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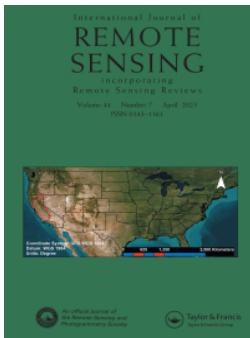
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Drought vulnerability of central Sahel agrosystems: a modelling-approach based on magnitudes of changes and machine learning techniques

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ABSTRACT

Agricultural drought is a complex phenomenon with numerous consequences and negative implications for agriculture and food systems. The Sahel is frequently affected by severe droughts, leading to significant losses in agricultural yields. Consequently, assessing vulnerability to agricultural drought is essential for strengthening early warning systems. The aim of this study is to develop a new multivariate agricultural drought vulnerability index (MADVI) that combines static and dynamic factors extracted from satellite data. First, pixel temporal regression from 1981 to 2021 was applied to climatic and biophysical covariates to determine the gradients of trend magnitudes. Second, principal component analysis was applied to groups of factors that indicate the same type of vulnerability to configure the basic equation of vulnerability to agricultural drought. Then, random forest (RF), K-nearest neighbours (KNN), support vector machine (SVM) and naïve Bayes (NB) were used to predict drought vulnerability classes using the 28 factors as inputs and 708 pts of randomly distributed class labels. The results showed statistical agreement between the predicted MADVI spatial variability and the reference model ($R=0.86$ for RF) and its statistical relationships with the vulnerability subcomponents, with an $R=0.73$ with exposure to climate risk, $R=0.64$ with the socioeconomic sensitivity index, $R=0.6$ with the biophysical sensitivity index and a relatively weak correlation ($R=0.21$) with the physiographic sensitivity index. The overall vulnerability situation in the watershed is 21.8% extreme, 10% very high, 16.8% high, 27.7% moderate, 22.2% low and 1.5% relatively low considering the cartographic results of the predicted vulnerability classes with SVM having the best performance (accuracy=0.96, Kappa=0.95). The study is the first approach that uses the gradients of magnitudes of satellite covariate anomaly trends in multivariate modelling of vulnerability to agricultural drought. It can be easily scaled up across the Sahel region to improve early warning measures related to the impacts of agricultural drought.

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1. Introduction

Over the past three decades, climate change studies have revealed a significant increase in climate extremes, putting forward the hypothesis of accelerated aridification of the climate of terrestrial ecosystems (Wu et al. 2017). The unpredictable vagaries of the climate today risk compromising sustainable development efforts and the fight against malnutrition and food and water insecurity (Bachmair et al. 2016; Daryanto et al. 2017; Le Page and Zribi, 2019; Hina et al. 2021). Among climate extremes of high intensity and often regional magnitude, drought has been recognized as one of the main climate risks contributing to the vulnerability of agricultural systems because of its unpredictable intensity (Bahta 2022; Costa, Sant'anna, and Young 2021; Dalezios et al. 2014; Shiferaw et al. 2014; Zhou et al. 2022; Zhu et al. 2021). It strikes more than half of the world each year (Arabameri et al. 2021), and the direct and indirect consequences of this climatic hazard on populations and agroecosystems are often very catastrophic and irreversible in places (Feller and Vaseva, 2014; Feller U. 2016). According to UNDRRI figures, in 2019, 61.7 million people were affected by the direct or indirect causes of natural disasters, and 4733 of them died. Similarly, over the period from 2003 to 2013, the FAO put the losses due to prolonged sequences of extreme droughts on the African continent at 23.5 billion dollars, making it the second most affected continent after Asia. Because of their geographical position and essentially arid climate, the countries of the Sahel are particularly sensitive to climate variability (Desquith and Renault 2021; Faye 2018; Serdeczny et al. 2017). The unpredictable and sometimes simultaneous occurrence of extreme weather events are the most formidable manifestations of climate change in terms of the risk of agricultural yield losses. At the same time, average isohyets have fallen by 100 to 150 km towards the south, and desertification of farmland is becoming increasingly irreversible in places. The populations of the central Sahel are the most vulnerable to extreme climatic risks, given the importance of the agroforestry sector, which is highly dependent on seasonal weather conditions. In addition, the extensive nature of production systems and the absence of modernization initiatives such as supplementary irrigation systems exacerbate the climatic sensitivity of the Sahelian agrosystems of the central Sahel. At the same time, the combined effects of climatic, environmental, and demographic factors result in a gradual expansion of arable land, soil encrustation, shorter fallow periods and a reversal in transhumance (Emeterio et al. 2013). These problems are now becoming real obstacles to the socioeconomic emergence of many countries in the central Sahel. This can be a long-term process because in the next thirty (30) years, the IPCC preestimates in its latest report that approximately 2 billion 500 million additional people will be affected by climate risks mainly in developing countries.

Of all sectors exposed to climate variability, according to the FAO, the agricultural sector already accounts for nearly 22% of all damage associated with climate risks. Around the world, despite technological advances in weather forecasting and crop system management, the vulnerability of the agricultural sector to climatic hazards, particularly those related to water stress, continues to increase (Banerjee and Pandey 2021; Latha 2021; Su et al. 2022). This growing vulnerability translates into situations of insufficient availability of water resources for agricultural production systems that directly affect the length of crop growth and phenophase, spatial patterns of cropping systems and loss of cultivated area (Bhavani et al. 2017; Monteleone et al. 2022). The state of vulnerability

depends on the exposure of agrosystems to climatic hazards, their climate sensitivity, and their resilience in terms of adaptive capacity. It varies from region to region, and the regions most affected by changes in key variables such as precipitation, temperature, soil structures, slope and low groundwater potential are generally the most vulnerable to drought (Wilhelmi and Wilhite, 2002; Xu and Zhang, 2018; Ilbahar 2022).

In the Central Sahel region, severe and prolonged droughts are part of the climatic hazards that undermine efforts to combat hunger and malnutrition. Today, more than nowhere else, the territorial and societal dynamics that shape the Sahelian space have their origins in the cumulative and/or delayed effects of the historical droughts experienced by the Sahel. Since the long dry decade of 1984 to 1998, the vulnerability of Sahelian agrosystems to drought has increased significantly (Guo, Chen, and Pan 2021; Nooni et al. 2021; Fall et al. 2021). It is reflected today by very contrasting local disparities considering highly differentiated ecosystem resiliencies. This vulnerability is governed by two types of factors. Static factors and evolutionary factors in time and space. Static factors are the geographic determinants of vulnerability, while dynamic factors are climate, environmental and sociodemographic determinants. The drought vulnerability of an agrosystem is a combination of multifactorial vulnerabilities that include climatic, socioeconomic, and environmental vulnerabilities (Hoque, Pradhan, and Ahmed 2020; Ortega-Gaucin, la Cruz Bartolón J, and Castellano Bahena 2018). It is the result of the complex interactions of several processes and nonlinear factors. For example, using a grey-tended relational clustering analysis approach applied to 42 factors, Zhang et al. (2021) identified 14 key factors influencing regional agricultural vulnerability to drought. In another context, in the city of Bengbu, using a diagnosis based on the overall subtraction potential, Zhou et al. (2022) found that the main factors that affect the vulnerability of agriculture are rainfall uncertainties, fluctuations in water use efficiency and irrigation protection rates. In contrast, based on the fuzzy-analytical hierarchy process (fuzzy-AHP) technique, Saha et al. (2021a) developed a drought vulnerability mapping approach that involves the use of 24 parameters of two forms of vulnerability (physical and socio-economic) in the state of Indian Odisha.

From the above, multivariate drought vulnerability mapping is indeed multifactorial mapping that includes factors of sensitivity, exposure, and adaptation. This includes objective classification of land suitability in drought-prone areas considering natural and anthropogenic sensitivity factors (Habibie et al. 2020) and mapping of drought-vulnerable agricultural areas (Arshad et al. 2008; Arabameri et al. 2021; Faridatul and Ahmed 2020; Sarkar et al. 2020; Ma et al. 2022). The assessment of agricultural vulnerabilities to drought is therefore an essential component for integrated drought risk assessment and management (Dalezios et al. 2014; Dunne and Kuleshov 2022; Elusma, Tung, and Lee 2022; Frischen et al. 2020; Guo, Chen, and Pan 2021; Hoque et al. 2021; Ortega-Gaucin et al. 2021; Zhang et al. 2021; Mohammadi et al. 2022). It is a prerequisite for decision support for planning and guiding drought mitigation measures (Murthy et al. 2015; Alamdarloo, Manesh, and Khosravi 2018; Zeng et al. 2019; Saha et al. 2021a; Arabameri et al. 2021; Hao et al. 2022).

Currently, several approaches have been proposed in the literature for multivariate mapping of drought vulnerabilities. Regardless of the method of weighting the variables, depending on the groups of factors used, drought vulnerability assessment approaches can be grouped into three categories. The assessment of agricultural vulnerability to

drought by composite indices that include exposure, sensitivity, and adaptation factors, as stated in the IPCC Fourth Report, is the most popular approach (Imani et al. 2014; Latha 2021; Liang, Zhang, and Qin 2021; Murthy et al. 2015; Sehgal and Dhakar 2016; Dilawar et al. 2022; Wu et al. 2017). The second category of approaches uses only two categories of factors, namely, drought susceptibility factors and drought resilience factors (Guo, Chen, and Pan 2021; Kafy et al. 2023; Ortega-Gaucin et al. 2021; Zhang et al. 2021; Durowoju et al. 2022; Singh et al. 2023). Recently, a third category of approach to assessing agricultural vulnerability to drought has emerged. The latter is based on an aggregation approach of hydrological, meteorological, agricultural, and socioeconomic variables (Arabameri et al. 2021; Hoque, Pradhan, and Ahmed 2020; Upadhyay and Avarachen, 2023) and to some extent considers the buffering capacity of soils and groundwater (Cruz, Hernandez, and Uddameri 2021). At the scale of China, Guo, Chen, and Pan (2021) developed an approach to mapping agricultural vulnerability to drought by considering two categories of factors, namely, drought susceptibility factors and drought resilience factors. In contrast, the Agricultural Drought Vulnerability Index (ADVI) proposed by Murthy et al. (2015) is a linear combination of the three indices that provide information on three components: exposure, sensitivity, and adaptive capacity. Similarly, Tallar and Dhian (2021) recently built a decision support system for vulnerability assessment for the small outermost islands of Indonesia. Some of the specific parameters involving meteorological, physical, and socioeconomic aspects were used to develop the sustainable drought vulnerability index. The latest trends in multivariate modelling of spatial drought vulnerability rely on the use of machine learning models and multisensor remote sensing data (Arabameri et al. 2021; Kafy et al. 2023; Saha et al. 2021a, 2023a), sometimes coupled with the use of cultivation models (Li, Zhang, and Zhang 2021).

Thus, in a global context marked by an increase in the frequency and severity of droughts, the application of new artificial intelligence methods in studies of vulnerability to agricultural drought has emerged and is gradually multiplying. Significant scientific progress has been made in the modelling of drought vulnerability using machine learning and deep learning models, as well as in the integration of multisource and multiformat data (Li, Zhang, and Zhang 2021; Mohan 2022; Rahmati et al. 2020; Saha et al. 2023b; Kafy et al. 2023). Algorithms such as support vector machines, artificial neural networks, random forests, and aggregation methods have been successfully used to predict and assess drought vulnerability in different systems (agriculture, hydrology, ecology, etc.). Indeed, these models can integrate multiple variables, such as meteorological data, soil data, satellite images and socioeconomic information, to improve predictions. However, their predictive performance is often highly dependent on the characteristics of the machine learning models, the type and volume of input datasets and the complexity of the problem to be solved. For these reasons, several evidence-based studies have developed approaches to modelling vulnerability to agricultural drought by comparing the predictive performance of several machine learning models. Saha et al. (2021b) investigated relative drought vulnerability by comparing the performance of bagging and artificial neural network (ANN) models in Karnataka State, India. Considering sensitivity factors (nine factors), exposure to hazards (ten factors) and resilience to drought (seven factors) as predictors of vulnerability status, the study found that the ANN model performed better than the bagging model, with a slightly higher prediction accuracy of 2.3%. On the other hand, in northern Iran, comparing the performance of three learning models,

random forest (RF), support vector regression (SVR) and their ensembles (i.e. bagging, boosting, and stacking), Arabameri et al. (2021) found that the SVR-Stacking model is the most robust model for the preparation of drought sensitivity maps (AUC = 0.94). In southeastern Queensland, Australia, Rahmati et al. (2020) developed a spatial and temporal machine learning approach for drought risk mapping by comparing the performance of six machine learning models that use eight hydro-geo-environmental factors as input predictors of relative soil moisture variance (RSMD). The study suggests that RF and MARS are better suited to cartographic modelling of spatial drought risk. Nevertheless, despite the innovative nature of the approach, several drought risk factors were not considered in the approach. Only the variability of average rainfall was considered in the approach as a climatic variable. The temporal and spatial variability of extreme temperatures, which very often lead to intense evaporation and aggravate the risk of drought even when rainfall is around average, was omitted. Similarly, indicators of the biophysical sensitivity of agricultural systems in response to climatic hazards have not been considered. However, researchers such as Roodposhti, Safarrad, and Shahabi (2017) have shown that drought sensitivity is an integral component of agricultural drought vulnerability and risk, given that the spatiotemporal patterns of drought impacts on plant cover have been shown to be very distinct depending on the characteristics of each zone. This variation in drought vulnerability is closely linked to the climatic resilience of each agri-environmental system, so indicators of vegetation quality and condition are potential variables for assessing the relationship and historical variance of vegetation sensitivity to drought (Choubin et al. 2019). Recently, using the RF model and Adaptive Neuro-fuzzy Inference Systems (ANFIS) model, Masroor et al. (2023) found that low NDVI values and an increasing trend in maximum and mean temperatures are the key factors influencing drought vulnerability in the Gadavari subwatershed in India. It should therefore be understood that scientific efforts are still required to substantiate the specific performance of each model by including as many of the variables that affect drought risk negatively and positively as possible. In this direction, a new approach proposed by Saha et al. (2023a) is one of the scientific breakthroughs in drought vulnerability modelling. By including 53 indicators of vulnerability subcomponents to feed four ensemble machine learning models (M5P, M5P-Dagging, M5P-Random SubSpace (RSS) and M5P-rotation forest (RTF)), the study provided a holistic assessment of the state of drought vulnerability in the state of Odisha in India, and in their analysis of the comparative performance of the models, the M5P-RFT model achieved the highest accuracy in modelling drought vulnerability with an AUC of 0.901. In the same vein of scientific progress in the multifactorial detection and mapping of drought-prone areas, Saha et al. (2023b) proposed the use of deep learning techniques with deep learning neural networks (DLNNs) by integrating factors from different forms of hydrological drought, agricultural drought, meteorological drought, and socioeconomic drought. They concluded that the performance of the DLNN model was very high (AUC of 94.8%) and superior to that of the ANN machine learning models and the multitask Gaussian process (MGP). In other words, approaches to predictive modelling of future vulnerability to drought should also be considered. In this direction, Al Kafia et al. (2023) proposed an approach based on cellular automata (CA) and artificial neural network (ANN) algorithms to predict the future severity of vulnerability to drought in the northwestern region of Bangladesh.

However, despite the algorithmic novelty and the large number of variables often included in drought vulnerability modelling in previous studies, it should be noted that no approach has focused on the gradients of magnitudes of trends of vulnerability factors in drought vulnerability modelling. Thus, unlike previous approaches, the objective of this study is to develop for the first time a multivariate index of vulnerability to agricultural drought by considering the gradients of magnitudes of trends in the anomalies of dynamic factors rather than the anomalies of variables or the intensity of their frequencies commonly used. This reflects the novelty of the study in terms of the very conclusive results obtained. The approach assumes that the state of global vulnerability to drought is a function of the magnitude of multihazard trends, exposure to climate risks, biophysical sensitivity of agrosystems, socioeconomic determinants and physiographic sensitivity of the watershed.

2. Materials and methods

2.1. The study area

The Central Sahel River Basin is the segment of the Niger River Basin straddling three countries, Niger, Mali, and Burkina Faso (Figure 1). It extends from its topographical limits on the borders of the Sahara in the north (Algeria) to the south, where climatic conditions are tropical humid. The basin is inactive on its topographical boundaries, which extend to Algeria by the fossil networks of Azaouagh. The active and exploited part remains very small compared to its geographical extent. Within its boundaries considered in this study, it drains an area of 340,723 km². It fully covers the two administrative regions of southwest Niger, part of the northern regions of Mali and Burkina Faso. In all these countries, which partially cover the river basin, agriculture and animal and plant production play a central role in the economy, employing 80% of the working population. Agricultural production, particularly cereal production, is concentrated in the river basin, whose geographical limits transcend national borders and reflect the region's agro-climatic diversity. Millet and sorghum account for 80% of cereal production, or almost 70% of cultivated land. Agricultural production, particularly of cereals, is dependent on the vagaries of the weather. It is most often in deficit, mainly because of recurrent droughts. Indeed, when seasonal rainfall is insufficient and poorly distributed, the risk of agricultural drought becomes obvious, regardless of the type of agrosystem, given that the arid conditions of Sahelian environments impose permanent intense evaporation. Subsequently, productivity per hectare is one of the lowest in the world, at approximately 1179 kg/ha compared with 6 to 12 tonnes in Asia and Europe according to data from the National Network of Chambers of Agriculture of Niger for the year 2010 (<https://reca-niger.org/spip.php?article142>). The historical deficits in agricultural productivity in the Sahel are well correlated with annual rainfall anomalies (Traore et al. 2020). These inseparable uncertainties exacerbate the risk of food and nutritional insecurity for the most fragile populations that are heavily dependent on agrosystem services.

In recent years, while the countries of the Sahel should be doubling their production to meet growing demand, the resurgence of more intense and more severe climatic extremes is threatening the sustainability of the production systems of Sahelian communities. In fact, in the current context of agrosystems in the central Sahel, the succession of years of agro-climatic drought has led to an unprecedented agro-pastoral crisis. One of the direct consequences of this climatic crisis is the regionalization of cross-border

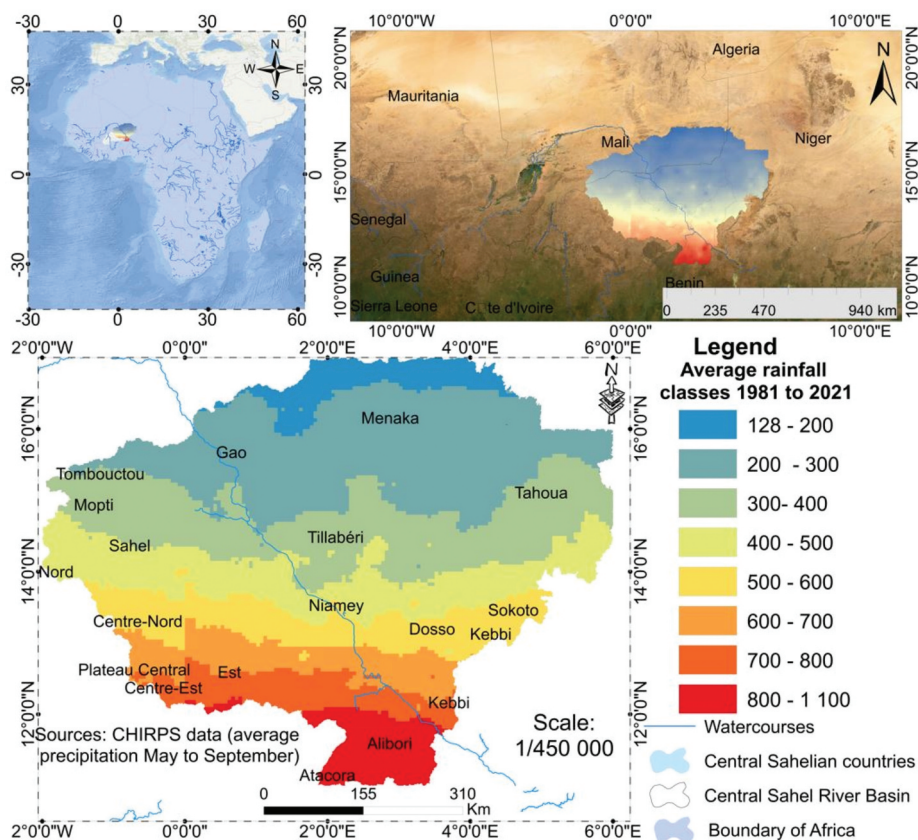


Figure 1. Geographical location of the study area.

insecurity in all its forms in the Sahel. Within the scientific community, it is now well established that the extreme manifestations and trends of climate change are one of the causes of the crisis in the central Sahel. The impacts of current climate change have been profound for communities in sub-Saharan Africa (Epule, Dhiba, and Chehbouni 2021). Throughout the central Sahel, climate vulnerability is a pervasive and multidimensional phenomenon that particularly affects people living in pastoral areas. Climatic hazards such as drought have a negative impact on the livelihoods of the most vulnerable populations. Food and nutritional security are strongly linked to the spatiotemporal imprint of drought severity. Indeed, when water stress is of considerable intensity, drought episodes reduce seasonal household harvests and livestock production (Sultana, Gazi, and Mia 2021). Consequently, the social impact of drought can take several forms depending on local endemic vulnerability. Thus, the climate crisis in the central Sahel region is currently considered to be the main factor amplifying intercommunity conflicts and violent extremism.

2.2. Data sources and their characteristics

A total of 28 factors of agricultural vulnerability to drought were considered in this analysis. These factors include 6 variables that provide information on seasonal climate risk, 4 factors of endogenous socioeconomic vulnerabilities, 6 biophysical sensitivity factors (vegetative response to drought), and 14 geoenvironmental factors consisting of physiographic factors and overall sensitivity of agrosystems. All factors were derived from medium and low spatial resolution open-source remote sensing data (Table 1). Image time series (NOAA, VIIRS, TerraClim, CHIRPS) from 1981 to 2021 were used to generate magnitude gradients in seasonal historical variability of climatic (precipitation, maximum temperature, climate water deficit) and biophysical (NDVI, FAPAR, soil moisture, land surface temperature) factors. Information on soil characteristics comes from machine learning predictions of soil properties available across the African continent from 0 to 200 cm deep (<https://registry.opendata.aws/isdasoil>). Topographic features (slope, elevation, flow accumulation) and physiographic models (facets of the basin) were extracted from the Global ALOS and SRTM datasets available on the Google Earth engine. Similarly, global WordPop data with a spatial resolution of 100 m were used as a source of information on the spatial distribution of population density. The number of people per pixel is the result of a semiautomated dasymetric modelling approach based on the random forest driven by population census data from each country and remotely sensed covariates (Stevens et al. 2015). DMSP VIIRS light intensity data were considered to distinguish rural and highly urbanized areas of the basin, and the socioeconomic dependence of the agricultural sector was integrated based on information from FAO's Forest Division on Forest Proximate People and Tree Proximate People-Croplands. Other data sources used in this analysis include monthly GRACE signal anomalies, cropland classes from Global Food Security Support Analysis Data, and the Global Human Change Index

Table 1. Data and their characteristics.

Parameters	Description	Source	Resolution
PDSI Index	Monthly 1981–2021	TerraClimate data	4638.3 m
Precipitations	Monthly 1981–2021	CHIRPS data	5566 m
Temperature	SMT 7 days (NOAA AVHRR) Monthly Tmax TerraClimate Monthly Tmax TerraClimate	GEE platform	4638.3 m
FAPAR	Global daily over land surfaces 1981–2021 1981–2021	NOAA Climate Data Record	0,05°
Soil characteristics	Clay Content, Soil Fertility, Organic Carbon, Soil Texture Class, Soil Depth	iSDAsoil USDA system	30 m 250 m
Soils moisture product	Global PALSAR/PALSAR-2 Soil moisture Monthly Soil moisture Monthly	GEE platform	25 m 4638.3 m
Population count	Global annual 2000–2020	WorldPop website	1 km
Groundwater	Monthly GRACE 2002–2017	NASA -JPL	111320 m
Landcover	Crop mask class	NASA GFSAD	1 km
Physiographic data	Landforms and Physiography, Slope, Elevation, flow accumulation area, CSP/ERGo	NASA SRTM Global/ ALOS_mTPI	30 m 270 m
FPP/TPP	Forest Proximate People, Tree Proximate People-Croplands	FAO Forestry Division	100 m
Lights Nighttime Day/Night	Monthly average radiance composite 2021-05-01 to 2021- 10-31 2021-05-01 to 2021-10-31	NOAA/VIIRS-EOG	463.83 m
gHM	Global Human Modification Index	Conservation Science Partners	1000 m

from Conservation Science Partners. In addition to [Table 1](#) below, all these data and their characteristics are available on the Google Earth Engine platform.

2.3. Methodology

Vulnerability to drought is a function of several climatic, biophysical, physiographic, and socioecological factors. In this study, the multivariate vulnerability of drought was obtained by aggregating 28 vulnerability factors. These factors have been grouped into four different forms of vulnerability according to the groups of factors considered. Climate vulnerability reflects the exposure of agrosystems to seasonal variance in climatic conditions, biophysical vulnerability is closely related to the sensitivity of vegetation cover (reaction of agrosystems in the case of water and/or heat stress), and physiographic vulnerability depends on the state of the environment and socioeconomic vulnerability. As a first step, a pixel temporal regression approach was applied to all dynamic covariates over the last four decades to generate magnitude gradients of trends per pixel and covariate. Second, the magnitudes of changes in dynamic covariate anomalies were combined by categories with static variables (physiographic, topographic, socioeconomic determinants) to generate different indicators of vulnerabilities, namely, the multivariate climate risk index, the biophysical sensitivity of agrosystems, the socioeconomic sensitivity index and the physiographic condition index of the basin. The variables considered for each type of vulnerability indicator are described in the following sections. In the final step, vulnerability classes were predicted automatically by testing the effectiveness of four machine learning algorithms. The simplified flowchart of the methodological approach is provided in [Figure 2](#).

2.3.1. Factors and determinants of vulnerability

2.3.1.1. Climate determinants. Sehgal and Dhakar [2016](#); Wu et al. [2017](#); Desquith and Renault [2021](#); The climatic determinants of drought vulnerability reflect the level of exposure of a territory to climatic hazards, including the frequency and intensity of extreme conditions (Sehgal and Dhakar [2016](#); Wu et al. [2017](#)). In the central Sahel region, because of their occurrence and spatiotemporal unpredictability, climatic hazards, particularly intraseasonal drought sequences, constitute the most formidable climate risk (). Thus, in this analysis, six climatic factors were considered to consider the seasonal risk of drought occurrence in the modelling of agricultural vulnerability to drought. Exposure to climatic hazards is based on the aggregation of anomalies of the magnitudes of historical trends of four climate indices: the magnitude of the variance of maximum temperatures and climate water deficit index (CWDI). The indices considered for this purpose are the standardized precipitation index (SPI), Palmer drought severity index (PDSI), precipitation conditions index (PCI), and precipitation deficit index (RDI). These indices were calculated at a six-month scale corresponding to the rainfed growing season in the study area. Given the limitations and advantages of the specifics of each index, principal component analysis was applied to merge these indices into a single variable that reflects the exposure of agrosystems to seasonal climate variance. Thus, the areas most exposed to the frequency and intensity of changes in local climatic conditions are obtained by thresholding in six classes of the multivariate synthetic indicator of exposure to climate risks.

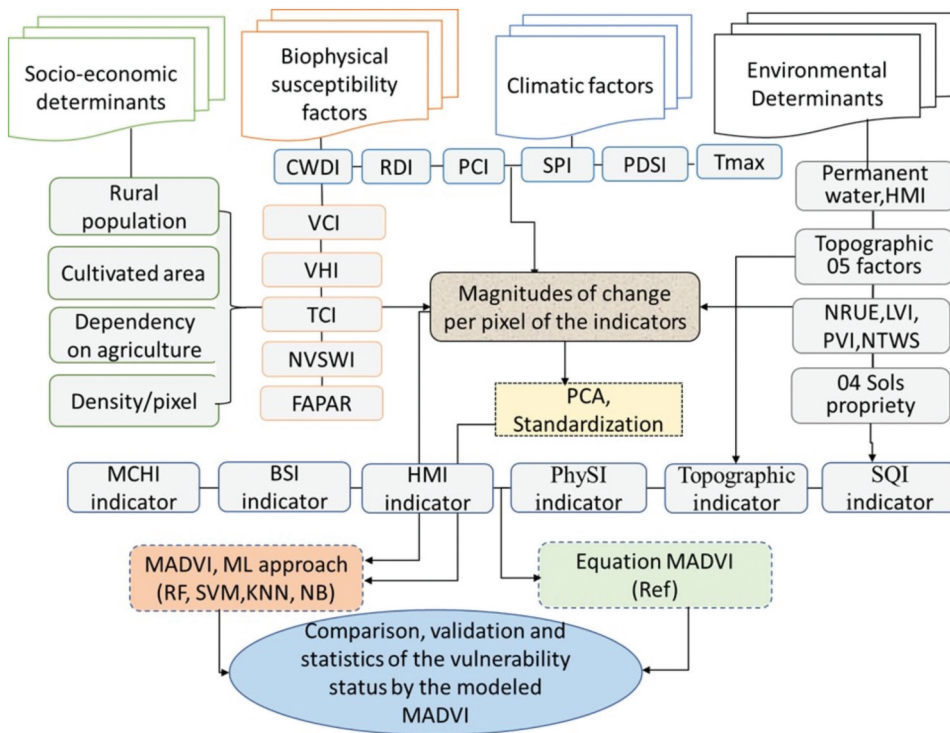


Figure 2. Simplified methodology flowchart.

2.3.1.2. Biophysical drought susceptibility factors. In addition to exposure to climatic hazards, the specific characteristics of each type of agrosystem can play an important role in assessing drought vulnerability. Drought susceptibility is a function of several surface and subsurface parameters, namely, the response of the short vegetation, the previous surface conditions of the soil water status and the overall efficiency of agrosystems. In this approach, seasonal anomaly trend magnitudes from six biophysical indicators were combined to assess the biophysical sensitivity of agrosystems. The vegetative response to drought of agrosystems is represented by the trend magnitude of vegetation health derived from three vegetation indices (VCI, VHI, FAPAR). Changes in soil water status are driven by the historical variance of the crop water supply index (NVSWI, TCI, SMCI). The pixel trend magnitudes of these indicators were combined to capture the historical trend in biophysical susceptibility of agrosystems in response to climate water deficit. The resulting biophysical susceptibility index was reclassified into six different intensity levels.

2.3.1.3. Physiographic and environmental determinants. In addition to extreme climate variability and biophysical sensitivity, physiographic determinants such as landscape shapes and topographies, LULC type, soil characteristics, internal water storage, continentality and altitude play an important role in the sensitivity and response to agricultural drought. In general, highly degraded agrosystems will tend to promote the loss of water available to crops by infiltration and/or runoff, which results in a higher risk of drying out than in agrosystems that have larger landscapes and vegetative and edaphic

structures. Similarly, very complex terrain with variable altitudes results in rough slopes that promote water loss through runoff. Thus, in this analysis, topographic parameters (slope, elevation, landforms, flow accumulation, topographic moisture), soil quality factors (soil fertility, organic matter levels, texture, clay percentage) and indicators of the state of degradation of agrosystems (NRUE, LVI, PVI, NDSI, HMI) as well as groundwater storage anomaly (NTWS) and availability of surface water resources were combined to assess the physiographic and environmental sensitivity of the pelvis. The integrated physiographic sensitivity index identified four groups of physiographic units of different sensitivities.

2.3.1.4. Socioeconomic determinants. Socioeconomic characteristics such as the population density of agricultural areas, livelihoods, poverty rate, income opportunities, cropland fragmentation and rain-fed dependence rate are the most important socioeconomic determinants of agricultural drought vulnerability (Saha et al. 2020; Guo et al. 2022; Heidari et al. 2020). The severity of the direct impacts of drought can be exacerbated by the number of people directly exposed and their degree of dependence on the most vulnerable sector, such as the agricultural sector (Cui et al. 2022). Other factors, such as irrigation level (Murthy et al. 2009; Sun et al. 2020) and the ratio of irrigated to non-irrigated cropland, can positively affect the vulnerability of agrosystems and dependent populations (Wu et al. 2017). In the region, land for agricultural use is limited due to the low available water holding capacity (AWC), which affects agricultural productivity, especially of rainfed crops (Ippolito et al. 2021). This characteristic related to the properties of the soil aggravates the state of vulnerability of peasant agriculture that is very dominant in the central Sahel region. In this analysis, five factors of socioeconomic vulnerability were considered: density, agricultural and forestry dependence, the size of cultivated areas and the proportion of the rural population. These factors were combined to generate a socioeconomic sensitivity indicator (SSI). The SSI does not include adaptation factors at the local level due to a lack of data on the existence of complementary irrigation systems.

2.3.2. Method for aggregating vulnerability covariates

2.3.2.1. 2.3.2.1. Magnitudes of historical trends in indicators. After generating the historical anomalies of the climatic and biophysical variables, a pixel temporal regression approach was applied to the series of anomaly images of each factor. The output method converts the time series of images into a single image that represents the gradient of magnitude of change per pixel (slope of change). Only thereafter were images of the magnitude of the dynamic variable trends combined with the static factors of vulnerability.

2.3.2.2. Standardization of vulnerability indicators. The assessment of agricultural vulnerability to drought can be established by jointly or separately considering two types of factors that may be factors that positively affect vulnerability and/or factors that negatively affect the state of vulnerability. In this analysis, all factors were normalized according to whether the vulnerability was negative (Equation 1) or positive (equation 2) so that the overall vulnerability index was between 0 and 1. Values close to zero indicate low vulnerability, and values close to 1 refer to extreme vulnerability. Normalization of vulnerability factors according to their positive or negative effects is widely practiced in

recent studies on multivariate vulnerability modelling (Bhavani et al. 2017; Guo, Chen, and Pan 2021; Murthy et al. 2015).

$$y_i = \frac{(X_i - \text{Min}(X_i))}{(\text{Max}(X_i) - \text{Min}(X_i))} \quad (1)$$

$$y_i = \frac{(\text{Max}(X_i) - X_i)}{(\text{Max}(X_i) - \text{Min}(X_i))} \quad (2)$$

Y_i is the normalized indicator, X_i is the actual value of the indicator and $\text{Max}(X_i)$ and $\text{Min}(X_i)$ represent the max and min values on each pixel position.

2.3.2.3. Multicollinearity analysis of vulnerability predictors. Some machine learning models, including the naïve Bayes algorithm, are very sensitive to problems of multicollinearity between explanatory covariates. Thus, an autocorrelation analysis (Figure 3) was applied to identify and remove variables that have a strong linear dependency relationship between more than two explanatory variables. This is the case for NVSWI_trend, TCI_trend, NTmax_Trend, and NRUE_trend. Then, the `live()` function of the package was executed to ensure the absence of multicollinearity with the VIF values of each variable. However, the performance of the random forest and SVM models showed a very low sensitivity to the problems of multicollinearity of variables, while the naïve Bayesian classification gradually improved by decreasing the effect of variables that have a strong correlation between them. Therefore, the optimization adjustments were applied exclusively to the naïve Bayes model.

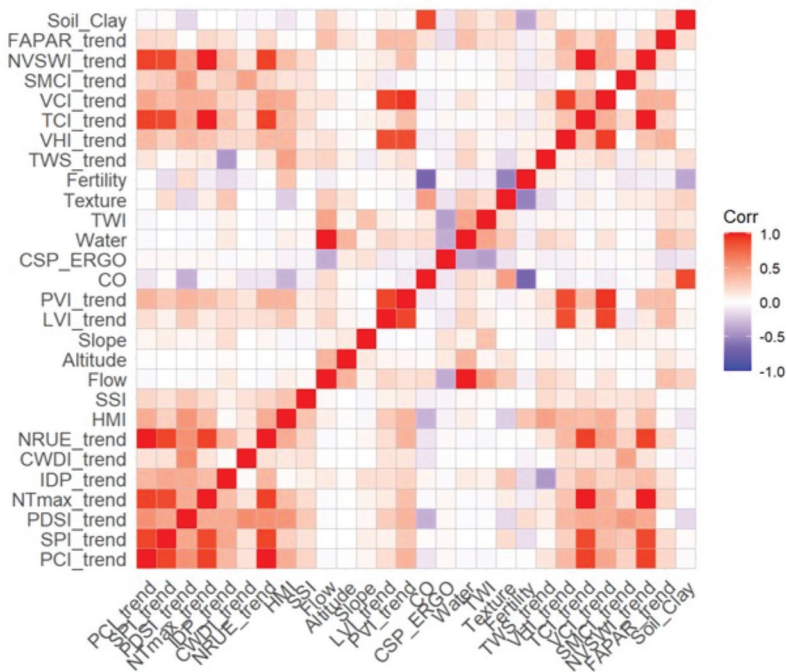


Figure 3. Multicorrelations of covariates.

The description of the acronyms and abbreviations of the different vulnerability factors is provided in the appendix (Table 2).

2.3.2.4. Reduction of data dimensionality. In the absence of baseline data from the field, principal component analysis was applied separately to each group of factors and then to 28 vulnerability factors to generate a synthetic indicator that served as a reference. This made it possible to configure the basic equation of the agricultural drought vulnerability index according to the classical approach of a linear intersection of exposure to hazards, biophysical sensitivity, and adaptive capacity. Then, in the second phase, to optimize the identification of vulnerability classes, points were randomly generated to produce the points of the different classes to train machine learning models on the 28 factors. Both results were then compared with the principal component analysis and the components of the basic equation. The idea is to configure an approach using as inputs directly the factors of vulnerabilities without them being transformed into an index of sensitivity, exposure, or adaptation. This should allow for an operational application to use in situ reference points and automatically generate agricultural vulnerability classes to drought.

$$\text{MADVI} = \text{SQI} + \text{BSI} + \text{MCHI} + \text{HMI} + \text{Topographic} + \text{SSI} \quad (3)$$

SQI: Soil Quality Index, BSI: Biophysical Sensivity Index, MCHI: Multivariate Climate Hazard Index, HMI: Human Modification index, Topographic factors and SSI: Socioeconomic Sensitivity Index. Sensitivity refers here to the susceptibility of a natural, human and/or anthropogenic system to be damaged by the impacts of agroclimatic drought. MADVI in its final configuration is an integrated model with six agricultural drought vulnerability subsystems.

Table 2. Summary of model performance evaluation metrics.

Metrics	RF	SVM	KNN	NB
AUC testing	92.5%	94.0%	85.5%	90.2%
MacroPrecision	0.8608744	0.9465246	0.8459434	0.8226174
MacroRecall	0.8684852	0.9475077	0.8234698	0.8162398
MacroF1	0.8632674	0.9451904	0.832956	0.8175571
Accuracy	0.87	0.9585	0.8512	0.827
Kappa	0.838	0.9477	0.8125	0.7831
95% CI	(0.9286, 0.9784)	(0.9286, 0.978)	(0.804, 0.890)	(0.7784, 0.8688)
Climate risk exposure classification (six factors)				
AUC testing	94.0	78.6	72.03	77.6
MacroPrecision	0.912479	0.9496049	0.8930169	0.8125817
MacroRecall	0.867097	0.9291485	0.7584772	0.8192119
MacroF1	0.8869478	0.9352513	0.7775332	0.8076479
Accuracy	0.8906	0.9705	0.8796	0.8337
Kappa	0.866	0.9639	0.8522	0.797
95% CI	(0.8685, 0.9101)	(0.9573, 0.980)	(0.8568, 0.9)	(0.8079, 0.8573)
Classification of biophysical sensitivity (six factors)				
AUC testing	92.5	82.0	71.5	67.9
MacroPrecision	0.9071283	0.9686322	0.8711166	0.6526896
MacroRecall	0.803858	0.9129006	0.7643209	0.5933681
MacroF1	0.8307062	0.9337946	0.7926914	0.5992689
Accuracy	0.8982	0.9672	0.8589	0.6411
Kappa	0.8706	0.9584	0.8203	0.5519
95% CI	(0.8768, 0.9171)	(0.9535, 0.977)	(0.834, 0.880)	(0.6091, 0.6723)
Global vulnerability classification (28 factors)				

2.3.2.5. Machine learning algorithms. Four machine learning algorithms were used to group pixels into several classes of agricultural vulnerability to drought. Machine learning models were implemented in R with the caret package using 28 predictors of the different components of vulnerabilities using the PCA-generated vulnerability classes applied across all vulnerability indicators. It was divided into two parts: 70% for training and 30% for model performance testing (random forest, SVM, KNN, NB). Six metrics (AUC, precision, recall, F1, accuracy and the kappa index) were generated step by step in the R environment for the evaluation of the performance of the models used for the identification of vulnerability classes with input of the 28 standardized vulnerability factors without being transformed into components of sensitivity or exposure.

- Random forest (RF) is a very popular nonparametric white-box machine learning algorithm due to its flexibility in terms of application. It has been used for various applications, including clustering, classification, regression, and multiple learning (Nsch et al. 2019). In the context of the Sahel, Leroux et al. (2019) found that the RF model performed better than the linear multiple regression model for estimating maize yields in Burkina Faso from biophysical indices. Recently, it has been used by Arabameri et al. (2021) for modelling agricultural vulnerability to drought. In this study, a random drill was trained on 28 vulnerability indicators with points corresponding to several levels of vulnerability. The learning error of the best model is less than 0.1 (Figure 4).
- Support vector machine (SVM) is an efficient ML model that can learn with a much smaller dataset. For this reason, it is very widely used for classification and prediction problems (Li et al. 2020; Zhu et al. 2021; Elbeltagi et al. 2021). It was trained in R using the library 'e1071' with a cross-validation process on training data for the selection of optimal values of hyperparameters C and gamma. After training, the performance of the best model achieves an ROC of 94.0% for the learning quality validation test.
- K-nearest neighbours (KNN) is a nonparametric supervised learning ML model suitable for classification and regression problems. It relies on the principle of proximity to a given query point to perform classifications or predictions. It requires only two adjustment hyperparameters: the value of K (number of neighbours) and a metric of distance. In our case, the KNN was implemented with the caret library of R, which provides using the TuneLength parameter an automatic fit of the model by

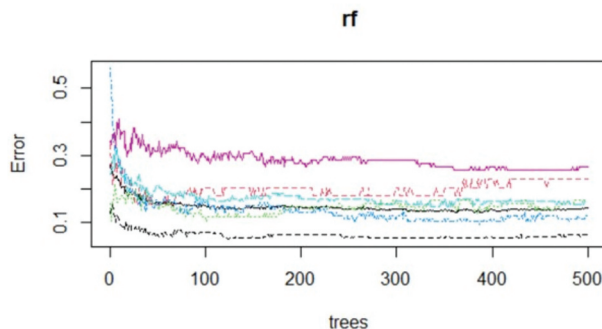


Figure 4. Learning performance of random forest.

testing different values of K . The precision of the model training is used to select the optimal model, and the best model was obtained with one of $K = 9$.

- Naïve Baye is a probabilistic machine learning algorithm inspired by Baye's theorem. It is based on strong assumptions of conditional independence between predictors. The algorithm was implemented in R using the caret library and the naïve Bayes package. Since hyperparameter adjustment is not a valid method to improve the performance of the naïve Bayes classifier, removing highly correlated predictors was used to improve model performance. Cross-validation was used to assess the learning quality of the model.

3. Results

3.1. Exposure to climate risk

Figure 5 shows six maps representing key indicators of the climatic vulnerability in the central Sahel for the period 1981–2021. These indicators are the magnitudes of trends in changes in the SPI (Figure 5 (a)), PDSI (Figure 5 (b)), maximum temperature anomalies (Figure 5 (c)), climatic water deficit (Figure 5 (d)), PCI (Figure 5 (e)), and RDI (Figure 5(f)). Analysis of the indicators reveals that the southern part of the catchment is more vulnerable to climate change. However, the extent of climate change trends varies considerably depending on the indicator considered. Trends in maximum temperatures in the catchment are the most significant over the historical period (1981–2021), followed by trends in climatic water deficit. The p values of the time regression per pixel indicate statistical significance for the magnitudes of the trends in maximum temperature anomalies ($p < 0.2$) and climatic water deficit ($p < 0.3$). These results suggest that agrosystems are more exposed to heat and evaporation stress than to the risk of seasonal rainfall deficits. On the other hand, exposure to the magnitude of seasonal rainfall trends, as assessed by rainfall indices (SPI, PDSI, PCI, RDI), was only significant in the southwestern part of the catchment (p value < 0.5). This indicates that this region is more sensitive to seasonal variations in precipitation. However, the results highlight the importance of taking into account the different seasonal variances and the complex interactions between climatic factors to fully understand the challenges facing agrosystems in the central Sahel.

The multivariate climate risk index is calculated to prioritize the level of exposure of agrosystems in the watershed according to the historical variance of local climate factors (Figure 6). The classification into four intensity levels of the MCHI reveals a very contrasting climatic vulnerability according to the bioclimatic stage with a very large north–south gradient. As with the individual indicators, exposure to climatic risks is significantly higher in the southwestern part of the basin. The MCHI revealed relatively low exposure to climate risks in the northern part of the basin, while the Sahel-Sudan zone shows greater seasonal variability in climatic conditions. This analysis provides a better understanding of the spatial variations in climate vulnerability in the catchment. This highlights the importance of taking into account the combined variance of several climatic factors and their interactions when assessing climate risks and adapting agrosystem management strategies.

The final machine learning exposure map of agrosystems to climate hazards is shown in Figure 7. It reproduces highly contrasting climate vulnerability in six intensity classes.

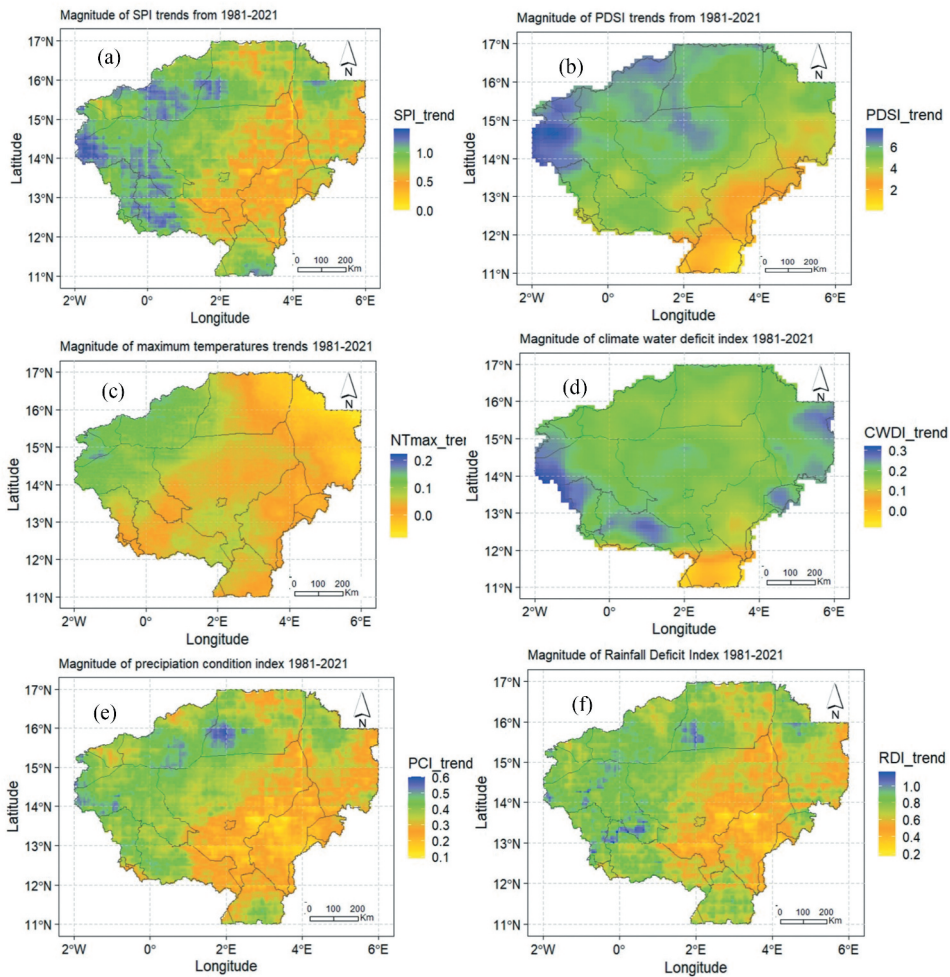


Figure 5. Magnitude of historical trends in watershed climate indicators.

Considering the trends in historical variability of climate stress indicators considered, the Nigerien part of the basin, particularly the southwest part of the Dosso region, is the most exposed to climate risk. The magnitudes of the combined changes in factors (maximum temperature anomaly, climate water deficit) and climate indices (SPI, PCI, PDSI, RDI) suggest a relatively high variance in climate stress in this part of the watershed. The results of the mapping of exposure to climatic risk, obtained using four machine learning algorithms, are clearly very comparable. They all indicate that the agrosystems on the Niger fringe of the basin are extremely vulnerable to climate change. Moreover, exposure to climatic risk decreases increasingly from east to west, with a predominance in the south. However, statistical analysis of the models' performance in predicting classes of climatic vulnerability of agrosystems revealed certain differences. Model performance tests revealed that the SVM (Support Vector Machine) model outperformed the other models with an AUC (Area Under the Curve) score of 94.0%. It was closely followed by the random forest model with an AUC score of 92.0%. The naïve Bayes model performed

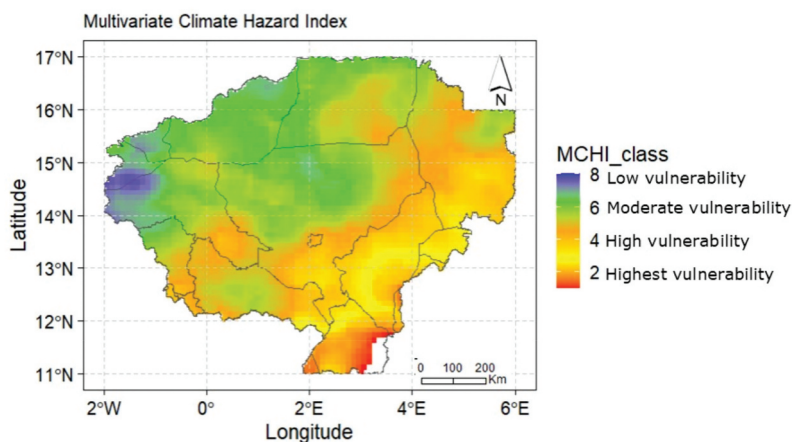


Figure 6. Climate risk at eight levels of intensity derived from the trend magnitudes of six climate indices (SPI, PDSI, PCI, NDRI, CWDI and Tmax).

intermediately with an AUC score of 90.2%. On the other hand, the KNN (K-Nearest Neighbors) model performed the worst of the four models, with an AUC score of 85.5%. Overall, these results highlight the high performance of the SVM and random forest models in predicting the climatic vulnerability classes of agrosystems. These models demonstrated their ability to capture the complex relationships between climate indicators and exposure to climate risk. The KNN model, on the other hand, performed relatively poorly, suggesting that it is less able to discriminate effectively between the different classes of climatic vulnerability.

3.2. Biophysical sensitivity of agrosystems

Figure 8 shows six maps of biophysical vulnerability indicators based on trend magnitudes for the period 1981–2021. Comparative analysis of the magnitudes of change shows very high spatial agreement between the indicators: Normalized Vegetation Supply Water Index (Figure 8 (a)), Vegetation Health Index (Figure 8(b)), Temperature Condition Index (Figure 8(c)), Vegetation Condition Index (Figure 8(d)), Fraction of Absorbed Photosynthetically Active Radiation (Figure 8 (e)), and Soil Moisture Condition Index (Figure 8(f)). The biophysical sensitivity of agrosystems as a function of their level of resistance to climatic stress was highlighted in very contrasting ways by the magnitudes of change in all six indicators. Negative values characterize agrosystems with low climatic resilience. In other words, they are frequently impacted by seasonal variability in climatic conditions. Change gradient values greater than zero indicate relatively high climatic resilience. Overall, the spatial distributions of the gradients of the magnitudes of the changes in the biophysical sensitivity indicators are higher in the catchment areas where the climate vulnerability indicators recorded the highest exposure to climate variability. However, irrespective of the overall spatial distribution of the intensity of the changes, in a very localized way, the maximum amplitude of the changes (red colour in the legend) is observed in different locations for each indicator. This shows the importance of

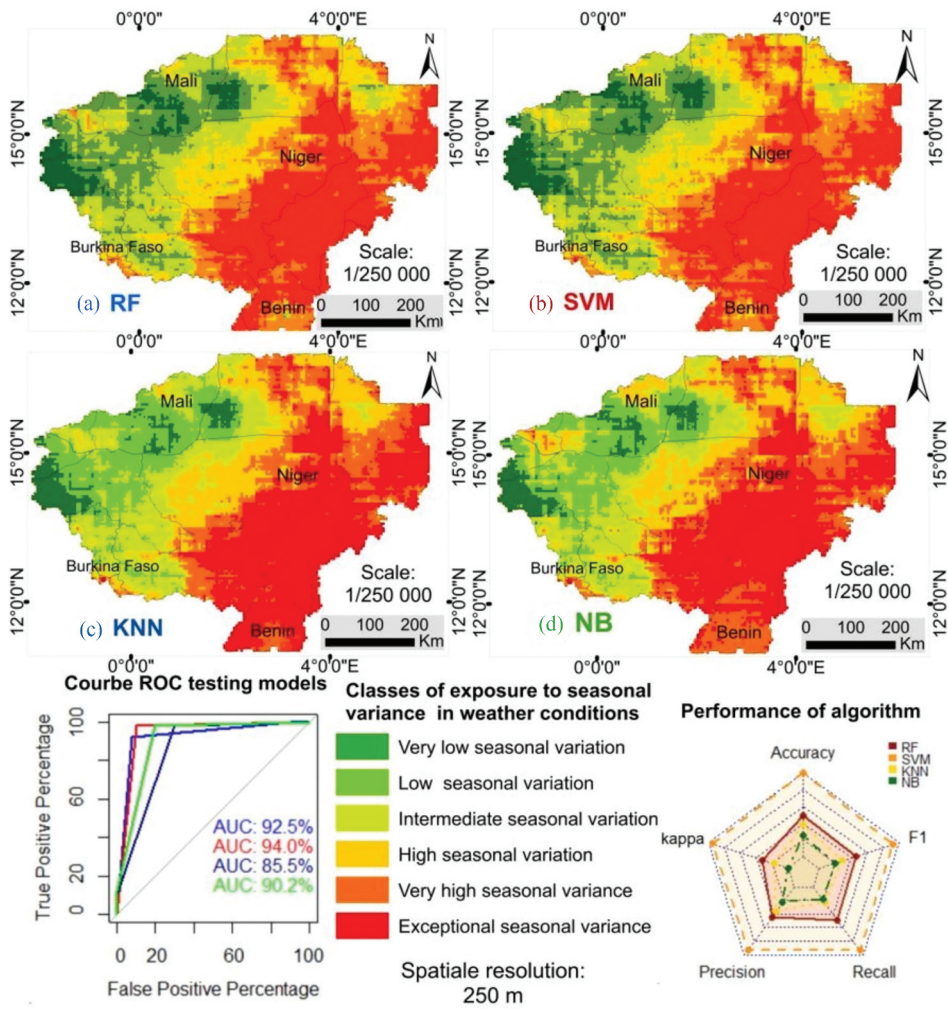


Figure 7. Climate risk exposure index maps of agrosystems and machine learning performance metrics (RF, SVM, KNN and NB).

combining the magnitudes of change in these indicators to provide a comprehensive assessment of the biophysical sensitivity of the agrosystems of the central Sahel.

Figure 9 presents the biophysical sensitivity index (Figure 9) by considering the magnitude of trends in six biophysical indicators (NVSWI, VHI, TCI, VCI, FAPAR and SMCI). It highlights different levels of biophysical susceptibility of agrosystems to be impacted by the effects of climatic water deficits. Classes of low to moderate vulnerability correspond to surface features that record reliable seasonal variations in the state of health of the biophysical cover. The very high and high vulnerability classes correspond to areas with the most sensitive types of plant cover, which are most affected by climate-related water deficits. Agrosystems with low climatic resilience are characterized by a negative trend. This mainly corresponds to areas with seasonal vegetation cover (crops and seasonal herbaceous cover). The lowest biophysical

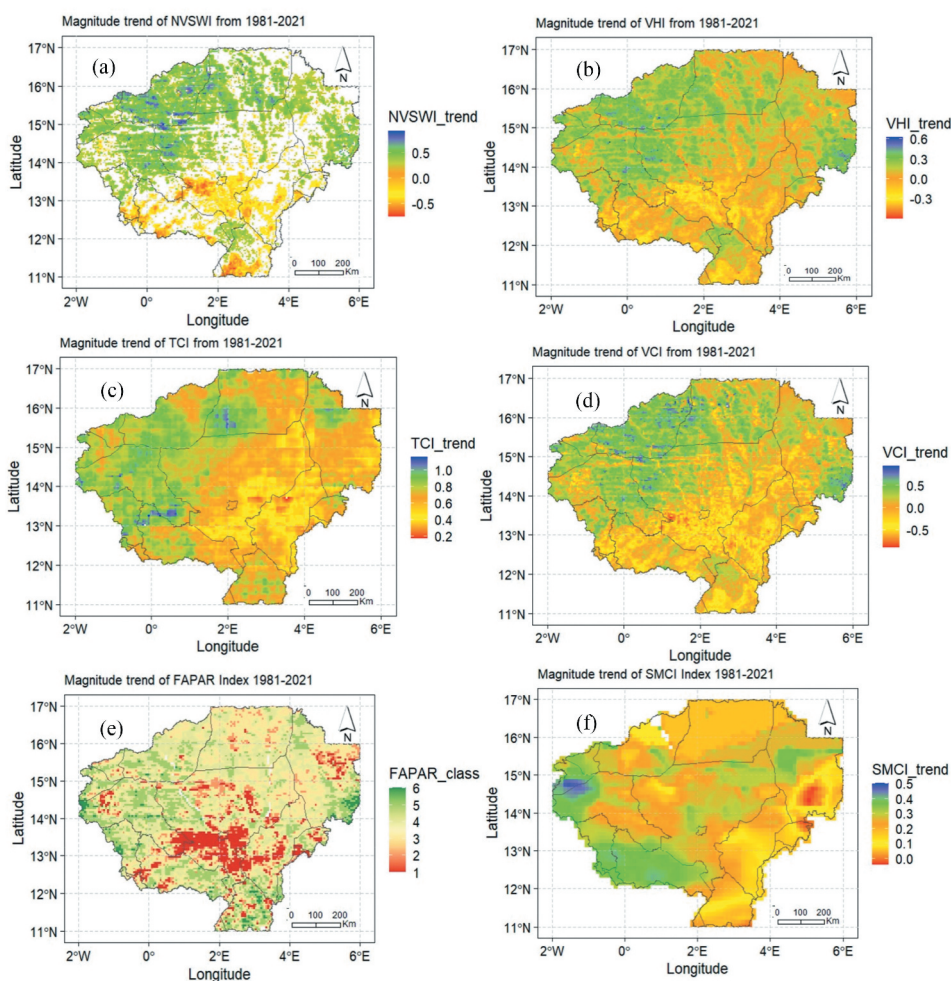


Figure 8. Magnitudes of historical changes in biophysical sensitivity indicators.

sensitivity (blue colour) on the map corresponds to rocky outcrops naturally characterized by a low density of permanent and/or seasonal vegetation cover, and the green colour corresponds mainly to permanent tree cover, which is characterized by a certain resilience to seasonal climatic deficits. As indicated by the multivariate index of exposure to climate risk, the southwestern part of the agricultural catchment has the highest biophysical vulnerability. Conversely, relatively low vulnerability is observed in the northern areas of the catchment, which are pastoral and partly desert in places.

Figure 10 shows the final map of biophysical susceptibility using RF, SVM, KNN and NB. It shows six different biophysical susceptibility classes that exhaust the contrast of exposure to climate risk. Thus, not surprisingly regarding the climate risk exposure map, the agrosystems of the portion of the basin on the Nigerien part concentrate the highest biophysical susceptibility. The results of the training model classification with very high performance (ROC = 94% for RF) suggest a particularly high sensitivity of cropland in the

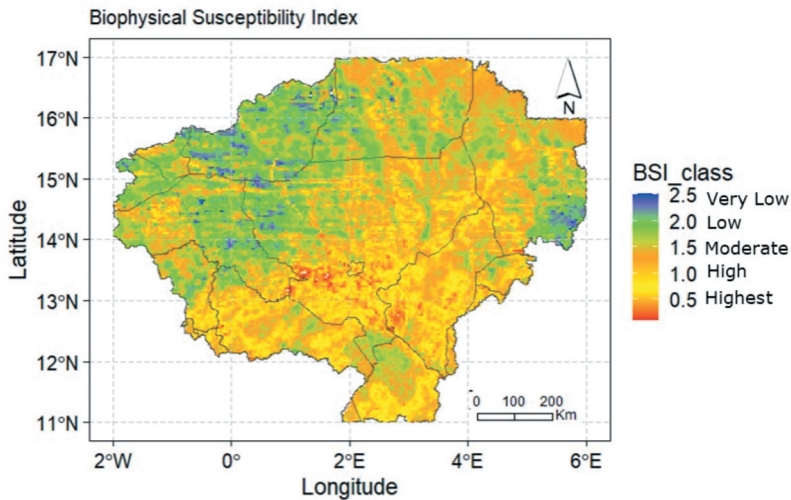


Figure 9. Biophysical susceptibility index derived from the trend magnitudes of four biophysical indices.

southwestern part of the basin. On the other hand, in contrast to the modelling of climate vulnerability, we can see that the performance of RF is much better than that of SVM (ROC = 78.6%), KNN (ROC = 72.3%) and NB (ROC = 77.6%). The superior performance of the random forest model compared with the other algorithms can be explained by the fact that random forest is an ensemble learning algorithm that combines several decision trees. This approach reduces the biases and errors of each individual tree by taking into account the diversity and combination of their predictions, as well as their sensitivity to missing values. This generally leads to better prediction performance and reduced variance. Random forest is also less susceptible to overfitting problems than some other algorithms. It uses random subsampling techniques and random selection of variables when constructing trees, which reduces the risk of overlearning.

3.3. Intrinsic vulnerability of agrosystems

The intrinsic vulnerability of agrosystems refers to endogenous characteristics that combine socioecological vulnerability, land vulnerability, soil quality status and physiographic sensitivity of the watershed. Thus, the intrinsic vulnerability of agrosystems in the central Sahel was analysed by considering six potential indicators that provide essential information on different aspects of intrinsic vulnerability. These are the Human Modification Index (Figure 11 (a)), Total Water Storage Anomaly (Figure 11 (b)), Normalized Rainfall Efficiency Index (Figure 11 (c)), Proportion of Vegetation cover Index (Figure 11 (d)), Socioeconomic Sensitivity Indicator (Figure 11 (e)) and Land Vulnerability Index (Figure 11 (f)). The anomalies of the water bodies in the GRACE data are consistent with the results of other vulnerability indicators and suggest a high variability of groundwater bodies in the extreme southeast of the basin and a very low variability in the extreme northeast. The result is that there should be a shallow aquifer whose recharge is closely linked to seasonal rainfall in the southeastern part of the basin to the extent that seasonal climatic

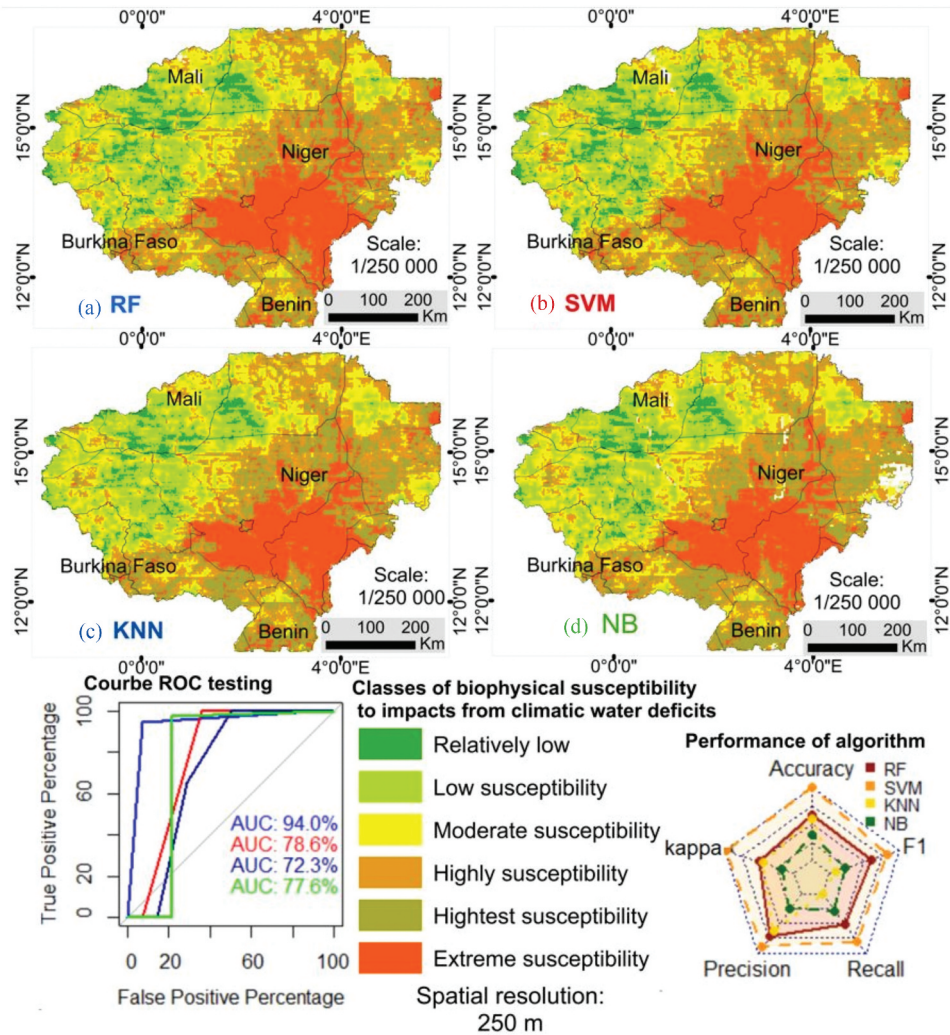


Figure 10. Agrosystems biophysical sensitivity index maps and machine learning performance metrics (RF, SVM, KNN and NB).

variability directly affects the volume of groundwater. When a correspondence analysis is carried out on the same area by considering the anthropogenic modification index and the extent of the change in the proportion of vegetation cover, a logical relationship emerges without it being possible to explain the exact determinants with any certainty, since the reduction in the proportion of vegetation cover can only be linked to a single factor (anthropization, climatic factors, etc.). Similarly, analysis of this result shows a close link between the degree of human modification of the environment and the magnitudes of historical changes in the efficiency of rainfall use for agricultural production (NRUE), the reduction in vegetation cover (PVI) and the vulnerability of agrosystems to environmental pressures (LVI). The four indicators showed very high spatial interrelations with the socioeconomic sensitivity index, which suggests that by using these six indicators, it will

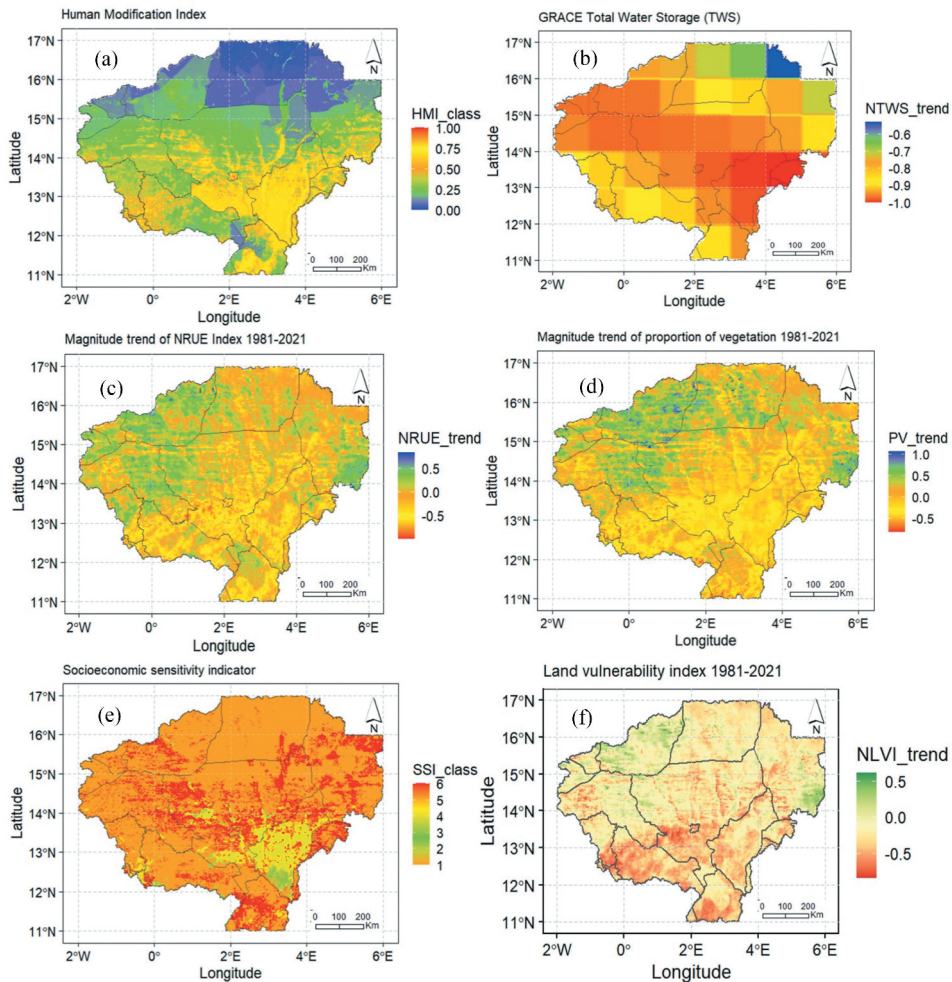


Figure 11. Key indicators of endogenous vulnerability.

be possible to obtain a more complete and detailed view of the intrinsic vulnerability of agrosystems in the central Sahel.

The combination of these indicators closely related to soil characteristics, topography and physiographic parameters of the basin made it possible to prioritize the basin into four levels of different physiographic sensitivities (Figure 12). The physiographic sensitivity index highlights the physiographic conditions most sensitive to climate deficits and the dynamics of local landscape transformations. Thus, the most sensitive physiographic units of the basin are visibly dominated by shelf and slope ecosystems, while shallows, streams and bedrock outcrops have low to moderate potential sensitivity. The analysis of this result confirms the concordance of the results of exposure to climate risk and the surface biophysical sensitivity (Figure 6 and 9). Thus, endogenous vulnerability factors were considered in the assessment of the overall vulnerability of agrosystems in the central Sahel River basin.

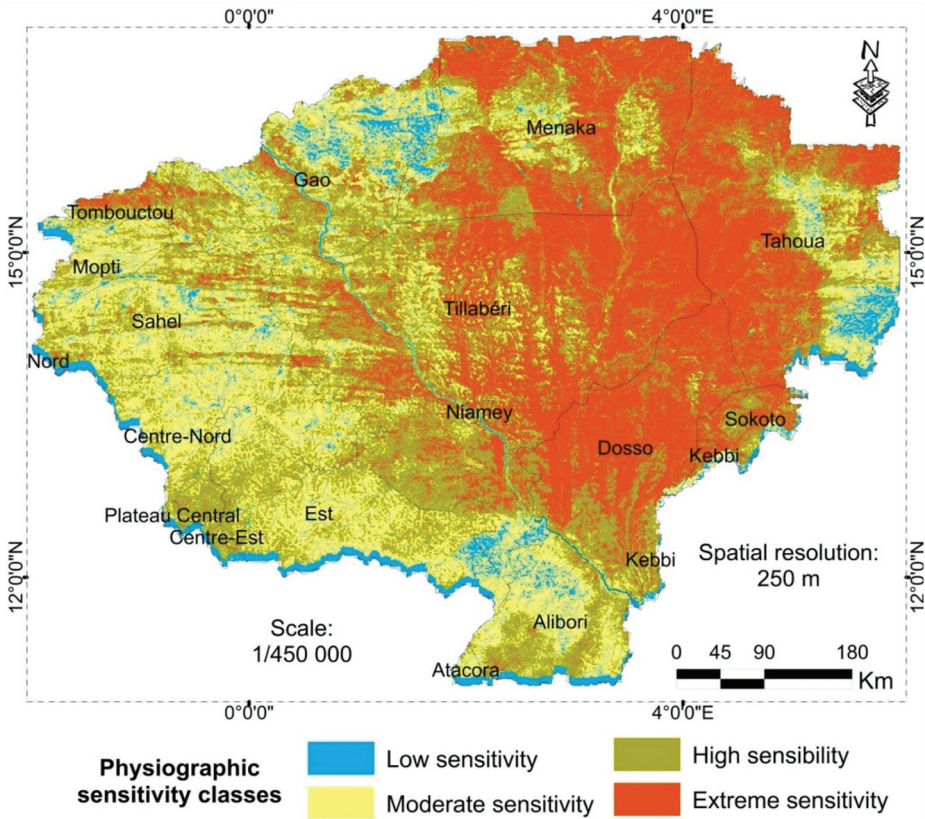


Figure 12. Potential physiographic sensitivity index.

3.4. Mapping agricultural vulnerability to drought

Figure 13 represents the mapping of global drought vulnerability of agrosystems obtained by considering biophysical sensitivities, climate risk exposure factors and endogenous vulnerability factors that include integrated physiographic sensitivity and socioeconomic sensitivity. It reproduces six classes of agricultural vulnerability to drought ranging from relatively very low to exceptional vulnerability. This last form of vulnerability is particularly observed in the agricultural areas of the basin, i.e. the limit of 400 mm to 800 mm. This suggests that these regions are the most likely to suffer significant negative impacts from drought, which can lead to difficulties for agriculture and the livelihoods of local populations. The northern part of the pastoral basin has a relatively low vulnerability to agricultural drought compared to that observed in the Sahelo-Sudanian and Sahelian zones. This could indicate that the agrosystems in this part of the catchment are better adapted to drought conditions, which reduces their vulnerability. Furthermore, the analysis of model performance indicators for the prediction of global vulnerability classes shows that random forest is a better fit than SVM, KNN and NB. It obtained the highest AUC (area under the curve) score (92.5%) against SVM (AUC: 82.0%), KNN (AUC: 71.5%) and NB obtained the

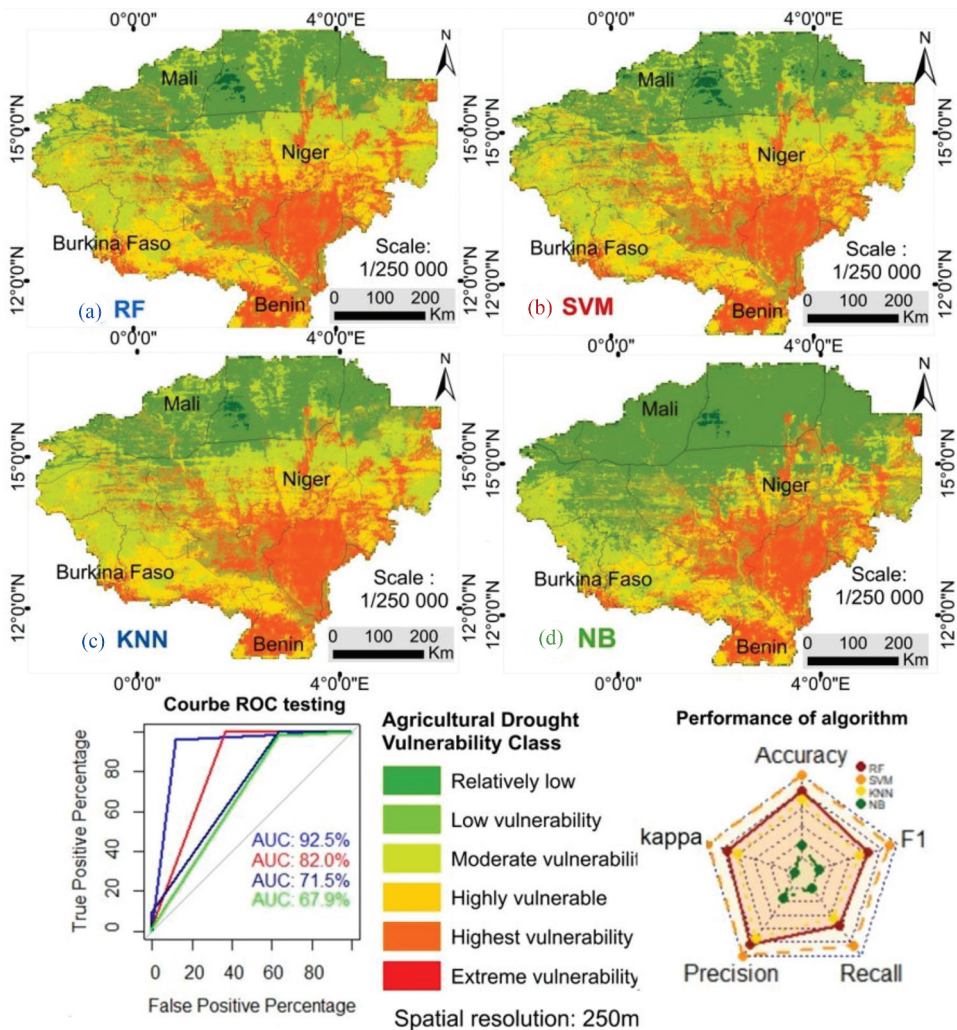


Figure 13. Global vulnerability indices to agricultural drought.

lowest performance (AUC: 67.9%). The poor performance of naïve Bayes (NB) compared to other algorithms, such as random forest, SVM and KNN, can be explained by the fact that naïve Bayes is based on the assumption of conditional independence between features. This means that the model assumes that the characteristics are all independent of each other when they are conditioned by the target class. This assumption may be too simplistic for some complex problems where the features are highly correlated. In the context of drought vulnerability prediction, some features are dependent on each other, which could lead to inferior performance for NB.

Figure 14 shows the proportions of the predicted vulnerability classes according to the performance of each machine learning algorithm. The result reflects the highly comparable performance of RF, SVM and KNN to some extent. However, NB shows poor prediction performance for the vulnerability classes. Interpretation of the figure reveals that NB overestimates the low vulnerability class and remarkably underestimates the moderate

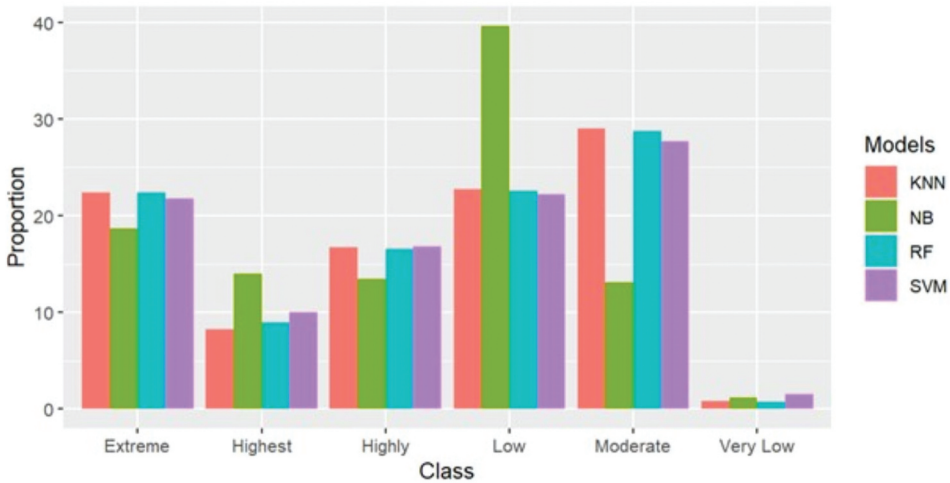


Figure 14. Relative proportions of vulnerability classes by machine learning model.

vulnerability class. This means that NB tends to predict lower vulnerability than is actually observed and underestimates moderate vulnerability. These prediction errors can be problematic, as they can lead to inadequate or insufficient measures being taken to mitigate the risks of drought in agrosystems. This observation reinforces the importance of the performance indicators used to evaluate machine learning models. All the performance measurement indicators converge towards the relatively poor performance of naïve Bayes in this specific case. Indeed, it is emphasized that NB is based on the principle of conditional independence between predictors, which makes it particularly sensitive to data multicollinearity. Multicollinearity occurs when the predictors (features) are highly correlated with each other.

3.5. Analyses of contributing factors

Global vulnerability is a multifactorial dimension that refers to several interactions and processes. In this analysis (Figure 15), the relative importance of 28 factors of overall vulnerability was examined. By considering physical, physiographic, climatic, and socioeconomic vulnerability factors. In this analysis, the socioeconomic sensitivity index (SSI) stood out with the greatest relative importance in multivariate modelling of global vulnerability. This suggests that socioeconomic aspects play a major role in the vulnerability of the Central Sahel region. It is followed by the Human Modification Index (HMI) and the magnitudes of the changes in the abnormalities of the biophysical sensitivity indices (slope of change of VCI and NRUE). The magnitude of climate risk exposure index anomalies (PDSI trend magnitude, PCI) is the third group of factors based on their importance in multivariate modelling of global vulnerability. This indicates that climate change and the associated risks also play a significant role in the region's vulnerability. The group of factors related to physiographic conditions and soil characteristics are found at the bottom of the scale according to their relative importance in multivariate modelling of global drought vulnerability. We can therefore conclude that these factors have less direct influence on the vulnerability of the Central Sahel region than the other factors mentioned above.

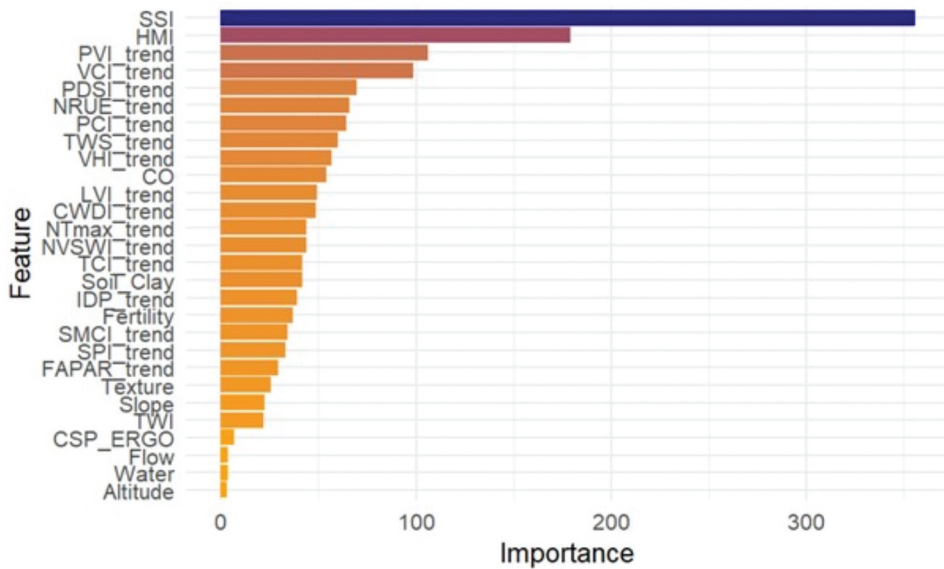


Figure 15. Relative importance of variables in modelling global drought vulnerability.

3.6. Performance indicators of the learning models used

In this analysis, machine learning models (RF, SVM, KNN and NB) were used to predict climate hazard exposure index classes, biophysical sensitivity index and global vulnerability classes by considering 28 factors. As shown in Table 3, in all three cases, regardless of the number of factors and the indicator of the performance measures considered, the random forest and SVM algorithms were superior to those of KNN and NB. They proved to be very insensitive to the problem of multicollinearity of variables and number of factors used to predict classes of vulnerability and biophysical sensitivity. The performance of the models has been evaluated using different measures for modelling climatic, biophysical and global vulnerability. For example, for the prediction of global vulnerability classes, RF's performance was found to have a macro precision of 0.90, a macro recall of 0.80, a macro F1 score of 0.83, a global precision of 0.89, and a kappa coefficient of 0.87, with a 95% confidence interval of (0.87, 0.91). The SVM model gave a macro precision of 0.96, a macro recall of 0.91, a macro F1 score of 0.93, an overall precision of 0.96, and a kappa coefficient of 0.95, with a 95% confidence interval of (0.95, 0.97). The two models (RF and SVM) are visibly very close in terms of performance in predicting global drought vulnerability classes. On the other hand, we can see that the KNN has intermediate predictive performance, and the performance of the NB model is relatively poor, with a macro precision of 0.65, a macro recall of 0.59, a macro F1 score of 0.59, an overall precision of 0.64, and a kappa coefficient of 0.55, with a 95% confidence interval of (0.60, 0.67).

Table 3. List of acronyms and abbreviations appendix.

Abbreviations	Names
PDSI	Palmer Drought Severity Index
SPI	Standardized Precipitation Index
PCI	Precipitation Conditions Index
CWDI	Climate Water Deficit Index
RDI	Rainfed Deficit Index
LULC	Land Use and Land Cover
VCI	Vegetation Condition Index
TCI	Temperature Condition Index
VHI	Vegetation Health Index
NVSWI	Normalized Vegetation Supply Water Index
SSI	Socio-economic Sensitivity Indicator
HMI	Human Modification Index
NRUE	Normalized Rainfall Efficiency Index
LVI	Land Vulnerability Index
NDSI	Normalized Difference Salinity Index
TWS	Total Water Storage
PVI	Proportion of Vegetation cover Index
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
SMCI	Soil Moisture Condition Index
NTmax	Normalized Temperature Maximal
TWI	Topographic Wetness Index
CSP/ERGo	Conservation Science Partners Ecologically Relevant Geomorphology
CO	Soil Organic Carbon
PhySI	Physiographic Sensitivity Index
BSI	Biophysical Sensitivity Index
MCHI	Multivariate Climate Hazard Index
PCA	Principal Component Analysis
SQI	Soil Quality Index
MADVI	Multivariate Agricultural Drought Vulnerability Index
ML	Machine Learning
IPCC	Intergovernmental Panel on Climate Change
GDP	Gross Domestic Product

3.7. Relationship vulnerability, climate risk, biophysical and physiographic sensitivity

Figure 16 presents the relationships of the spatial distributions of the subcomponents of global vulnerability to five vulnerability classes in the reference model. Analysis of this result shows linearly increasing relationships along the gradient of vulnerability intensity for all components under vulnerability. This means that the more pronounced the spatial distribution of the subcomponents of vulnerability, the higher the overall vulnerability of the catchment will be in proportion to the biophysical sensitivity of the agrosystems, their climatic vulnerability and the extent of endogenous socioeconomic vulnerability. The highest correlations, reaching a coefficient of 0.96, are observed between the variability of the spatial distribution of the predicted multivariate index of vulnerability to agricultural drought and the reference model. These correlations are statistically significant with a p value of less than 0.0000, reinforcing the validity of the relationship between these variables. A p value of less than 0.0000 indicates that the probability of obtaining such a high correlation by pure chance is extremely low. This reinforces the statistical validity of the relationship between the variability of the predicted multivariate index of vulnerability to agricultural drought and the reference model and suggests that this relationship is not simply the result of random coincidence. However, only the spatial variability of the physiographic sensitivity index (PhySI) shows a weak correlation with the MADVI

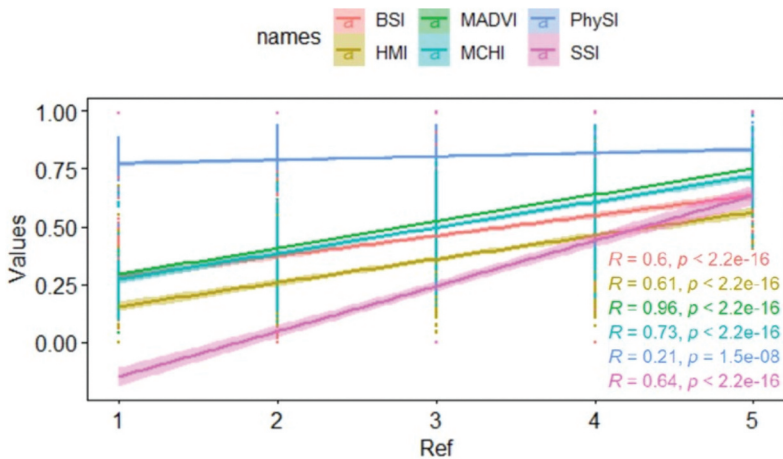


Figure 16. Statistical relationships between modelled MADVI, SSI, HMI, MCHI, PhySI, BSI relative to baseline.

reference. Despite this weak correlation, the p value was statistically significant, indicating a significant relationship between these two variables despite its reduced intensity. This means that despite the low strength of the correlation, there is sufficient statistical evidence to support the existence of a relationship between these two variables. However, it is important to note that the low correlation suggests that other factors or variables may be more predominant in determining vulnerability to agricultural drought than physiographic sensitivity alone.

3.8. Validation statistics of MADVI predicted by the ML

The comparative representation on the Taylor Diagram (Figure 17) made it possible to assess the reliability of the approach developed. The multivariate vulnerability index from Equation (3) was considered a reference because it is based on the universal vulnerability assessment equation as recommended in the IPCC Fourth Report. Thus, the spatial distributions of vulnerability subsystems (components) and the multivariate index of vulnerability to agricultural drought from machine learning were statistically compared to that of the reference equation. Analysis based on the three components of the Taylor diagram shows that the spatial variability of MADVI from machine learning models is statistically close to that of the reference model with an $R = 0.86$. This high statistical relationship indicates that the machine learning models are capable of accurately and consistently reproducing the spatial variations in MADVI as represented by the reference model. The machine learning models were trained on a dataset including information on climate risk, biophysical sensitivity and socioeconomic sensitivity in relation to vulnerability to agricultural drought in the central Sahel region. Similarly, the spatial variability of the distribution of the multivariate climate hazard index (MCHI), the biophysical sensitivity index and the socioeconomic sensitivity (SSI) results are in good agreement with that of the reference ($R = 0.74$). The relatively high agreement ($R = 0.74$) between the subcomponents of overall vulnerability derived from the machine learning models and the reference

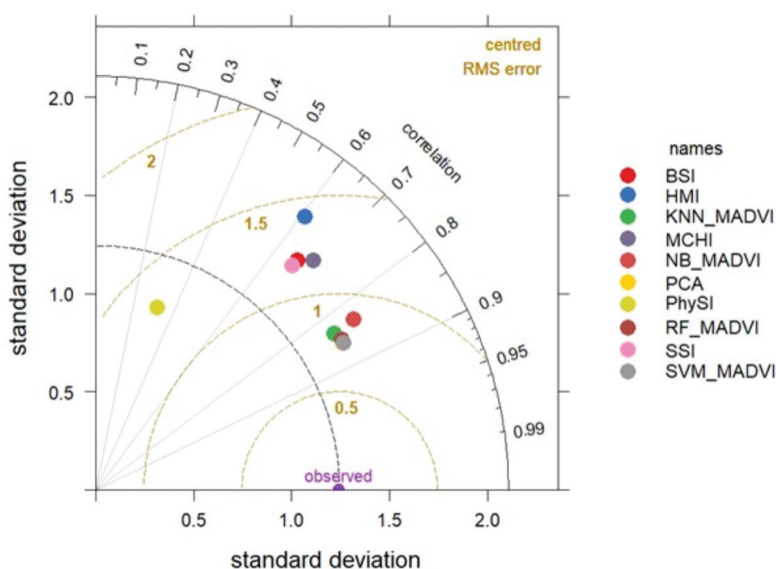


Figure 17. Predicted MADVI statistical concordance and reference (Equation 3).

model shows that machine learning models can be used as an effective alternative for assessing vulnerability in the Central Sahel region, providing estimates comparable to those obtained with the reference model. Nevertheless, the spatial variability of the physiographic sensitivity index is weakly correlated with the overall distribution of vulnerability. This can be explained by the lack of a close linear relationship between the physiographic diversity of the basin and the intensity of vulnerability to agricultural drought. Indeed, physiographic sensitivity can be influenced by many geographical factors, such as topography, geology, and hydrology. These factors can interact in a complex way with vulnerability to agricultural drought. These factors can interact in complex ways with vulnerability to agricultural drought, which makes it difficult to establish a close linear relationship between the physiographic sensitivity index and the distribution of vulnerability.

4. Discussion

In several regions of the world, as climate change intensifies, agrosystems in arid and semiarid environments will be particularly exposed to extreme climate variability. The Central Sahel region is one of the most sensitive environmental conditions to extreme climate variability due to infrequent precipitation, very high temperatures, and highly degraded land (Noureldeen et al. 2020). Since the historic droughts of 1972–1973 and 1984–1985, the overall vulnerability of agricultural systems in the central Sahel has continued to increase under the combined effect of the vagaries of the climate and endogenous environmental dynamics. This overall vulnerability of agrosystems is gradually affecting plant and animal productivity in a context where animal resources contribute to 40% of GDP and employ approximately 80% of the active population (Adamou et al. 2021; Traore et al. 2020). The mass production system is essentially rainfed and is

characterized by a low technological capacity with only 4% irrigated land, which limits the climate resilience of production systems. In all countries of the Central Sahel River basin, reactive climate risk management is largely dominant compared to proactive management. Reactive hazard management requires a better territorial diagnosis, which requires the identification of the area most vulnerable to agricultural drought to guide and optimize the efficiency of resources dedicated to mitigation measures for the impacts associated with drought. Studies on multivariate modelling of vulnerability to agricultural drought are very marginal.

In this study, a new multivariate modelling approach to agricultural vulnerability to drought was developed based on the basic principle of the vulnerability equation from the recommendations of the IPCC Fourth Report. However, unlike a linear intersection of anomalies of vulnerability factors, here, the approach is an objective combination that uses the gradient of magnitudes of historical trends in climate risk exposure (climate vulnerability), biophysical sensitivity of agrosystems (biophysical vulnerability), and physiographic and socioeconomic sensitivity (potential endogenous vulnerability). The vulnerability classes were predicted by machine learning using 28 factors from the six subsystems of global vulnerability to agricultural drought. The approach is based on a complementarity between statistical methods (pixel time regression, PCA) and machine learning (RF, SVM, KNN, Naves Bayes). It has the advantage that it uses only remotely sensed geospatial data and does not necessarily require field data. The historical availability of open-source remote sensing data over the last forty years has been exploited to generate magnitudes of changes in anomalies in climate risk exposure factors and biophysical sensitivity factors. To overcome the limitations of approaches commonly used in assessing agricultural vulnerability to drought, trend magnitude gradients of historical anomalies of dynamic vulnerability variables over the period 1981–2021 were considered in conjunction with static factors instead of a simple combination of anomalies of commonly used variables.

This new approach is supported by the hypothesis that aggregating the gradients of magnitudes of changes in covariate anomalies would better reflect the state of vulnerability rather than considering anomalies or the intensity of the frequency of anomalies. A first approach in this direction based on the coefficients of variation of vulnerability factors has been proposed in the literature by Murthy et al. (2015) in the state of Haryana in India. However, contrary to this approach, here, the magnitudes of the changes per pixel of the trends of the historical anomalies of the dynamic variables were considered as vectors of vulnerability. The results obtained show significant agreement between the different subcomponents of the overall vulnerability of agrosystems. This is consistent with the findings of the study by Murthy et al. (2015), who adopted the empirical composite index approach for assessing the state of vulnerability. This is also the case in the study by Saha et al. (2023b), who found that overall vulnerability to drought is strongly correlated with the subcomponents of vulnerability, reaching a maximum correlation of 0.99 with the exposure index and 0.984 with the drought sensitivity index. On the other hand, in the same geographical context, the relationship between exposure, sensitivity, adaptive capacity and overall vulnerability may vary from one province to another, depending mainly on the extent of adaptation measures specific to each area and on geographical and economic conditions. This was demonstrated by Wu et al. (2017) in a study carried out in Yunnan Province. The contribution values of each indicator

identified three distinct zones in Yunnan Province. Adaptability was the most important factor in the most remote prefectures where farmer support policies were weak. In prefectures with high population density and a high proportion of cultivated land, exposure was recognized as the dominant subcomponent, while sensitivity to drought was the most important subcomponent in areas with high topography, low forest cover and water resources. This reflects the highly variable multifactorial dimension of drought vulnerability conditions and the value of endogenous approaches specific to each geographical context. In the context of the Sahel, Noureldeen et al. (2020) revealed significant statistical relationships ($r > -0.676$; $P < 0.00$) between the biophysical indices, the composite index, and the vulnerability index (VI) at the Sahel country level. The study also demonstrated very similar performance in their ability to highlight the areas most affected by agricultural drought. The results of this study support this conclusion. The patterns of spatial distribution of biophysical indices and their composites are highly comparable and reflect to some extent the distribution of the multivariate index of vulnerability to agricultural drought.

Here, from the first analyses of this investigation, the index of multivariate exposure to climate risk has revealed a very high territorial contrast. The climatic vulnerability of agrosystems in the Central Sahel Basin followed a north–south gradient in opposition to the south–north isohyetic gradient. Although studies agree on a decline in rainfall isohyets at the northern boundary of agricultural land, this result suggests greater variability in precipitation patterns as they move from north to south. This characteristic reinforces the overall state of vulnerability of agrosystems in the central Sahel since the bioclimatic stages that cover the rainfed crop zone are the most exposed to the seasonal variance of the climatic water deficit. The assessment of the biophysical sensitivity of agrosystems confirmed the territorial contrast of exposure to multivariate climate risks. Similarly, when biophysical sensitivity factors, climate risk exposure, and endogenous vulnerability factors were combined using a two-tiered approach that included PCR and machine learning models (RF, SVM, KNN, NB), the spatial distribution of vulnerability status remained visible the same. In terms of the performance of the machine learning models used, RF and SVM are particularly suitable for predictive modelling of agricultural drought vulnerability classes better than KNN and NB. The latter showed a very high sensitivity to problems of collinearities of covariates, data structure, and the number of variables used for training.

The representation of the spatial distribution on the Taylor diagram and the p value dependency test revealed statistically significant relationships between the subcomponents of vulnerability. The modelled and calculated global vulnerability index was positively correlated with each other ($r = 0.96$, p value $< 2.2e-16$) as well as with the multivariate climate risk exposure index ($r = 0.7$, p value $< 2.2e-16$) and the biophysical sensitivity index ($r = 0.6$, p value $< 2.2e-16$). Statistics of the percentages of vulnerability classes in the final MADVI map indicate that approximately 22.4% of the basin, mainly in the agricultural zone, is extremely vulnerable to agricultural drought. The analysis of contributing factors showed the importance of socioeconomic determinants, including dependence on the agricultural sector and the proportion of the rural population. The same analysis also contributes sensitivity factors greater than exposure to climate risks. Indeed, several other previous studies (Ayantunde, Turner, and Kalilou 2015; Tschakert 2007) highlighted the social dimension of drought vulnerability in the context of the Sahel. In terms of climate vulnerability when considering climate factors separately, the analysis suggests that the exposure of

watershed agrosystems to heat stress is more significant than the resurgence of rainfall deficit conditions. The results of the historical magnitudes of heat stress indicators reveal a more obvious gradient in heat stress exposure than in rainfall water stress. This can be understood by the fact that average temperatures and their extremes, which have an aggravating effect on the state of vulnerability, have increased markedly in recent decades. At the same time, throughout the Sahel, studies agree on a gradual return of precipitation in terms of average annual accumulations (Chen et al. 2020; Dardel et al. 2014; Vicente-Serrano et al. 2015). However, in terms of exposure to climate risks in the agricultural sense, the spatiotemporal variability of precipitation is the first characteristic of annual risk exposure.

In contrast, in the middle Godavari subbasin in India, Masroor et al. (2023) found that characteristics related to vegetation conditions and the upwards trend in maximum temperatures are the main drivers of vulnerability. However, the conclusions of the study referring to socioeconomic vulnerability factors corroborate the results of this approach. In the context of the central Sahel River basin, socioeconomic sensitivity factors, in particular dependence on agrosystem services, were identified as the most important vulnerability factors to agricultural drought. These are followed by the biophysical sensitivity factors of the agrosystems, in particular the vegetation condition indices (VCI and PVI). This is consistent with the conclusions of the study by Saha et al. (2021b). By adopting an approach combining the frequency dimension and magnitude of historical drought trends, sensitivity factors and drought resilience, the authors found that sensitivity indicators mainly contribute to drought vulnerability in Bagalkote district. Conversely, their study suggests a greater influence of exposure factors in Yadgir district, while explicitly mentioning that in all district's factors such as water use efficiency, return period of severe droughts as well as forest area and income index are the major determinants of drought vulnerability in the state of Karnataka in India.

5. Challenges, limitations, and perspectives

Comprehensively measuring the vulnerability of agricultural systems to drought is a particularly challenging exercise because vulnerability is the result of complex interactions of several factors in the climate, geoenvironmental and socioeconomic systems. In this study, a new multivariate modelling approach to agricultural vulnerability to drought in the Sahel region was proposed. The multivariate agricultural drought vulnerability index (MADVI) is based on the combination of gradients in historical magnitudes of changes in climatic variables (exposure) and biophysical variables (drought resistance) that were combined for the first time with the human modification index, soil quality index, basin physiographic sensitivity, and socioeconomic sensitivity. The approach is based on a complementarity between statistical methods (pixel time regression, PCA) and machine learning (RF, SVM, KNN, Naive Bayes). However, we acknowledge here some limitations and uncertainties that should be improved. Indeed, the MADVI approach includes only 28 vulnerability factors. Some vulnerability factors, such as those related to adaptive capacity, were not considered due to a lack of data. Therefore, adding information on local adaptive capacity (irrigation level, water conservation, land ownership), water supply constraints, the adoption of new technologies, access to financial instruments for transferring risk such as insurance harvests, and Human Development Index (HDI) information can improve the assessment of agricultural vulnerability to drought. Similarly, MADVI was developed solely on open-source remote sensing data

with coarse spatial resolution, which does not allow reliable analysis on a small scale. This can be inaccurate since the data labels used in machine learning are derived from the result of principal component analysis applied to 28 covariates resampled at 250 m. Therefore, in future studies, it is important that the labels of machine learning data come from vulnerability state inventory based on field truth. As our study area is currently at high risk of insecurity, we had not been able to carry out an inventory of vulnerability through field missions for a complete validation of the MADVI model. Nevertheless, it should be emphasized that MADVI has been validated in two ways, namely, the learning quality indicators (MacroPrecision, Accuracy, MacroF1, Kappa) and its strong agreement with the MADVI result calculated by considering the equation of the five IPCC reports, which guarantees its applicability as a new approach to assessing vulnerability to agricultural drought. Similarly, MADVI was found to be very strongly correlated with the different vulnerability subsystems, namely, the exposure to climatic hazards, the biophysical sensitivity component (drought resistance), the intrinsic physiographic sensitivity of agrosystems and socioeconomic sensitivity.

6. Conclusion

The assessment of agricultural vulnerability to drought is an essential step in planning measures to mitigate climate impacts on agricultural production. The most popular vulnerability assessment indicators are based on frequency anomalies in exposure variables, biophysical sensitivity, and the adaptive capacity of exposed systems to climate damage. In this study, the main objective is to test a spatial modelling approach of vulnerability to agricultural drought based on the magnitude gradients of pixel trends of dynamic factor anomalies rather than considering factor anomalies directly or their frequency intensities. The Multivariate Agricultural Drought Vulnerability Index (MADVI) developed in its current configuration considers 28 factors of six subsystems of vulnerabilities to agricultural drought: exposure to multivariate climate risk, biophysical sensitivity, soil quality, topographic factors, human modification index, physiographic and socioeconomic sensitivity. ML algorithms (RF, SVM, KNN and NB) were used to automatically predict six vulnerability classes for the final mapping of MADVI.

The results of the validation of the MADVI modelled by machine learning showed a high match between the spatial variability of the MADVI vulnerability classes and those of the reference model based on the standard equation of vulnerability modelling with an $R > 0.85$ and a very significant p value < 0.0000 . The spatial variability of the indicators of the six subcomponents of vulnerability is also highly correlated with that of MADVI. The results of all subsystem indicators (components) of global vulnerability and that of MADVI highlight a particularly high vulnerability to agricultural drought in the southwestern part of the basin dominated by the Dosso region. The result is such that there should be higher climate variability (exposure to climate risk) of the wettest climate zones with a clearly contrasted climate vulnerability gradient in North–South climate vulnerability. Overall, according to the predictions of the vulnerability classes of the best learning models, the assessment of the overall vulnerability to agricultural drought in the watershed is 21.8% extreme; 10% very high; 16.8% high; 27.7% moderate; 22.2% low and 1.5% relatively low SVM model approximately comparable with RF result which provides an extreme estimate of 22.4% proportions; 9% very high; 16.6% high; 28.8% moderate; 22.5% low and 0.8% relatively very low.

This study is an assessment based solely on remotely sensed covariates that do not include some factors of the adaptation component of vulnerability, such as the irrigation index (percentage of irrigated area as a measure of adaptive capacity to climate stress) and the human development index. Nevertheless, the approach has the advantage of providing an integrated assessment of vulnerability to agricultural drought with or without in situ data that can be easily replicated across the Sahel region with a view to improving the seasonal assessment of the impacts of climate stress on agricultural production systems.

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Data available

All data supporting the findings of this study are available and publicly accessible on the Google Earth Engine platform via <https://developers.google.com/earth-engine/datasets/>. The results data is also available upon reasonable request from the corresponding author, [IHH].

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