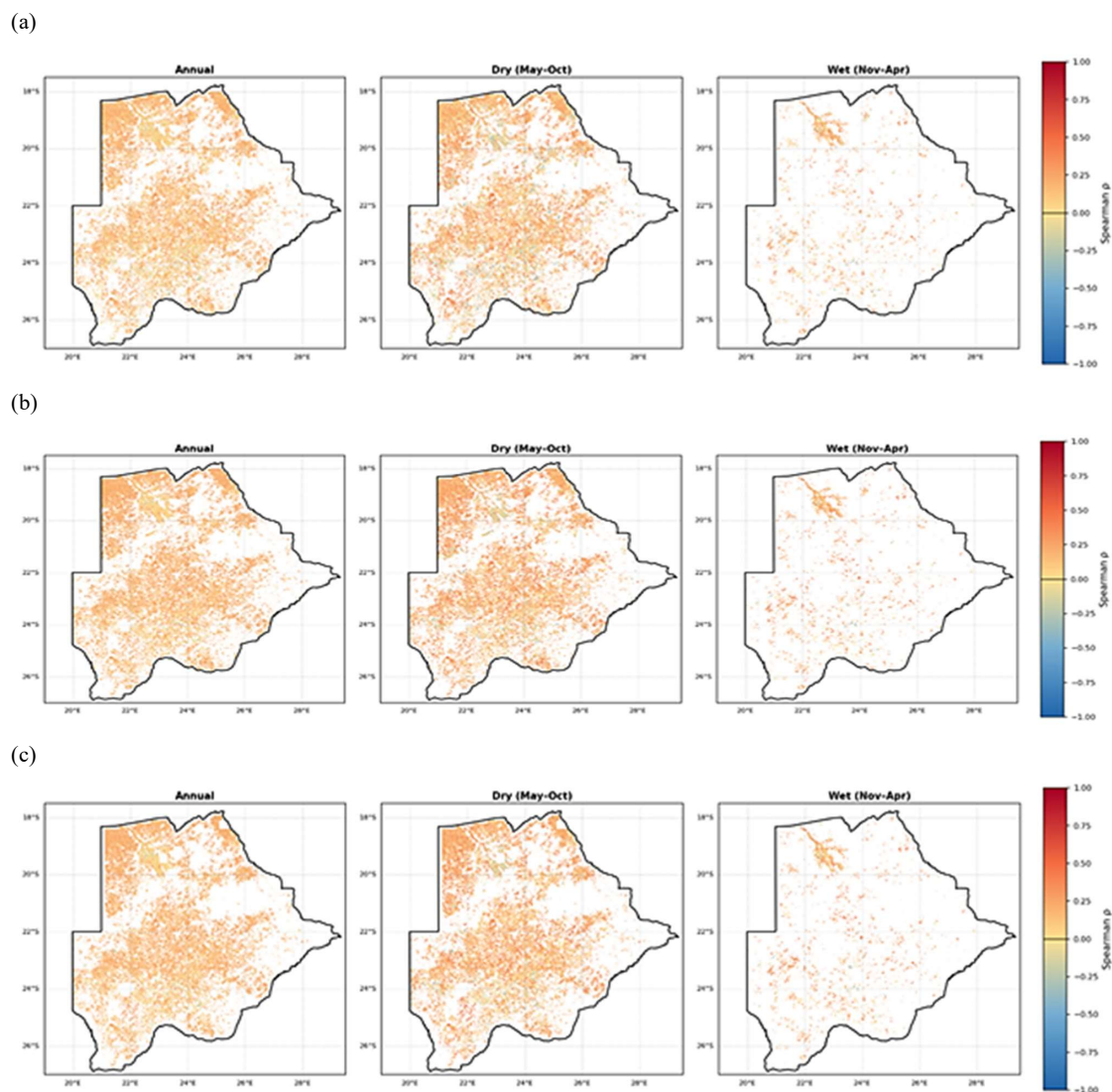
### 4.1 Overview and Analytical Framework

In this paper the evaluation of well-established fire danger indices against MODIS derived fire occurrence data across Botswana for the period 2001–2024 was performed. The assessment addressed three distinct objectives through correlation-based and discrimination-based evaluations.

### 4.2 Landscape – Scale Index – Fire Associations

The spatial distribution of pixel-wise Spearman correlations between selected fire danger indices and MODIS fire occurrence is shown in Fig. 2 for FWI (Fig. 2a), FFMCI (Fig. 2b) and FFDI (Fig. 2c) across the annual, dry season, and wet season analyses. Correlations were generally positive across all three indices and time periods, with only a few isolated negative values.

A consistent spatial pattern was evident across all three indices. Positive correlations were more widespread across the northern and central parts of the country and became less extensive towards the south and southeast. Seasonal differences were also apparent with positive correlations covering a larger area during the dry season than during the annual or wet season analyses. During the wet season, positive correlations were largely confined to the northern part of the country. The weaker wet season signal reflects the low frequency of fires during this period.



**Figure 2.** Spearman correlation between each index and MODIS derived fire occurrence, aggregated at  $0.1^\circ$  resolution from ERA5-derived daily index calculations over the study period. (a) FWI, (b) FPMC, and (c) FFDI

255 Spearman rank correlations between spatially averaged index values and MODIS derived fire occurrence are presented in Table 1 (final column: 'vs Fire'). For all the eight indices and across annual, dry, and wet season windows, correlations were consistently weak ( $p = 0.003$  to  $0.213$ ) and none reached statistical significance (all  $p > 0.05$ ).



This finding reflects a fundamental characteristic of savanna fire systems. The total amount of fire that occurs across a landscape in any given year is influenced by many factors beyond daily weather. These include how much grass grew during the previous wet season, how heavily an area was grazed, whether people were present to start fires, and whether or how actively fires were suppressed (Archibald et al., 2009; Hantson et al., 2017). Weather-based fire danger indices, by design, capture only the meteorological side of this picture. When fire occurrence is aggregated to the seasonal or annual level and correlated with aggregated index values, the non-meteorological drivers dominate the signal and the weather component becomes difficult to detect.

An equally important pattern emerges from the inter-index portion of Table 1. Several indices were strongly correlated, particularly DMC and BUI ( $\rho > 0.95$  across all seasons), as well as FWI and its component codes. These strong correlations indicate substantial overlap among the FWI System components at the daily scale, suggesting that some indices provide similar information at this temporal resolution. In contrast, DC shows near-zero or even negative correlations with FFMC and ISI during the wet season ( $\rho = -0.089$  and  $-0.058$  respectively), confirming that deep drought moisture and short-term surface fuel flammability are measuring fundamentally different things in Botswana's savanna environment.

In summary, none of the eight indices showed a meaningful association with year-to-year or seasonal variation in landscape-scale fire occurrence in Botswana. These findings highlight the limitations of using weather-based fire danger indices alone to explain landscape-scale fire variability. The following sections examine whether the indices provide greater value at daily and sub-seasonal timescales, where their ability to distinguish fire from non-fire conditions can be assessed directly.

**Table 1.** Spearman rank correlation matrix among eight fire danger indices and with MODIS derived fire occurrence, Botswana 2001–2024.

| Index                       | FFDI     | FWI      | DC       | DMC      | ISI      | BUI      | KBDI     | FFMC  | vs Fire  |
|-----------------------------|----------|----------|----------|----------|----------|----------|----------|-------|----------|
| <b>Annual (Jan–Dec)</b>     |          |          |          |          |          |          |          |       |          |
| FFDI                        | 1.000    | —        | —        | —        | —        | —        | —        | —     | 0.169 ns |
| FWI                         | 0.533*** | 1.000    | —        | —        | —        | —        | —        | —     | 0.141 ns |
| DC                          | 0.115*** | 0.719*** | 1.000    | —        | —        | —        | —        | —     | 0.028 ns |
| DMC                         | 0.421*** | 0.894*** | 0.783*** | 1.000    | —        | —        | —        | —     | 0.106 ns |
| ISI                         | 0.656*** | 0.731*** | 0.224*** | 0.493*** | 1.000    | —        | —        | —     | 0.163 ns |
| BUI                         | 0.331*** | 0.876*** | 0.882*** | 0.971*** | 0.424*** | 1.000    | —        | —     | 0.094 ns |
| KBDI                        | 0.602*** | 0.422*** | 0.076*** | 0.417*** | 0.459*** | 0.322*** | 1.000    | —     | 0.128 ns |
| FFMC                        | 0.704*** | 0.672*** | 0.190*** | 0.548*** | 0.773*** | 0.455*** | 0.542*** | 1.000 | 0.166 ns |
| <b>Dry Season (May–Oct)</b> |          |          |          |          |          |          |          |       |          |
| FFDI                        | 1.000    | —        | —        | —        | —        | —        | —        | —     | 0.197 ns |
| FWI                         | 0.470*** | 1.000    | —        | —        | —        | —        | —        | —     | 0.149 ns |
| DC                          | 0.125*** | 0.764*** | 1.000    | —        | —        | —        | —        | —     | 0.038 ns |
| DMC                         | 0.390*** | 0.898*** | 0.819*** | 1.000    | —        | —        | —        | —     | 0.109 ns |
| ISI                         | 0.588*** | 0.701*** | 0.252*** | 0.474*** | 1.000    | —        | —        | —     | 0.177 ns |
| BUI                         | 0.301*** | 0.880*** | 0.906*** | 0.969*** | 0.407*** | 1.000    | —        | —     | 0.091 ns |
| KBDI                        | 0.701*** | 0.456*** | 0.092*** | 0.456*** | 0.511*** | 0.341*** | 1.000    | —     | 0.176 ns |
| FFMC                        | 0.655*** | 0.623*** | 0.212*** | 0.529*** | 0.714*** | 0.437*** | 0.640*** | 1.000 | 0.186 ns |
| <b>Wet Season (Nov–Apr)</b> |          |          |          |          |          |          |          |       |          |
| FFDI                        | 1.000    | —        | —        | —        | —        | —        | —        | —     | 0.217 ns |
| FWI                         | 0.377*** | 1.000    | —        | —        | —        | —        | —        | —     | 0.168 ns |



|             |           |          |           |          |          |          |          |       |          |
|-------------|-----------|----------|-----------|----------|----------|----------|----------|-------|----------|
| <b>DC</b>   | -0.175*** | 0.469*** | 1.000     | —        | —        | —        | —        | —     | 0.003 ns |
| <b>DMC</b>  | 0.160***  | 0.857*** | 0.634***  | 1.000    | —        | —        | —        | —     | 0.137 ns |
| <b>ISI</b>  | 0.630***  | 0.707*** | -0.058*** | 0.399*** | 1.000    | —        | —        | —     | 0.188 ns |
| <b>BUI</b>  | 0.092***  | 0.815*** | 0.758***  | 0.958*** | 0.316*** | 1.000    | —        | —     | 0.117 ns |
| <b>KBDI</b> | 0.650***  | 0.305*** | -0.078*** | 0.159*** | 0.455*** | 0.109*** | 1.000    | —     | 0.165 ns |
| <b>FFMC</b> | 0.656***  | 0.673*** | -0.089*** | 0.421*** | 0.871*** | 0.318*** | 0.478*** | 1.000 | 0.213 ns |

Lower triangle: pairwise Spearman  $\rho$  between indices. Final column (vs Fire): spatially averaged pixel-wise  $\rho$  between each index and fire occurrence. Results are shown for three temporal windows. Significance: \*\*\* $p < 0.001$ , \*\* $p < 0.01$ , \* $p < 0.05$ ;

280 ns = not significant ( $p > 0.05$ ). All 'vs Fire' correlations were non-significant across all indices and seasons.

### 4.3 Daily Discrimination Performance of Fire Danger Indices

Since none of the eight indices showed a meaningful association with annual or seasonal fire totals at the landscape scale, attention is now directed to whether index values can distinguish between fire and non-fire conditions at the pixel level. This is evaluated using binary logistic regression with five-fold stratified cross-validation, with discriminatory performance assessed via the Area Under the Receiver Operating Characteristic Curve (AUC-CV). ROC curves for all eight indices across the three temporal windows are presented in Figs. 3-5. Table 2 summarizes the 24-year mean AUC-CV and logistic odds ratio (OR-L) for each index and season, and Table 3 presents the full year-by-year AUC-CV record for the annual season.

**Table 2.** Logistic regression performance summary for the fire danger indices across three evaluation periods, Botswana 2001–2024

|             | Annual (Jan–Dec) |               | Dry Season (May–Oct) |               | Wet Season (Nov–Apr) |               |
|-------------|------------------|---------------|----------------------|---------------|----------------------|---------------|
| Index       | OR-L             | AUC-CV        | OR-L                 | AUC-CV        | OR-L                 | AUC-CV        |
| <b>FFMC</b> | 12.70 ± 9.23     | 0.821 ± 0.061 | 13.26 ± 8.57         | 0.787 ± 0.046 | 6.00 ± 4.24          | 0.770 ± 0.099 |
| <b>FFDI</b> | 6.30 ± 3.09      | 0.806 ± 0.066 | 5.76 ± 2.50          | 0.776 ± 0.049 | 4.27 ± 2.98          | 0.744 ± 0.105 |
| <b>FWI</b>  | 3.81 ± 1.76      | 0.767 ± 0.070 | 2.93 ± 1.10          | 0.733 ± 0.051 | 4.97 ± 5.92          | 0.716 ± 0.114 |
| <b>ISI</b>  | 5.12 ± 2.54      | 0.766 ± 0.076 | 3.57 ± 1.39          | 0.715 ± 0.054 | 4.57 ± 4.24          | 0.705 ± 0.118 |
| <b>DMC</b>  | 2.77 ± 1.09      | 0.736 ± 0.063 | 2.38 ± 0.77          | 0.718 ± 0.057 | 3.10 ± 2.35          | 0.710 ± 0.101 |
| <b>BUI</b>  | 2.49 ± 0.79      | 0.709 ± 0.060 | 2.16 ± 0.56          | 0.685 ± 0.056 | 2.57 ± 1.52          | 0.682 ± 0.098 |
| <b>KBDI</b> | 3.41 ± 8.34      | 0.617 ± 0.094 | 2.79 ± 5.16          | 0.631 ± 0.091 | 2.78 ± 3.11          | 0.659 ± 0.095 |
| <b>DC</b>   | 1.44 ± 0.30      | 0.577 ± 0.046 | 1.56 ± 0.37          | 0.593 ± 0.057 | 1.17 ± 0.51          | 0.580 ± 0.072 |

OR-L = odds ratio from logistic regression. AUC-CV = area under ROC curve (5-fold cross-validated). Values are means across 24 years ± one standard deviation. Indices ranked by descending annual AUC-CV.



The FFMCI index was the strongest and most consistent performer across all three temporal windows, achieving cross-validated AUC values of  $(0.821 \pm 0.061)$  annually,  $(0.787 \pm 0.046)$  in the dry season, and  $(0.770 \pm 0.099)$  in the wet season. According to Hosmer et al., (2013), AUC values above 0.75 indicate good discriminatory skill and values above 0.90 indicate excellent skill. This places FFMCI in the good category across all temporal windows and approaching excellent in individual high-performance years (e.g. AUC = 0.912 in 2020, AUC = 0.884 in 2008; Table 3).

As shown in all three ROC figures (Figs. 3-5), FFMCI's curve is clearly and consistently above all other indices across the entire range of operating thresholds confirming its dominance at every sensitivity–specificity trade-off. The corresponding odds ratios were notably high:  $(12.70 \pm 9.23)$  annually and  $(13.26 \pm 8.57)$  in the dry season. This indicates that each one-standard-deviation increase in FFMCI was associated with an approximately 13-fold increase in the odds of fire occurrence. The large standard deviation of the annual OR-L ( $\pm 9.23$ ) reflects real year-to-year variation in the strength of the fire weather relationship, rather than measurement error. In years with strong dry-season fire weather, the relationship between fire and FFMCI is much stronger than the 24-year mean suggests. FFMCI's strong performance reflects its design as a near-surface moisture index, responding quickly to temperature, humidity, wind, and rainfall (Van Wagner, 1987).

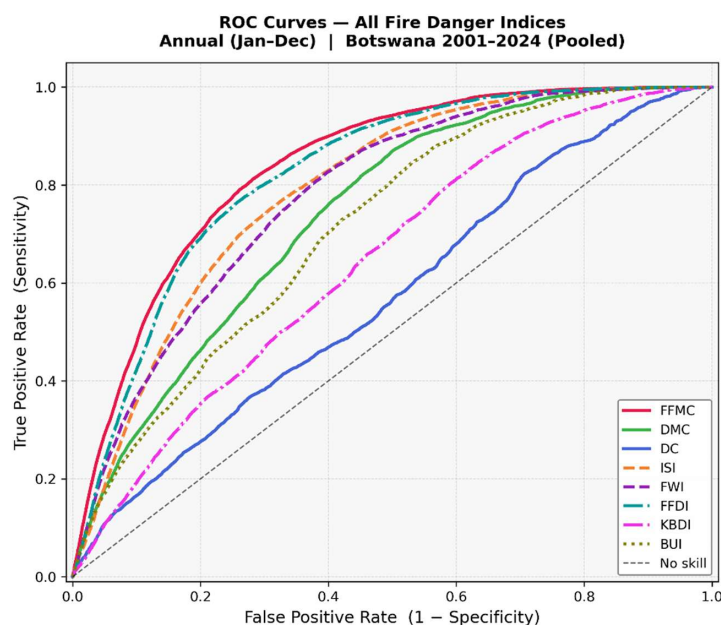
FFDI ranked second overall across all three seasons (annual AUC =  $0.806 \pm 0.066$ , OR-L =  $6.30 \pm 3.09$ ), followed by FWI and ISI, which performed closely throughout. FWI ranked third as it marginally outperforms ISI across all temporal windows. In the annual assessment margin was quite smaller (FWI:  $0.767 \pm 0.070$ ; ISI:  $0.766 \pm 0.076$ ), and widened slightly in the dry and wet seasons (dry: FWI 0.733, ISI 0.715; wet: FWI 0.716, ISI 0.705). FWI incorporates both FFMCI and DMC, whereas ISI combines FFMCI with wind speed. The consistently slightly higher AUC for FWI may reflect the additional information represented by DMC, although the small differences indicate broadly similar discrimination between the two indices.

The comparable performance of FFDI, FWI, and ISI across all seasons is noteworthy. FFDI was developed in Australia (Noble et al., 1980) and FWI in Canada (Van Wagner, 1987) where fire environments are markedly different from Botswana's savannas, yet they both achieve discrimination skill comparable to indices sharing the same atmospheric inputs. Their performance suggests that indices incorporating short-term fuel-moisture conditions and wind speed can provide useful discrimination of fire and non-fire conditions in Botswana. In the dry season (Fig. 4), the ROC curves for FWI, ISI, and DMC cluster closely together between false positive rates of 0.2 and 0.6. This indicates that these indices offer similar discrimination skill during the peak fire period and only begin to diverge at the most extreme thresholds. DMC and BUI performed at an intermediate level (annual AUC = 0.736 and 0.709), suggesting that their additional representation of longer-term moisture conditions does not provide the same level of discrimination as the indices that respond more directly to short-term fire-weather conditions.

DC ranked last consistently across all three temporal windows (annual AUC =  $0.577 \pm 0.046$ , OR-L =  $1.44 \pm 0.30$ ; dry: 0.593; wet: 0.580). In all the ROC curves, it remained close to the no-skill diagonal. This indicates its weak ability to distinguish fire from non-fire days at the pixel level. KBDI also ranked low compared to the top indices (annual AUC =

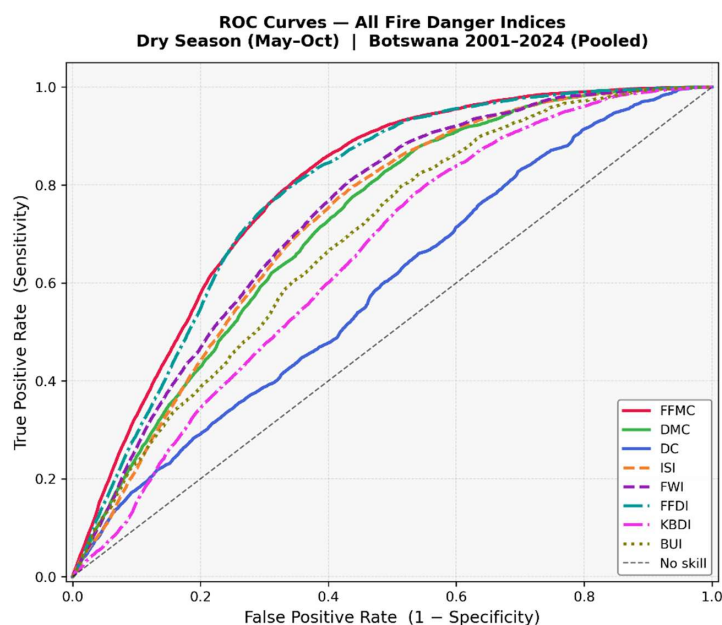


0.617 ± 0.094, OR-L = 3.41 ± 8.34), though its large standard deviation in both AUC and OR-L indicate that its relationship with fire days varies considerably from year to year. The weak performance of both DC and KBDI is consistent with the temporal characteristics of these indices. Both were developed to track deeper moisture deficits that accumulate over weeks to months. In Botswana's savanna landscapes, the stronger performance of indices that respond more rapidly to surface conditions suggests that short-term changes in fuel moisture may be more closely associated with daily fire occurrence than the longer-term moisture conditions represented by DC and KBDI.



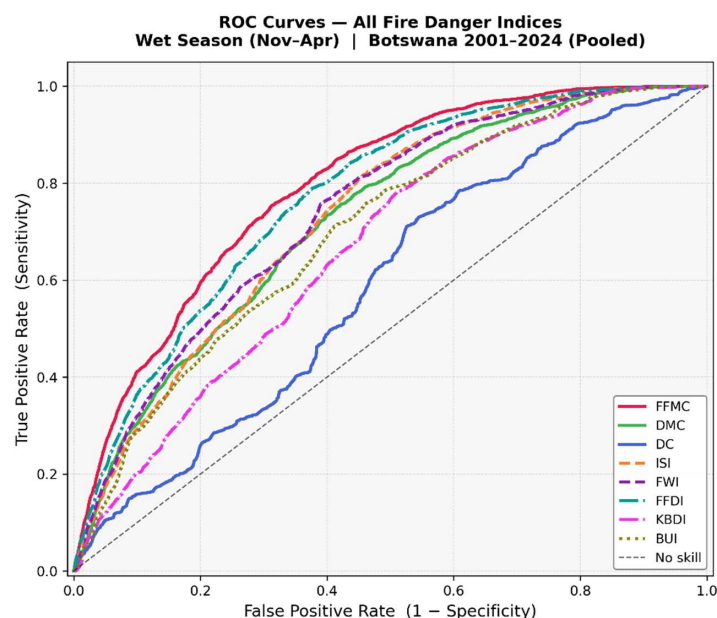
**Figure 3.** ROC curves – all fire danger indices against MODIS fire occurrence over Botswana, annual season (January–December), 2001–2024 (pooled). The dashed diagonal represents a no-skill classifier.

Comparing the three ROC figures reveals seasonal differences in index performance. AUC-CV values span 0.593–0.787 in the dry season (Fig. 4), a range of 0.194 compared with a range of 0.244 in the annual analysis. The curves are more closely clustered, particularly among the mid-performing indices at false-positive rates between 0.2 and 0.6. This pattern may reflect reduced separation between index values on fire and non-fire days during the dry season, when fire-danger conditions are generally more widespread and persistent.



**Figure 4.** ROC curves – all fire danger indices, dry season (May–October), 2001–2024 (pooled).

345 The wet season (Fig. 5) shows a different pattern. Despite lower absolute AUC-CV values across all indices, curve separation particularly at low false positive rates is more pronounced than in the dry season. This may reflect greater variability in atmospheric conditions during the wet season, when fire-conductive and less conductive conditions occur over the same period. KBDI is the only index showing a consistent increase in AUC across the seasonal analyses, although it remains among the weaker discriminators overall.



**Figure 5.** ROC curves – all fire danger indices, wet season (November–April), 2001–2024 (pooled).

The year-by-year AUC values in Table 3 show clear variation from year-to-year that is consistent across indices. This suggests that some years are simply more or less meteorologically predictable regardless of which index is used. Low AUC values across all indices ranging from 0.495 are observed in some years such as 2002, 2019, and 2023. These years may reflect periods of anomalous rainfall or broader climatic variability that weaken the relationship between fire occurrence and fire weather conditions (Matt Jolly et al., 2015). During wetter years, fire occurrence may be influenced more by fuel accumulation than by day-to-day atmospheric conditions. Above-average rainfall promotes grass growth and increases fuel loads. As a result, fuel availability rather than concurrent weather becomes the main control on where and when fires occur (Archibald et al., 2010). This reduces the discrimination skill of all indices at the same time. Low performance of KBDI in 2002 (AUC = 0.495, effectively no skill) despite strong performance in adjacent years reflects a known weakness of the index. KBDI is known to build up slowly over many weeks of dry conditions and drops sharply when rain falls (Keetch and Byram, 1968; Finkle et al., 2006). Consequently, unusual rainfall patterns may alter the cumulative moisture deficit tracked by the index reducing its ability to distinguish fire from non-fire conditions. Years such as 2008, 2011, 2014, and 2020 on the other hand show uniformly high AUC values across the top-ranked indices. These years coincide with periods of widespread fire activity in Botswana when extensive burned areas were recorded across multiple regions. For example, 2008 was marked by a severe fire season in the Central Kalahari Game Reserve including a megafire event (Dube, 2013), while 2011 also experienced large burned areas linked to high fuel loads following above-average rainfall (Maabong and Mphale,



2021). The consistently high AUC values in these years suggest that the leading indices were better able to distinguish fire from non-fire conditions when fire activity was widespread. In contrast, DC remained near or below 0.650 in almost every year (Table 3), indicating consistently weak discrimination and limited value for distinguishing daily fire and non-fire conditions in Botswana.

**Table 3.** Annual cross-validated AUC (AUC-CV) for eight fire danger indices – Annual Season (January–December), Botswana 2001–2024

| Year | FFMC  | FFDI  | ISI   | FWI   | DMC   | BUI   | KBDI  | DC    |
|------|-------|-------|-------|-------|-------|-------|-------|-------|
| 2001 | 0.870 | 0.866 | 0.841 | 0.850 | 0.807 | 0.788 | 0.822 | 0.633 |
| 2002 | 0.706 | 0.676 | 0.648 | 0.635 | 0.600 | 0.590 | 0.495 | 0.529 |
| 2003 | 0.769 | 0.737 | 0.678 | 0.683 | 0.659 | 0.632 | 0.721 | 0.511 |
| 2004 | 0.862 | 0.850 | 0.782 | 0.780 | 0.808 | 0.757 | 0.669 | 0.547 |
| 2005 | 0.805 | 0.789 | 0.763 | 0.758 | 0.724 | 0.703 | 0.495 | 0.619 |
| 2006 | 0.874 | 0.860 | 0.828 | 0.824 | 0.778 | 0.757 | 0.723 | 0.603 |
| 2007 | 0.801 | 0.787 | 0.737 | 0.733 | 0.701 | 0.674 | 0.513 | 0.562 |
| 2008 | 0.884 | 0.869 | 0.828 | 0.813 | 0.755 | 0.719 | 0.598 | 0.542 |
| 2009 | 0.862 | 0.843 | 0.804 | 0.831 | 0.822 | 0.805 | 0.687 | 0.681 |
| 2010 | 0.849 | 0.834 | 0.816 | 0.825 | 0.784 | 0.768 | 0.691 | 0.625 |
| 2011 | 0.840 | 0.835 | 0.826 | 0.810 | 0.754 | 0.730 | 0.673 | 0.578 |
| 2012 | 0.834 | 0.805 | 0.739 | 0.729 | 0.702 | 0.663 | 0.479 | 0.521 |
| 2013 | 0.831 | 0.804 | 0.748 | 0.735 | 0.704 | 0.665 | 0.523 | 0.531 |
| 2014 | 0.880 | 0.864 | 0.823 | 0.839 | 0.813 | 0.779 | 0.688 | 0.619 |
| 2015 | 0.733 | 0.715 | 0.660 | 0.678 | 0.683 | 0.660 | 0.603 | 0.586 |
| 2016 | 0.789 | 0.764 | 0.695 | 0.722 | 0.743 | 0.716 | 0.642 | 0.565 |
| 2017 | 0.852 | 0.846 | 0.815 | 0.816 | 0.777 | 0.744 | 0.634 | 0.596 |
| 2018 | 0.781 | 0.760 | 0.719 | 0.727 | 0.702 | 0.671 | 0.496 | 0.557 |
| 2019 | 0.673 | 0.645 | 0.569 | 0.637 | 0.689 | 0.672 | 0.556 | 0.628 |
| 2020 | 0.912 | 0.907 | 0.864 | 0.870 | 0.832 | 0.801 | 0.569 | 0.652 |
| 2021 | 0.862 | 0.866 | 0.842 | 0.820 | 0.735 | 0.702 | 0.737 | 0.559 |
| 2022 | 0.880 | 0.863 | 0.862 | 0.849 | 0.790 | 0.747 | 0.675 | 0.548 |



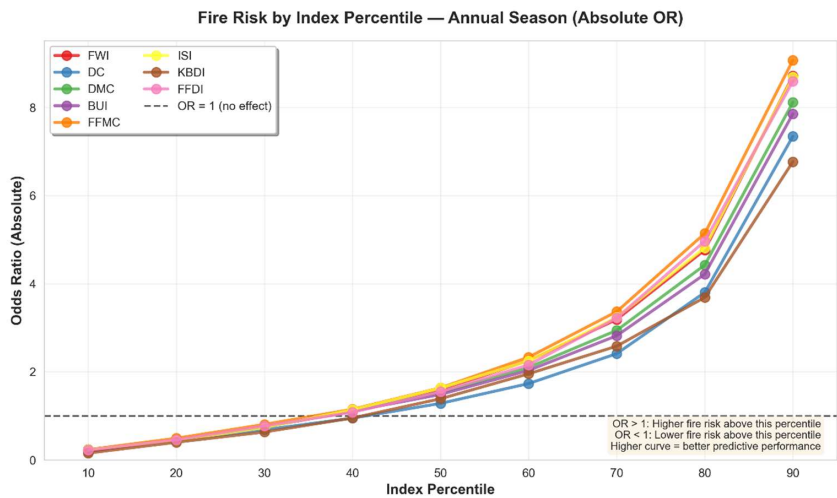
|             |              |              |              |              |              |              |              |              |
|-------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| <b>2023</b> | 0.764        | 0.755        | 0.760        | 0.705        | 0.633        | 0.620        | 0.521        | 0.540        |
| <b>2024</b> | 0.796        | 0.791        | 0.728        | 0.734        | 0.675        | 0.644        | 0.595        | 0.523        |
| <b>Mean</b> | <b>0.821</b> | <b>0.805</b> | <b>0.766</b> | <b>0.767</b> | <b>0.736</b> | <b>0.709</b> | <b>0.617</b> | <b>0.577</b> |

375 AUC-CV = cross-validated AUC from 5-fold stratified logistic regression fitted separately per year.

**4.4 Nonlinear Risk Amplification at Extreme Index Values**

Percentile-based odds ratios were calculated at the 10th to 90th percentile thresholds, with the odds of fire occurrence above each threshold compared with those below it. Figure 6 illustrates how the odds of fire occurrence change with increasing index percentiles for all eight indices across the annual, dry, and wet seasons. A consistent nonlinear pattern was observed from the results with the odds of fire occurrence remaining low ( $OR < 1$ ) below the 50th percentile and starts to increase above the 60th percentile, then increases steeply beyond the 75th percentile across all indices.

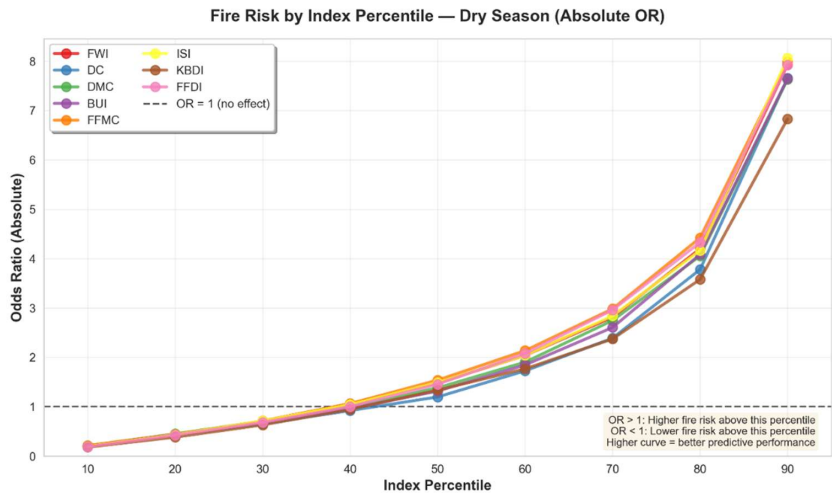
(a)



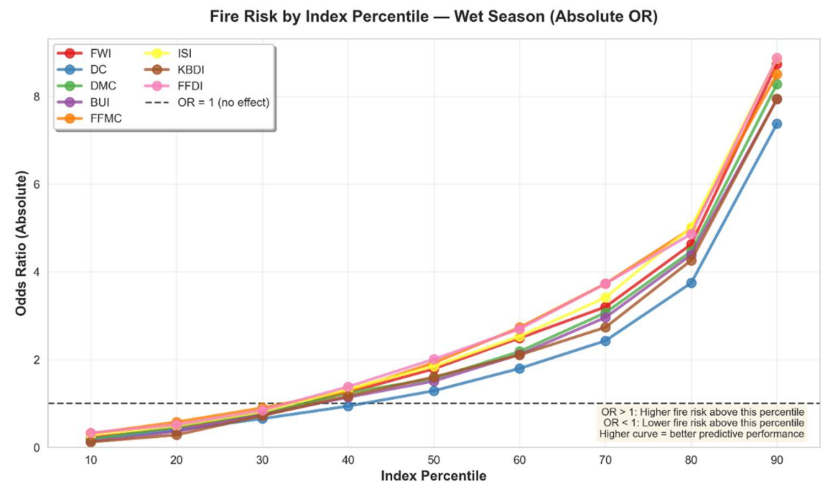


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(b)



(c)



390 **Figure 6.** Fire risk (odds ratio) increases nonlinearly with fire weather index percentiles across Botswana's savannas for (a) Annual season, (b) Dry season, and (c) Wet season (2001–2024). Dashed line indicates OR = 1 (no effect).

As summarized in Table 4, FFMFC recorded the highest P90 odds ratio (OR-P90) annually (9.08), although its ranking varied slightly by season (see Sect. 4.5). It was followed by FFDI (8.75), FWI (8.72), and ISI (8.69). The corresponding dry-season



values were 7.99, 8.10, 7.93, and 8.06 respectively, while wet-season values were 8.50, 8.63, 8.74, and 8.86. These results indicate that fire occurrence had substantially higher odds at the 90th percentile than below the corresponding threshold. The progressive increase in odds at higher index percentiles is consistent with the nonlinear relationship between fire occurrence and extreme fire-weather conditions reported in previous studies (Bedia et al., 2015).

**Table 4.** Fire danger index performance at critical percentile thresholds, Botswana 2001–2024.

| Rank | Index | Annual Season |      | Dry Season (May–Oct) |      | Wet Season (Nov–Apr) |      |
|------|-------|---------------|------|----------------------|------|----------------------|------|
|      |       | P75           | P90  | P75                  | P90  | P75                  | P90  |
| 1    | FFMC  | 4.26          | 9.08 | 3.70                 | 7.99 | 4.36                 | 8.50 |
| 2    | FFDI  | 4.19          | 8.75 | 3.66                 | 8.10 | 4.30                 | 8.63 |
| 3    | FWI   | 3.98          | 8.72 | 3.51                 | 7.93 | 3.91                 | 8.74 |
| 4    | ISI   | 4.03          | 8.69 | 3.50                 | 8.06 | 4.21                 | 8.86 |
| 5    | DMC   | 3.68          | 8.12 | 3.40                 | 7.63 | 3.77                 | 8.28 |
| 6    | BUI   | 3.52          | 7.86 | 3.35                 | 7.65 | 3.67                 | 7.94 |
| 7    | DC    | 3.11          | 7.35 | 3.08                 | 7.66 | 3.09                 | 7.38 |
| 8    | KBDI  | 3.00          | 6.63 | 2.93                 | 6.78 | 3.40                 | 7.66 |

P75 = 75<sup>th</sup> percentile (suggested 'High Danger' threshold); P90 = 90<sup>th</sup> percentile (suggested 'Extreme Danger' threshold). Indices ranked by descending Annual P90 performance. Rankings are consistent across all three temporal windows, with FFMC, FWI, ISI, and FFDI forming the top tier in all seasons.

Importantly, the percentile-based ranking agrees closely with the discrimination-based (AUC) and correlation-based rankings (see Sect. 4.2 and 4.3). FFMC, FFDI, FWI, and ISI consistently rank highest across all three methods, while DC and KBDI remain the lowest. This consistency across analytically distinct evaluation frameworks, each assessing a different aspect of the index–fire relationship strengthens confidence in the observed ranking.

The increase in odds at higher percentiles highlights the threshold-dependent nature of the relationship between fire weather and fire occurrence in Botswana's savannas. As shown in Table 4, odds ratios increased progressively from the 75th percentile (P75 OR range: 2.93–4.36 across indices and seasons) to the 90th percentile (P90 OR range: 6.63–9.08). This increase becomes particularly evident around the 70th–75th percentiles in Fig. 6, where the index curves shift from a gradual to a steeper increase. The pattern suggests that fire occurrence becomes increasingly associated with high fire-danger conditions as index values move into the upper part of their distribution. Percentile-based thresholds therefore provide a useful way of identifying conditions associated with elevated fire occurrence.



Clear operational benchmarks emerge from the percentile-based analysis, with increasing odds of fire occurrence at higher thresholds supporting a simple tiered fire-danger framework. The 75th percentile (P75), where odds ratios were generally above 3 across indices and seasons could serve as a practical “High Danger” threshold for increased preparedness and resource monitoring. The 90th percentile (P90), where the odds of fire occurrence were approximately seven to nine times those below the threshold, could define an “Extreme Danger” level warranting heightened preparedness. The consistency of the index rankings across annual, dry, and wet season analyses supports the potential use of percentile-based thresholds for fire-danger assessment in Botswana’s savanna landscapes.

#### 4.5 Seasonal Variation in Extreme Fire Weather Performance

Analysis of the seasonal odds ratio curves (Figs. 6b and 6c) and percentile thresholds show small but consistent differences in index performance between the dry and wet seasons. The rankings of mid-performing indices shift slightly in the dry season as FFDI records the highest P90 OR (8.10), just above ISI (8.06), FFMC (7.99) and FWI (7.93). ISI records the highest in the wet season (8.86), ranking just above FWI (8.74). The relatively strong performance of the wind-sensitive indices during the dry season may reflect the contribution of wind to fire-weather conditions during the peak fire period. ISI, which also captures wind effects along with temperature, performs best in the wet season (P90 OR = 8.86). In this season, short lived wind events combined with temporary drying help separate the rare fire days from mostly non fire conditions.

#### 4.6 Implementation Framework for Operational Fire Danger Rating

Based on the evidence presented in Sect. 4.2–4.5, we propose a percentile-based fire danger rating framework for Botswana comprising three categories: Moderate (P50–P75), High (P75–P90), and Extreme (>P90). These thresholds are based on the observed increase in fire occurrence at higher index percentiles. At P75, odds ratios ranged from 2.93 to 4.36 across indices and seasons (Table 4), indicating that the odds of fire occurrence above the P75 threshold were approximately three to four times those below the threshold. At P90, odds ratios ranged from 6.63 to 9.08 (Table 4), indicating approximately seven- to ninefold higher odds of fire occurrence above the threshold than below it. Anchoring the categories to locally derived percentile thresholds provides a context-specific framework for fire-danger assessment and allows index values to be interpreted relative to the observed distribution of fire-weather conditions during the study period.

FFMC emerged as the most suitable candidate for operational application given its consistently highest AUC (0.821 annually) and P90 OR (9.08) across all three evaluation methods and all seasons. FFDI and FWI could serve as secondary confirmation indices as both achieved AUC > 0.76 and P90 OR > 8.6 (Tables 2 and 4). Their inclusion could provide complementary perspectives on fire danger derived from different index formulations. DC and KBDI, despite their poor discrimination performance (AUC < 0.65 in all seasons; Table 2), may retain value as seasonal drought indicators for assessing longer term fuel dryness rather than day to day ignition risk, a role distinct from daily warning.

Operationally, FFMC, FFDI, and FWI can all be computed in near real time from ERA5 Land reanalysis data which is available via the Copernicus Climate Change Service, or from surface weather station observations at Botswana



Meteorological Services (BMS) stations where available. The percentile climatologies required to define the P75 and P90 thresholds can be precomputed from the 2001–2024 ERA5 Land record presented in this study providing a ready to use operational baseline. For community scale fire risk communication, vegetation dryness products such as NDVI or EVI from MODIS or Sentinel 2 can complement the weather-based system by capturing spatial variability in fuel load and curing state that atmospheric indices alone cannot resolve, particularly along the pronounced north south rainfall gradient.

The proposed framework could be integrated into Botswana's existing fire-management structure. The Department of Forestry and Range Resources (DFRR) and Botswana Meteorological Services (BMS) already issue seasonal fire outlooks; incorporating a daily FFM-based alert layer could provide a relatively low-cost, evidence-based complement to these existing systems. More broadly, the approach used here which combines multi-method evaluation of fire-danger indices with locally derived percentile thresholds, provides a basis for developing context-specific fire-danger assessment systems in other southern African savanna environments.

#### 4.7 Limitations

Several methodological limitations should be considered when interpreting these results. MODIS MOD14A2 provides 8-day composite fire detections, and fire weather indices were aggregated to the same temporal resolution. This approach may obscure short term fire weather relationships, particularly during the dry season when atmospheric conditions can change rapidly. ERA5 Land data were resampled from their native spatial resolution (~9 km) to 1 km using nearest neighbour interpolation. Therefore, the analysis does not capture sub grid variability in fire weather conditions within individual ERA5 Land cells. KBDI was implemented using a spatially uniform mean annual precipitation parameter (475 mm), which may introduce regional biases because it does not account for Botswana's pronounced rainfall gradient. In addition, the analysis was based on binary fire detections and therefore does not account for variation in fire intensity, burned area, or rate of spread, all of which are operationally relevant aspects of wildfire behaviour.

#### 5 Conclusions

The aim of this study was achieved by evaluating eight fire danger indices against 24 years of MODIS derived fire occurrence in Botswana using three complementary methods, Spearman correlation, logistic discrimination (AUC-ROC), and percentile-based odds. The consistency of results across the three approaches strengthens confidence in the overall findings.

First, weather-based fire danger indices showed limited ability to explain annual and seasonal variation in landscape-scale fire activity. Spearman correlations between the eight indices and spatially aggregated fire occurrence were weak and non-significant across all temporal windows ( $\rho = 0.003\text{--}0.213$ ; all  $p > 0.05$ ). This pattern reflects the complexity of fire activity in Botswana's savannas, where weather conditions are only one of several factors that may influence burning. Fuel availability,



land use, and ignition sources may also contribute to this variability, which limits the ability of weather-based indices alone to explain fire activity.

480 At the daily scale, the eight fire danger indices differed substantially in their ability to discriminate between fire and non-fire conditions, with indices that track fine fuel moisture consistently outperforming drought-based indices across all evaluation metrics. FPMC was the strongest overall performer (AUC = 0.821, P90 OR = 9.08), followed by FFDI (0.806, 8.75), FWI (0.767, 8.72), and ISI (0.766, 8.69). The Drought Code was regularly the weakest (AUC = 0.577, P90 OR = 7.35), with KBDI only marginally better (0.617, 6.63). This ranking is consistent with the importance of short-term surface fuel  
485 conditions for fire occurrence in Botswana's grass-dominated savannas. The substantially higher overall logistic OR-L for FPMC (12.70) compared with the other indices ( $OR \leq 6.30$ ) further indicates its stronger ability to discriminate between fire and non-fire observations.

Finally, fire occurrence odds increased sharply and nonlinearly toward the upper end of the index distributions, supporting the use of percentile-based thresholds in fire-danger warning systems. Across the evaluated indices, the odds of fire  
490 occurrence at or above the 90th-percentile threshold were approximately 7–9 times those below the threshold, with the steepest increase occurring around the 70th–75th percentile range. These findings support prioritizing FPMC, FFDI, and FWI for daily fire danger assessment in Botswana. Focusing on these indices could simplify operational fire danger monitoring while retaining good discrimination between fire and non-fire conditions. The Drought Code and KBDI showed weaker discrimination at the daily scale but may still provide useful information on longer-term moisture conditions.  
495 Combining fire weather indices with satellite-derived information on vegetation and fuel conditions may provide a more complete assessment for fire occurrence.

### Code and data availability

The meteorological data used to compute the fire danger indices in this study are freely available from the ERA5-Land hourly reanalysis dataset, produced by the ECMWF and distributed through the Copernicus Climate Change Service (C3S)  
500 Climate Data Store at <https://cds.climate.copernicus.eu>. Fire occurrence data were obtained from the MODIS Terra Active Fire product (MOD14A2 Version 6.1), freely available from NASA's Land Processes Distributed Active Archive Center (LP DAAC) at <https://lpdaac.usgs.gov>.

### Author contributions

KEM and THT developed the methodology and code used to compute and analyse the data. KEM performed the analysis,  
505 produced the figures and prepared the original draft of the manuscript. THT and OC contributed to the analysis and reviewed the manuscript. KMM and DL supervised the study and reviewed and edited the manuscript. All authors contributed to and approved the final manuscript.



### Competing interests

The contact author has declared that none of the authors has any competing interests.

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