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Research Article

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Geospatial Analysis of Drought Impacts on Maize Millet and Sorghum in Burkina Faso

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Abstract

Maize, millet, and sorghum are the main cereal crops in Burkina Faso, accounting for 91% of overall cereal production in the country. These are some of the pillars of the country's food and nutritional security, hence the decision to choose these as reference crops for African Risk Capacity's parametric insurance.

The overall objective of this study was to use WRSI images from Africa RiskView, ARC's technical tool and early warning system, to analyse drought dynamics over the period 20012020 in Burkina Faso to help define an agricultural insurance strategy.

The methodology used is based on the customisation of the Africa RiskView agricultural drought model, and on the classification of images of WRSI compared to normal using pretrained Convolutional Neural Networks (Pre-trained CNN).

This study showed the presence of widespread droughts between 2001 and 2013, and partial droughts spread throughout the study period. The provinces most exposed to severe droughts are those located in the northern Sudanian belt, with a probability of exposure of over 20%.

The frequency of droughts occurrence has an impact on the progress of the agricultural season and on cereal production levels. In addition, the trend towards wetter weather with a predominance of average droughts is disrupting the start of the agricultural season and sowing periods. Hence, there is need for an insurance strategy tailored to the dynamics of drought in the country.

The Anticipatory Insurance strategy is emerging as a new approach to mitigate the effects of drought on agricultural production.

Keywords: WRSI Compared to Normal, Drought, Agricultural Insurance, Africa Risk View, Convolutional Neural Networks, Burkina Faso

1. Introduction

Burkina Faso's agriculture is largely rain-fed, with little total water control [1,2]. Cereal crop yields are highly sensitive to temperature increases and rainfall distribution during the rainy season [3]. Agro-climatic analyses show that cereal production and yields are adversely affected by delays in the onset of the rains, early cessation of the rainy season, frequent dry spells, and excess or deficit rainfall [4]. Dry years lead to acute food insecurity, affecting the poorest people. To deal with the recurrence of food insecurity, the Government of Burkina Faso, with the support of partners, has drawn up and implemented an annual Response and Support Plan for Populations Vulnerable to Food Insecurity (PRSPV) [5,6]. This practice has been in place since the 2012 food crisis when the adoption of a national food and nutrition security policy was adopted. The PRSPV provides responses to major risks, including drought, floods, locust attacks, malnutrition, soaring prices and insecurity limiting agro-pastoral production.

However, the PRSPV faces a real challenge in mobilising resources to implement the actions in the response plan. The financial implementation rate for the PRSPV 2023 was 68.20% at 31 December 2023, and the PRSPV 2024 budget showed a deficit of 92 billion CFA francs as at 10 April 2024, even though more than 50% of this budget is allocated to drought- and floodrelated contingency actions [7]. This low coverage of risks in general, and of drought and flood risks in particular, is the result of limited access to the climate finance market or the lack of opportunity to seize existing opportunities at international level [8].

Access to the climate finance market is not just a local problem but rather a continental one. Given this challenge, in March 2012, the Conference of African Finance Ministers unanimously adopted Resolution 16 to establish African Risk Capacity (ARC) as a specialised Institution of the African Union to help African governments improve their capacity to plan, prepare and Respond to Extreme Weather Events and Natural Disasters. Through collaboration and innovative financing, ARC enables countries to strengthen their disaster risk management systems and access rapid and predictable disaster funding to protect the food security and livelihoods of their vulnerable populations.

Burkina Faso joined ARC in 2012 and has been participating in ARC insurance pool since 2016. This gives it access to Africa Risk View as the main tool for modelling agricultural and pastoral drought risks.

Recent studies have contributed to understanding of agricultural and pastoral drought risks in Burkina Faso by using various indicators (SPEI, SPI, CSDI, WSDI, NDVI, VHI, PCI and LST) to analyse spatio-temporal trends, plant sensitivity and resistance and the spatio-temporal distribution of vegetation condition [9-11].

As part of its index insurance, ARC uses the Water Requirement Satisfaction Index (WRSI), an operational crop model originally developed by the Food and Agriculture Organization of the United Nations (FAO), and widely used across Africa and beyond, including by early warning institutions as a meaningful indicator of the impact of a lack of rainfall on crop yields and pasture availability. WRSI has been adapted and extended by the United States Geological Survey (USGS) into a geospatial application to meet the monitoring needs of the Famine Early Warning Systems Network (FEWS NET). Like FEWS NET, ARC has implemented in Africa Risk View, a WRSI adapted to its insurance needs. This version of WRSI available in Africa Risk View can be customised.

Africa RiskView uses satellite rainfall data, combined with agronomic parameters for specific crops to produce a spatial drought index (WRSI) that can be displayed on a map. ARC's WRSI is therefore geospatial data specific to a given crop and is used to monitor crop performance during the agricultural season and assess the level of water requirements at the end of the season. Characterisation of the drought situation involves a variant of the WRSI synonymous with the presence or absence of drought: the WRSI compared to normal.

This index can be customised to reduce the basis risk associated with the discrepancy between the estimated results and the reality on the ground as experienced by farmers (Ntukamazina et al., 2017). Its customisation is a sovereign task and is the responsibility of the Technical Working Group (TWG). The TWG is a team composed of experts from various fields of activity and other representative stakeholders, capable of providing the information and expertise needed for all technical work of the ARC programme in a given country. For Burkina Faso, this technical team is made up of experts from Ministry of Agriculture, Animal Resources and Fisheries, Ministry of the Economy, Finance and Prospects, Ministry of the Environment, Water and Sanitation, Ministry of Health and Public Hygiene, National Meteorological Agency and World Food Programme.

The overall objective of this study is to use the WRSI images resulting from the customisation work to analyse the dynamics of drought between 2001 and 2020 in Burkina Faso for the three main cereals, namely maize, millet and sorghum. In addition, secondary objectives relating to the results of the customisation work exist, including the search for the best historical profiles and the improvement of the decision-making system aimed at triggering the payment of insurance premiums.

2. Materials and Methods

2.1. Study Area

Burkina Faso lies at the heart of West Africa and is crossed by two climatic bands: the Sahelian and the Sudanian (northern and southern Sudanian). According to the World map of KöppenGeiger classification, the country lies within a band that ranges from a dry sub-humid tropical climate (BSh) to a semi-arid climate (BWh), passing through a cold semi-arid climate (BSk). The 600 and 900 mm isohyets divide the country into three rainfall zones [12]. These three rainfall zones are marked by a gradual widening from north to south as a result of the migration of isohyets observed at the end of the 20th century. Since the period 1931-1960, the rainfall isohyets have not returned to normal. In agro-ecological terms, this has resulted in a tendency for the agricultural front to impact more areas, making it very difficult to grow traditional crops or long-cycle varieties, hence the need for insurance products to help farmers adapt to the climate. The study will therefore cover all the regions of Burkina Faso to take account of the random nature of these cropping practices. Figure 1 is an overview of the different geographic areas covered by the study.

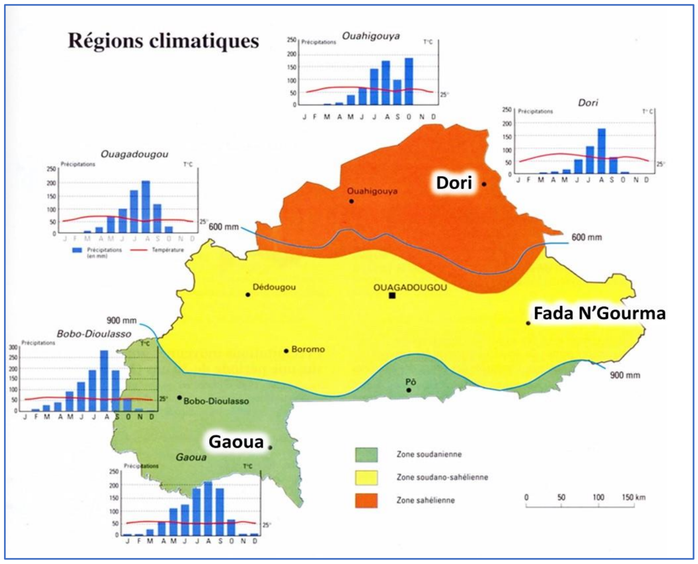

Figure 1: Climatic Regions of Burkina Faso and Location
(Source: illustration adapted from "Les Atlas de l'Afrique, Burkina-Faso", Editions J.A. 2001)

2.2. WRSI Model and Input Data for Africa Risk View

2.2.1. Introducing Africa Risk View

Africa Risk View software is ARC's technical engine designed to monitor seasons and estimate the impact of natural disasters in terms of the number of people affected and the associated response costs. It is a suite of software that includes Africa Risk View Drought and Arc Calculator Drought (for drought), Africa Risk View River Flood and Tropical Cyclone) which are currently under development [13].

Africa Risk View Drought is a feature-rich desktop application that provides extensive functions for visualising drought indicators and customising the Africa Risk View Drought Model, including importing custom datasets, location-specific parameters, viewing in-season graphs and historical data sets, and exporting model results to other formats. It uses satellitebased rainfall information to model the progression of agricultural and grazing seasons across the continent to quantify the impact on the population and to estimate the cost of assisting those affected in response to a drought event.

Africa RiskView is available in two versions: the desktop version which is "customisable", and the online version which is "non-customisable". Figure 2 shows the architecture of Africa Risk View.

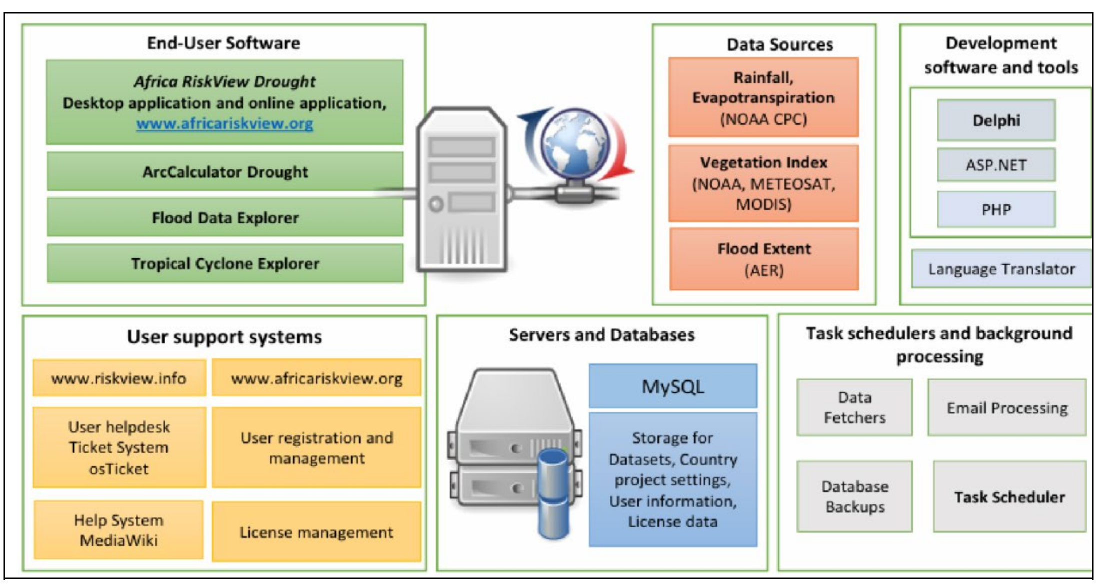

Figure 2: Africa Risk View Architecture

2.2.2. Agricultural Drought Model

The Africa RiskView agricultural drought model uses the Water Requirement Satisfaction Index (WRSI), a crop-specific index that assesses the impact of the amount and distribution of rainfall on crop growth at each phase, from sowing to maturity. This drought index is based on a water balance model developed by the Food and Agriculture Organisation of the United Nations (FAO), and the approach involves comparing the water available to the crop with its specific needs. Water deficits and excesses have a negative impact on crop performance. WRSI calculations can be extended to the end of the season using normal rainfall to provide a forecast of end-of-season conditions.

Details of how this index is calculated can be found in the article "Crop Water Requirement Satisfaction Index (WRSI) Model Description" by Gabriel Senay, published in July 2004.

2.2.3. WRSI Customisation

The Africa RiskView customisation process is a phase of modifying the default parameters of Africa RiskView adapted to the local conditions of the targeted crops. The calculation of WRSI requires several sets of input data and user-defined parameters, including sowing dates, rainfall estimates, soil water holding capacity, crop types and water requirement.

WRSI is a function dependent on the following main parameters:

WRSI=f (PPT, PER, CT, PET, WHC, SOS, EOS, LPG, SC)

with:
PPT = Precipitation
PER = Percentage of Effective Rainfall
CT = Type of Crop
PET = Potential Evapo Transpiration
WHC = Water Holding Capacity
SOS = Start of Season decade
EOS = End of Season decade
LGP = Length of Growing Period
SC = Sowing Criterion

Table 1 shows the parameters defined for calculating the WRSI for the 2023-2024 season.

Parameters	Reference crop	Observations
Reference crop	The reference crops chosen are: • Maize • Millet • Sorghum	In 2022, the contribution of the main cereal crops to national cereal production was 39% for sorghum, 35% for maize and 18% for millet.
Calculation mask	The crop zones cover all 45 provinces of the country except for maize, which covers only 43 provinces. The provinces of Oudalan and Seno are not included in the maize calculation mask.	Maize is hardly grown at all in the Seno and Oudalan provinces, where the area under cultivation is virtually non-existent (<1.0% of the total area under the three crops).
Water Holding Capacity (en mm)	ISRIC for each of the 3 reference crops	FAO and ISRIC are the two datasets available for customization.
Reference evapotranspiration	NOAA for each of the 3 reference crops	FAO and NOAA are the two data sets available for customisation.
Rainfall dataset	CHIRPS for all reference crops	Africa RiskView has 5 satellite data sets (ARC2 and RFE2, CHIRP, CHIRPS and TAMSAT). Since 2022, only CHIRP, CHIRPS and TAMSAT have been operational
Effective rainfall	60% for each crop	This value is valid throughout the country.
Length of growth period	• Maize between dekad 9 and 11 • Millet between dekad 9 and 11 • Sorghum from dekad 10 to 12	The length of the growing season for millet, maize and sorghum depends on the predominant variety in each administrative subdivision of the country. This choice therefore depends on the latitude gradient, which is early in the north and late in the south.
Sowing window	• Maize sowing window: • beginning between decade 15-17 and the end of sowing is set for decade 19. • Millet and Sorghum sowing window: beginning between dekad 13-17 and end between dekad 20-21	Based on the historical series of sowing dates provided by the Burkina Faso Technical Working Group
Sowing Criterion	• 20 mm for the first dekad • 5 mm for the second dekad • 5 mm for the third dekad	This criterion reflects the amount of rainfall received over three successive decades, guaranteeing successful sowing.

Pre-season crop Coefficient (Kcr)	0,25	The default value provided by the FAO and available in Africa RiskView.
Aggregation method	Average	The aggregation method reflects the farmer's behaviour with regard to sowing opportunities. Three aggregation methods are available: First (the WRSI value is calculated from the first possible sowing decade identified in the sowing period), Average (the arithmetic mean of all WRSI values calculated from all possible sowing decades identified in the sowing period) and Maximum (the maximum WRSI value calculated from all possible sowing decades identified in the sowing period).

Table 1: Parameters for Africa Risk View Customization to Local Conditions of Burkina Faso in 2023

Customisation in Burkina Faso began in 2019. This process has undergone significant changes due to the modification of certain parameters, the most significant of which are sowing dates, the length of the growing period, satellite data and vulnerability data, all of which have an impact on the WRSI results for each year of customisation. This customization work is carried out by a multidisciplinary working group in the country, supported by ARC's technical team.

- **Drought Severity**

The index used to detect drought is WRSI compared to normal. It is obtained by calculating the difference between the WRSI and the normal value of the WRSI (benchmark value). The Benchmark is the normal value of the fixed value or can be determined either by a moving function (mean or moving variance) or by any other function, enabling this reference value to be determined.

In general, the four most used benchmark values are the moving averages or medians of the last 5 or 10 years: "5-year average", "5-year median", "10-year average" and "10-year median". For Burkina Faso, the benchmark is the moving average of the last 5 years (5-year average).

WRSI compared to normal is calculated as follows:

$$WRSI \quad comped\,to \quad normal = WRSI - Benchmark$$

If WRSI compared to normal < 0 then Drought

$6If$ WRSI compared to normal ≥ 0 then No drought

If the WRSI compared to normal is negative, then the severity of the drought is calculated as follows:

$$Severity = \frac{WRSI\ compared\ to\ normal}{Benchmark} \times 100$$

As the Severity value moves away from zero, the drought becomes more severe.

2.2.4. Vulnerability

- **Data**

Vulnerability data comes from different sources. Table 2 gives an overview of the sources used to analyse vulnerability.

Data	Sources
Agricultural populations at provincial level	Projections of population data for Burkina Faso for the year (INSD)
Agricultural household income and wealth index	• Global Analysis of Vulnerability and Food security and NutriIon (AGVSAN/CFSVA) • Integrated NaIonal Food Security and NutriIon Survey (ENISAN)
Poverty rate	• Human Development Report • Harmonised Survey of Household Living CondiIons (EHCVM)
Quantities and yields of agricultural products and populations affected by drought	Permanent Agricultural Survey (EPA)

Table 2: Vulnerability Data Sources in Burkina Faso

- **Vulnerability Parameters**

The vulnerability parameters allow the severity of the drought to be translated into the impact of the drought using an approach based on a linear relationship determined by the scaling factor between the severity of the drought and the loss of drought-sensitive income for each household. The scaling factor is a factor that defines the relationship between the deviation of the WRSI index from its reference value (drought index) and the loss of income following a drought. The scaling factor varies between 1 and 2. This approach assumes that income from agricultural production and labour is immediately affected, whereas income from livestock is only affected at a certain level of drought severity. It therefore assumes that the sensitivity of livelihoods, casual farm labour and livestock income to drought is taken into account.

Parameters	2023 review
Scaling facteur	1,7
Loss of livelihood threshold	20%
Sensitivity of casual labour to drought	0%
Sensitivity of livestock income to drought	20%
Poverty rate	36,2%

Table 3: Vulnerability Parameters for Burkina Faso During The 2023 Drought Model Review

These parameters are provided by the members of the Technical Working Group, and are used to calibrate the vulnerability function.

- **Vulnerability Profile**

The vulnerability profile, a functional relationship established based on vulnerability data and parameters, enables the severity of drought and its impact on the agricultural population to be linked. Each level of drought severity can be associated with a percentage of the population affected by the drought. These linking points between the severity of the drought and the populations affected are called calibration points.

Africa RiskView has three (3) calibration points determined by positioning three points on the vulnerability curve obtained using the vulnerability parameters and variables such that the junction of these points allows a mathematical function to be drawn, reproducing the vulnerability curve as faithfully as possible (Figure.3).

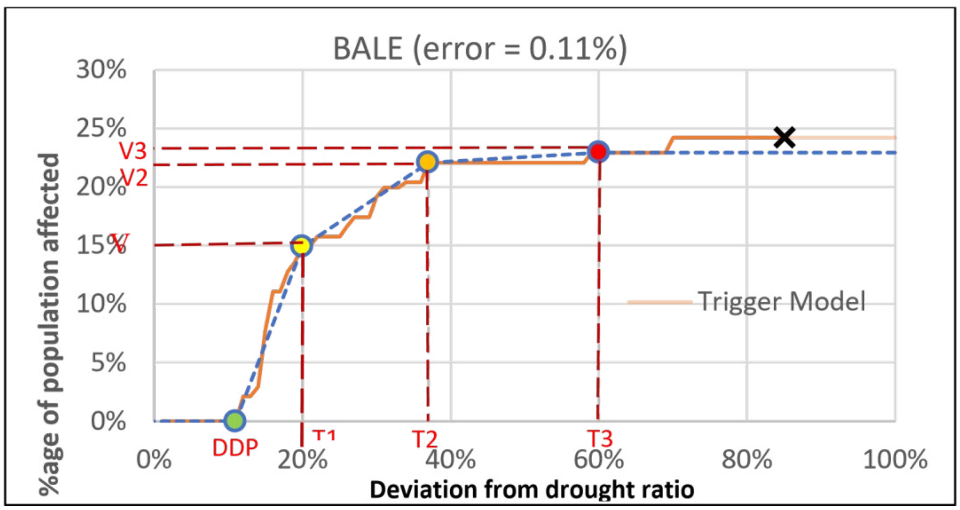

Figure 3: Example of the Relationship Between the Severity of The Drought and Its Impact on The Population

DDP = Drought Detection Point (% du benchmark)
T1, T2, T3 = Respectively 1st, 2nd and 3rd calibration points for the impact of drought V1, V2, V3 = Respectively 1st, 2nd and 3rd level of vulnerability (%)

Figure 3 shows that for a severity level T1, V1 percent of the population is affected by drought. At severity level T2, V2 percent of the population is affected by the drought, and at severity level T3, V3 percentage of the population is affected by drought. Above V3, it is estimated that the entire agricultural population is affected by drought.

2.3. Risk Profile

The risk profile is based on the following assumption: if the current conditions (population, farming practices, etc.) and if similar rainfall had been received in previous years, and based on the current population and vulnerability, then a historical series of affected populations can be generated. The customised and validated WRSI model is used to generate the country's risk profile. This profile represents the historical population affected by drought, based on customised information from Africa Risk View for the year in question and rainfall data from previous years.

Figure 4 shows the risk profile for Burkina Faso resulting from the customisation in 2019 and simulated with rainfall data for the period 2001 to 2019. From 2019 to 2023, five risk profiles have been established for Burkina Faso.

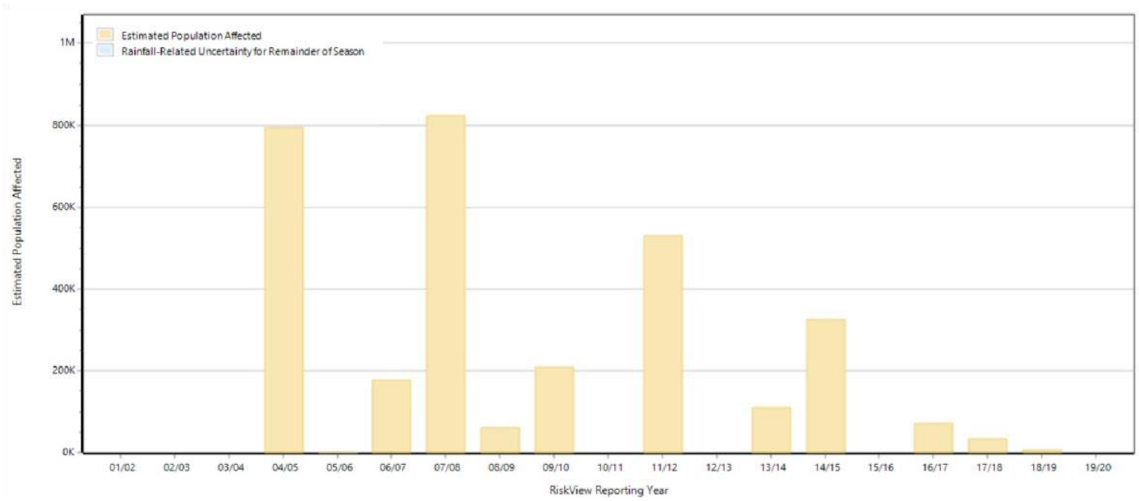

Figure 4: Burkina Faso Maize Risk Profile for the 2019/2020 Crop Year

- **Historical Drought Profile in Burkina Faso**

The final reports of the Permanent Agricultural Surveys (EPA) from 1997 to 2021 have enabled the creation of a historical record of the agricultural droughts that occurred between 1997 and 2021. This history also identifies the number of people affected for each year of drought, therefore allowing the drawing up of a historical profile that serves as a basis for validating the agricultural drought model during the Africa Risk View customisation process.

- **Comparison of Risk and Historical Profiles**

The customisation of Africa Risk View covered the 2019/2020, 2020/2021, 2021/2022, 2022/2023 and 2023/2024 crop years, i.e. 5 consecutive years of customisation. Each customised year produces a different type of historical profile. These different risk profiles have therefore been validated by comparing with the historical profile data provided by the country.

Based on Figure 5, we can observe that:

- The 2020 customisation best reflects the drought situation in the years 2004, 2005, 2006, 2008, 2009, 2011, 2014, 2016 and 2017.
- The 2021 customisation best identifies the drought situation in the years 2001, 2007, 2010, 2018, 2019 and 2020
- The 2022 customisation best reproduces the drought situation of the years 2002, 2003, 2013
- The 2023 customisation best detects the drought periods of the years 2012 and 2015.

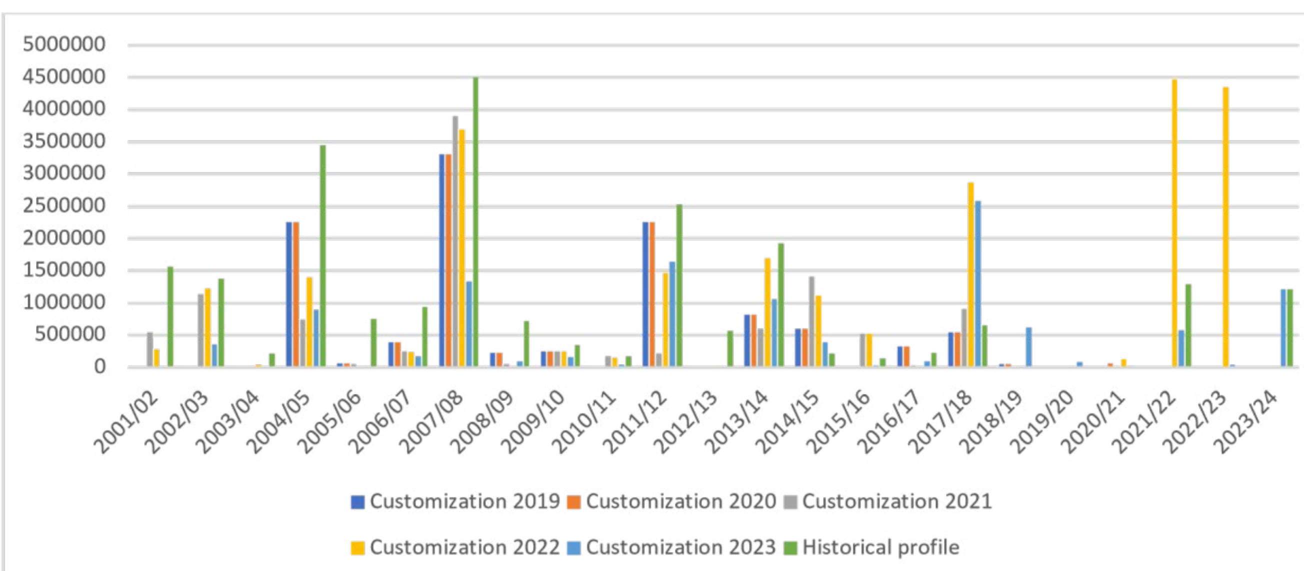

Figure 5: Results of Comparisons between the Historical Profile and the Risk Profiles Derived from the Different Years of Customisation

The 5 years of customisation have made it possible, on the basis of the above findings, to produce a synthetic historical profile of all the years of the historical profile between 2001 and 2020.

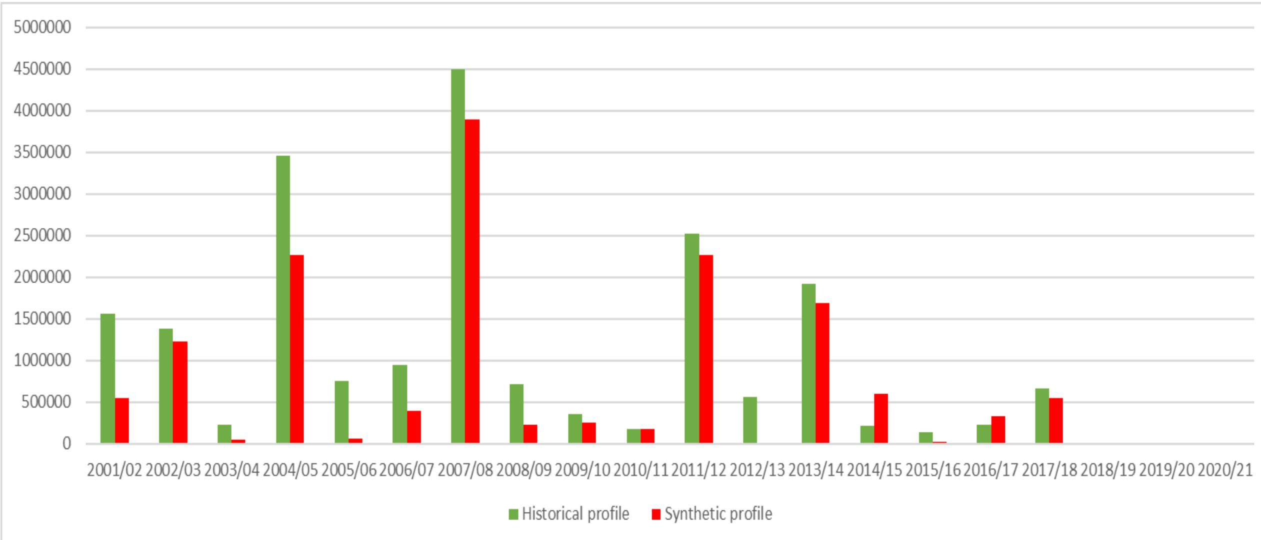

Figure 6: Comparaison Profile Historique/Profil Synthétique

2018, 2019 and 2020 are extremely wet years. This has been well captured by the historical profile and the synthetic profile, hence they are not reflected in Figure 6. This synthetic result allows the generation of 20 images of WRSI compared to normal for each speculation. A total of 60 images of WRSI compared to normal have been generated for the three speculations over the period 2001 to 2020.

2.4. Drought Classification

2.4.1. Images Processing

This was achieved using deep learning techniques, in particular Convolutional Neural Networks (CNN) [14]. In terms of image analysis and recognition, a category of CNNs, the pre-trained CNNs have been specially trained for this purpose.

Concluded that "even for unsupervised classication tasks, features extracted from deep CNN trained on large and diverse datasets, combined with classic clustering algorithms, can compete with more sophisticated and tuned image set clustering methods" [15]. This approach is therefore to combine a pre-trained CNN and a well-known classification algorithm, namely the hierarchical classification technique, to analyse WRSI compared to normal images.

The "Image Analytics" package in the Orange 3.36.2 software contains six (6) pre-trained CNNs:

- Inception V3: Google's Inception V3 model trained on Imagenet
- Squeezenet: Small and fast model for image recognition trained on ImageNet
- VGG16 (Visual Geometry Group with 16 layers): 16-layer image recognition model trained on ImageNet
- VGG19 (Visual Geometry Group with 19 layers): 19-layer image recognition model trained on ImageNet
- Painters: A model trained to predict painters from artwork images
- DeepLoc: A model trained to analyze yeast cell images

Orange is data mining software based on a catalogue of widgets/components. Details of its components can be consulted at the following address: Orange Data Mining - Widget Catalog [16].

The WRSI compared to normal images are therefore analysed using the following methodology:

- Import the images using the "Import Images" function.
- Convert the images into numerical variables using "Image Embedding", which contains the 6 pre-entrained CNNs to create numerical variables (features).
- The distances between the different features are then calculated using the "Distances" function.
- Finally, Hierarchical Classification "Hierarchical Classification" is used to create clusters.
- The quality of the classification is assessed using the "Silhouette Plot" function and the final result is displayed using the "Scatter Plot" function.
- Once the quality is satisfactory, the images from each cluster are displayed using the "Image Viewer" function.

In Orange Data Mining software, this methodology is implemented according to the work flow below (figure 7).

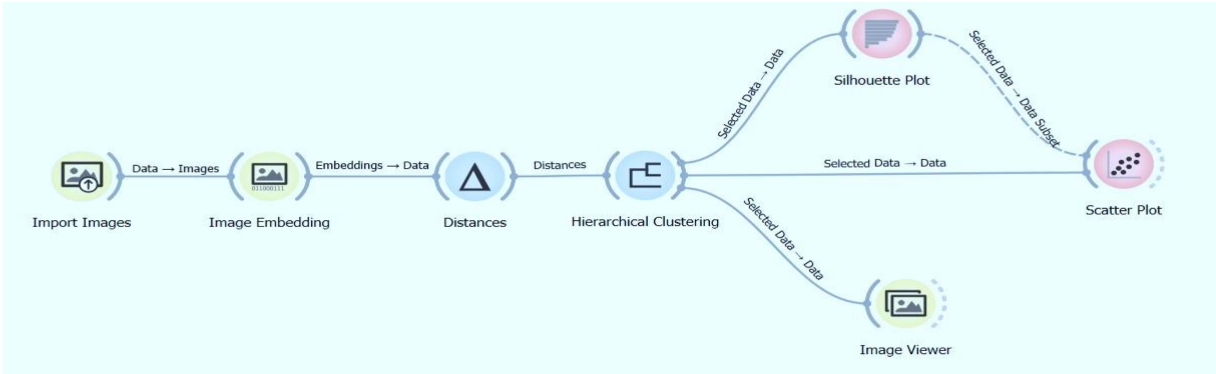

Figure 7: Image Analytics Workflow

2.4.2. Selecting the Best Clusters

The choice of the model is made by testing various parameters. The results of these tests are shown in Table 4

Embedder (Pre-trained CNN)	Distance	Silhouette (Distance = cosine)			
		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Inception V3	Euclidian normalized	0.736	0.122		
Squeeze Net	Manhattan normalized	0.551	0.324	0.631	0.218
VGG16	Manhattan normalized	0.531	0.587	0.235	
VGG19	Euclidian normalized	0.504	0.603	0.211	
Painters	Manhattan	0.511	0.510	0.574	0.026
DeepLoc	Euclidian normalized	0.559	0.493	0.420	0.26

Table 4: Classification Results from Pre-Trained CNN

The graphical representation of the classes enabled the results of each classification to be controlled [17] in order to:

- Visually check the relevance of the classification;
- Help to choose the appropriate number of classes;
- Easily isolate certain individuals whose data appear to be outliers, perhaps due to a data entry error
- Select the most atypical individuals in a class

This visual check (Figure 8), whatever the parameters used, revealed the existence of isolated individuals, making this initial classification result of little relevance due to the difficulty in determining the exact number of classes. These six (6) isolated individuals are the images from 2012 and 2015 for each of the three speculations. Because of their weight (10%) in the total number of observations, these have beeb replaced with images from similar profiles.

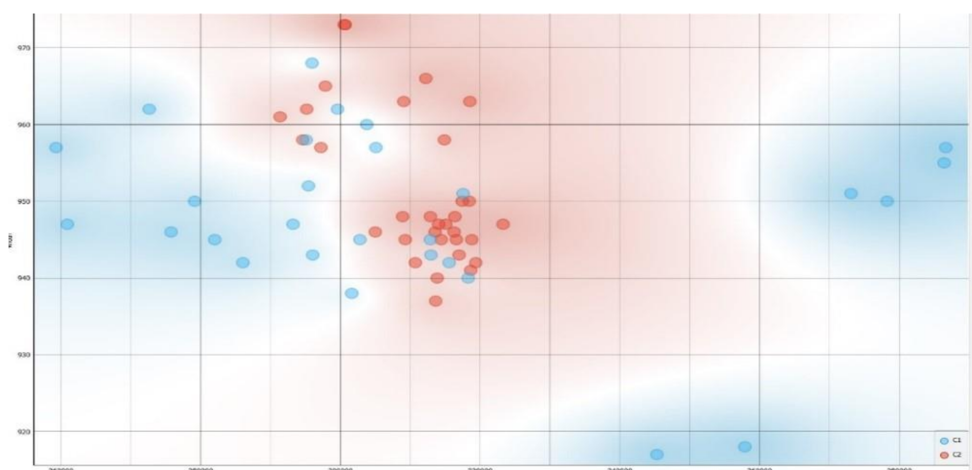

Figure 8: Example of a Graphic Representation of The Classification

The close profiles used to replace the 2012 and 2015 images were taken from the 2005 and 2010 profiles. The images from 2012 were replaced by those from 2005, 2015 and 2010. The results obtained after these corrections are shown in Table 5.

Embedder (Pre-trained CNN)	Distance	Silhouette (Distance = cosine)	
		Cluster 1	Cluster2
Inception V3	Euclidian normalized	0.715	0.661
SqueezeNet	Cosine	0.609	0.393
VGG16	Manhattan	0.461	0.382
VGG19	Manhattan	0.584	0.480
Painters	Manhattan normalized	0.610	0.536
DeepLoc	Hamming	0.659	0.327

Table 5: Classification Results After Correction

Visual inspection of this new classification shows better results than the previous ones (Figure 9).

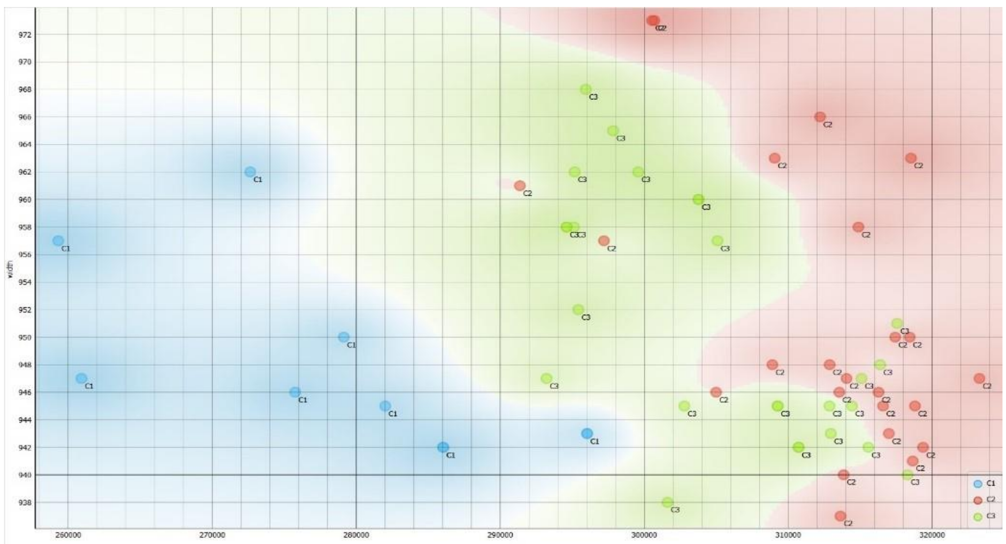

Figure 9: Final Result of Clustering

The figure shows that there are 3 clusters for all the simulations (except DeepLoc).

The combination of the performance of the classifications based on the Silhouette indicator and the visual check enabled select the model based on the Painters pre-trained CNN as the model providing the best results.

Finally, the classification model selected comes from the configuration with the following characteristics:

- Embedder: Painters
- Distance: Manhattan normalised
- Clustering method: Hierarchical clustering
- Clustrering linkage: Ward
- Silhouette plot distance: Cosine

2.4.3. Cluster Comparison

An ANOVA test was used to compare the means of the three clusters. However, as the number of clusters was greater than 2, a post-hoc test was required to establish the real difference between the means of these three clusters. The post-hoc test used was the Tukey test.

3. Results and Discussion

3.1. Results

- **Cluster 1:** No drought

Few years record a complete absence of drought. There are two years (2019 and 2020) where there was drought for maize and four years (2010, 2015, 2019 and 2020) where there was drought for millet and sorghum.

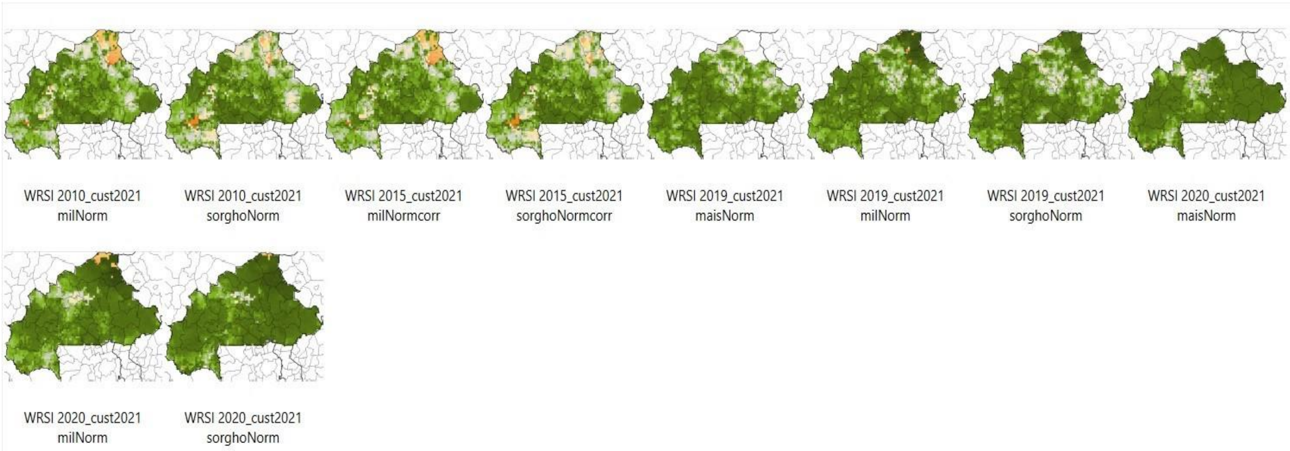

Figure 10: Cluster 1 Maps of WRSI Compared to The Normal

However, in 2010 and 2015, maize was affected by drought while other crops were not. This case shows that climatic conditions (water requirements) can be unfavourable for some crops while they are favourable for others.

- **Cluster 2:** Generalised drought

This cluster highlights a situation of generalised drought throughout the country. The years of widespread drought fall between 2001 and 2013 (2001, 2002, 2004, 2006, 2007, 2008, 2011 and 2013) and are characterised by the existence of droughts of varying intensity throughout the country, affecting all the reference crops simultaneously.

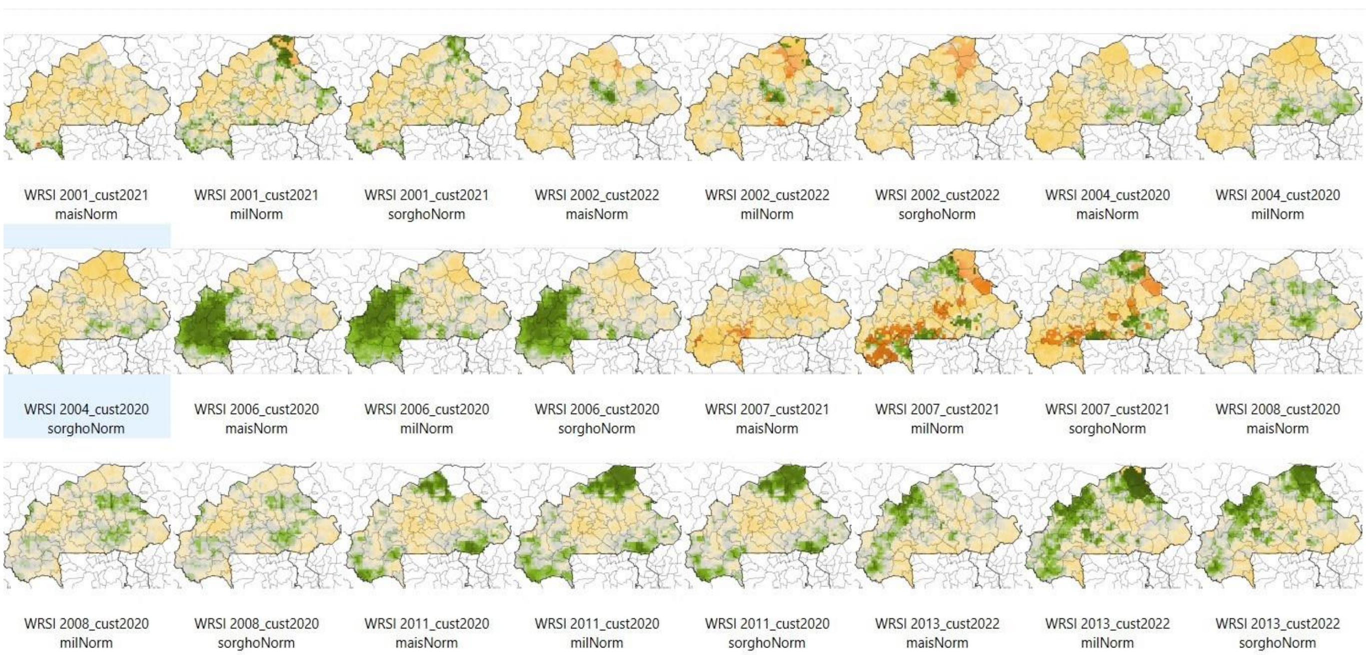

Figure 11: Cluster 2 Maps of WRSI Compared to The Normal

- **Cluster 3:** Partial Drought

Some parts of the country are suffering from drought, while other parts are experiencing abovenormal production conditions. This situation manifests itself randomly, whatever the crop. It is difficult to know which area will be affected by the drought.

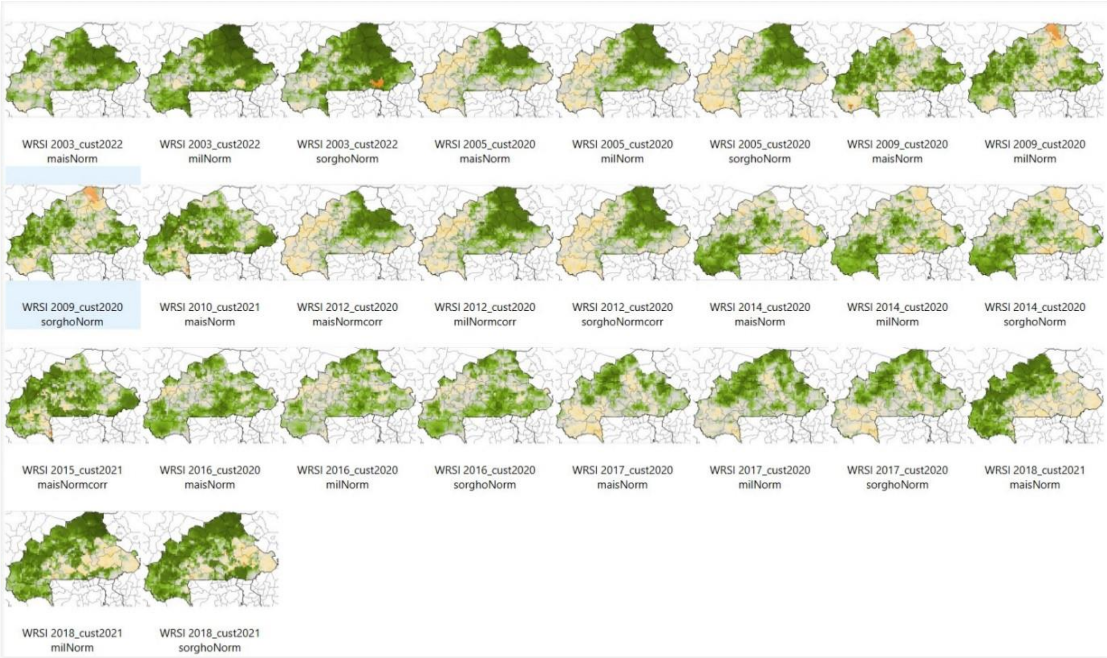

Figure 12: Cluster 3 Maps of WRSI Compared to The Normal

3.2. Cluster Analysis

Descriptive analysis of the clusters shows a significant difference between them. Indeed, the average WRSI compared to the normal is different from one cluster to another. It is 8.56 in the case of no drought, 2.69 in the case of partial drought and -6.06 in the case of generalised drought (see table 6).

Clusters	Obs	Mean	Std-Dev	Std- Err	Min	Max	IC (95%)	
c1	10	8,56	3,56	1,13	4,51	14,30	6,02	11,11
c2	24	- 6,06	5,30	1,08	- 20,51	0,23	- 8,30	- 3,83
c3		2,69	2,43	0,48	0,28	8,97	1,71	3,67
Total	**60**	**0,17**	**6,78**	**0,87**	**- 20,51**	**14,30**	**- 1,58**	**1,92**

Table 6: Descriptive Statistics for Clusters

However, the minimum and maximum overlap, particularly for Cluster 1 (C1) and Cluster 3 (C3). Similarly, the box and whisker plots show the possibility of overlapping data, particularly at the end of each confidence interval as indicated in Figure 13 below.

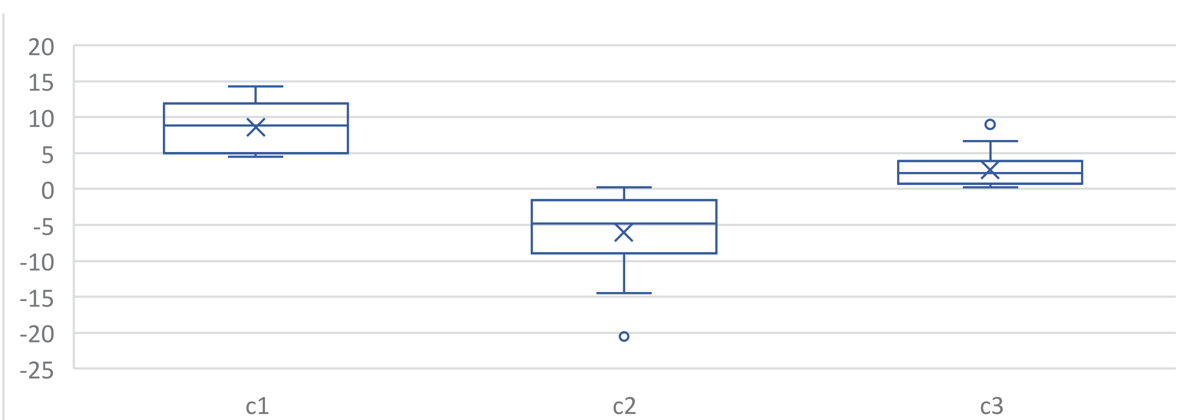

Figure 13: Cluster Box and Whisker Plots

To ensure that the means of the three clusters are indeed different, an ANOVA test was performed (table 7). The results of this test show that at least one mean among the means of the 3 clusters is different from the others ((Prob>F) = 0).

Source	Partial SS	df	MS	F	Prob>F
Model	1 802,85	2,00	901,43	56,67	0,0000
Cluster	1 802,85	2,00	901,43	56,67	0,0000
Residual	906,70	57,00	15,91		
Total	**2 709,55**	**59,00**	**45,92**		

Table 7: ANOVA Test for Means Comparison

A post-hoc test is therefore necessary to determine which of the means is different from the others. In this study, the post-hoc test chosen is the Tukey test (Table 8) and the result of this test shows that the three means are different. In fact, the probabilities of equality of mean from one cluster to another are equal or close to zero ((P>t) = 0).

Cluster	Contrast*	Std. Err.	t	P>t	Tukey	
					[95% Conf. Interval]	
2 vs 1	-14,63	1,50	-9,75	0,000	- 18,24	- 11,02
3 vs 1	-5,87	1,48	-3,96	0,001	- 9,45	- 2,30
3 vs 2	8,76	1,13	7,76	0,000	6,04	11,47

Table 8: Tukey's Test

(*): Difference between 2 averages. For example, 2 vs 1 = -6,06-8,56 = -14,63

Therefore, it can be concluded that the average WRSI compared to normal is different from one cluster to another.

This difference in the mean of the WRSI compared to normal according to the spatial distribution of the drought is an excellent indication of the type of drought experienced by the country at the end of the season, whether the country is facing a drought situation, and if there is a drought, whether it affects the whole country.

3.3. Drought Severity

According to the 2021 customisation report, 2002, 2004, 2007, 2011, and 2013 are severe drought years. The other drought years are average drought years. Cross-referencing this information with the clusters allows for the drawing up of a table showing droughts according to their severity [18].

Crops	Type of drought	Severity			Total
		Severe	Medium	Low/No drought	
Maize	Generalized Partial No drought	5 0 0	3 10 0	0 0 2	8 10 2
	Total	**5**	**13**	**2**	**20**
Millet	Generalized Partial No drought	5 0 0	3 8 0	0 0 4	8 8 4
	Total	**5**	**11**	**4**	**20**
Sorghum	Generalized Partial No drought	5 0 0	3 8 0	0 0 4	8 8 4
	Total	**5**	**11**	**4**	**20**
Total		**15**	**35**	**10**	**60**

Table 9: Distribution of the Types of Drought According to Their Severity and By Crop

Over the 20 years of the study, five (5) severe droughts were observed, i.e., an average of one drought every four years, whatever the crop. 11 to 13 medium droughts were also observed over the same period, an average of one medium drought every 2 years. Periods without drought occur every ten years on average for maize and every five years for millet and sorghum.

3.4. Provinces Most Exposed to Drought

Severe droughts are of particular interest to the insurance provided by ARC, hence the need to calculate the probability of a province being subject to severe drought by cross-referencing WRSI compared to normal and years of severe drought (see Table 10).

Classes	Probabilities	Climatic regions		
		North soudanian	South soudanian	Sahelian
1	≤ 20%	Kompienga, Koulpelogo, Kourweogo, Loroum, Zondoma, Ganzourgou, Komonjdjari, Kossi, Mouhoun, Nayala, Passore, Zoundweogo	Bougouriba, Comoe, Ioba, Leraba, Noumbiel	Oudalan, Seno, Soum, Yatenga, Sourou
2	20% - 25%	Banwa, Gourma, Kadiogo, Oubritenga, Sanguie, Tapoa, Ziro, Bale, Bazega, Boulgou, Boulkiemde, Gnagna, Kouritenga, Sissili	Houet, Poni, Kenedougou, Nahouri, Tuy	Bam, Namentenga, Sanmatenga, Yagha

Table 10: Probability of Exposure to Severe Drought by Province

The results show that the provinces most exposed to severe droughts are those located in the northern Sudanian strip where most provinces have a probability of exposure of over 20% (Figure 14).

Similarly, the Hauts-Bassins provinces (Houet, Kenedougou and Tuy), which had been declared as areas with zero probability of drought (Dembélé et al., 2016), are in fact provinces that are just as exposed to drought as the country's other provinces (Figure 14). The drought in this southern part of Burkina Faso is confirmed by the existence of drought in the north-eastern part of Côte d'Ivoire (KANGA et al. (2016), which borders this part of Burkina Faso.

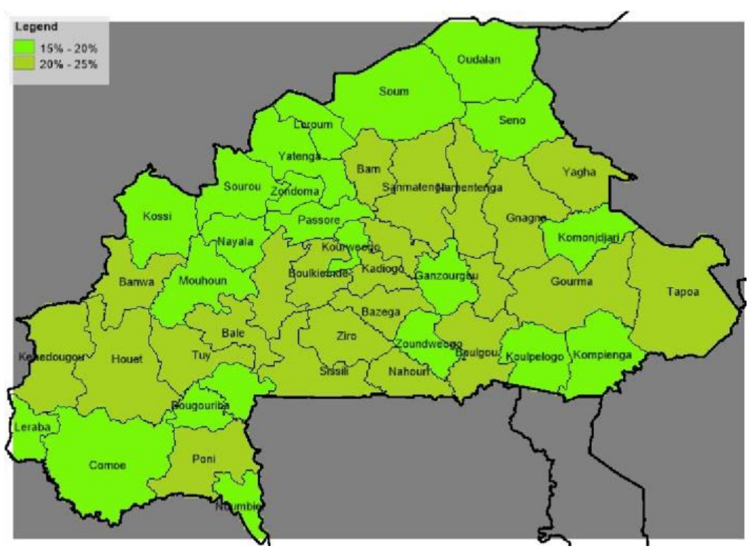

Figure 14: Probability of Exposure to Severe Drought

3.5. Rules for Identifying Drought Severity

From Table 6 above, the following rules can be formulated at the national level:

- If average WRSI compared to normal < = - 3.83 then generalized drought o If average WRSI compared to normal < = - 4.28 then severe drought o If - 4.28 < average WRSI compared to normal < = - 3.83 then medium drought
- If - 3.83 < average WRSI compared to normal <= 3.67, then average partial drought o If - 3.83 < average WRSI compared to normal < 0, then partial drought average o If 0 <= average WRSI compared to normal < 3.67, then there is probably drought, but it is localised and of low amplitude.
- Otherwise, there is no drought at all.

4. Discussion

Recent studies have contributed to understanding drought in Burkina Faso using various indicators to analyse the phenomenon as indicated in Table 11 below:

Authors	Area of study	Drought indicators	Years of severe drought
Sawadogo, 2022	Burkina Faso	SPEI	2011–2012, 2013–2014 et 2018–2019
Bontogho et al., 2022	Massili basin	SPEI	2000 - 2010
Sanou et al., 2023	Burkina Faso	SPEI, SPI, CSDI, WSDI, CDD	2001 - 2010
Dembelé et al. 2016	Burkina Faso	NDVI, VHI, PCI, LST, TCI, VCI	2001, 2004, 2011, 2014

Table 11: Comparison of Studies on Agricultural Drought

SPEI: Standardized Precipitation Evapotranspiration Index
SPI: Standardized Precipitation Index
CSDI: Cold spell duration indicator
WSDI: Warm spell duration indicator
CDD: consecutive dry days
NDVI: Normalized Difference Vegetation Index
VHI: Vegetation Health Index
LST: Land surface temperature
PCI: Precipitation Condition Index
TCI: Temperature Condition Index
VCI: Vegetation Condition Index

Have provided details of severe drought years. However, these years do not all converge with the history of severe drought years identified at the national level and compiled in the Burkina Faso drought model customisation report [19,20]. The other authors indicated a decadal range of drought severity over the period 2000-2020, without giving details of the years that are really incriminated.

Regarding the location of severe droughts, only did not identify any droughts affecting crops in western Burkina Faso. Western Burkina Faso borders the northeastern part of Côte d'Ivoire [21]. KANGA et al. (2016) use the Nicholson and McKee indices (SPI) to demonstrate that there are meteorological and agricultural drought episodes of varying intensities in this part of Côte d'Ivoire. This reasonably attests to the presence of drought in western Burkina Faso. Finally, no region in the country has been spared by drought.

All this shows the reliability of the results provided by Africa Risk View in terms of the geographical location of droughts, but also in terms of the years of occurrence of these events, which are closer to the reality on the ground than those provided by the most recent studies identified in this study.

Over the five years of customisation, Africa Risk View has performed very well as indicated in Table 12 below.

Years	Accuracy	Sensitivity	Precision	F1 score
2019	68,42%	64,71%	100%	78,57%
2020	89,47%	88,24%	100%	93,75%
2021	76%	72%	100%	84%
2022	67%	72%	87%	79%
2023	67%	72%	87%	79%

Table 12: Customisation Performance Indicators

The lowest performances correspond to the customisation years with RFE2 in 2022 and CHIRPS in 2023. The changes in rainfall datasets from ARC2 to RFE2 and then from RFE2 to CHIRPS were justified by anomalies found in ARC2 and RFE2, which led to their temporary suspension.

There is still considerable scope for improving the performance of the Africa Risk View Agricultural Drought Model, and this can be pursued by continuing the customisation exercise, considering satellite data with characteristics similar to those of ARC2.

Apart from rainfall data sets, other parameters influence the model's performance, in particular agronomic variables such as crop variety, cycle length and sowing period. Burkina Faso has a database that is used to identify the start and end dates of sowing by province.

Although there are variations in sowing periods influenced by the start of the rainy season, this database makes it possible to draw up a distribution of sowing dates and to determine the optimum sowing window for most farmers (95% of farmers) [22]. Africa Risk View should offer new functionalities integrating a sowing calendar for reference crops based on historical sowing date data to help farmers better identify optimal sowing periods [23].

Furthermore, the most direct link between the WRSI compared to normal and the response cost can lead to spurious payments being triggered if there is an anomaly in the final WRSI result [24-26]. Figure 15 below shows an example of anomalies. There are isolated pockets of drought where there should not have been any. This situation can trigger payments if there is a high concentration of farming populations in these areas [27]. A similar case has already been observed in the northern part of Côte d'Ivoire for the 2022 customisation where pockets of missed sowings in the departments of Poro (Korhogo, Koni and Niofoin) and Worodougou (Fadiadougou and Kani) triggered a payment even though the level of water satisfaction was above average for the entire northern part of the country. The introduction of a decision rule between the WRSI compared to normal and the calculation of the number of people affected by the drought is therefore justified. Therefore, the implementation of such rules is essential to reduce the risk of false payments based on drought intensity as defined in this study [28].

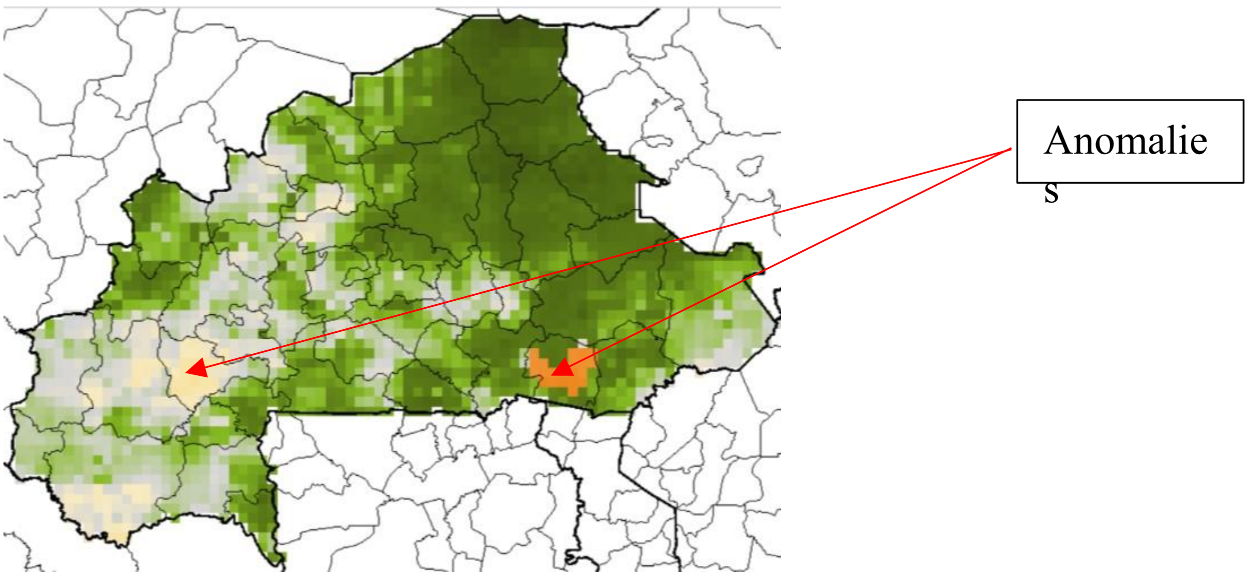

Figure 15: WRSI Anomalies Compared to Normal That Could Lead to A Wrong Payment

Over and above the model's performance and the improvements to be made to Africa Risk View, the results of this study could lead to an improvement in the country's agricultural insurance strategy.

Current insurance strategies are based on the frequency of drought risks. Indeed, the definition of risk transfer parameters is based on the number of severe droughts historically identified in the country.

The results of this study corroborated the occurrence of a severe drought every four years. This reinforces the country's choice regarding the frequency of severe droughts as part of the implementation of the insurance contract with ARC. Moderate drought occurs very frequently, happening every two years. The frequency with which moderate droughts occur makes it possible to develop an agricultural micro-insurance strategy involving local private insurance companies.

Meanwhile, the results of recent studies indicate a wetting trend observed in Burkina Faso from 2010 onwards (Bontogo et al., 2022), with the persistence of moderate droughts and decadal variability in rainfall. In the case of Burkina Faso, three (3) options can be considered to effectively cover farmers against the risk of agricultural drought:

- **Severe drought insurance:** this is justified by the fact that the study showed a concentration of severe droughts over the period from 2002 to 2013. Accordingly, it is advisable to take out severe drought insurance every four years with the support of partners.
- **Insurance for moderate droughts:** The micro-insurance sector needs to be encouraged and boosted. In this regard, the state should promote the emergence of private sector micro-insurance to support its actions to continue to improve drought risk cover. Developing a micro-insurance strategy is necessary to structure the agricultural insurance sector and improve food security for the most vulnerable.
- **Anticipatory insurance:** to protect against risks associated with the start of the agricultural season and the sowing period. This type of insurance is designed to cover communication costs and problems with the distribution of improved seeds and plant protection products, to minimise the effects of climatic hazards on the start of the agricultural season and the sowing period.

5. Conclusion

This study, which uses WRSI compared to normal images to analyse the drought situation in Burkina Faso between 2001 and 2020, provides an additional element in the techniques used to analyse drought in countries.

This image classification technique has shown that the drought in Burkina Faso is not only a national phenomenon but also affects the country's main cereal crops (maize, millet, and sorghum) in the same way, whatever the agro-ecological zone.

While the importance of agricultural insurance no longer needs to be demonstrated, the trend towards wetter weather with a predominance of moderate droughts impacts the beginning of the agricultural season and sowing periods has been observed. The anticipatory insurance strategy is emerging as a new approach to mitigating the effects of drought on agricultural production.

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