ANALYSIS OF THE VULNERABILITY OF AGRICULTURE TO CLIMATE AND ANTHROPOGENIC CHANGE IN MARRAKECH SAFI REGION, MOROCCO

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Abstract. The consequences of global warming, represented by excessive temperatures, irregular rains and an increased frequency of drought, lead to negative impacts on different sectors such as agriculture. Its exposure is a key element in assessing risk and the degree of vulnerability. In this context, the current study aims to analyze the vulnerability of agriculture to climate and anthropogenic change in Marrakech Safi region, Morocco. To achieve this, an index has been developed, which is based on an innovative methodology that includes six components (population, crop and animal production, water resources, geography and climate). The results of the Agriculture Vulnerability Index (AVI) indicates that the province of Youssoufia is the most vulnerable with a score equal to 1, followed successively by Rhamna, Marrakech, Chichaoua with a scores equal to 0,482, 0,411, 0,351. While the least vulnerable province is Kelaa des Sraghna with a score of vulnerability equal to 0. This index represents a decision support tool, thus useful for the design and implementation of adaptation measures and desired policies in agricultural sector.
Keywords: *composite index, vulnerability, impact, climate change, agriculture, Marrakech Safi*

Introduction

The current changes in the climate of Earth are obvious, they are manifested mainly by an increase in average temperatures of + 1.5 °C (Swynghedauw et al., 2021), a decrease in rainfall, and an increase of some extreme events frequency such as drought (Thibaudon et al., 2020). The impacts vary depending on the economic and social sector of a country or a region. Extreme daily temperatures frequently affect less developed populations around the world (Harrington et al., 2016). Generally, poorer countries are the most vulnerable to the impacts of climate change (CC), they are both more exposed, more sensitive to these impacts and have less adaptive capacity (Guivarch and Taconet, 2020). The high vulnerability of these countries is explained by the important place of the agricultural, forestry and fishing sectors in the economy, they benefit from the services dependent on nature (Noack et al., 2015), which can be at risk from the impacts of CC. Specifically, the agricultural sector is highly dependent on the climate, and among the expected impacts, the modification of agricultural yields is at the forefront (GIEC, 2014).

Future climate projections for North Africa indicate changes in average, and extremes in temperature and precipitation over the Twenty First century (Schilling et al., 2020). A decrease in winter rainfall, drier summers, and increased droughts (Hertig and Tramblay, 2017) are expected. Regarding the temperature, an annual and seasonal warming is predicted by different global and general circulation models (RCM) (Bucchignani et al.,

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2018), making the region one of the main hot spots of CC (GIEC, 2014). This region will be more exposed to future climatic hazards (Lionello and Scarascia, 2020). Thus, North Africa is expected to have serious consequences that will negatively affect natural resources and agriculture. An increase of 1% in temperature in winter that causes a decrease of about 1.12% in agricultural production in the North African region (Alboghdady and El-Hendawy, 2016) is an example of this impact.

Located in the northwest of Africa, Morocco is very vulnerable to climate change. Most forecasts show that over the next decades the country will show signs of increasing aridity due to rising temperatures and decreasing precipitation (Harbouze and Khechimi, 2021). Temperature projections showed a clear warming trend at the national level of around 1.7 °C and 2.6 °C, an increase in the trend of warm days as well as the expansion of the arid climate from the southern regions to the north of Morocco (Aoubouazza et al., 2019). The increase in extreme weather events such as thunderstorms, severe and frequent droughts is also observed (IRES, 2016). Agriculture represents 15% of the Moroccan economy and employs 37.3% of jobs (Ait Houssa et al., 2016). However, it is vulnerable to CC, especially in arid and semi-arid areas. This study was carried out on the region of Marrakech-Safi, which is located in central western Morocco. It has an arid to semi-arid climate, it is subjected to a range of CC, which have a negative impact on agriculture, mainly a decrease in agricultural production and deterioration in crop performance (Kahime et al., 2018). In this context, this research aims to assess the exposure of agriculture to climate and anthropogenic change in this region. To reach this objective, a new tool was developed based on 23 indicators classified into six components: Climate, plant production, animal production, water resources, geographic, and anthropogenic factors. This tool is used to determine the degree of affectation of agriculture, to better identify the adaptation measures necessary for this sector to face climate-related challenges.

Material and methods

Study area

The Marrakech-Safi region covers an area of 39000 km², with 5.5% of the territory, has a varied geographical setting, consisting in the south of a large mountain range culminating at more than 4000 m (the top Atlas), vast arid plains (the plains of Haouz, Abda, and Rehamna), and oceanic coast (Atlantic coast) (Choukrani et al., 2018).

The climate characterized by apparent variability, arid to semi-arid, in general, and sub-humid to humid in the Atlas, and the coast (DGCL, 2015). As for rainfall, less than half of the regional surface has rainfall less than 300 mm / year on average. In the Atlas range, low temperatures allow the formation of snowflake precipitation from an altitude of 2500 m. The region is subject to the influences of the Atlantic Ocean and the high altitudes of the High Atlas. Current climate trends in the Marrakech-Safi region are an important element to assess the impact of CC in the region (DGCL, 2015).

The region of Marrakech-Safi benefits from the inflow of water from two hydraulic basins, the Tensift basin and the Oum-Er-Rbia basin. The renewable water resources are evaluated as follows:

- Oum Rbia basin with an area of 48,070 Km², surface water is 3450 Mm³/ year; groundwater is 580 Mm³/ year.

- Tensift basin with a surface area of 24800 Km², surface water is 870 Mm³/ year, groundwater 640 Mm³/year.

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Surface water is irregular and unevenly distributed. The average annual inflow is estimated at about 877 Mm³/year.

The exploited groundwater reservoirs are mainly: The Haouz aquifer, the Mejjate aquifer, the Bahira aquifer and the aquifer of the Abda plain. The potential of usable underground resources is estimated at about 451 Mm³/year. The current withdrawals in the different aquifers are estimated at 520 Mm³/year (Direction Regionale Du Plan De La Region De Marrakech, 2020).

The region includes eight provinces and a prefecture: Chichaoua, Essaouira, al Haouz, El Kelaa des Sraghna, Rehamna, Safi, Youssoufia and the prefecture of Marrakech (*Figure 1*). The total number of municipalities is 215 including 18 urban municipalities and 197 rural municipalities (Direction Regionale Du Plan De La Region De Marrakech, 2020).

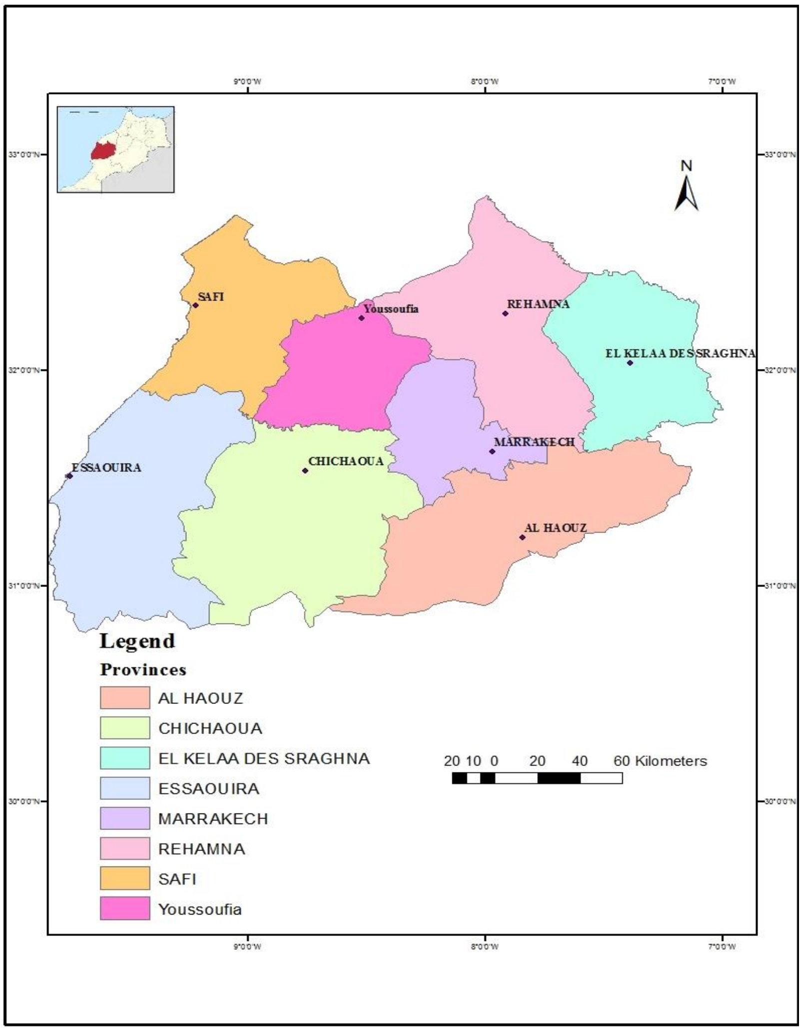

Figure 1. *Localization of the study area, including the eight selected provinces, Marrakech Safi region, Morocco*

The region's population is about 4.52 million inhabitants. The Marrakech Safi region is a predominantly rural region. And the rural population reached 2 582 553 inhabitants. The region's population experienced an overall growth rate of 5.6% during the period

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2014-2020, with an average annual increase of 0.9% (Direction Regionale Du Plan De La Region De Marrakech, 2020). The prefecture of Marrakech hosts nearly a third of the region's population while Youssoufia is the least populated province (6% of the region's total population). The population density of the region is 115.4 inhabitants per km². Compared to the national density, the region is the fourth and most densely populated in the country (DGCL, 2015).

The agriculture sector is among the primary sectors, which has one of the pillars of the regional economy. Indeed, nearly 42.49% of the region's workforce works in this sector according to the national employment survey (Direction Regionale Du Plan De La Region De Marrakech, 2020). The region covers more than 22% of the useful agricultural area (UAA) of the country. This area represents 48.6% of the total regional surface (1,904,363 hectares), the characteristic of the agricultural vocation of the region, is predominantly agro-sylvo-pastoral (DGCL, 2015). Cereal crops predominate with nearly 78% of the UAA, occupying an area of 1,355,500 hectares in the region, ensuring a production of 1,257,020 ton in 2016-2017.

The Marrakech-Safi region was chosen as the study area because it is renowned for the importance of crop and animal production, as well as the agricultural sector which is an important pillar of the regional economy. Although it has experienced a rainfall deficit in recent years.

Methodology

The Agriculture Vulnerability Index (AVI) developed in the current study is an index to assess and map the exposure and vulnerability of agriculture to climatic and anthropogenic hazards in the Marrakech-Safi region. It is a decision-making tool for the identification and planning of appropriate adaptation measures necessary to face climate-related challenges.

The AVI is a tool that uses 23 indicators organized in six components: Climate, Plant production, animal production, water resources, geographic, and anthropogenic. These components are different depending on the number and type of indicators.

The development of the index is carried out following four main stages: acquisition and processing of indicators, standardization, weighting and aggregation, and presentation of results.

Data aquisition and processing

A good indicator will help to better represent exposure and vulnerability in the study area. For this, high data availability is necessary. We chose the period 1982-2015 as the study period, this choice was made in such a way as to allow the most homogeneous coverage possible of the data over the entire period considered. Once the data has been collected and documented; we have obtained the final list of indicators that will be ready for use. Data collected or generated from surveys, documents and reports from ministries, scientific articles, and expert opinions. The identified indicators were classified, and normalized.

Normalization

Normalization refers to the transformation of the values of indicators measured on different scales and with different unit of measurement, into values without unit on a common scale. This step transforms the values of the indicators from the metric scale to

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a standardized field of values ranging from 0 to 1. The indicators in our study are normalized using the min-max method (*Eq.1*) which has the advantage that no potential bias in the data is introduced, it preserves the relationships between data values (Li and Liu, 2011). The following formula is used to apply the min-max method:

$$Xi, 0\ to\ 1 = \frac{\text{Xi}-\text{XMin}}{XMax-XMin} \quad \text{(Eq.1)}$$

where:
X_i represents the data point of the province to transform;
X_{Min} the lowest value for this indicator within this province;
X_{Max} the highest value for this indicator within this province and Xi, 0 to 1 the new value that we want to calculate, i.e. the normalized data points in the scale from 0 to 1.

Weighting

Indices do not necessarily have the same effect on vulnerability; some have more influence than others. So, different weights can be affected to them, which mean that the indicators that are given more or less imploring weight thus have more or less influence on the exposure. Several methods can be used to assign weights to the different factors chosen GIZ (2014) states that the weights assigned to the different indicators (or components of vulnerability) can come from existing literature, information provided by stakeholders or expert opinion (Fritzsche et al., 2015). Stakeholder surveys make it possible to assign weights to the various factors. For this study, we carried out an "expert opinion" survey with experts forming a team of more than 20 experts in agriculture and climate change, including university professors in the field of the environment, climate change, vulnerability and adaptation. Members of the Management of Natural Hazards and Sustainable Development, Mapping specialists, members of NASA's Earth Observation Science Group (GEO) and members of the National Weather Service, as well as researchers in hydrology, environment, vulnerability and remote sensing. To determine the degree of importance of the indicators, the team of experts assigned a score (from 0 to 5) to all the indicators, with a score of "0" indicating no importance and "5" indicating very great importance.

To determine the weighting coefficients of the indicators, we called upon the opinion of the experts on the degree of importance of the indicators, we made the average of the answers of the experts and according to this average we attributed the coefficients, such as the indicators which have an average of the answers equal to 5 (that means that all the team gives a note of 5 and that it is about an indicator of "very important" criterion) we attribute it a weighting coefficient equal to 1 , for the average of the answers superior or equal to 4 it is attributed a weighting coefficient equal to 0.75, the indicators whose average of the answers is superior or equal to 3 it is attributed a weighting coefficient equal to 0.5, the indicators whose average of the answers is superior or equal to 2 it is attributed a coefficient equal to 0.25 and finally the indicators whose average is inferior or equal to 1 it is attributed a coefficient of 0.

Once the indicators have been weighted, as a first step, these separate standardized indicators should be grouped together into an indicator representing the vulnerability index.

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Aggregation

The aggregation of indicators is the addition of the indicator values of different components and generates an overall value of the agricultural vulnerability index between 0 and 1 for the study area. We used the "Weighted Arithmetic Aggregation" Method. This is a common, simple and transparent aggregation method (Dialga and Le, 2016). There are many ways to present and illustrate the results, in the form of maps, diagrams and graphs.

The following are the equations used to estimate agricultural vulnerability according to the factors climate (*Eq.1*), crop production (*Eq.2*), animal production (*Eq.3*), water resources (*Eq.4*), geographic (*Eq.5*) anthropogenic (*Eq.6*).

All the indicators used in these equations are normalized.

Climate Component= Temperature+ Precipitation+ Normalized difference vegetation index (NDVI) + Standardized Precipitation Index (SPI) + Vegetation Condition Index (VCI) (Eq.2)

Crop production Component= Total area+ Irrigated UAA+ Production of main cereals (Eq.3)

Animal production Component = Cattle + Sheep + Goats (Eq.4)

Water resources= Surface Water+ Underground water+ Number of large dams (Eq.5)

Geographic Component= Total area+ average altitude (Eq.6)

Anthropogenic Component= Demography+ Illiteracy+ Unemployment rate+ Net employment+ Poverty (Eq.7)

To calculate the composite indicator CI of each component of agricultural vulnerability (Climate, Crop production…), the indicators (In) normalized are multiplied by their respective weighting coefficients (Wn), added and then divided by the sum of all their coefficients, as indicated in the following formula:

$$CI = \frac{\mathrm{I1} * \mathrm{W1} + \mathrm{I2} * \mathrm{W2} + \cdots + \mathrm{In} * \mathrm{Wn}}{\Sigma W} \quad \text{(Eq.8)}$$

The sum of the 6 components (ΣCI) used gives the total index of agricultural vulnerability (See formula *Eq.9*), each category was given a designation of the level of vulnerability, see *Table 1*.

$$\begin{aligned}\text{Score AVI} = {} & \text{CI Climate } + \text{CI Crop production} \\ & + \text{CI Animal production} + \text{CI Water resources} \\ & + \text{CI Geographical} + \text{CI Anthropogenic}\end{aligned} \quad \text{(Eq.9)}$$

In order to study the relationship between the values of two indicators or two components, we used the statistical method based on a correlation test between two quantitative variables. For this purpose, we calculated the Pearson correlation coefficient

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r (significant at 0.05) that will reflect the linear relationship between these continuous variables, as indicated in the following formula for eight selected provinces.

$$r = \frac{\sum\left[\left(x_i - \overline{x}\right)\left(y_i - \overline{y}\right)\right]}{\sqrt{\Sigma\left(x_i - \overline{x}\right)^2 * \Sigma\left(y_i - \overline{y}\right)^2}}$$

where, X and Y are the correlated variables, and, ¯**X** the mains of variable X, and ¯**Y** the mains of variable Y. To carry out the statistical analysis, we used the free software environment R for statistical calculation and graphics (Rstudio and R version 3.6.3).

Table 1. *Agriculural Vulnerability Index designaions*

Index Value	Designations
<0.2	Very low agriculture vulnerability
0.2-0.4	low agriculture vulnerability
0.4-0.6	Medium agriculture vulnerability
0.6-0.8	High agriculture vulnerability
0.8-1	very high agriculture vulnerability

Data source

Meteorological data used in this study presents a monthly observed series: of average temperature, maximum temperature, minimum temperature, and cumulative precipitation for the period 1982-2015, are provided via a NASA web data portal available on http://power.larc.nasa.gov. All the parameters of which are available on a global grid of 0.5° x 0.5° latitude and longitude.

The anthropogenic data, agricultural, water resource, and geographic data used in the calculation of the index represents a value of each indicator for the year 2015 (*Table 2*). According to the census of the High Commission for Planning, the SPI has been adopted as a universal drought index (Organisation Météorologique Mondiale, 2012). It is designed to qualify the precipitation deficit on multiple time scales. These timescales reflect the impacts of drought on the availability of different types of water resources. (In 2, WMO recommended that SPI be used primarily to monitor changes in drought weather conditions). This index was created by McKee et al. (1993) and has the *Equation 10*:

$$SPI = \frac{\mathrm{Xi} - \mathrm{Xm}}{Si} \quad \text{(Eq.10)}$$

where:
Xi: The cumulative rainfall for year i;
Xm: The average annual precipitation observed for a long data series;
Si: Standard deviation.

To calculate the SPI, it is necessary to have a long-term rainfall history corresponding to the period studied (preferably more than 20). Positive values of the SPI index indicate precipitation above the median and negative values indicate precipitation below the median. Since the index is normalized, it is possible to represent wet and dry climates in the same way.

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Table 2. *Indicators used in the calculation of the AVI and their data sources*

Indicator names / Variable	Unit	References
Temperature	°C	http://power.larc.nasa.gov
Precipitation	mm	http://power.larc.nasa.gov
Normalized Difference Vegetation Index (NDVI)	-	NOAA-AVHRR
Standardized Precipitation Index (SPI)	-	calculated
Vegetation Condition Index (VCI)	-	calculated
Total area	Ha	Marrakech Safi Monograph 2018 (Regionale and Plan 2020)
Irrigated UAA	Ha	Marrakech Safi Monograph 2018 Local monograph of the Essaouira environment Safi Monograph 2017
UAA	Ha	Marrakech Safi Monograph 2015 (DGCL 2015) Local monograph of the Essaouira environment (HAUT-COMMISSARIAT-AU-PLAN-ROYAUME-DU-MAROC 2017) Safi Monograph 2017 (HAUT-COMMISSARIAT-AU-PLAN-ROYAUME-DU-MAROC 2017)
production of the main cereals	thousands of quintals	Marrakech Safi Monograph 2015 (DGCL 2015)
Cattle	in thousands	Marrakech Safi Monograph 2015 (DGCL 2015)
Sheep	in thousands	Marrakech Safi Monograph 2015 (DGCL 2015)
Goats	in thousands	Marrakech Safi Monograph 2015 (DGCL 2015)
Surface water	-	ABHT, 2016
Underground waters	-	Marrakech Safi Monograph 2015 (DGCL 2015)
number of large dams		ABHT, 2016
Total area	Km²	Marrakech Safi Monograph 2018 (Regionale and Plan 2020)
average altitude	m	topographique-map.com
Demography	capita	Marrakech Safi Monograph 2015 (DGCL 2015)
Illiteracy (Number)	person %	HCP, 2014
Unemployment Rate	%	HCP, 2014
Net employment rate	%	HCP, 2014
poverty	%	HCP, 2014

McKee et al. (1993) used the classification system presented in the table of values of the SPI (*Table 3*) to define the intensity of drought episodes according to the value of the index.

The SPI index is a meteorological drought indicator based solely on precipitation data. To calculate the SPI index, it is ideal to have monthly statements covering at least 20 to 30 years. In this study, the cumulative rainfall (for the period 1982-2015), was processed and then used to calculate the SPI index using the free software environment R for

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statistical calculation and graphics (Rstudio and R version 3.6.3), using the package (SPEI: Standardized Precipitation-Evaporation Index). This includes the calculation of the SPI and SPEI indices, based on the *Equation 8*.

Table 3. *Classification of drought in relation to the value of Standardized Precipitation Index (SPI)*

SPI	Drought classification
SPI>2	Extreme humidity
1<SPI<2	High humidity
0<SPI<1	Moderate humidity
-1<SPI<0	Moderate drought
-2<SPI<-1	Severe drought
SPI<-2	Extreme drought

The NDVI is based on the work of Tarpley and colleagues (Becker et al., 2015) and Kogan (1995) of the National Oceanic and Atmospheric Administration (NOAA), U.S. governmental agency. It is also constructed from the red (R) and near infrared (NIR) channels. The normalized vegetation index highlights the difference between the visible red band and the near infrared band (*Equation 11*).

$$NDVI = \frac{\mathrm{NIR} - \mathrm{Red}}{NIR + Red} \tag{Eq.11}$$

where:
NIR: Near-infrared regions spectral reflectance;
Red: Red spectral reflectance.

The values of NDVI range from -1 to +1, with negative values corresponding to areas other than vegetation cover, such as snow, water, or clouds. For bare soil, NDVI values are close to 0, while plant formations usually have positive NDVI values between 0.1 and 0.7. The highest values correspond to the densest canopies. For this index, we used time series from 1982 to 2015 derived from NOAA-AVHRR (the Advanced Very High Resolution Radiometer) 8 km provided by the Pathfinder program.

The VCI was derived from Kogan's work at NOAA, the index uses thermal bands from AVHRR radiometers to detect drought conditions and their onset, especially in areas where the phenomenon is not widespread and poorly defined. It targets effects on vegetation and provides early information on the onset, duration and intensity of drought by detecting changes in vegetation and comparing it to historical values. The NDVI time series (AVHRR satellite platforms) were used for the calculation of the VCI according to the formula mentioned below. The higher values indicate that the vegetation cover is in good vigor, the lower values indicate the drought and its intensity.

$$VCI(i) = \frac{\mathrm{NDVI\ (i)} - \mathrm{NDVI\ min}}{NDVI\ max - NDVI\ min} * 100 \tag{Eq.12}$$

where:
NDVI (i) de la période étudiée;
NDVI min : minimum de la série temporelle étudiée;
NDVI max : maximum de la série temporelle étudiée.

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The NDVI time series provided by the AVHRR satellite platforms were used to calculate the VCI.

Concept of vulnerability

Vulnerability has become a fundamental concept in various scientific research subjects, especially those linked to natural and anthropogenic risks, such as drought, floods, and erosion (Boultif, 2018; Membele et al., 2021; Pandey et al., 2021) as well as social impacts such as poverty and health (Bonkoungou et al., 2019). Vulnerability is defined as the degree to which a human or environmental system is susceptible to damage (Turner et al., 2003). It is also defined as a plural and multiscalar process: it encompasses both susceptibility, coping skills, but also adaptation (Turner et al., 2003) and physical exposure to different domains of society, environment, and economy. Recently, this notion of vulnerability has gained great importance in scientific research on global changes. The Fourth Assessment IPCC report defined vulnerability to climate change as "the degree to which a system is likely to be adversely affected by climate change, including climate variability and extreme events" (GIEC, 2007).

Thus, vulnerability is a function of the character, magnitude and rate of climate change and variation to which a system is exposed, its sensitivity and its adaptive capacity (GIEC, 2007). Academic definitions appear to be much more complicated than those used in everyday language, because they mobilize other concepts such as: impact, danger, risk, adaptive capacity, or resilience, the majority of which require a definition in themselves (Quenault, 2015). Vulnerability assessments should focus on identifying the variables that influence and modify the vulnerability of the exposed items: the so-called vulnerability indicators (Birkmann and Welle, 2015). Comprehensive approaches to a vulnerability assessment can be categorized into three groups: vulnerability matrices, vulnerability curves and vulnerability indicators (Papathoma-Köhle et al., 2017).

According to the 4th report of IPCC AR4, vulnerability is a function of three factors which are exposure, sensitivity and adaptive capacity. Exposure in RA4 is defined by the magnitude and duration of climate-related stress, such as drought or change in precipitation, while sensitivity is the degree to which the system is affected by climate-related stress or extreme events. Adaptive capacity in AR4 refers to the ability of the system to withstand or recover from extreme events (GIEC, 2007).

Concept of indicator and index

An indicator is a variable or data whose values are significant in relation to the issue being addressed. The purpose of establishing an indicator is to convey understandable and simplistic information that can be assessed and quickly analyzed on a particular topic (Wu et al., 2019). Thus, they reduce complexity, as these indicators describe the state of a complex system in simpler terms for general purposes and uses.

A vulnerability indicator in the context of natural hazards refers to a variable which is an operational representation of a characteristic or quality of a system capable of providing information concerning the susceptibility, the adaptive capacity and the resilience of a system to an impact of an event, although ill-defined (Birkmann, 2006). The main mission of these vulnerability indicators is, on the one hand, to provide elements for the diagnosis of vulnerability at the level of the region in question which would serve as a reference in relation to changes over time; and on the -based approach, is a newer method that emphasizes multiple indicators for the assessment other hand, to establish comparisons and measure any changes. Vulnerability Indicators is an indicator of

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physical vulnerability. This method helps to the selection of vulnerability indicators, their weight allocation and aggregation for the development of the vulnerability index (Bera et al., 2020). Indicators also provide the opportunity to develop a scale to measure the vulnerability of a system (Kumar et al., 2021).

Usually to quantify or assess a multidimensional problem, an index combines a set of variables or indicators into a scalar variable called a composite indicator or Index. So the indices constitute an approach to make the theoretical concepts operational (Hinkel, 2011). In recent years, a proliferation of CC vulnerability indices has developed. The majority of them are based on the three key aspects of IPCC vulnerability: exposure, magnitude and adaptive capacity (Feindouno et al., 2020), or exposure, susceptibility, and resilience (Karmaoui et al., 2021). The assessment of the vulnerability of systems to climate change adopts the vulnerability indices that serve to improve the understanding of vulnerability and to perform this assessment. These indices are necessary for decision-making, allowing the regional governments to locate the most vulnerable systems as well as the appropriate actions.

Results

Evaluation of climate variability in Marrakech Safi region in the period of 1982-2015

The evolution of climate variability in the Marrakech Safi region is taken into account in the assessment of CC impacts on the region's agricultural sector. The different provinces of the Marrakech-Safi region are characterized by irregular temperatures due to the geographical position, but in general, the average annual temperature of the region has continued to increase over the period 1982-2015 (*Figure 2a*). According to the trend line, we can conclude that there is a tendency for the temperature to increase in the region. A significant upward trend of 0.71 °C compared to the period observed for the study region. The precipitation is much more variable from year to year. The temporal distribution of annual precipitation in the region is subject to several fluctuations with a very slight increasing trend, particularly due to the exceptional precipitations of the last years 1996, 2009, 2013, which exceed 500 mm (*Figure 2b*).

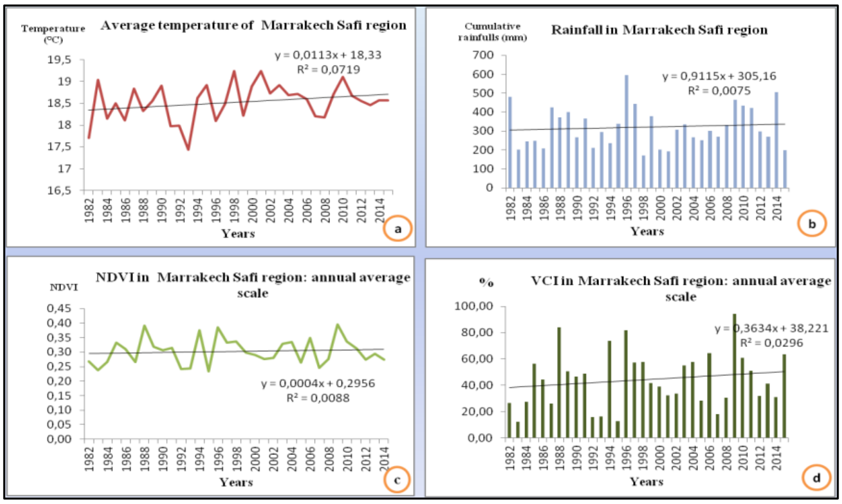

Figure 2. *a, Evolution of the annual mean temperature in the region of Marrakech Safi. b, Evolution of the annual rainfall in the region of Marrakech Safi. c, Evolution of the NDVI (1982-2015) at annual mean scale. d, Evolution of the VCI (1982-2015) at annual mean scale*

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The NDVI values in the region shows an almost stable trend over the period (1982-2015) (*Figure 2c*). The magnitude of change of NDVI in the region was small and maintained a stable fluctuation. The multi-year mean NDVI value was 0.3, with a minimum value of 0.23 in 1995 and a maximum value of 0.4 in 2009 (*Figure 2c*).

From the result of the evolution of the VCI at the annual average scale, the graph shows a clear variability with an increasing trend of VCI values in the region during the period (*Figure 2d*). The multi-year average value of the VCI was 44.58%, with a minimum value of 12.44% in 1983 and a maximum value of 94.43% in 2009 (*Figure 2d*).

Evaluation of climatic drought in Marrakech Safi region, from 1982 to 2015

This part aims to characterize the climatic drought in the region Marrakech Safi based on the calculation of the normalized index of precipitation SPI. The results of the SPI index in the Marrakech Safi region show a succession of dry years and wet years (*Figure 3*). For the years 1983, 1984, 1985, and 1986, the results show moderately dry years. After these years, an alternation of dry and wet years was observed, but the period 1996-1997 is characterized by a remarkable wet period, followed by a period of drought in 1998-2001.

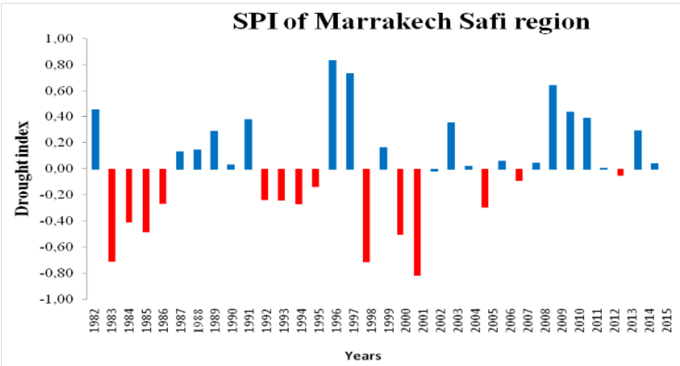

Figure 3. *Standardized precipitation index average for the Marrakech Safi region during the period 1982-2015*

The agriculture vulnerabilty to climate change

According to the results only the precipitation indicator has the weighting coefficient equal to 1, the indicators (Sheep, underground waters, altitude, illiteracy, Unemployment rate, employment rate, and poverty) have weighting coefficient equal to 0.5, the other remaining indicators all have the weighting coefficient equal to 0.75 (Demography, Number of large dams, surface water, Goat, Cattle, Irrigated UAA, Production of main cereal, Temperature, SPI, NDVI and VCI).

In terms of climate vulnerability (*Table 4*, *Figures 4 and 5*), the province of Chichaoua is the most vulnerable followed by Marrakech and Youssoufia respectively and Al'Haouz is the least vulnerable. Regarding the crop production component, the agriculture vulnerability score indicates that the most vulnerable province is Youssoufia with a score of 1 (critical state) followed by Essaouira and Al'Haouz is the least vulnerable province with the lowest score.For the crop production component, the total vulnerability score for agriculture indicates that the most vulnerable province is Youssoufia (Scores =1) in critical condition followed by Essaouira while Al 'Haouz is the least vulnerable province

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with the minimum score.In terms of animal production, the most vulnerable provinces are Al 'Haouz, Youssoufia and Rehamna, which is mainly due to a low livestock activity in these provinces. The province of Kelaa des Sraghna has the least vulnerability due to a very imploring number of livestock: cattle and sheep.

Table 4. *Indicators scores (normalized values) of Agriculture sector following the six proposed categories or components for the eight selected provinces of Marrakesh Safi region (Morocco)*

Component	N	Indicators	Chichaoua	Essaouira	Kelaa des sraghna	Marrakech	Rehamna	Safi	Al haouz	Youssoufia
Climate	1	Temperature	0,924	0,836	0,949	0,716	1	0,860	0	0,919
	2	Precipitation	0,709	1	0	0,720	0,316	0,419	0,580	0,312
	3	Normalized Difference Vegetation Index (NDVI)	1	0,5	0,571	0,714	0,714	0	0,214	0,429
	4	Standardized Precipitation Index (SPI)	0,5	1	1	1	0,5	0,5	0	1
	5	Vegetation Condition Index (VCI)	1	0	0,804	0,856	0,860	0,23	0,567	0,833
Crop Production	6	Total area	0,273	0,664	0,894	0,305	0,329	0,121	0	1
	7	Irrigated UAA	0,343	0,906	0,885	0,286	0,248	0.879	0	1
	8	production of the main cereals	0,967	0,499	0	0,98	0,997	0,556	1	1
Animal Production	9	Cattle	0,597	0,547	0	0,333	1	0,339	1	1
	10	Sheep	0,404	0,548	0	0,457	1	0,458	1	1
	11	Goats	0,527	0	0,809	0,187	1	0,897	1	1
Water resources	12	Surface water	0	0	0	0	0	0	0	0
	13	Underground waters	0	0	0	0	0	0	0	0
	14	number of large dams	0,75	0,5	0,75	0,75	1	0,25	0	0,25
Geographic	15	Total area	0	0,192	0,659	1	0,297	0,843	0,132	0,918
	16	average altitude	0,862	0	0,391	0,536	0,310	0,202	1	0,202
Anthropogenic	17	Demography	0,11	0,184	0,265	1	0,056	0,411	0,299	0
	18	Illiteracy (Number)	1	0,938	0,637	0	0,766	0,453	0,750	0,699
	19	Unemployment Rate	0,07	0,07	0,282	0,549	0,296	0,901	0	1
	20	Net employment rate	0,727	0;727	1	0,273	0,333	0	0,636	0,636
	21	Poverty	0,970	1	0,291	0	0,540	0,468	0,620	0,861

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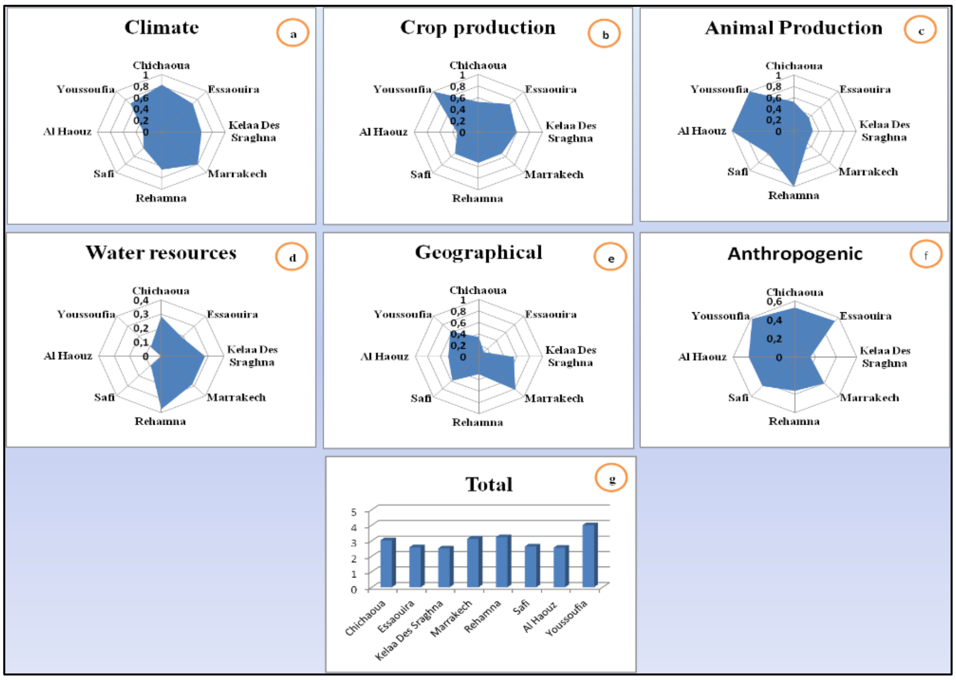

Figure 4. *Agricultural vulnerability of the selected provinces classified following the six components, comparison of Agricultural vulnerability for the eight selected Agricultural vulnerability provinces; a. Climate, b. crop production, c. animal production, d. water resources, e. geographical, f. anthropogenic and f. total scores*

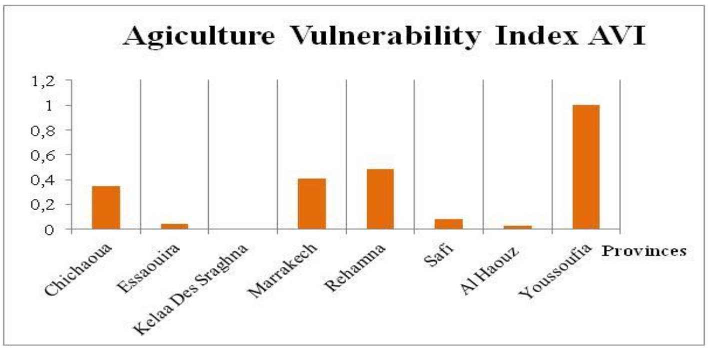

Figure 5. *Vulnerability of agriculture Index in Marrakech Safi region*

Agriculture is highly dependent on water and is often susceptible to water-related risks. Insufficient water resources are one of the most serious threats to this sector. According to findings, the vulnerability of the water resources component is very important in several provinces namely: Rehamna and which is mainly due to the absence of large dams in this province as well as it is characterized by discontinuous and not very extensive water tables, then hydrogeological resources, waters flow at low depth, generally, they undergo evaporation. Rehamna is followed by Chichaoua, Kelaa des Sraghna, and Marrakech. The least vulnerable province is Al 'Haouz due to the large number of large dams and groundwater and surface water resources that are quite abundant compared to the other provinces.

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Regarding geographical vulnerability, the province of Marrakech has a high vulnerability due to a small total area followed respectively by Youssoufia, Safi, Kelaa des Sraghna. The province of Essaouira is the least vulnerable.

For anthropogenic vulnerability, the province of Youssoufia is the most vulnerable; the latter is mainly due to: the poverty rate which is important and the rate of thatching which is quite high compared to other provinces, followed respectively by the province of Essaouira, and Chichaoua. The province of Marrakech is moderately vulnerable even though it has a maximum population number but at the same time it is characterized by a low percentage of illiteracy and a high activity rate. The least vulnerable province is that of Kelaa des Sraghna with a minimum score of 0.15 which is mainly due to the low percentage of illiteracy and poverty.

The component indices were aggregated into a single index, the Agricultural Vulnerability Index (*Eq.5*). The normalization is applied for a second time to the values summed; to be compared in the interval used 0-1.

Regarding the vulnerability of agriculture to climate and anthropogenic change according to the Agricultural Vulnerability Index (*Figures 5 and 6*), the most vulnerable province is: Youssoufia with a maximum index score of vulnerability equal to 1, and which is classified as the province with Very High Agricultural Vulnerability. Followed by the province of Rehamna , Marrakech with medium Agricultural Vulnerability , and then Chichaoua with low Agricultural Vulnerability. However, the least vulnerable province is Kelaa des Sraghna with a minimum score of 0 and which is classified as the province with Very low Agriculture Vulnerability.

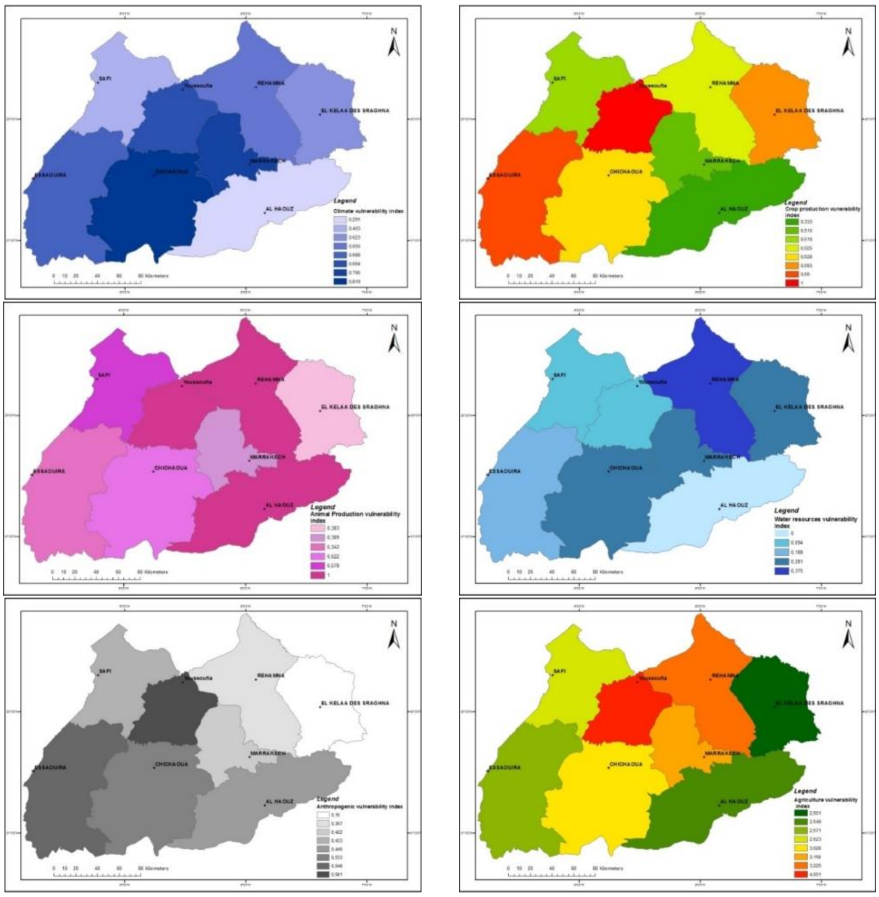

Figure 6. *Maps of the components and vulnerability of agriculture in Marrakech Safi region*

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The interaction between components of agricultural vulnerability

The *Table 5* shows strong to very strong positive significant correlations between Climate and water resources components (r= 0.715), a medium positive significant correlation was found between Climate and crop production (r= 0.439), Anthropogenic and crop production (r= 0.364).

Table 5. *Pearson correlations (r) between the six used components (Climate, Crop production, Animal Production, Water resources, Geographical and Anthropogenic)*

Climate	**Climate**					
Crop production	0.439	**Crop prod**				
Animal production	-0.40	0.08	**Animal prod**			
Water resources	0.715	-0.04	-0.353	**Water resources**		
Geographical	-0.03	0.04	-0.05	-0.165	**Geographical**	
Anthropogenic	0.13	0.364	0.304	-0.4	-0.242	**Anthropogenic**

	IS.Climate	CP	AP	WR	GEO	AN
IS.Climate	1.00000000	0.43902242	-0.40778281	0.71516040	-0.03806062	0.1335951
CP	0.43902242	1.00000000	0.08517849	-0.04520938	0.04648312	0.3649367
AP	-0.40778281	0.08517849	1.00000000	-0.35376447	-0.05360243	0.3041052
WR	0.71516040	-0.04520938	-0.35376447	1.00000000	-0.16556262	-0.4081876
GEO	-0.03806062	0.04648312	-0.05360243	-0.16556262	1.00000000	-0.2420421
AN	0.13359507	0.36493672	0.30410523	-0.40818762	-0.24204214	1.0000000

However, the table shows an average negative correlation between the Animal Production and Water Resources component (r= -0.353) and the Animal Production and Climate component (r= -0.40).

The other components and indicators are not correlated with each other (weak positive or negative relationship non-significant), so it is necessary to look for strongly related indicators to obtain strongly correlated components and to be able to give a good and significant index of vulnerability of agriculture overall. For example, the geographic component has no correlation with the other components, and climate has 4 significant correlations (with crop production, water resources, anthropogenic factors, animal production). This allows us to say that the climate component is a relevant and correctly selected component and that the geographic component needs to be improved by selecting indicators that have an impact on the total score of the agricultural vulnerability index.

The interaction between agricultural vulnerability component indicators (intra-component correlation)

Regarding the Climate component, the *Table 6* shows strong to very strong positive significant correlations between the SPI and temperature indicators (r= 0.645), as well as strong to very strong positive significant correlations between NDVI and VCI (0.606). A moderate positive correlation was found between the indicators Temperature and NDVI (r= 0.409).

The table also shows a mean negative correlation between Precipitation and VCI (r= -420).

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Table 6. *Pearson correlations (r) between climate component Indicators*

Temperature	**Temperature**				
Precipitations	-0.249	**Precipitations**			
NDVI	0.409	0.157	**NDVI**		
SPI	0.645	-0.042	0.275	**SPI**	
VCI	0.061	-0.420	0.606	-0.080	**VCI**

```
               Tempeture Precipitations       NDVI         SPI         VCI
Tempeture      1.00000000    -0.24913094 0.4097992  0.64594382  0.06139116
Precipitations -0.24913094    1.00000000 0.1574838 -0.04270037 -0.42083048
NDVI           0.40979923     0.15748377 1.0000000  0.27502442  0.60621106
SPI            0.64594382    -0.04270037 0.2750244  1.00000000 -0.08021513
VCI            0.06139116    -0.42083048 0.6062111 -0.08021513  1.00000000
```

Regarding the anthropogenic component, the table shows a very strong positive significant correlation between the indicators Literacy and Poverty (r= 0.881) (*Table 7*). A positive mean significant correlation was found between the indicators Literacy and Net Employment Rate (r= 0.548).

Table 7. *Pearson correlations (r) between anthropogenic component Indicators*

Demography	**Demography**				
Illiteracy	-0.887	**Illiteracy**			
Unemployment Rate	0.129	-0.504	**Unemployment Rate**		
Net employment rate	-0.423	0.548	-0.523	**Net employment rate**	
Poverty	-0.786	0.881	-0.234	0.353	**poverty**

```
                    Demography Illiteracy Unemployment.Rate Net.employment.rate
Demography           1.0000000 -0.8875674         0.1292502          -0.4238763
Illiteracy          -0.8875674  1.0000000        -0.5042545           0.5485482
Unemployment.Rate    0.1292502 -0.5042545         1.0000000          -0.5231684
Net.employment.rate -0.4238763  0.5485482        -0.5231684           1.0000000
poverty             -0.7864405  0.8812859        -0.2340754           0.3539832
                       poverty
Demography          -0.7864405
Illiteracy           0.8812859
Unemployment.Rate   -0.2340754
Net.employment.rate  0.3539832
poverty              1.0000000
```

The table also shows a very strong negative mean significant correlation between Demographics and Illiteracy (r= -887). A mean negative significant correlation was also found between the indicators Unemployment Rate and Net Employment Rate (r= -0.523).

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Discussion

Evolution of climate variability in the Marrakech Safi region in the period 1982-2015

The climate of Marrakech Safi region characterized by an apparent variability with the dominance of the arid and semi-arid climate; the sub-humid character appears only in the High Atlas (Direction Regionale Du Plan De La Region De Marrakech, 2020). Rainfall generally varies between 190 mm/year in the plain and 800 mm/year in the high mountains of Haouz (Saidi et al., 2012), maximum temperatures are around 38°C and minimums around 4.9°C (Choukrani et al., 2018). According to the results of the current study there is an increase in temperature and a decrease in precipitation in the region of Marrakech Safi. These results confirm the scientific research carried out at the level of the city of Marrakech and Essaouira, which have shown that over the past five decades a clear trend towards higher temperatures and lower rainfall where recorded (Brahim et al., 2017; Choukrani et al., 2018). This is not only the case for Marrakech Safi, recent climate conditions and future climate change projections can confirm similar results at national scale (Brahim et al., 2017), Morocco is among the most arid regions of the world, characterized by a very variable rainfall, it undergoes recurrent droughts. a strong rise in temperature is observed by the end of the century and a decrease in total precipitation in the various simulations following a north-south gradient (Almazroui et al., 2020), future climate conditions over Morocco also show a change in the distribution of rainfall and extreme events (Driouech et al., 2010). Consequently, an increase in climatic, hydrological and agricultural droughts is expected in Morocco by the end of the twenty first century.

The consequences of drought are considerable and extensive, affecting several economic sectors. To evaluate this drought, several indicators are necessary; in our study we chose the most commonly used indicators in drought prone regions, namely: SPI, NDVI and VCI. Strengths of the SPI indicator: Precipitation is the only parameter needed. SPI can be calculated for different time scales, allowing to detect drought situations and to assess their severity. It is less complex than other indices. For the NDVI indicator is an index used to detect and monitor droughts that affect agriculture among its strengths: Innovative use of satellite data to monitor the state of vegetation in relation to drought, very high resolution and wide spatial coverage. For the VCI indicator, it is combined with NDVI; the index is used to assess vegetation in drought situations that affect agriculture among these strengths: the resolution is high and the spatial coverage is good.

This work has confirmed the warming trend of the central region and especially the drying and aridification of the central area (Abdelali et al., 2012).

Evolution of climatic drought in the Marrakech Safi region, from 1982 to 2015

Drought is a natural phenomenon that affects several countries in the world, including Morocco. The expectation of the Intergovernmental Panel on Climate Change (GIEC) confirms that droughts and floods will be more frequent due to climate change in the Mediterranean region, including Morocco (GIEC, 2007). The same is true for Born et al. (2008), showing that the Moroccan climate tends to evolve towards warmer and drier conditions.

Currently, Morocco is experiencing the longest period of drought characterized by a decrease in rainfall and an increase in temperature (Stour and Agoumi, 2009), it has been at risk of drought several times during the years 1944-1945, 1965-1966, 1980-1985, 1994-1995 and 2000-2001 (El Hafid et al., 2017).

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The different regions of Morocco have experienced intense drought periods in the last decades; this period has a major impact on water resources, energy and especially agriculture. According to the spatio-temporal monitoring of drought (SPI), drought can occur randomly in different regions of Morocco during the autumn, winter and spring seasons and on an annual scale (Ezzine et al., 2014).

The Standardized Precipitation Index (SPI) is used to analyze the evolution of drought severity degrees in the Marrakech Safi region during the period 1982-2015. The results show a succession of dry and wet years, but over the past two decades, the Marrakech-Tensift region has experienced a substantial increase in the dry land regime due to global warming and the reduction in measured precipitation (according to the Marton aridity index) (Fniguire and Laftouhi, 2014).

The agriculture vulnerability to climate change

Agriculture is one of the main economic activities in the region of Marrakech Safi. This region is characterized by an arid climate, low rainfall, an unequal distribution of resources and anthropogenic pressure. All these factors contribute to the vulnerability of agriculture due to the multiple interactions between these factors.

Using the correlation coefficient, the results show a strong correlation between climate and water resources. This means that water resources are very dependent on climate and more specifically on climate change. Generally, the hydrological cycle depends on climate and any climatic disruption affects both the quantity and quality of this resource, an increase in air temperature induces an increase in evaporation from the water surface, change in the intensity and frequency of rainfall events induces the reduction of groundwater recharge and runoff, so the renewal of this resource is ensured by the recharge of aquifers which depends on its share of precipitation.

In Morocco, several studies have shown the impact of climate on water resources (El Assaoui and Amraoui, 2015; El Houssaine et al., 2018), These impacts include a downward trend in the volume of water resources, which varies between 7.6% and 40.8%, an increase in the overexploitation of groundwater (Sinan and Belhouji, 2016). Studies have also shown the dependence of aquifer recharge (Ouhamdouch et al., 2020). It is concluded that climate change has accentuated the negative impact on ground and surface water resources (Hssaisoune et al., 2020).

The climate not only affects water resources, but also agricultural production. From this, we find that all types of crops have requirements for the climate in which they grow. Thus, CC is altering the biophysical environment of crops and how these crops respond to certain CC factors (such as temperature and precipitation, and thus these elements of climate can be a limiting factor for crop production. According to the results, the climate component had statistically significant and strong correlations with crop production, this result is consistent with the findings of other recent studies (Yang et al., 2015; Wollenberg et al., 2016; Xu et al., 2019; Chi et al., 2020). For Morocco, there are still few specific studies on the impact of climate on crop production, but generally, the overall effect of CC on crop production will be negative for low latitudes due to excessive temperatures and increased drought frequency. Several studies have shown that climate affects food production and that periods of drought could have dramatic consequences on crop productivity and yield and lead to total crop losses (Laux et al., 2010; Baffour-Ata et al., 2021). An increase in temperature reducing the growth cycle also leads to a decrease in crop productivity. But the impact of climate on production varies according to location, crop type and climate scenarios (Zhang et al., 2019).

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Regarding the relationship between crop production and anthropogenic factors, population growth means an increasing demand for food, so increasing crop productivity to meet needs is a challenge especially for developing countries. The social and demographic characteristics of a country and CC could influence its agricultural production. According to the results, the plant production component is correlated with the anthropogenic component, which means a strong association between the two components, but remains a very complicated relationship. This study concludes that the total population is positively correlated with crop and animal production (strong association between population and agricultural production) (Chi et al., 2020), in contrast another study concludes that concludes that total population have significant and negative relationships with crop yields (considering that if the population increases the cultivated land decreases due to rapid urban expansion and population growth) (Xu et al., 2019).

Finally, we can conclude that the assessment of the vulnerability of agriculture to climate change constitutes a simple process for expressing the interactions between climate, water resources, agricultural production and anthropogenic factors.

Climate change and its impact on the agricultural sector in developing economies is the subject of several studies. According to the FAO (2015), the impacts of climate on agriculture in developing countries account for 23% (93 billion dollars) of the total loss and damage of this sector, caused mainly by floods and droughts. So the rise in temperatures, the change in precipitation patterns mainly causes the decline in yields and productivity of crops.

Generally the assessment of vulnerability using the index method has been widely applied in the world, a range of vulnerability indexes have been developed, such as: DRASTIC index which allows to assess the vulnerability of groundwater using seven geological and hydro geological parameters (Heiß et al., 2020), the new composite vulnerability index (Edmonds et al., 2020), The physical vulnerability index to climate change (PVCCI) (Feindouno et al., 2020), Environmental Vulnerability Index EVI (Skondras et al., 2011). Similarly for agriculture, various assessments of the vulnerability of agriculture to climate change have been conducted, generating composite indices based on sets of indicators (Dong et al., 2015). The general process of this method consists of the selection of indicators using the weighted average, the principal component analysis, the expert notion to determine the weight of each indicator and the calculation of the vulnerability according to the corresponding formula. Depending on the method of weighting and synthesis used, the vulnerability maps may appear different even if the indicators and classifications are the same (Wiréhn et al., 2015). The indicators used cover several dimensions of the concept of vulnerability, namely exposure, sensitivity and adaptive capacity of a system. Several studies have proposed a method for assessing agricultural vulnerability to climate change according to the definition of vulnerability of the Intergovernmental Panel on Climate Change (IPCC) (in a framework of exposure, sensitivity and adaptive capacity), for example: Dong et al. (2015); Murthy et al. (2015); Neset et al. (2019); Singh and Kumar (2021); and Swami and Parthasarathy (2021).

For this study, the result of the assessment of agriculture according to the AVI (*Table 8*), the province most vulnerable to climate change is that of Youssoufia, even if it was not the most vulnerable in terms of climate component, and the province that has the lowest score of agriculture index is that of kelaa des Sraghna because it was the least vulnerable in terms of animal production, geographical and anthropogenic and moderately vulnerable in terms of water resources. Thus we can draw conclusions that the vulnerability of the system is not influenced only to the sensitivity and that any change

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in adaptive capacity would also have an impact on the overall agricultural vulnerability of the system (Singh and Kumar, 2021). Also we can conclude that the vulnerability is not influenced only by the exposure, it is the case of several studies on agricultural vulnerability that have shown that some regions are vulnerable although they are the least exposed to vulnerability, which means the contribution of sensitivity and adaptive capacity to their vulnerability. Therefore, in order to correctly assess the vulnerability of agriculture to climate change and identify adaptation measures, it is necessary to improve our knowledge of the biophysical and socio-economic factors that decrease the sensitivity or increase the adaptive capacity of agriculture.

Table 8. *Description of the AVI index developed in this study and some other existing indicators*

Index	**Turner's model**	**indice intégré de vulnérabilité multidimensionnelle aux crues**	**Pressure and Release model**	**Driver-Pressure-State-Impact-Response model**	**Agricultural Vulnerability Index**
Abbreviation	-	IMVI	PAR	DPSIR	AVI
Aim	Vulnerability results from exposure to hazards and the resilience of the system experiencing those hazards. Coupled human-environmental systems and the linkages within and outside the systems affect their vulnerability.	Vulnerability is characterized in a holistic way, integrating in the index all the dimensions and components involved. IMVI makes it possible to identify the sources of vulnerability and their underlying causes, thus contributing to improving flood risk management	Risk is defined as a function of the disturbance, the stressor or stress and the vulnerability of the exposed unit.	This method treats vulnerability in terms of analysis of human and environmental systems from application of the driver-pressure-state-impact-response (DPSIR) framework.	To assess vulnerability to CC, we integrated the social dimension to agriculture by grouping the indices into 5 main components: Climate, Crop Production, Animal Production, Geography and Anthropic. despite limited data sources, and some data are limited in time, the method is easy to interpret, characterized by transparency of use
Reference	(Turner et al., 2003)	(Aroca-Jiménez et al., 2022)	(Blaikie et al., 1994)	(Malekmohammadi and Jahanishakib, 2017)	This study

Limits and strengths

Limitations and difficulties in the study methodology include the difficulty of obtaining data, particularly, related to the agricultural sector and water resources, limited data sources, and some data are limited in time, particularly those obtained from statistical databases collected from national surveys. The strengths of the study presented by the simplicity and ease of use of the index, the transmission of an important and clear data grouping different indicators in an easy to understand format, the index can be used to map vulnerability in spatial representations.

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The Agricultural Vulnerability Index provides an assessment tool on what causes vulnerability and how to reduce it, thus a valuable decision-making tool, easy to interpret, characterized by transparency of use and pure replication of the index composition. It allows decision makers to make spatial comparisons and multidimensional analysis and conclusions for decision making, highlighting areas of concern within the region and also determining which sectors need to be improved.

Conclusion

Agriculture is often described as one of the most vulnerable sectors to climate change, and its vulnerability is usually assessed through composite indices. These can draw simplistic policy conclusions. Using the Agricultural Vulnerability Index (AVI), this study examined the vulnerability of the agricultural sector to CC in the 8 provinces of the Marrakech Safi region. The results show the regional vulnerability at the level of provinces in the distribution of resources, which require special attention from the government and policy makers to reduce their vulnerability and improve their adaptive capacity, the results also identify which province is most vulnerable to climate change the case of the province Youssoufia followed successively by Rehamna, Marrakech and Chichaoua and the least vulnerable province is that of Kelaa des Sraghna, this helps policy makers to propose mitigation measures in the future.

AVI is a decision support tool for the identification and planning of adaptation measures needed to cope with climate challenges. Faced with the effects of climate change, different adaptation strategies are possible, to minimize the expected impacts. Among the strategies that need to be adopted to reduce the vulnerability of agriculture: Improving research on climate and agriculture and access to knowledge on climate risks, disaster risk management, improving agricultural infrastructure and access to natural resources and adaptation technologies.

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