GEOSPATIAL ANALYSIS OF VEGETATION DISTRIBUTION AND RAINFALL PATTERNS IN A SEMIARID REGION OF MEXICO USING REMOTE SENSING

OLMOS-TRUJILLO, E.[1] – ÀVILA-SANDOVAL, C.[1] – CASTRO-GUIJARRO, J. I.[2] – RAMIREZ-JUÁREZ, J. E.[1] – VILLALOBOS DE ALBA, Á. A.[1] – PACHECO-GUERRERO, A.[1*] – BADILLO-OLVERA, A.[1]

[1]*Unidad Académica de Ingeniería 1, Universidad Autonóma de Zacatecas (UAZ), Zacatecas 98000, México*
(e-mail: eolmos@uaz.edu.mx; claudia_avila@uaz.edu.mx; j.ernesto.ramirez@uaz.edu.mx; angelalfonsovillalobos@uaz.edu.mx; anuard.pacheco@uaz.edu.mx; anuar.badillo@uaz.edu.mx)

[2]*Universidad Internacional Ignacio Castro Pérez (UNICAP), C. del Ángel 76-B, Centro, 98600 Guadalupe, Zacatecas, México*
(e-mail: rectoria@unicap.edu.mx)

[*]*Corresponding author*
e-mail: anuard.pacheco@uaz.edu.mx

(Received 14th Aug 2024; accepted 3rd Dec 2024)

Abstract. The objective of this research is to document and analyze quantitatively and qualitatively the relationship between the spatial distribution of vegetation and rainfall patterns, using the central region of the state of Zacatecas, Mexico, as a reference. The importance of this geospatial analysis, which utilizes Vegetation Indices (VIs) and rainfall data, lies in its scientific contribution that can be reproduced under the specific characteristics of other latitudes on the planet. The methodology includes monthly rainfall records through the web-based application GIOVANNI (Geospatial Interactive Online Visualization and Analysis Infrastructure) and VIs from the period of 2014 to 2021. With these data, trends are inferred up to 2030 for VIs correlated with rainfall levels under drought and water stress conditions in semiarid regions. Additionally, the results prompt the consideration of the current situation of this region under the interpretation of the Sustainable Development Goals (SDGs) through a holistic approach. The results infer that the current situation of the region is unsustainable, combined with projected drought conditions and circumstances of water stress. From this work, it is deduced that understanding vegetation and rainfall patterns as fundamental indicators for sustainable management in semi-arid areas, is key to preserving ecosystems.
Keywords: *spatial data analysis, NDMI, SDGs, IWRM*

Introduction

In semiarid regions, the analysis of the relationship between vegetation and rainfall patterns plays a crucial role in understanding the complexity of these ecosystems. The combination of advanced technologies, such as geospatial analysis, remote sensing, and Geographic Information Systems (GIS), provides valuable tools for exploring and comprehending these dynamics. Some researchers like Choo et al. (2018) and Elçi (2019), suggest incorporating remote sensing data into the usual approaches, as this allows for the determination of various parameters related to the environment, such as land use and its coverages. Furthermore, it can also be used to detect future hydroclimatic changes in the susceptibility of certain regions.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

Addressing the challenges associated with water availability in semiarid regions requires a comprehensive understanding of the intricate relationships between rainfall, vegetation, and other variables (Ahmed et al., 2020).

Geospatial analysis provides the capability to examine and understand the spatial distribution of vegetation and climatic patterns in detail. By employing techniques such as satellite image processing and digital mapping, it becomes possible to identify geographical patterns that reveal the complex interactions between vegetation and variability in rainfall patterns. Nowadays, GIS continue to be the best methods for studying spatial distributions and the evolution of geographic phenomena in relation to changes in land use and land cover (Stojković, 2017). The underlying technologies for geospatial data analysis involve GIS technology, remote sensors, satellite data, such as images and climatic factors, amongst others (Das et al., 2020).

By utilizing remote sensors, multispectral images can be obtained, enabling the continuous monitoring of vegetation and the identification of changes over time. These remotely sensed data provide valuable information for understanding seasonal variations and vegetation responses to fluctuations in rainfall regimes (Zewdie et al., 2017; Zhang et al., 2019). One of the most commonly used indicators in ecosystem monitoring is vegetation, (LaPaix et al., 2009); Being "a natural element that responds to the characteristics of the environment to which it belongs” (Soledad Duval et al., 2015), it can be correlated with other variables, such as ecohydrological factors (Keersmaecker et al., 2015). The information obtained through remote sensing regarding the vigor and dynamics of terrestrial vegetation is extremely useful in environmental monitoring. Vegetation indices (VIs), which can be derived from a spectral range, serve as indicators of plant water status as well as biotic/abiotic stress levels (Xue and Su, 2017).

It is well known that the Normalized Difference Vegetation Index (NDVI) is now the most popular index used for vegetation assessment (Huang et al., 2021). Approaches using NDVI in geospatial studies are numerous. These include the detection of seasonal pauses in NDVI, indicating changes in phenology due to land use changes, the identification and mapping of degraded ecosystems, as well as temperature and NDVI used as indicators of ecosystem recovery (Vlassova and Pérez-Cabello, 2016; Zewdie et al., 2017; Valle Júnior et al., 2019). Of the many techniques offered by satellites and the variety of indices, Normalized Difference Moisture Index (NDMI) and the Enhanced Vegetation Index (EVI) are commonly used in a wide variety of terrestrial science applications that aim to monitor and characterize the earth's vegetation cover from space, as an alternative indicator (Jiang et al., 2008; Mihai and Horoias, 2022). Trough years, several remote sensing VIs have been employed and developed by many researches studies to investigate changes in patterns of vegetation and other variables, some of this VIs can be found in the literature (Ayanlade, 2017).

Likewise, it is well known that water scarcity and soil degradation (loss of vegetation) are often consequences of each other, vegetation plays a decisive role in the generation, protection, and conservation of soil, for example, shrub species allow for the infiltration of water to greater depths (Serrato, 1998). In Mexico in 2002, there was only 0.5 ha of forest cover per capita, and the prediction for 2025 will be 0.3 ha per capita (Velázquez et al., 2002), to semiarid regions, one of the central characteristics is the spatio-temporal variability of rainfall (Batisani and Yarnal, 2010), where precipitation is the only source of natural recharge (Jafari et al., 2019); According to the National Commission for the Knowledge and Use of Biodiversity (CONABIO), land use change refers to changes in vegetation coverage due to urbanization, deforestation, soil degradation and

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

intensification of agricultural and livestock activity, in addition, the change in vegetation affects precipitation and temperature regimes (CONABIO, 2020). Previous research, where VIs and climatic data were analyzed, it was found that rainfall is possibly the most relevant factor for the temporal lag in vegetation response in semiarid regions, as the abrupt variation in rainfall between the dry and rainy seasons is much more pronounced compared to the gradual temperature changes during the annual cycle (Olmos-Trujillo et al., 2020a); In semiarid environments, such as the state of Zacatecas, Mexico, it is essential to understand the dynamic vegetation response to climatic data (rainfall). Given that the processes involved are crucial, and that water availability affects everything from biological productivity to human development, it is essential to implement effective management strategies to ensure sustainable water resources (Wilcox et al., 2011).

Besides, precipitation data, based on remote sensing measurement technology is widely used, because, it is one of the most important input condition for hydrological simulations and for the high spatial resolution as an indispensable factor for research (Zhang et al., 2019), the use of satellite data is taken into account as a complement to the scarcity of pluviometric information in areas without weather stations or where data is missing, for instance, using precipitation time series (Escobar, 2014). Furthermore, precipitation data must be accurate for rainwater management. The variability of precipitation exists across a wide range of spatial and temporal scales and cannot be well captured using sparse networks of rain gauges. Recent advances in remote sensing techniques make it possible to monitor precipitation in larger areas with more regular resolutions than conventional rain gauge networks (Hosseini, 2022).

The main objective of this research is to document the relationships between the spatial distribution of vegetation and rainfall patterns in a semiarid region of Zacatecas, Mexico. Monthly VIs (2014-2021) were calculated and correlated with the monthly accumulated rainfall. The most significant correlation of VIs and rainfall data was projected to 2030. The aforementioned information is related to other indicators such as the Natural Capital Sustainability Index and drought data in the region, provided by CONABIO. This type of analysis in semi-arid regions not only contributes to the sustainable water management but also directly addresses several Sustainable Development Goals (SDGs), promoting a holistic approach to sustainable development, enabling the detection of management areas in the context of sustainable vegetation preservation in semi-arid ecosystems and as a basis for Integrated Water Resources Management (IWRM). The utilization of vegetation indices such as the NDMI, in conjunction with other factors such as rainfall, drought parameters, and sustainability considerations, strengthens its capacity as a valuable indicator of water stress, drought conditions, and sustainability in semiarid areas with low rainfall availability, providing a solid basis for planning and resource management.

Materials and methods

Study area

The study area corresponds to the State of Zacatecas, Mexico, with an area of 11,141.56 km^2. The average annual temperature is estimated to range between 18 and 20 °C, with precipitation ranging between 400-450 mm and small intermittent streams. The climate in Zacatecas is mostly semiarid, and half of the population lives in rural areas (Pacheco-Guerrero et al., 2019). It experiences average monthly minimum and maximum temperatures of 6.5°C (January) and 29.6°C (May), respectively. The average annual

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

precipitation is approximately 350 mm, with 80% occurring from June to September (Bautista-Capetillo et al., 2016). According to the land use classification by Olmos-Trujillo et al. (2020), it corresponds to 792.82 km^2 of forest (7.12%), 915.40 km^2 of irrigated agriculture (8.22%), 4487.39 km^2 of rainfed agriculture (40.28%), 3207.27 km^2 of shrubland (28.79%), 1430.74 km^2 of grasslands, 28.13 km^2 of water bodies (0.25%), and 279.82 km^2 of urban area (2.51%). Out of the 7 identified classes, rainfed agriculture (distributed towards the central zones of each aquifer) and shrublands represent the highest percentage in the study area.

The National Water Commission (CONAGUA) in Mexico, defined and delimited Hydrological-Administrative Regions (RHA) with the purpose of facilitating water administration. The RHA are territorial areas formed based on their morphological, orographic and hydrological characteristics, in which considers the hydrological basin as the basic unit for the management of water resources (SEMARNAT, 2013).

The majority of Zacatecas is located in the hydrological regions of El Salado and Lerma-Santiago (39.9% and 32.7% of the territory, respectively). These regions are situated in the central and southern parts of the state and are characterized by their high availability of surface and groundwater. In contrast, the Nazas-Aguanaval hydrological region, which encompasses a significant portion of the northern state (23.6%), is characterized by its very dry climate, making it more susceptible to water scarcity. The rest of the state (3.8%) is located in the Presidio-San Pedro river hydrological region and has little influence on the state's hydrological system (Pita-Díaz and Ortega-Gaucin, 2020).

The above information can be seen in *Figure 1*.

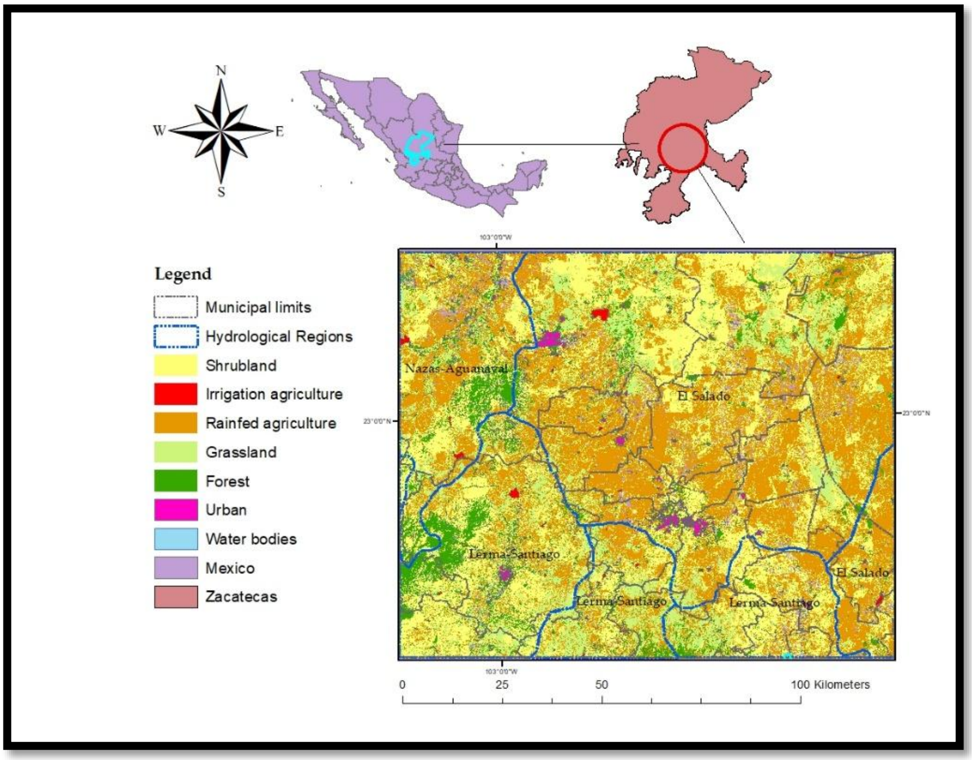


Figure 1. *Land use, vegetation and hydrological region of the study area (adapted from (Olmos-Trujillo et al., 2020b) classification and data Conabio (Conabio, 2023)*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

The area of interest is characterized as a "zone with low availability of surface water" (Flores-Rodarte et al., 2019b). The aquifers found here serve as the main source of supply, nevertheless, "the extraction of groundwater for irrigation, urban, and industrial uses has increased in recent decades to unsustainable levels" (Garbrecht et al., 2013).

The design of planning instruments considers that the productive activities of interest employ a considerable volume of water, and the condition of the groundwater in Zacatecas, mostly overexploited, demands careful management of water resources. In the region, about 1,688 hm^3 are used, of which 85% is allocated to agricultural activities, 11% to public supply, and 4% for self-supplied industry (CONAGUA, 2019).

The results will be useful for understanding the spatiotemporal response dynamics, with vegetation being the key factor in regulating rainfall patterns and water conservation in the region.

Acquisition and management of data

The rainfall data was collected using a web-based application (GIOVANNI – Geospatial Interactive Online Visualization and Analysis Infraestructure) developed by the Goddard Earth Sciences Data and Information Services Center (GES DISC) that provides a simple and intuitive way to visualize, analyze, and access vast amounts of Earth science remote sensing data (NASA, 2023); the rainfall was collected from the NASA's Integrated Multi-satellite Retrivals (IMERGE) which combines information from the Global Precipitation Measurement (GPM). This data was obtained on a monthly basis for the period from January 2014 to September 2021. Satellite images from LANDSAT 8 (L8), one image per month, from the same period of the rainfall data, were downloaded from the website of the United States Geological Survey (USGS), (https://earthexplorer.usgs.gov/).

The images to be downloaded have the following general characteristics (*Table 1*):

Table 1. *Properties of Lansat 8 images*

Longitude and latitude values	Zone and projected coordinate system	Spatial resolution	Temporal resolution
Path/Row, 29/44	WGS 84, 13 N	30,30	16 days
Landsat 8 Operational Land Imager (OLI) And Thermal Infrared Sensor (TIRS) Launched February 11, 2013			

Landsat 8, Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) Launched February 11, 2013, was used, OLI spectral radiance data can also be converted to a top of atmosphere (TOA) planetary reflectance using rescaling coefficient provided in the Landsat 8 OLI (Olmos-Trujillo et al., 2020a). Then, it is possible to use ArcGIS to obtain VIs data such as NDVI by employing map algebra. ArcGIS offers tools and functions enabling the computation of NDVI from raster images, which can include satellite imagery like those provided by Landsat.

Table 2 shows and summarizes the VIs used, each with its equation and main interpretation.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

Table 2. *Vegetation indices used and main interpretation*

Vegetation index	Equation	Description	Interpretation
Normalized Difference Vegetation Index (NDVI)	$Equation\ (1)$ $$NDVI = \frac{NIR - R}{NIR + R}$$	NIR corresponds to the near infrared band, and R corresponds to the red band.	Values vary between +1 and −1 with higher values for dense vegetation and very low (or negative) values for snow, water and clouds. The variability of NDVI is a function of prevalent climatic conditions such as rainfall and temperature, and this relationship is well established at various spatial and temporal scales (Fabricante et al., 2009). The NDVI-rainfall relationship varies spatially and temporally depending on land cover, soil type, vegetation composition and structure, microclimatic conditions and human impact (Propastin, 2009).
Enhanced Vegetation Index (EVI)	$Equation\ (2)$ $$EVI = G\frac{\rho NIR - \rho R}{\rho NIR + C_1 * \rho R - C_{2*}\rho BLUE + L}$$	ρ is the atmospherically corrected or partially atmospherically corrected surface reflectance, L is the canopy background adjustment that addresses nonlinear and different NIR and R radiant transfer through the canopy, and C1 and C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the EVI algorithm are L = 1, C1 = 6, C2 = 7.5 and G (gain factor) = 2.5.	The EVI corrects for some atmospheric conditions and canopy background noise and is more sensitive in areas with dense vegetation. It incorporates an “L” value to adjust for canopy background, “C” values as coefficients for atmospheric resistance and values from the blue band.
Soil Adjusted Vegetation Index (SAVI)	$Equation\ (3)$ $$SAVI = \frac{NIR - R}{NIR + R + L} * (1 + L)$$	The SAVI derived from the surface reflectance of Landsat is calculated as a ratio between the values of R and NIR with a soil brightness correction factor (L) defined as 0.5 to accommodate most types of ground cover	The SAVI is used to correct the NDVI for the influence of soil brightness in areas where the vegetation cover is low.
Modified Soil Adjusted Vegetation Index (MSAVI)	$Equation\ (4)$ $$MSAVI = 2 * \rho NIR + 1 - \frac{\sqrt{(2\rho NIR + 1)^2 - 8(\rho NIR - \rho RED)}}{2}$$	It is calculated as a ratio between the values of R and NIR with an inducing function L applied to maximize the reduction of soil effects in the vegetation signal.	The MSAVI minimizes the effect of bare soil on the SAVI

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

Vegetation index	Equation	Description	Interpretation
Normalized Difference Moisture Index (NDMI)	$Equation\ (5)$ $$NDMI = \frac{NIR - SWIR\ 1}{NIR + SWIR\ 1}$$	It is calculated as a traditional ratio between the NIR and SWIR values, where SWIR stands for shortwave infrared.	The NDMI is used to determine the water content of vegetation. Values of NDMI range from −1 to 1, with negative values indicating dry conditions and positive values indicating moist conditions. It can help identify areas of drought and detect changes in vegetation moisture content over time (Alharbi et al., 2022). NDMI can monitor soil moisture and identify areas with potential irrigation issues (van Vliet, 2019). Soil moisture is widely recognized as the key factor that links rainfall to vegetation growth (Jamali et al., 2011).

*Adapted from Olmos-Trujillo et al. (2020)

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

ArcGIS 10.8.2 was used to obtain VIs values, descriptive statistics were used to summarize the data, a Pearson correlation analysis was performed to examine the relationship between variables (Sedgwick, 2012). During the analyzed time period (2014-2021), a total of 93 images were used. Because of the different resolution these, it was necessary the use of a methodology to extract the same value information in terms of space from all images (Musiaka and Nalej, 2021), the distance between two points of the grid is 2 km. This grid allowed for the generation of monthly data, comprising 3162 attributes, containing information at each point for NDVI, SAVI, MSAVI, EVI, NDMI, and monthly accumulated rainfall. *Figure 2* illustrates the generation of the fishnet, as an example, for the month of January 2014:

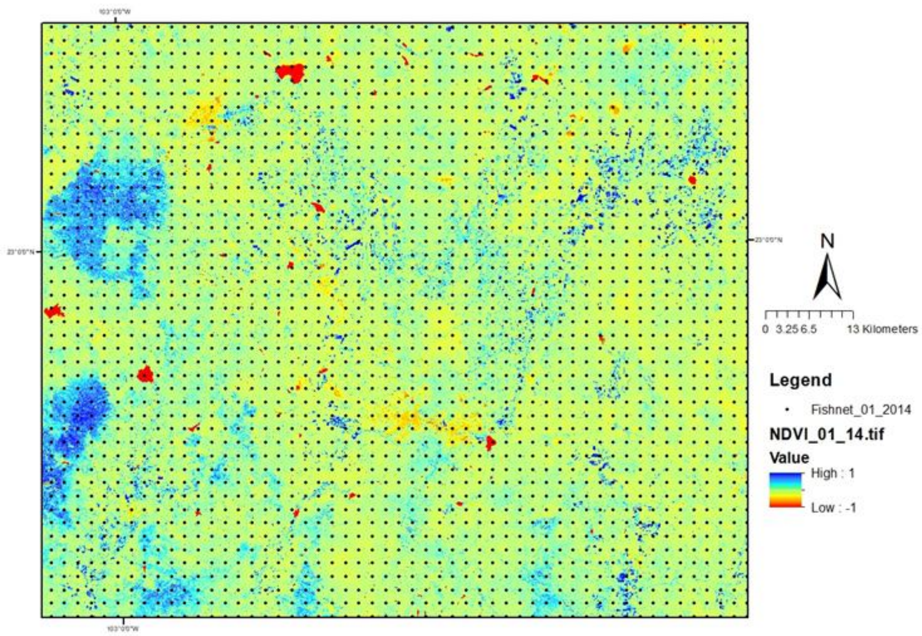


Figure 2. *Fishnet generated for the study area, January 2014. With the NDVI index as example*

The averages of rainy and dry seasons are shown, and a Pearson correlation between rainfall and VIs is presented from 2014 to 2021 (test period). Next, the behavior of rainfall and NDMI during the test period is analyzed. Subsequently, rainfall and NDMI trends are projected for the period from 2022 to 2030. The estimation or prediction is formulated up to 2030, which is contemplate as the medium term, considering the effects of climate change and factors influencing rainfall in this region of the state of Zacatecas, as well as the soil potential for vegetation. Estimating until the end of the decade is deemed a reasonable time horizon, taking into account observed data exhibiting certain qualities of seasonality and temporal trends, or a time budget for the relationship between rainfall and vegetation.

In addition, the data is related with respect to the information about sustainability ecosystems and drought risks, provided by CONABIO., by analyzing connection with one of the most synthetic indices, *Natural Capital Sustainability Index (ISCN)*, this index is an approximation of the terrestrial and aquatic biodiversity of natural ecosystems and agricultural ecosystems. It is the product of the size of the remaining ecosystem (quantity) and its quality (ecological integrity). It is an indicator of the state and change in biodiversity (CONABIO, 2022).

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

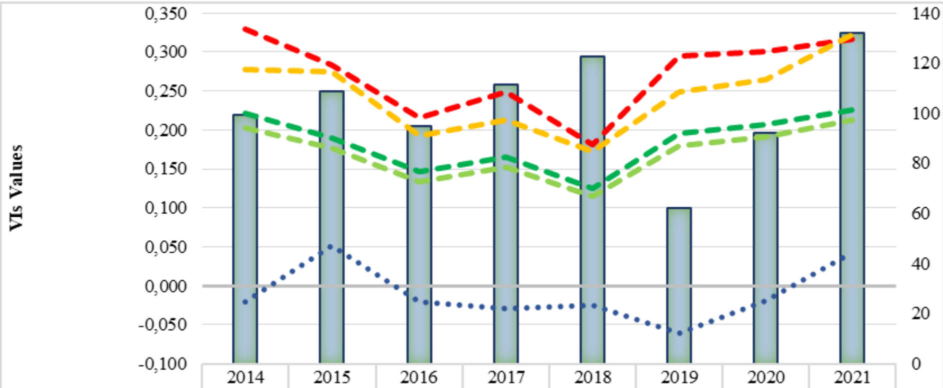
Regarding drought, the degree of danger due to *drought* by municipality in Mexico is taken into account. Finally, all information is analyzed, including key factors for managing sustainability indicators to IWRM.

Results

Testing period (2014-2021)

Averages of the rainy and dry seasons and VIs (2014-2021 – testing period)

In *Figure 3* average seasonal rainfall pattern for the months of June to September is presented, as these months have been identified as the rainy season in the state of Zacatecas, Mexico. Additionally, the values of the analyzed vegetation indices (VIs) are provided.



	2014	2015	2016	2017	2018	2019	2020	2021
RAINFALL	99,38	108,65	94,97	111,40	122,66	62,16	92,03	132,05
NDVI	0,330	0,283	0,216	0,248	0,181	0,294	0,3007	0,317
SAVI	0,221	0,190	0,146	0,165	0,125	0,196	0,2075	0,226
MSAVI	0,203	0,176	0,134	0,152	0,115	0,179	0,1906	0,213
EVI	0,277	0,275	0,193	0,213	0,172	0,249	0,2651	0,322
NDMI	-0,020	0,051	-0,020	-0,029	-0,025	-0,061	-0,0187	0,043

Figure 3. *Averages of the rainy season and VIs (2014-2021 – test period)*

According to the data, the years with the highest recorded accumulated rainfall were 2021, 2018, 2017 and 2015, respectively. If the values of the VIs are considered, this information suggests that although there has been precipitation (around 100 mm), its impact on vegetation vigor and soil moisture retention is limited. This is typical of semi-arid regions or areas where vegetation responds slowly to available water.

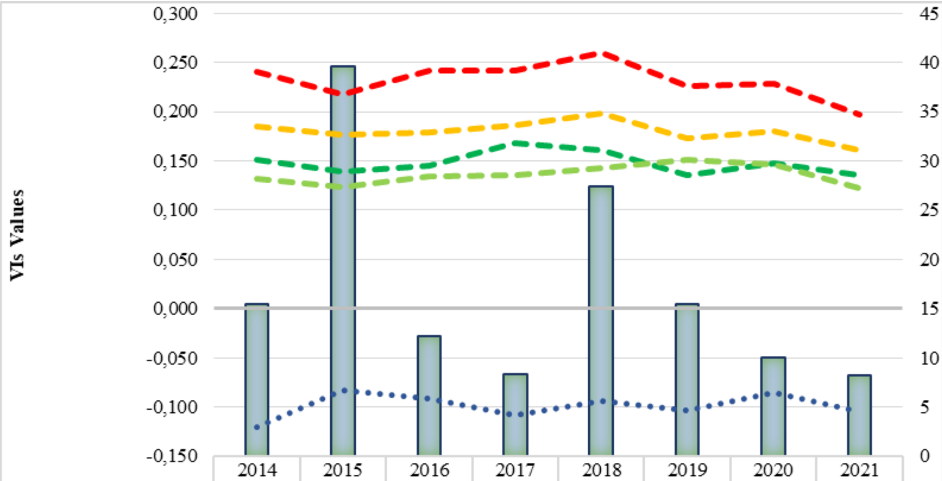
For the dry period, the remaining months of the year were considered (October to May). A relationship is also observed with VIs and the precipitation values, which do not exceed the 40 mm. Furthermore, these values reflect that the low rainfall is insufficient to sustain vegetation vigor, a characteristic typically seen in arid or semi-arid regions during dry periods (see *Figure 4*).

Person correlation (Rainfall vs VIs)

For the test period (2014-2021), correlation coefficients were analyzed: rainfall with each vegetation index. In 2014, all correlation coefficients are positive, suggesting that as one variable increases, the other tends to increase as well. The value of 0.430 indicates

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

the strongest correlation between the analyzed variables, corresponding to rainfall and NDMI, showing a high positive correlation.



	2014	2015	2016	2017	2018	2019	2020	2021
RAINFALL	15,39	39,64	12,14	8,29	27,39	15,46	10,04	8,164
NDVI	0,241	0,217	0,241	0,241	0,260	0,227	0,228	0,197
SAVI	0,151	0,140	0,146	0,168	0,161	0,136	0,147	0,136
MSAVI	0,132	0,123	0,134	0,136	0,142	0,151	0,146	0,122
EVI	0,185	0,177	0,178	0,186	0,199	0,173	0,180	0,160
NDMI	-0,120	-0,083	-0,092	-0,108	-0,094	-0,104	-0,085	-0,105

Figure 4. *Averages of the dry season and VIs (2014-2021 – test period)*

For 2015, the strongest correlation is 0.445 for NDMI, suggesting a moderate and significant positive relationship between the two variables. In 2016, NDMI shows the most significant correlation with a value of 0.275. In 2017, NDMI again has the most significant correlation at 0.446; in 2018, is the NDMI, it is 0.307, and in 2019, is the NDMI, it is 0.371. In 2020, the most significant correlation is EVI at 0.217, while in 2021, NDMI shows the most significant correlation again at 0.589.

There is a statistically significant relationship between the analyzed variables, with a p-value less than 0.05 considered significant.

The Pearson Correlation analysis is presented in *Table 3.*

Table 3. *Person Correlation (Rainfall vs Vegetation Indices)*

PEARSON CORRELATION	YEAR	NDVI	SAVI	MSAVI	EVI	NDMI
RAINFALL	2014	.336**	.387**	.404**	.391**	.430**
	2015	-.115**	-0.009	.020**	.157**	.445**
	2016	.039**	.104**	.103**	.128**	.275**
	2017	.079**	.036**	.123**	.146**	.446**
	2018	-.213**	-.139**	-.109**	-.025**	.307**
	2019	.180**	.249**	.164**	.261**	.371**
	2020	.175**	.205**	.169**	.217**	.098**
	2021	.397**	.419**	.430**	.517**	.589**

**Two-tailed sig =0.000. The correlation is significant at the 0.01 level (two-tailed)

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

A positive linear correlation is observed between the VIs and rainfall; Nevertheless, NDMI, shows the best correlation with rainfall. Trends between these two variables are presented.

Rainfall and NDMIfor the test period 2014-2021

Figure 5, provide valuable information on the health of the vegetation (NDMI) and water availability in the region, crucial to understanding the dynamics of ecosystems and detecting possible impacts, such as desertification or changes in land use. One of the main observations is the behavior of NDMI and rainfall, where the lag in the response of the vegetation is identified. It is possible to notice how the vegetation can show a lag in its response even when there is an increase in rainfall. The increases in precipitation occur according to the seasonal rainfall towards the middle of each year (which corresponds to June to September).

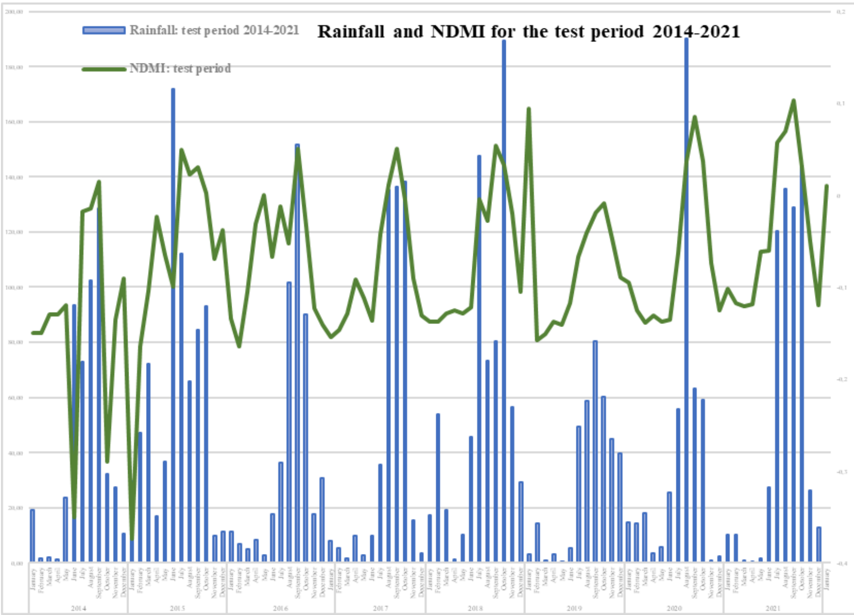


Figure 5. *Rainfall and NDMI for the test period 2014-2021*

The temporal lag of rainfall can have a significant impact on NDMI values and vegetation health. During the rainy season in semiarid areas, there is typically an increase in water availability due to precipitation. This will be reflected in higher NDMI values as vegetation benefits from the additional moisture and exhibits greater vigor. The temporal lag of rainfall can influence the duration of changes in NDMI values.

Rainfall and NDMI for the projected period 2022-2030

Projecting NDMI data and rainfall patterns allows evaluation of the relationship between water availability and vegetation health. According to the data projection, there is a pattern in the NDMI of the last four years suggesting conditions of drought or water stress in the vegetation and soil.

NDMI can remain high even after rainfall has decreased if the soil retains enough moisture (see *Figure 6*). See *Appendix 1* of monthly graphs of NDMI and Rainfall values from 2014 to 2030.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

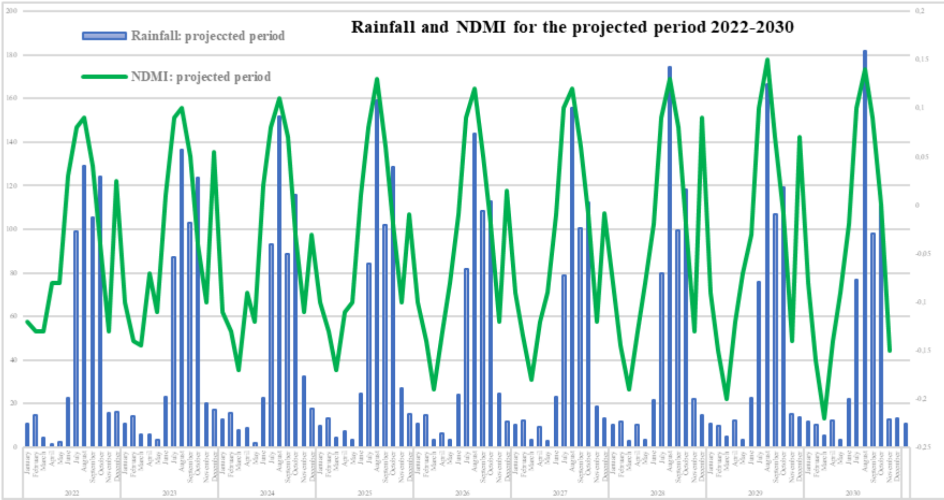


Figure 6. *Rainfall and NDMI for the projected period 2022-2030*

ISCN and drought risks

According to the ISCN in Mexico, it can be deduced that two thirds of the country present high levels of degradation, and only 12 states maintain sustainable conditions where ecosystem goods and services can still be generated without putting the Capital at risk. Nine states have their natural capital at risk, that is, with a high probability of reaching unsustainable levels, and eleven states have practically exhausted their natural capital, which represents an important gap in the ecological-evolutionary legacy to maintain the natural capital of future generations (CONABIO, 2022). According to this classification, for the study area, sustainable conditions represent only 10%, 11% are at risk and 78% of the region reports unsustainable conditions (*Figure 7*).

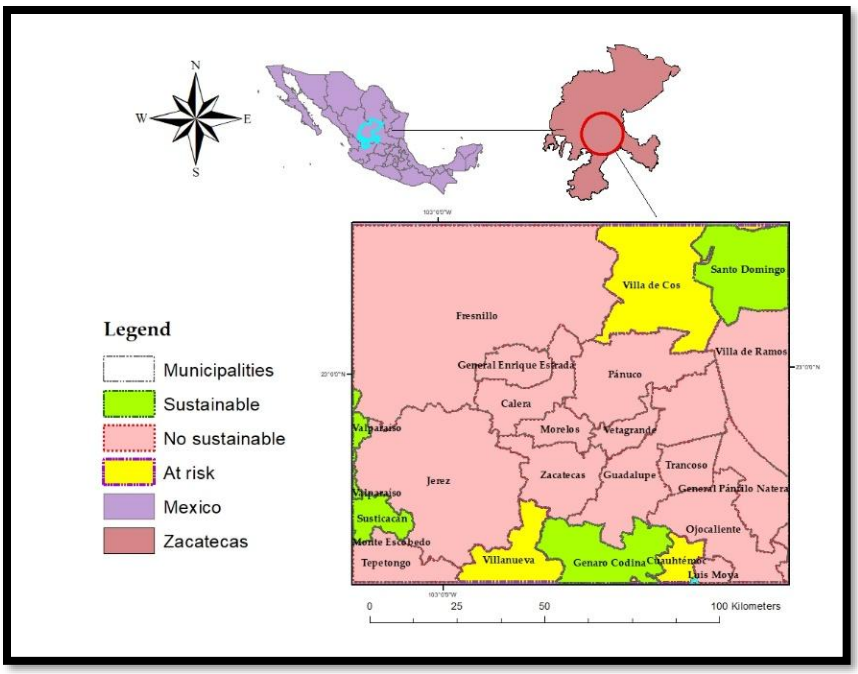


Figure 7. *Conditions of sustainabilty in the area of study*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

Drought is based on the rainfall deficit and its duration, 10 categories are presented, ranging from moderate (lowest category) to very criticism (as the highest category), *Table 4* (Espinosa et al., 2012). The average rainfall deficit with respect to its average annual rainfall, shows vast (25%), very vast (30%), critical (12%), extremely vast (12%), and very critical (20%) droughts conditions to the study area as can see in *Figure 8*.

Table 4. *Classification of drought based on rainfall deficit*

Average rainfall deficit (%) with respect to to its average annual rainfall	**Average drought duration D (years)**		
	1 ≤ D < 2	**2 ≤ D < 3**	**3 ≤ D < 4**
0 ≤ deficit (%) < 10	Normal	Moderate	Extraordinary
10 ≤ deficit (%) < 20	Severe	Very Severe	Extremely severe
20 ≤ deficit (%) < 30	Vast	Very vast	Extremely vast
30 ≤ deficit (%) < 40	Critical	Very critical	Catastrophic

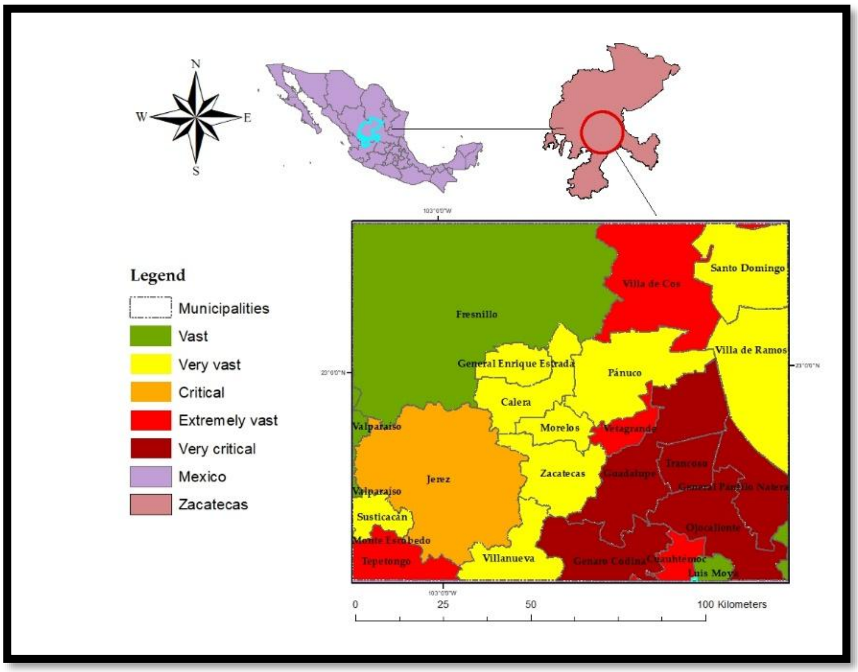


Figure 8. *Conditions of droughts in the area of study*

Discussion

According to the results, a very relevant aspect is the temporal lag in the response of vegetation to rainfall; it is a crucial factor to understand the dynamics of semiarid ecosystems. Although rains may provide temporary relief from drought, vegetation may take time to recover due to limited soil water availability. This mismatch between rainfall and vegetation response can exacerbate water stress and have long-term consequences for the sustainability of the region.

The utility of NDMI in semi-arid environments has proven to be highly valuable for detecting spectral changes in ecosystems, even more so than other VIs (Shafeian et al., 2023). Similar to other results, VIs values show the growth of vegetation cover and soil moisture content, which promote an increase in vegetation health and soil moisture (Shahfahad et al., 2023).

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

Due to the rainy season, in general, the values of VIs decrease during the dry season because of the reduced availability of water. VIs, particularly NDMI, decrease during periods of drought; changes in NDMI values in an analyzed period may indicate the presence of drought or changes in humidity conditions in a specific area. It is suggested that NDMI can be a valuable indicator reflecting the availability of water and vegetation in ecosystems, as well as rainfall levels. The valuable information obtained can contribute to the description of drought events and their consequences for the change in ecosystem vitality (Hais et al., 2019).

The actual scenarios have emphasized the vulnerability of the of water resources in the study area, for example: Calera and Chupaderos are two of the most overexploited aquifers from the drainage area of the North Central Basin, where groundwater represents 95% of available water, becoming the main source of water for the development of various activities of the population, as well, the agriculture is a major economic activity and irrigated agriculture occupies 20% of the cultivable area and consumes 88% of the water extracted from aquifers (McCulligh, 2018; Flores-Rodarte et al., 2019a).

In addition, economic wealth, population and natural resources are distributed unequally throughout the Zacatecan territory. Economic wealth, like the population, is concentrated in the municipalities that are in the center of the state, around the capital. Regarding natural resources, precipitation regimes (mainly) imply different vegetation in each municipality, different types of crops and level of risk of agricultural production units, which are distributed throughout the state territory (Chávez Ruiz et al., 2022).

The sustainable management of anthropogenic ecosystems, such as agricultural areas in semi-arid zones, to preserve aquifers and ecosystems involves adopting integrated approaches and practices that balance human activity with environmental conservation, identifying and preserving natural aquifer recharge areas. Considering that rainfed agriculture represents 40.28% of the study area's surface and aquifer recharge can also result from return flows from irrigation (deep percolation of irrigation water) (Jafari et al., 2019), it is essential to search for parameters for the management of aquifers, such as efficient water use, irrigation techniques, among others.

In the same way, understanding vegetation and rainfall dynamics in semi-arid regions is crucial because climate change promotes these areas will become even more arid in the future (Tariq et al., 2022). The 32% of the state's municipalities of Zacatecas are at high and very high risk of agricultural drought; these municipalities are located mainly in the center and north of the state, where 75.8% of agriculture is rainfed, 63.6% of production units are located, and 67.4% of the state's population depends on agricultural activity (Ortega-Gaucin et al., 2021).

In this sense, the current situation of a non-sustainable region, combined with drought conditions and the data projection to 2030 suggests situations of water stress, taking into account the NDMI and rainfall data as indicators.

Due to this, multispectral analysis allows addressing critical information regarding water availability, understanding rainfall and vegetation patterns in semiarid areas, and monitoring changes in vegetation and climatic patterns. Therefore, it is crucial to incorporate and consider the SDGs, mainly for Clean Water and Sanitation (SDG 6), Sustainable Cities and Communities (SDG 11), Climate Action (SDG 13), Life on Land (SDG 15), Zero Hunger (SDG 2), and Responsible Production and Consumption (SDG 12), that involve sustainable management strategies for the region.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

This knowledge is vital to assess the adaptation capacity of vegetation to drier conditions and understand how changes in precipitation could directly affect biodiversity, water resource availability and ecosystem sustainability in these vulnerable areas.

Conclusions

The results of this work lead to the assertion that one of the key elements in the preservation of ecosystems is the understanding of vegetation patterns (NDMI) and rainfall as a fundamental indicator for sustainable management in these regions. These results demonstrate a positive linear correlation between VIs and rainfall; however, the NDMI shows a significant correlation with precipitation based on the R^2 value for the rainy and dry periods. The analysis of time series and predictive models contributes to projecting future conditions of water stress in semi-arid areas.

This work documents the spatiotemporal dynamics of vegetation and precipitation for the region and suggests VIs as the main indicators for sustainable management in semi-arid regions. This study is essential to determine the types of policies for natural resource management and climate change adaptation in semiarid regions. The implementation of water conservation practices, the promotion of sustainable agriculture, and the restoration of degraded ecosystems are some of the measures that can contribute to improving the resilience of these regions to drought and promoting their long-term sustainability.

Future research on this subject should take into account the impact factors on water resources, such as agriculture, droughts, and the deficiency of management in the preservation of ecosystems, as well as the long-term water supply and preservation of local ecosystems.

The use of multitemporal data in semiarid environments provides a comprehensive view of the dynamics of land use, vegetation cover, and rainfall patterns, which is essential for the sustainable management of these ecosystems and the effective planning of resources under changing climatic conditions. This research serves as a basis for Integrated Water Resources Management in semiarid regions of our planet, considering the method presented here with the geospatial reference of the state of Zacatecas, Mexico. Therefore, this is an important contribution to the knowledge on this topic.

REFERENCES

[1] Ahmed, A., Nawaz, R., Woulds, C., Drake, F. (2020): Influence of hydro-climatic factors on future coastal land susceptibility to erosion in Bangladesh: a geospatial modelling approach. – J. Geovisualization Spat. Anal. 4: 6. https://doi.org/10.1007/s41651-020-00050-x.

[2] Alharbi, R. S., Nath, S., Faizan, O. M., Hasan, M. S. U., Alam, S., Khan, M. A., Bakshi, S., Sahana, M., Saif, M. M. (2022): Assessment of Drought vulnerability through an integrated approach using AHP and Geoinformatics in the Kangsabati River Basin. – J. King Saud Univ - Sci. 34(8): 102332. https://doi.org/10.1016/j.jksus.2022.102332.

[3] Ayanlade, A. (2017): Remote sensing vegetation dynamics analytical methods: a review of vegetation indices techniques. – Geoinformatica Pol. 16: 7-17. https://doi.org/10.4467/21995923GP.17.001.7188.

[4] Batisani, N., Yarnal, B. (2010): Rainfall variability and trends in semi-arid Botswana: Implications for climate change adaptation policy. – Appl. Geogr., Climate Change and Applied Geography – Place, Policy, and Practice 30: 483-489. https://doi.org/10.1016/j.apgeog.2009.10.007.

[5] Bautista-Capetillo, C., Carrillo, B., Picazo, G., Júnez-Ferreira, H. (2016): Drought Assessment in Zacatecas, Mexico. – Water 8: 416. https://doi.org/10.3390/w8100416.
[6] Chávez Ruiz, L., Alcalá Gurrola, L., Esparza Flores, M. (2022): El desarrollo económico en los municipios de Zacatecas. – UNAM-AMECIDER, México, pp. 543-558. http://ru.iiec.unam.mx/5982/.
[7] Choo, Y., Kang, G., Kim, D., Lee, S. (2018): A study on the evaluation of water-bloom using image processing. – Environ. Sci. Pollut. Res. 25. https://doi.org/10.1007/s11356-018-3578-6.
[8] CONABIO (2020): Monitoreo de la cobertura de suelo. – WWW Document, Biodivers. Mex. URL https://www.biodiversidad.gob.mx/monitoreo/cobertura-suelo (accessed 2.27.24).
[9] CONABIO (2022): Índice de Capital Natural. – WWW Document, Biodivers. Mex. URL https://www.biodiversidad.gob.mx/pais/indice_capnat (accessed 3.4.24).
[10] CONABIO (2023): Portal de Información Geográfica. – WWW Document, URL http://www.conabio.gob.mx/informacion/gis/ (accessed 10.20.24).
[11] CONAGUA (2019): Estadísticas del agua en México. – La Comisión Nacional del Agua.
[12] Das, S. K., Pant, M., Bebortta, S. (2020): Geospatial Data Analytics: A Machine Learning Perspective. – SSRN, https://doi.org/10.2139/ssrn.3599656.
[13] Elçi, A. (2019): Analysis of Satellite Imagery to Determine Spatial-Temporal Changes of Surface Water Bodies: A Case Study of Burdur River Basin, Turkey. – Presented at the 38th IAHR World Congress, pp. 840-845. https://doi.org/10.3850/38WC092019-0550.
[14] Escobar, J. A. R. (2014): Análisis De La Correlación De Datos De Precipitación Entre El Satélite Trmm Y Las Estaciones Pluviometricas Ubicadas En La Cuenca Del Rio Bogota. – Universidad Santo Tomas.
[15] Espinosa, M. J., Ramírez, C. B., Ramírez, L. G. M., Morales, H. E. (2012): Mapas De Índices De Riesgo. – A Escala Municipal Por Fenómenos Hidrometeorológicos.
[16] Fabricante, I., Oesterheld, M., Paruelo, J. M. (2009): Annual and seasonal variation of NDVI explained by current and previous precipitation across Northern Patagonia. – J. Arid Environ. 73: 745-753. https://doi.org/10.1016/j.jaridenv.2009.02.006.
[17] Flores-Rodarte, A., Cristóbal-Acevedo, D., Pascual-Ramírez, F., de León-Mojarro, B., Prado-Hernández, J. V. (2019): Agricultural water productivity in the central zone of the Calera aquifer, Zacatecas. – Ing. Agríc. Biosist. 11: 181-199.
[18] Garbrecht, J., Mojarro, F., Bautista-Capetillo, C., Brauer, D., Steiner, J., Chairez, F. (2013): Sustainable Utilization of the Calera Aquifer, Zacatecas, Mexico. – Appl. Eng. Agric. 29: 67-75. https://doi.org/10.13031/2013.42535.
[19] Hais, M., Neudertová Hellebrandová, K., Šrámek, V. (2019): Potential of Landsat spectral indices in regard to the detection of forest health changes due to drought effects. – J. For. Sci. 65: 70-78. https://doi.org/10.17221/137/2018-JFS.
[20] Hosseini, S. H. (2022): Advanced Remote Sensing Precipitation Input for Improved Runoff Simulation: Local to regional scale modelling. – Doctoral Thesis, Water Resources Engineering, Lund University.
[21] Huang, S., Tang, L., Hupy, J. P., Wang, Y., Shao, G. (2021): A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. – J. For. Res. 32: 1-6. https://doi.org/10.1007/s11676-020-01155-1.
[22] Jafari, H., Sudegi, A., Bagheri, R. (2019): Contribution of rainfall and agricultural returns to groundwater recharge in arid areas. – J. Hydrol. 575: 1230-1238. https://doi.org/10.1016/j.jhydrol.2019.06.029.
[23] Jamali, S., Seaquist, J., Ardö, J., Eklundh, L. (2011): Investigating temporal relationships between rainfall, soil moisture and MODIS-derived NDVI and EVI for six sites in Africa. –Savanna 21.
[24] Jiang, Z., Huete, A. R., Didan, K., Miura, T. (2008): Development of a two-band enhanced vegetation index without a blue band. – Remote Sens. Environ. 112: 3833-3845. https://doi.org/10.1016/j.rse.2008.06.006.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

[25] Keersmaecker, W. D., Lhermitte, S., Tits, L., Honnay, O., Somers, B., Coppin, P. (2015): A model quantifying global vegetation resistance and resilience to short-term climate anomalies and their relationship with vegetation cover. – Glob. Ecol. Biogeogr. 24: 539-548. https://doi.org/10.1111/geb.12279.

[26] LaPaix, R., Freedman, B., Patriquin, D. (2009): Ground vegetation as an indicator of ecological integrity. – Environ. Rev. 17: 249-265. https://doi.org/10.1139/A09-012.

[27] McCulligh, C., Tetreault, D. (2018): Water Grabbing via Institutionalised Corruption in Zacatecas, Mexico. – Water Alternatives 11(3): 572-591.

[28] Mihai, B., Horoias, R. (2022): NDMI Use in Recognition of Water Stress Issues, Related to Winter Wheat Yields In Southern Romania. – Conference: Agriculture for Life, Life for Agriculture.

[29] Musiaka, Ł., Nalej, M. (2021): Application of GIS Tools in the Measurement Analysis of Urban Spatial Layouts Using the Square Grid Method. – ISPRS Int. J. Geo-Inf. 10: 558. https://doi.org/10.3390/ijgi10080558.

[30] NASA (2023) Giovanni | NASA Global Precipitation Measurement Mission. – WWW Document, URL https://gpm.nasa.gov/data/sources/giovanni (accessed 6.3.23).

[31] Olmos-Trujillo, E., González-Trinidad, J., Júnez-Ferreira, H., Pacheco-Guerrero, A., Bautista-Capetillo, C., Avila-Sandoval, C., Galván-Tejada, E. (2020): Spatio-Temporal Response of Vegetation Indices to Rainfall and Temperature in A Semiarid Region. – Sustainability 12: 1939. https://doi.org/10.3390/su12051939.

[32] Ortega-Gaucin, D., Ceballos-Tavares, J. A., Ordoñez Sánchez, A., Castellano-Bahena, H. V. (2021): Agricultural Drought Risk Assessment: A Spatial Analysis of Hazard, Exposure, and Vulnerability in Zacatecas, Mexico. – Water 13: 1431. https://doi.org/10.3390/w13101431.

[33] Pacheco-Guerrero, A., González-Trinidad, J., Júnez-Ferreira, H., Bautista-Capetillo, C., Hernández-Antonio, A., Olmos-Trujillo, E., Ávila-Sandoval, C. (2019): Integration of isotopic (2H and 18O) and geophysical applications to define a groundwater conceptual model in semiarid regions. – Water Switz. 11, undefined-undefined. https://doi.org/10.3390/w11030488.

[34] Pita-Díaz, O., Ortega-Gaucin, D. (2020): Analysis of Anomalies and Trends of Climate Change Indices in Zacatecas, Mexico. – Climate 8: 55. https://doi.org/10.3390/cli8040055.

[35] Propastin, P. A. (2009): Spatial non-stationarity and scale-dependency of prediction accuracy in the remote estimation of LAI over a tropical rainforest in Sulawesi, Indonesia. – Remote Sens. Environ. 113: 2234-2242. https://doi.org/10.1016/j.rse.2009.06.007.

[36] Sedgwick, P. (2012): Pearson's correlation coefficient. – BMJ 345: e4483-e4483. https://doi.org/10.1136/bmj.e4483.

[37] SEMARNAT (2013): Atlas / Agua. – WWW Document. URL https://gisviewer.semarnat.gob.mx/aplicaciones/Atlas2015/agua_RHA.html (accessed 3.3.24).

[38] Serrato, F. B. (1998): La cubierta vegetal en las regiones áridas y semiáridas: consecuencias de la interceptación de la lluvia en la protección del suelo y los recursos hídricos. – Departamento de Geografia Fisica, Universidad de Murcia.

[39] Shafeian, E., Fassnacht, F. E., Latifi, H. (2023): Detecting semi-arid forest decline using time series of Landsat data. – Eur. J. Remote Sens. 56: 2260549. https://doi.org/10.1080/22797254.2023.2260549.

[40] Shahfahad, Bindajam, A. A., Waseem Naikoo, M., Horo, J., Mallick, J., Rihan, M., Malcoti, M., Talukdar, S., Rahman, M., Rahman, A. (2023): Response of soil moisture and vegetation conditions in seasonal variation of land surface temperature and surface urban heat island intensity in sub-tropical semi-arid cities. – Theor. Appl. Climatol. 153: 367-395. https://doi.org/10.1007/s00704-023-04477-2.

[41] Soledad Duval, V., María Benedetti, G., María Campo, A. (2015): Relación clima-vegetación: adaptaciones de la comunidad del jarillal al clima semiárido, Parque Nacional Lihué Calel, provincia de La Pampa, Argentina. – Trabajo realizado en el marco del

proyecto Geografía Física aplicada al estudio de la interacción sociedad-naturaleza. Problemáticas a diferentes escalas témporo-espaciales, dirigido por la Dra. Alicia M. Campo, Secretaría de Ciencia y Tecnología, Universidad Nacional del Sur. Investig. Geográficas Bol. Inst. Geogr. pp. 33-44. https://doi.org/10.14350/rig.48033.

[42] Stojković, S. (2017): GIS analysis of land use changes: Case study: The Stara Pazova municipality, Serbia. Zb. Rad. – Geogr. Fak. Univ. U Beogr. pp. 295-306. https://doi.org/10.5937/zrgfub1765295G.

[43] Tariq, S., Nawaz, H., ul Haq, Z., Mehmood, U. (2022): Response of enhanced vegetation index changes to latent/sensible heat flux and precipitation over Pakistan using remote sensing. – Environ. Sci. Pollut. Res. 29: 1-20. https://doi.org/10.1007/s11356-022-20391-y.

[44] do Valle Júnior, R. F., Siqueira, H. E., Valera, C. A., Oliveira, C. F., Sanches Fernandes, L. F., Moura, J. P., Pacheco, F. A. L. (2019): Diagnosis of degraded pastures using an improved NDVI-based remote sensing approach: An application to the Environmental Protection Area of Uberaba River Basin (Minas Gerais, Brazil). – Remote Sens. Appl. Soc. Environ. 14: 20-33. https://doi.org/10.1016/j.rsase.2019.02.001.

[45] van Vliet, J. (2019): Direct and indirect loss of natural area from urban expansion. – Nat. Sustain. 2: 755-763. https://doi.org/10.1038/s41893-019-0340-0.

[46] Velázquez, A., Mas, J. F., Díaz-Gallegos, J. R., Mayorga-Saucedo, R., Alcántara, P. C., Castro, R., Fernández, T., Bocco, G. (2002): Patrones y tasas de cambio de uso del suelo en México. – Gaceata Ecológica, Mexico.

[47] Vlassova, L., Pérez-Cabello, F. (2016): Effects of post-fire wood management strategies on vegetation recovery and land surface temperature (LST) estimated from Landsat images. – Int. J. Appl. Earth Obs. Geoinformation 44: 171-183. https://doi.org/10.1016/j.jag.2015.08.011.

[48] Wilcox, B. P., Sorice, M. G., Young, M. H. (2011): Dryland Ecohydrology in the Anthropocene: Taking Stock of Human–Ecological Interactions. – Geogr. Compass 5: 112-127. https://doi.org/10.1111/j.1749-8198.2011.00413.x.

[49] Xue, J., Su, B. (2017): Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. – J. Sens. 2017: e1353691. https://doi.org/10.1155/2017/1353691.

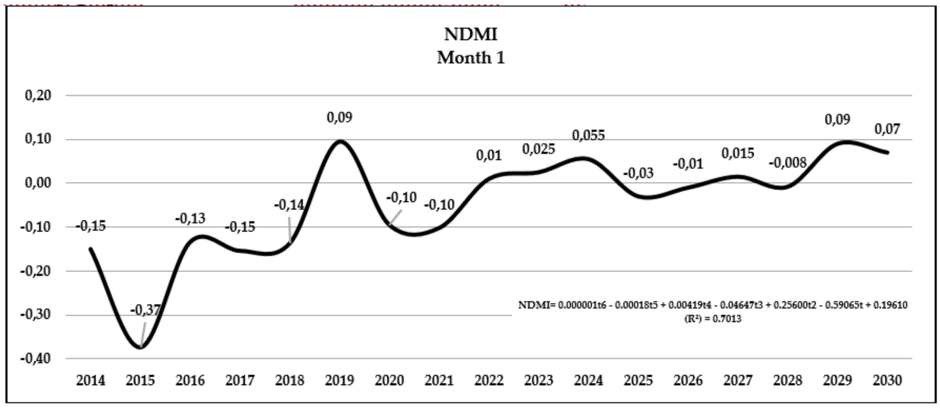
[50] Zewdie, W., Csaplovics, E., Inostroza, L. (2017): Monitoring ecosystem dynamics in northwestern Ethiopia using NDVI and climate variables to assess long term trends in dryland vegetation variability. – Appl. Geogr. 79: 167-178. https://doi.org/10.1016/j.apgeog.2016.12.019.

[51] Zhang, M., Lall, U., Hu, P. (2019): Spatial Downscaling of TRMM Precipitation Data Using NDVI. – American Geophysical Union, Fall Meeting.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

APPENDIX

Monthly graphs of NDMI and Rainfall values from 2014 to 2030



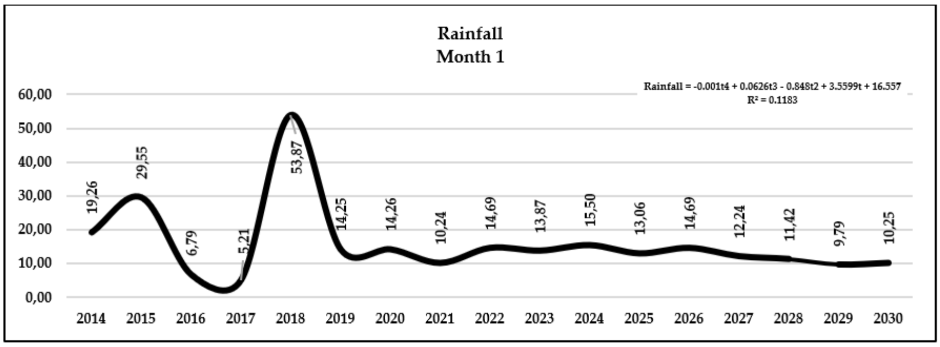
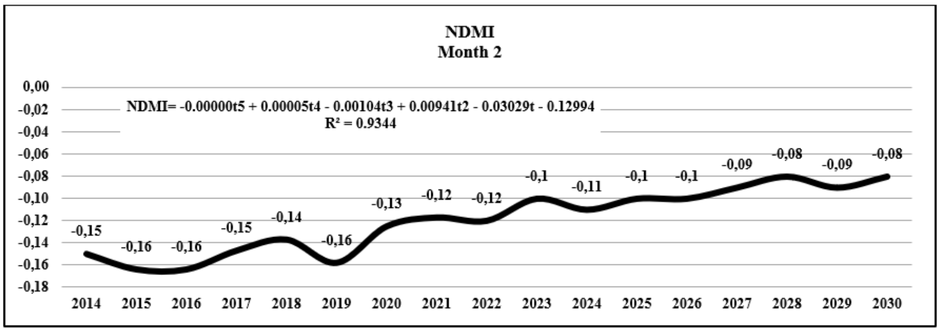


Figure 1, 2. *NDMI and rainfall patterns, for January 2014-2030*



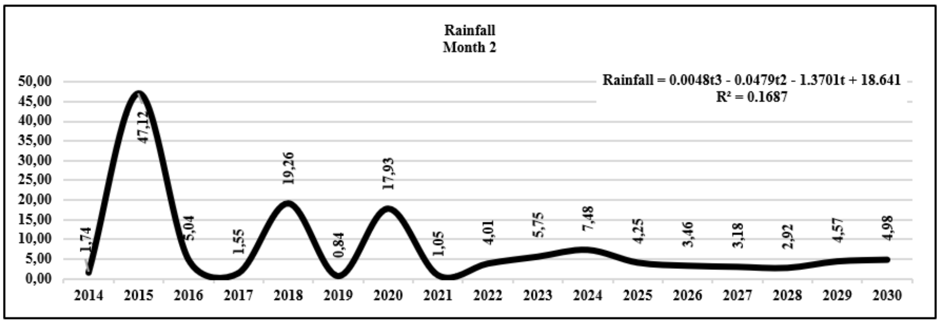


Figure 3, 4. *NDMI and rainfall patterns, for February 2014-2030*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

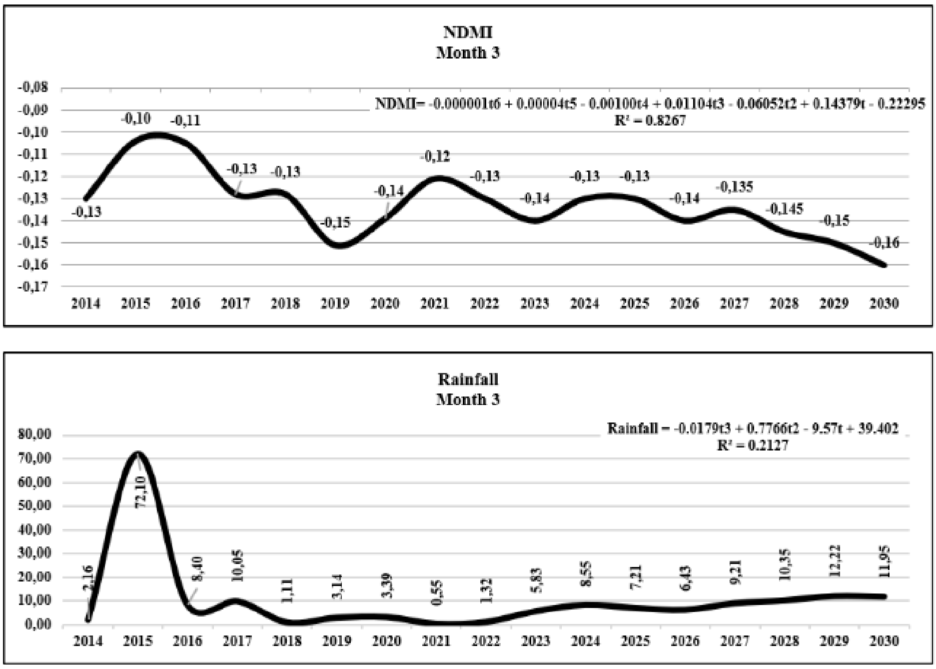


Figure 5, 6. *NDMI and rainfall patterns, for March 2014-2030*

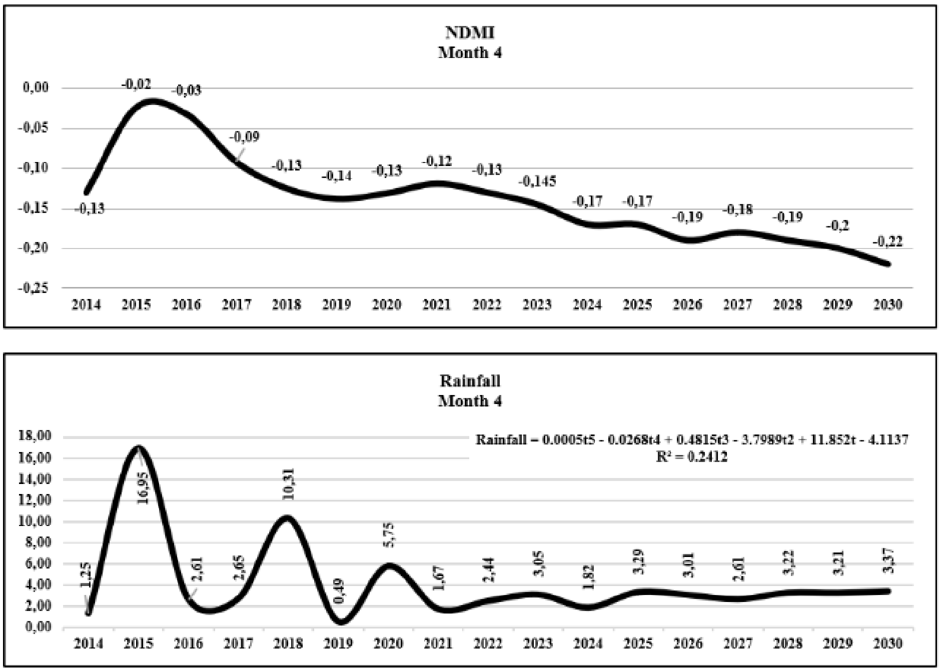


Figure 7, 8. *NDMI and rainfall patterns, for April 2014-2030*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

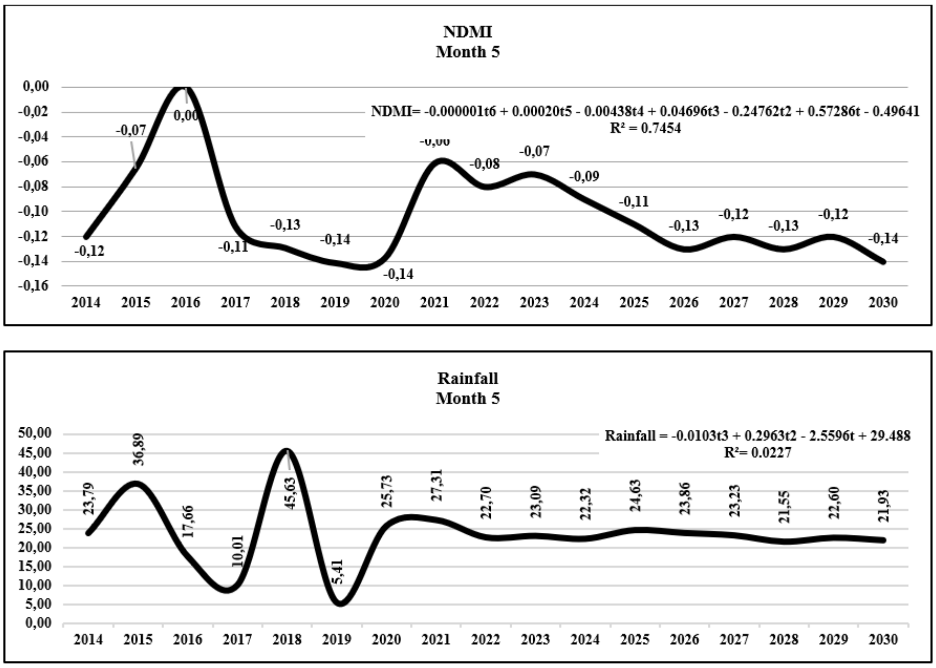


Figure 9, 10. *NDMI and rainfall patterns, for May 2014-2030*

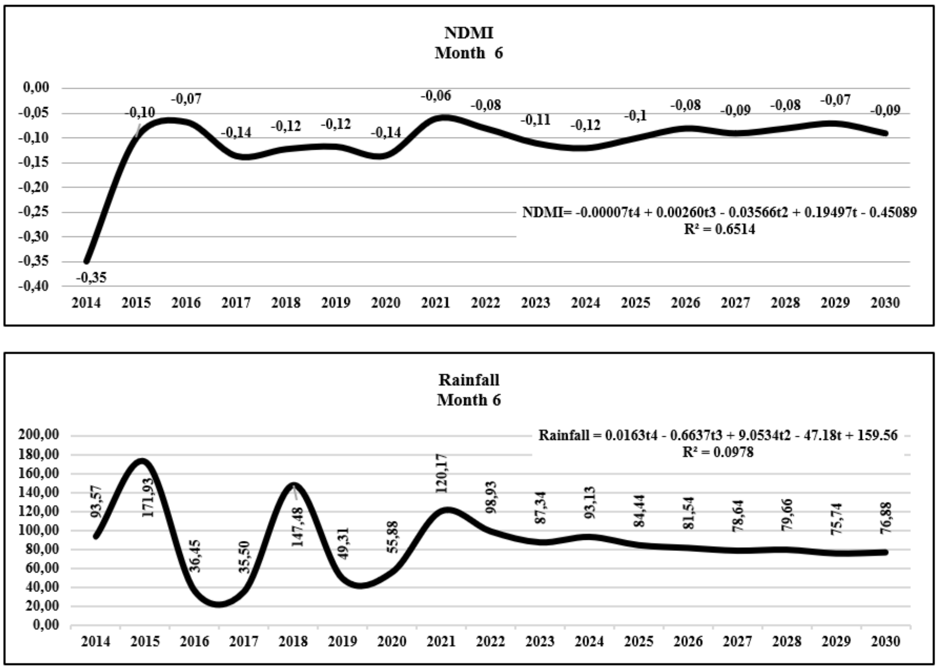


Figure 11, 12. *NDMI and rainfall patterns, for June 2014-2030*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

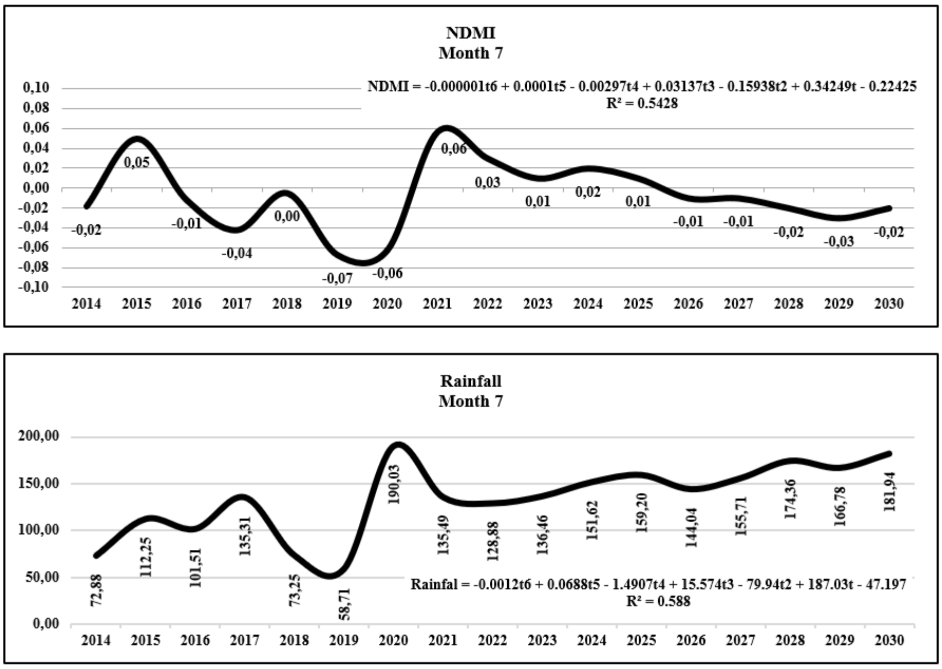


Figure 13, 14. *NDMI and rainfall patterns, for July 2014-2030*

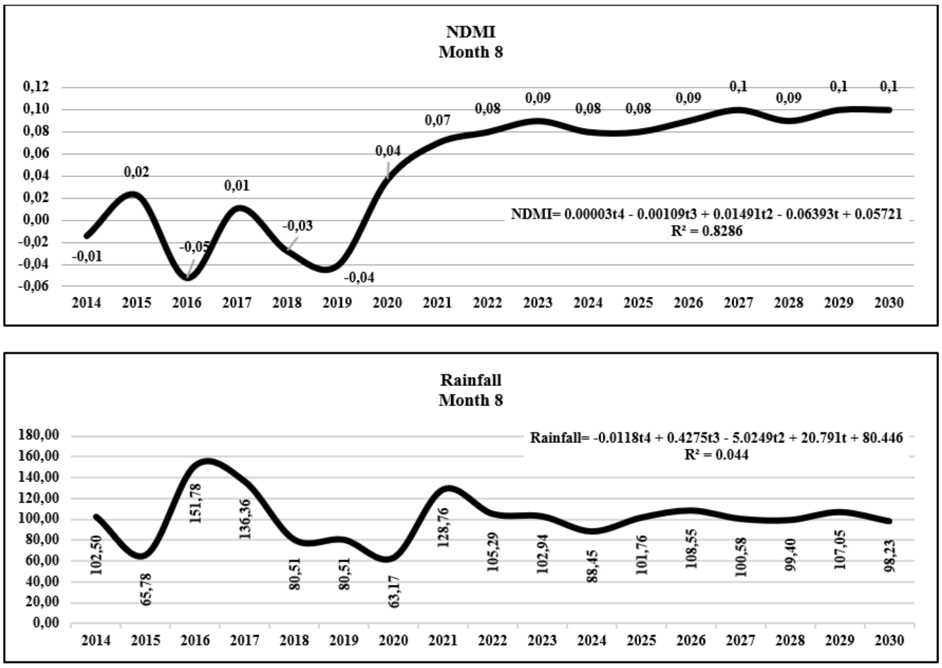


Figure 15, 16. *NDMI and rainfall patterns, for August 2014-2030*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

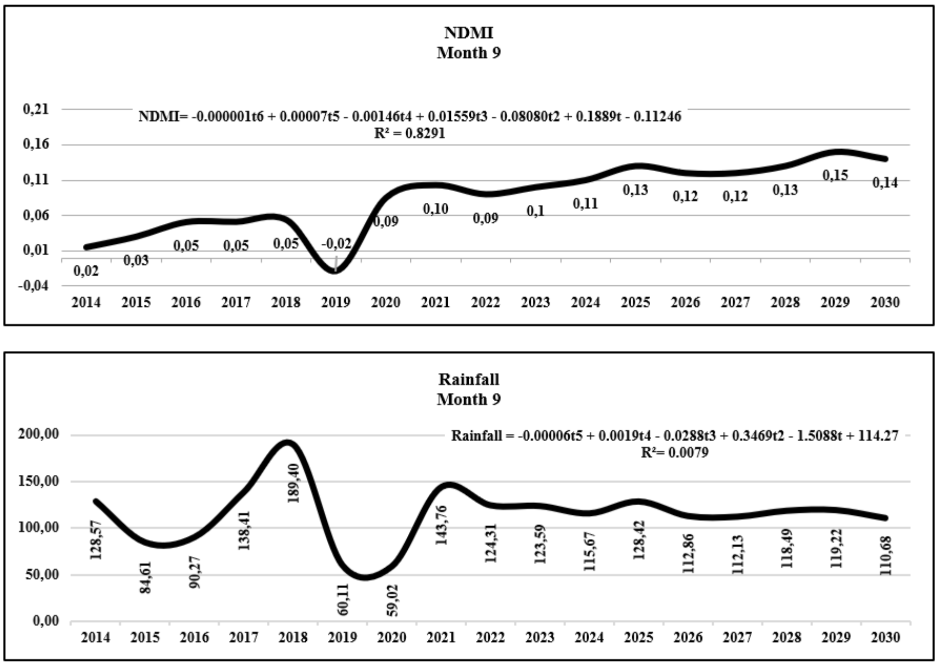


Figure 17, 18. *NDMI and rainfall patterns, for September 2014-2030*

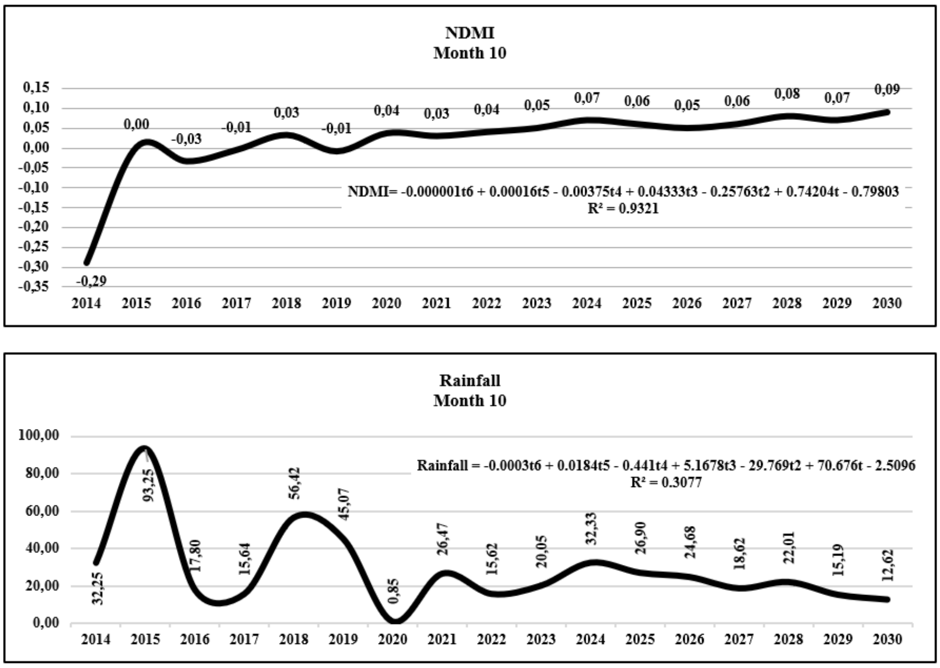


Figure 19, 20. *NDMI and rainfall patterns, for October 2014-2030*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782

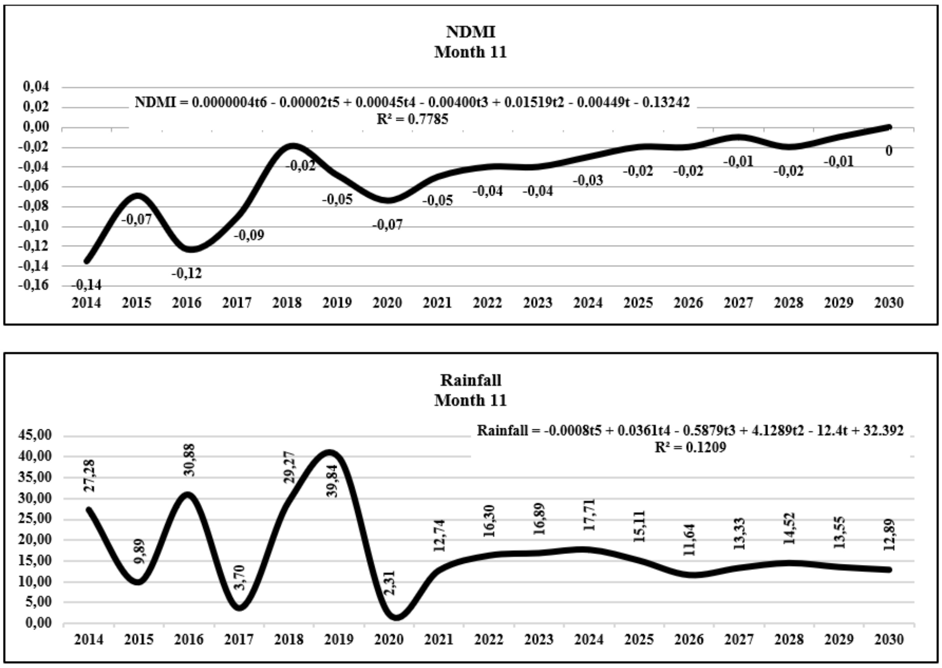


Figure 21, 22. *NDMI and rainfall patterns, for November 2014-2030*

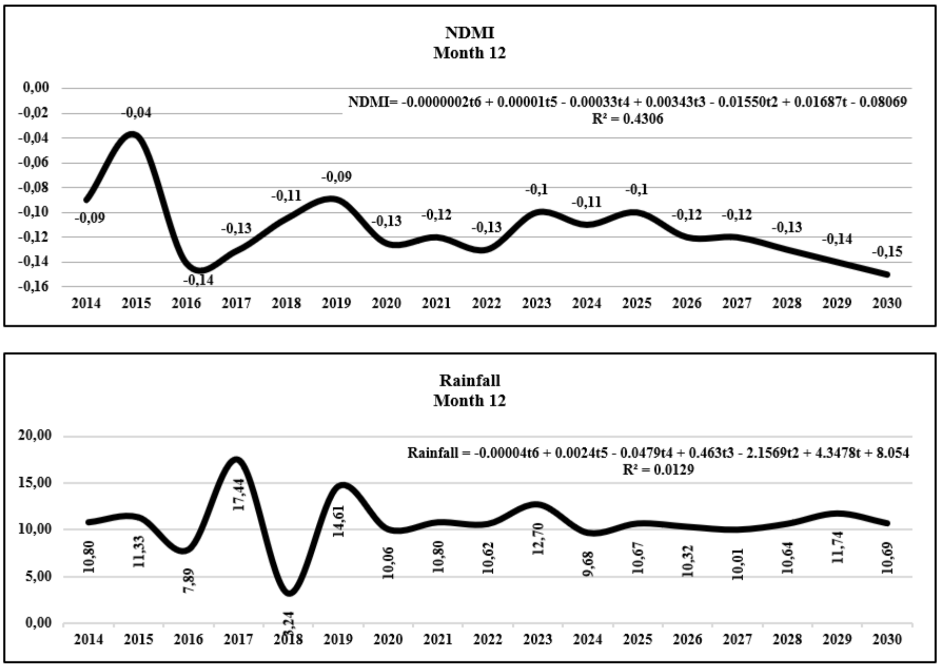


Figure 23, 24. *NDMI and rainfall patterns, for December 2014-203*

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2302_17591782