JOURNAL OF DESIGN FOR RESILIENCE
IN ARCHITECTURE & PLANNING

Research Article
Online: www.drarch.org
Volume 5, Issue 2, (287-299), 2024
DOI: 10.47818/DRArch.2024.v5i2132

Utilizing the vegetation health index to assess agricultural drought in the Constantine Region of Algeria

Maya Benoumeldjadj*
Malika Rached-Kanouni**
Abdelouahab Bouchareb***

Abstract

This research employs remote sensing techniques to map agricultural drought in the Constantine region of Algeria during the years 2021 to 2023. Using Landsat images processed through the Google Earth Engine platform, three indices (NDVI, VHI, and SPI) were calculated. The findings indicate deterioration in both climatic conditions and vegetation health. Specifically, NDVI and SPI exhibit decreases, while VHI shows an increase, signaling heightened water stress. The inverse relationship between NDVI and VHI underscores the connection between water availability and vegetation health. Additionally, a detailed analysis reveals severe drought conditions in the Southwestern part of the region. This study showcases the value of utilizing remote sensing technology on the Google Earth Engine platform for monitoring climate and vegetation patterns over space and time. These insights can help in forecasting the effects of climate change on agriculture and inform the adoption of suitable strategies to ensure food security.

Keywords: remote sensing, drought, VHI, Google Earth Engine, Constantine

1. Introduction

Drought, a consequence of climate change, is increasingly impacting regions globally, characterized by a temporary imbalance in water availability due to reduced precipitation levels. This phenomenon poses significant socio-economic challenges, especially in the agriculture sector, which is highly vulnerable to such climatic risks. Insufficient irrigation leads to struggles for farmers in maintaining healthy crops, resulting in diminished agricultural productivity, crop failures, and compromised food security. These concerns were prominently addressed at the recent Conference of the Parties in Egypt in November 2022, emphasizing the scientific consensus on the correlation between drought and climate change (Mostafa, 2023). Ongoing research endeavors are exploring innovative technologies and methodologies to tackle these urgent issues (Thomke, 2023).

Technological advancements, particularly in remote sensing, have revolutionized drought monitoring on a large scale. Remote sensing data provides a comprehensive perspective of the Earth's surface, facilitating the assessment of drought occurrences over vast regions. Various remote-sensing-based drought indices have been developed to quantify the duration, intensity, and severity of drought events. The Normalized Difference Vegetation Index (NDVI) has emerged as a widely accepted indicator for this purpose.

Combining vegetation indices with land surface temperature (LST) measurements has become a common practice for robust drought monitoring (Zhou et al., 2020). The Vegetation Health Index (VHI) stands out as a valuable tool for identifying agricultural drought and issuing early warnings (Bento, 2018). By integrating vegetation condition (VCI) and thermal condition (TCI) over a specific timeframe, the VHI provides a comprehensive evaluation of drought impacts. Utilizing remote

*(Corresponding author) Assist. Prof. Dr., Larbi Ben M'hidi Oum El Bouaghi University, Algeria, mayalabed@gmail.com
**Prof. Dr., Larbi Ben M'hidi University Oum El Bouaghi University, Algeria, kmalikbio@yahoo.fr
***Prof. Dr., Constantine 3-Salah Boubnider University, Algeria, abdelouahab.bouchareb@univ-constantine3.dz
Article history: Received 16 June 2024, Accepted 26 July 2024, Published 30 August 2024

sensing data, including NDVI and LST, the VHI facilitates accurate drought assessments in agricultural regions.

The critical need for implementing adaptive measures to combat drought is apparent in today's context. Strategies include embracing resilient agricultural practices like cultivating drought-tolerant crop varieties and employing efficient irrigation systems. Strengthening drought monitoring and forecasting capabilities is essential to enable timely proactive interventions, such as implementing water management strategies and conducting awareness campaigns on drought mitigation. The data generated from these efforts serves as valuable decision-making resources.

Algeria, particularly the Constantine region, faces significant drought challenges due to climatic changes marked by decreasing rainfall and increasing temperatures, exacerbating agricultural vulnerabilities in a region reliant on rain-fed agriculture. Historical patterns reveal alarming reductions in precipitation, which threaten food security and economic stability, while the reliance on inadequate irrigation infrastructure further compounds these issues. The ecological impacts include soil degradation and reduced biodiversity, necessitating urgent policy interventions focused on effective water resource management, the adoption of drought-resistant crops, and sustainable land practices. Integrating remote sensing technologies with meteorological data enables policymakers to make informed decisions, while community engagement is crucial for developing resilience to ongoing climate challenges and ensuring sustainable agricultural practices.

In our study, two approaches were employed. The first approach utilized spatial remote sensing data from Landsat satellite imagery, focusing on key indices such as the Normalized Difference Vegetation Index (NDVI), the VCI, and the VHI to evaluate vegetation health and drought conditions. The second approach involved calculating the Standardized Precipitation Index (SPI), a crucial meteorological indicator for assessing drought severity. By correlating VCI, VHI, and SPI, a comprehensive understanding of drought origins was achieved. The study period covered the last three years (2021, 2022, and 2023) during the agricultural season from October to May.

The main objective of this research is to map agricultural drought in the Constantine region by leveraging specific indices derived from Landsat satellite data. Additionally, a comparative analysis of drought conditions across 2021-2023 was conducted to assess temporal variations and the extent of drought impact during the specified timeframe.

The unique contribution of this study is its synthesis of remote sensing technology and meteorological data, which cultivates a deeper understanding of agricultural drought within a specific region. This comprehensive approach equips policymakers and stakeholders with practical insights that can improve drought management strategies and advance sustainable agricultural practices. By analyzing patterns and trends over multiple growing seasons, this research seeks to guide decision-making, optimize resource distribution, and bolster resilience against the ongoing challenges posed by climate change.

1.1. The Study Area

Located between coastal cities and the Aurès massif, Constantine spans an area of 2 297.20 km^2 and sits at 36° 17' latitude and 6° 37' longitude, with elevations ranging from 350 to 1100 meters. The city experiences a climatic pattern characterized by cold winters and hot summers, influenced by continentality. Annual rainfall typically falls between 350 to 700 mm, varying notably from north to south. Precipitation often manifests in heavy showers or sudden storms, with spring frosts occurring around 17 days per year. The region grapples with a persistent aridity threat, exemplified by a cyclical pattern of a wet year succeeded by two dry years.

In 2018, Constantine boasted a population of 1 272488 residents, displaying a growth rate of 1.5% (Figure 1).

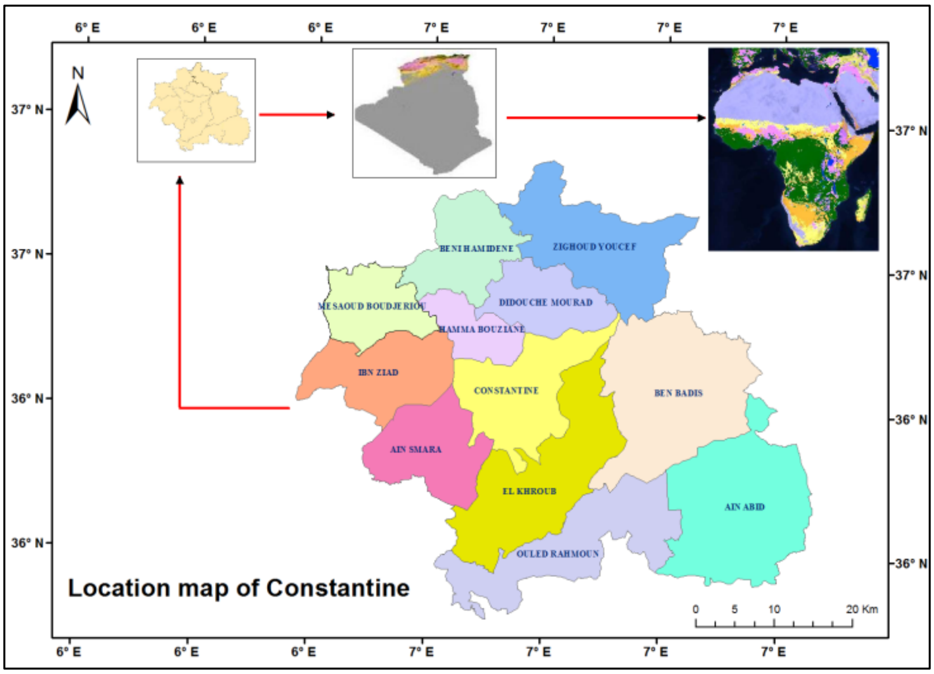


Figure 1 Location map of the Constantine

2. Method and Materials

The research methodology adopted in this study is centered on characterizing meteorological drought during the agricultural seasons from October to May across the years 2021, 2022, and 2023. The primary goal is to evaluate the severity of drought in the Constantine region and its implications for agriculture.

Multiple indices have been employed to enhance the identification and assessment of drought, with a specific focus on the normalized difference vegetation index (NDVI). NDVI is a well-established metric for gauging vegetation health, determining plant growth stages, and estimating biomass (Yengoh et al., 2015). Recognized for its sensitivity to the presence of green vegetation and its effectiveness in drought monitoring, NDVI is computed as the ratio of the difference to the sum of near-infrared (NIR) and red band reflectance.

The Normalized Difference Vegetation Index (NDVI) values range from -1 to +1, with specific ranges that correspond to different types of land cover and vegetation health:

NDVI < 0: Values less than zero typically indicate non-vegetated surfaces, such as water bodies, barren land, or areas with snow and ice.

NDVI 0 - 0.2: This range is associated with sparse vegetation, such as grasslands or areas with low plant cover. It indicates stressed or low biomass vegetation.

NDVI 0.2 - 0.5: Values in this range are indicative of moderate vegetation cover, such as shrublands or agricultural areas with healthy crops.

NDVI 0.5 - 0.75: This range reflects high vegetation density and health, typical of healthy forests or dense crops. It suggests robust and productive plant growth.

NDVI > 0.75: Values above 0.75 indicate very high vegetation density, often associated with dense forests or lush vegetation, reflecting optimal conditions for plant growth.

This index highlights the disparity between the visible red band (R) and the near-infrared band (NIR) and is mathematically expressed as follows:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Another significant index developed based on NDVI to minimize the influence of soil reflectance and atmospheric effects is the "Vegetation Condition Index" (VCI) introduced by F. N. Kogan in 1995 (Yengoh et al., 2015). VCI normalizes the minimum and maximum interannual NDVI values at a specific location, making it a widely utilized normalized index for monitoring drought conditions (Gidey et al., 2023). It captures the spatial and temporal variations in vegetation, enabling the quantification of climate-induced impacts on vegetation health (Ramo et al., 2018). VCI is valued for its reliability and efficiency in detecting drought conditions across various vegetation types.

This index provides insights into the vegetation status relative to extreme conditions (Min and Max) over the analyzed period. It is calculated using the formula introduced by F. N. Kogan in 1995 :

$$VCI = \left(\frac{NDVI(a) - NDVI(\min)}{NDVI(\max) - NDVI(\min)}\right) x100$$

In the VCI calculation, NDVI(a) represents the NDVI value for the current period, while NDVI(min) and NDVI(max) correspond to the minimum and maximum NDVI values observed over the entire monitoring period. As outlined by Kogan (2002), the Vegetation Condition Index (VCI) is categorized into five classes, as detailed in Table 1.

Table 1 Classification of VCI Degrees

Drought classes	**VCI(%)**
Extreme drought	0<VCI<20
Severe drought	20<VCI<40
Moderate drougt	40<VCI<60
Mild drought	60<VCI<80
No drought	80<VCI<100

To enhance the accuracy of drought analysis beyond the Vegetation Condition Index (VCI), a new index called the Temperature Condition Index (TCI) was developed (Zambrano et al., 2016). The objective was to consider diverse vegetation reactions to local temperature variations by incorporating thermal channels for drought monitoring (Tsiros et al., 2004). TCI, rooted in brightness temperature data, is suitable for regional or continental-scale applications, providing real-time insights or assessments over extended time frames, up to one year. TCI serves as a valuable indicator of vegetation stress triggered by soil moisture deficits (Chuvieco et al., 2010).

The formula for calculating the Temperature Condition Index (TCI) as provided by Kogan (1995) is:

$$TCI = \left(\frac{LST(max) - LST(\mathrm{a})}{LST(\max) + LST(\min)}\right) x100$$

Land Surface Temperature (LST) is a critical parameter that represents the temperature of the Earth's surface as measured by remote sensing techniques, typically using thermal infrared sensors. LST is significant in various applications, including climate studies, land cover classification, and, notably, in assessing vegetation health and drought conditions.

LST(max): This represents the maximum land surface temperature recorded for a specific time period, typically over a season or yearly cycle. LST(max) is crucial as it reflects the potential upper limit of temperature that vegetation can experience. It serves as a baseline reference for assessing thermal stress on plants.

LST(min): This denotes the minimum land surface temperature recorded over the same time period. LST(min) indicates the lower threshold of temperature that vegetation can endure. It helps to establish the range of temperature fluctuations that plants are exposed to and is essential for understanding the thermal dynamics affecting vegetation health.

LST(a): This is the actual land surface temperature at a specific point in time, which may vary daily and is subject to environmental influences. LST(a) reflects the current thermal condition of the land surface and is used in conjunction with LST(max) and LST(min) to evaluate whether the vegetation is experiencing stress due to elevated temperatures.

Given the diverse agricultural land use in the study area of Constantine, which includes cereals, orchards, market gardening, pulses, olive trees, and fodder, the need for a versatile vegetation index was evident. The Vegetation Health Index (VHI) has emerged as an effective tool for drought monitoring and assessment across various crop types (Nasser et al., 2020). VHI is instrumental for near real-time monitoring of vegetation health and climate impacts, particularly in agriculture. When combined with field data, these indices serve as robust tools for drought monitoring.

The Vegetation Health Index (VHI) combines two key indicators, as outlined by Kogan (1997): one for vegetation health (Vegetation Condition Index, VCI) and the other for temperature conditions (Temperature Condition Index, TCI). VCI is derived from vegetation index data, such as the Normalized Difference Vegetation Index (NDVI), and is calculated using the following formula (Unganai & Kogan, 1998):

$$VHI = \lambda VCI + (1 - \lambda) TCI$$

The Vegetation Health Index (VHI) serves as a versatile tool with various applications, including drought detection, assessment of drought duration, and prediction of crop yield and production over the vegetation period (Gomes et al., 2017). The research utilized a uniform weighting factor (λ) of 0.5 for index weighting, in line with previous studies (Clarke et al., 2006). Furthermore, this study introduces a specific classification system for drought monitoring, as detailed in Table 2.

Table 2 Drought Mapping Classification (Diédhiou et al., 2020)

Drought classes	VHI %
Extreme drought	<10
Severe drought	10-20
Moderate drought	20-30
Mild drought	30-40
No drought	>40

The Standardized Precipitation Index (SPI) is a widely employed metric for detecting meteorological drought owing to its flexibility across various timescales and climatic settings (Zhu et al., 2016). It enables the identification of drought events and assessment of drought severity over periods ranging from one month to 48 months. In our study, SPI was computed for an eight-month duration spanning from October to May. The calculation of SPI involves the following formula:

Where: SPI = Standardized Precipitation Index, Pi = Precipitation for the ith period

$\overline{P}$ = Mean precipitation for the n periods, σ = Standard deviation of the n periods

$$SPI = \frac{(Pi - Pm)}{\sigma} x\ 100$$

This study utilized variograms in Python to evaluate the correlation between variables, process measurements, calculate averages, and generate diagrams. Landsat 8 data was employed to identify drought conditions through the analysis of the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST). Maps derived from the multispectral and thermal data were created in Google Earth Engine and then exported to ArcMap for further analysis (Mälicke, 2022).

The minimum and maximum reflectance values of NDVI and LST were extracted to compute the Vegetation Condition Index (VCI) and Temperature Condition Index (TCI). By combining VCI and TCI through an algorithm, Vegetation Health Index (VHI) images were produced, representing both thermal stress and vegetation health. Subsequently, a correlation analysis was conducted between the spectral indices using MiniTable Software to understand their impacts on biomass and urban agriculture (Figure 2).

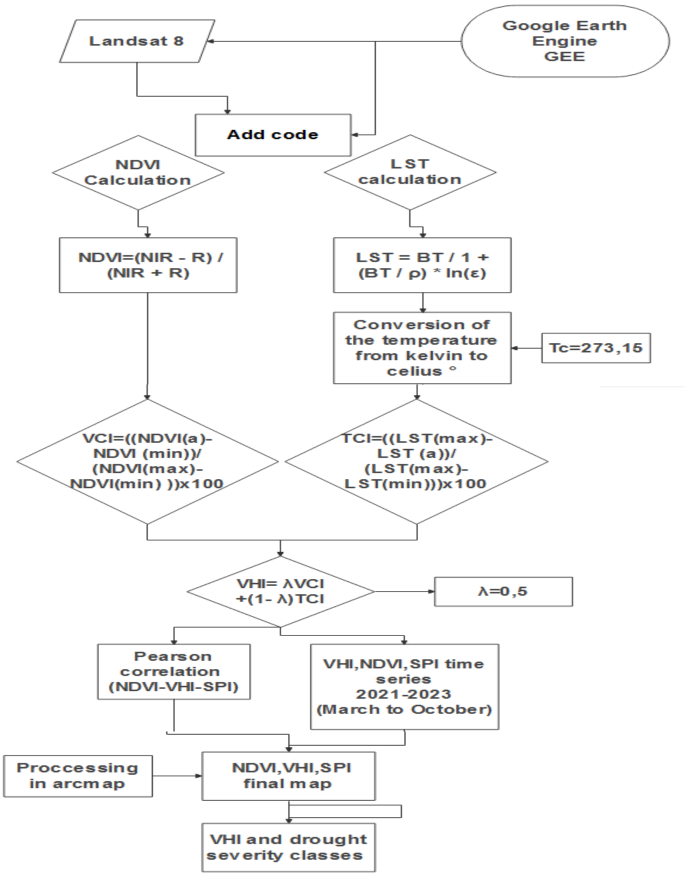


Figure 2 Flowchart of the study

3. Results

Spectral Indices Used

The NDVI values for the years 2021 (NDVI21), 2022 (NDVI22), and 2023 (NDVI23), representing photosynthetic activity and plant biomass, averaged at 0.123 in 2021, decreased to 0.121 in 2022, and further declined to 0.101 in 2023. These values fall within the range of 0.01 to 0.35.

Specifically:

- Regions with low NDVI values (0.01-0.10) were observed in the Northeast and Southwest areas.

- Moderate NDVI values (0.10-0.20) were noted in the central region (Figure 3).

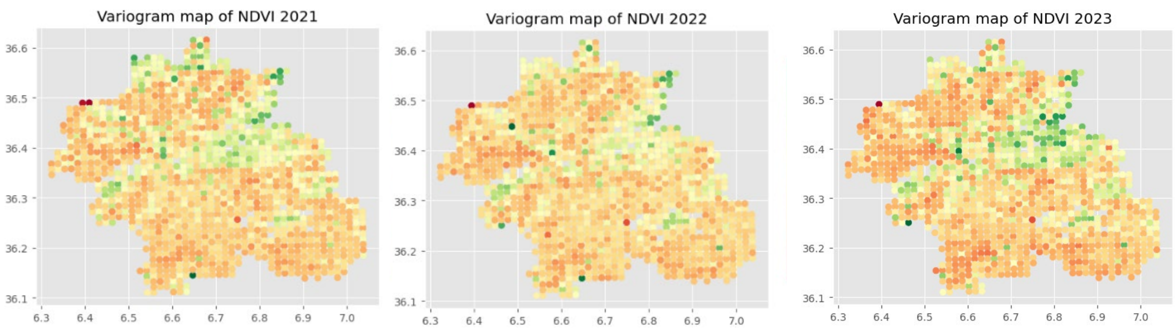


Figure 3 Variogram map of NDVI

The Vegetation Health Index (VHI), utilized for evaluating the water status of vegetation, demonstrated average values of 10.90 in 2021, 14.69 in 2022, and 13.61 in 2023, with a range from 7.45 to 19.9. Nevertheless, there is notable spatial variability in VHI:

- Low values (< 11) were observed in the Southwest and East of the area.

- High values (> 14) were seen in the Northwest and center regions (Figure 4).

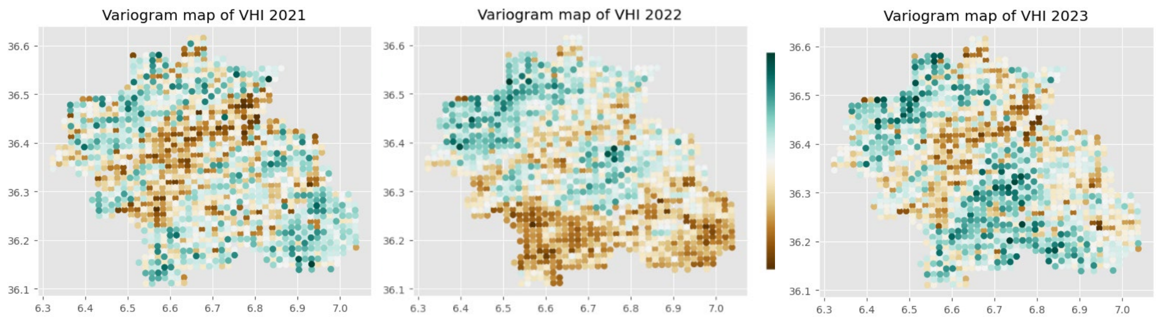


Figure 4 Viogram map of VHI

The Standardized Precipitation Index (SPI) is utilized as an indicator of chlorophyll content in vegetation. Elevated SPI values indicate vegetation rich in chlorophyll, with an average value of 6.62 in 2021, 0.58 in 2022, and 0.51 in 2023. Spatially, significant variations in SPI are noted:

- Lower values (< 0.5) are observed in the Southwest and Northeast regions.

- Moderate to high values (> 0.6) is present in the central and northwest areas (Figures 5, 6, and 7).

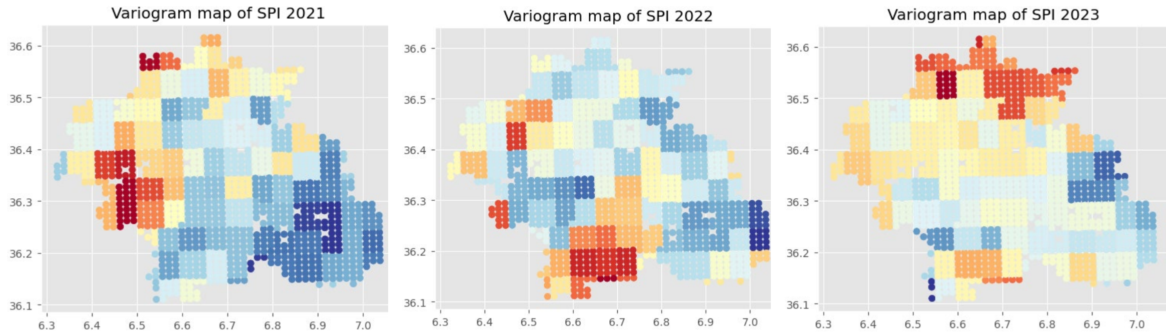


Figure 5 Viogram map of SPI

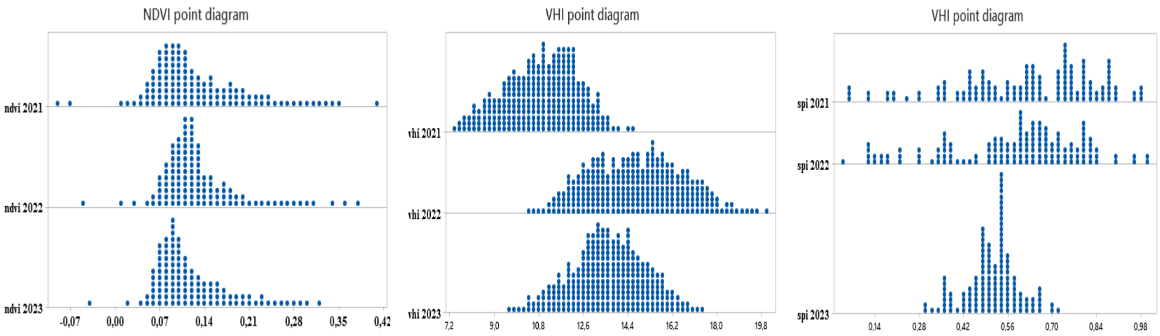


Figure 6 NDVI, VHI, SPI' points diagrams

The point diagram graphs analyze and express different environmental indices over three years (2021, 2022, and 2023).

NDVI point diagram: Distribution of points shows variability in vegetation health. Peaks indicate common NDVI values, while spreads reflect health variability. Trends over the years reveal changes in vegetation health.

VHI point diagram: Similar to NDVI, the distribution shows health trends in vegetation. Peaks and spreads provide insights into changes in vegetation condition.

SPI point diagram: The diagrams collectively provide insights into vegetation health and environmental conditions over the years, informing strategies for land management and conservation based on observed trends.

Between 2021 and 2022, there was a slight increase in NDVI followed by a decrease in 2023. The NDVI levels remained relatively low at around 0.12, suggesting sparse vegetation with low density, likely dominated by bare soils and/or an herbaceous layer.

The Vegetation Health Index (VHI) exhibited a notable increase from 2021 to 2022, indicating improved water conditions for vegetation. In 2023, the VHI slightly decreased but remained at a high level. Conversely, the Standardized Precipitation Index (SPI) showed a gradual decrease over the period, reflecting a decline in chlorophyll content in vegetation.

In summary, the spectral indices demonstrate a modest enhancement in vegetation conditions from 2021 to 2022, followed by a slight deterioration in 2023, while maintaining relatively low NDVI levels and high VHI. The declining SPI indicates a reduction in chlorophyll content over the three-year period (Figure 8).

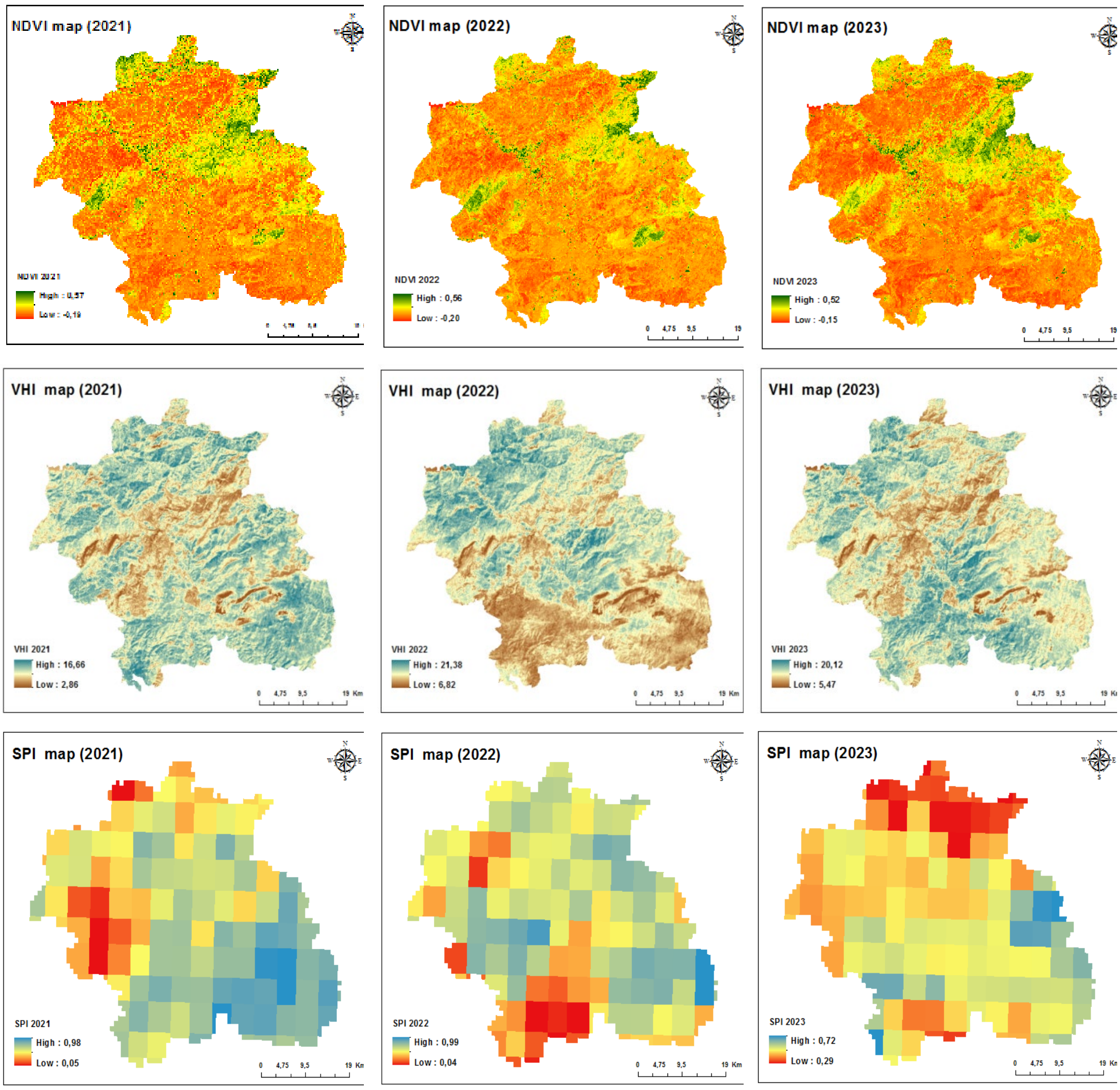


Figure 7 NDVI, VHI and SPI maps (2021-2022-2023) in order

The drought classification system for the Constantine region from 2021 to 2023 reveals significant variations in precipitation and moisture levels over the years.

In 2021, the Southwest and Eastern regions experienced moderate drought, indicating a substantial moisture deficit that adversely affected both vegetation and water resources. In contrast, the central areas maintained near-normal conditions, indicating an adequate supply of moisture that supported healthy plant growth. Additionally, the Northwest region reported mild wetness, suggesting surplus rainfall that could benefit agricultural practices.

By 2022, the overall moisture conditions in the Constantine region improved, with most areas experiencing near-normal levels. This shift indicated sufficient precipitation throughout the year. Nevertheless, some regions in the center and north exhibited mild wetness, indicating localized rainfall events that enhanced soil moisture and promoted vegetation health.

In 2023, moderate drought conditions resurged in the Eastern and Southwestern regions, mirroring the challenges faced in 2021. The Northwest continued to show near-normal moisture levels, highlighting its resilience to potential water shortages. Notably, mild wetness was again recorded in the central region, reflecting fluctuating precipitation patterns that allowed for some recovery and growth, even amid surrounding drought conditions.

In summary, the drought classification data from these three years paints a complex picture of changing moisture dynamics, emphasizing the region's susceptibility to climatic fluctuations and the pressing need for robust water management strategies to address these ongoing challenges (Table 3).

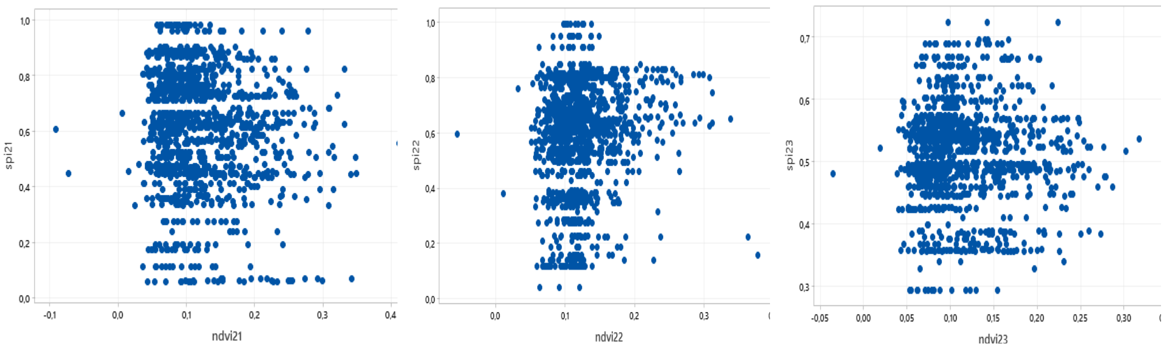
Table 3 The VHI and Drought Severity Classes in Constantine

Year	VHI %	Drought classes
2021	10.90	Severe drought
2022	14.69	Severe drought
2023	13.61	Severe drought

Correlation Between Indices

A negative correlation between NDVI and VHI was observed for the years 2021, 2022, and 2023, with correlation coefficients of -0.42 in 2021, -0.46 in 2022, and -0.51 in 2023.

An integrated analysis of NDVI, VHI, and SPI indicates a decline in climatic conditions in the studied area from 2021 to 2023. This decline involved decreased rainfall and increased water stress on vegetation, resulting in a slight reduction in plant photosynthetic activity (Figure 8).



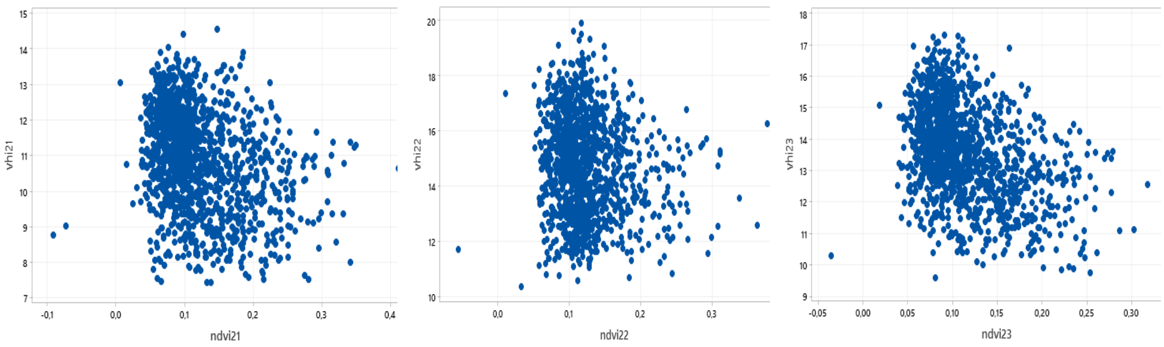


Figure 8 Correlation between indexes

The decline in the Normalized Difference Vegetation Index (NDVI) observed in the Constantine region from 2021 to 2023 mirrors trends documented in other semi-arid regions in recent years. For example, a study in West Africa by Andrieu (2008) noted a significant 15% reduction in NDVI values across several Sahelian countries between 1982 and 2003, correlating this loss with decreased rainfall and soil degradation. Similarly, research by Luis et al. (2009), highlighted an 8% decline in NDVI in the Sahel over the same timeframe, primarily attributed to prolonged drought conditions and human activities impacting vegetation cover.

In contrast, the Vegetation Humidity Index (VHI) showed an increasing trend from 2021 to 2023, indicating heightened moisture stress in vegetation and the impact of rising temperatures that worsen water scarcity. These observed trends can be largely attributed to reduced rainfall during this period, leading to soil drying and heightened evapotranspiration rates due to climate change. Supporting this, For (2016) found VHI to have a stronger correlation with vegetation conditions compared to both the Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI).

Moreover, changes in the Standardized Precipitation Index (SPI) signal a drought episode in 2022, characterized by below-average rainfall compared to seasonal norms. In contrast, precipitation levels in 2021 and 2023 either met or slightly exceeded the seasonal averages. The rainfall decline in 2022 may be explained by a temporary disruption in established precipitation patterns, potentially linked to natural climate variability and the broader effects of climate change.

The negative correlation between NDVI and VHI, as identified by Wang et al. (2010), underscores the relationship that as NDVI increases—indicating greater photosynthetic activity—VHI decreases, reflecting reduced water availability and heightened vegetation stress. This connection between vegetation health and moisture levels is further supported by an increasing strength of correlation from moderate to medium between 2021 and 2023, as evidenced by the coefficients. This trend suggests enhanced sensitivity of vegetation's water status in relation to chlorophyll activity during this period.

While this study effectively identifies temporal and spatial variations in vegetation health and moisture conditions, it falls short in addressing relevant policy and planning measures to counteract these findings. To enhance the significance and applicability of the research, it is essential to discuss potential policy implications and strategies to address the ecological challenges identified. For example, implementing sustainable water management practices, promoting reforestation efforts, and adapting agricultural practices could significantly improve the Constantine region's resilience to ongoing climate variability and drought conditions.

Furthermore, engaging stakeholders and incorporating community-level planning can lead to more effective responses to moisture and vegetation challenges. Policymakers should leverage insights derived from NDVI, VHI, and SPI analyses to create adaptive strategies aimed at strengthening ecosystem resilience and ensuring the sustainable management of natural resources amid changing climatic conditions. A thorough revision of the discussion section that incorporates these considerations would greatly enhance the study's relevance and its practical implications for local and regional decision-makers (Figure 9).

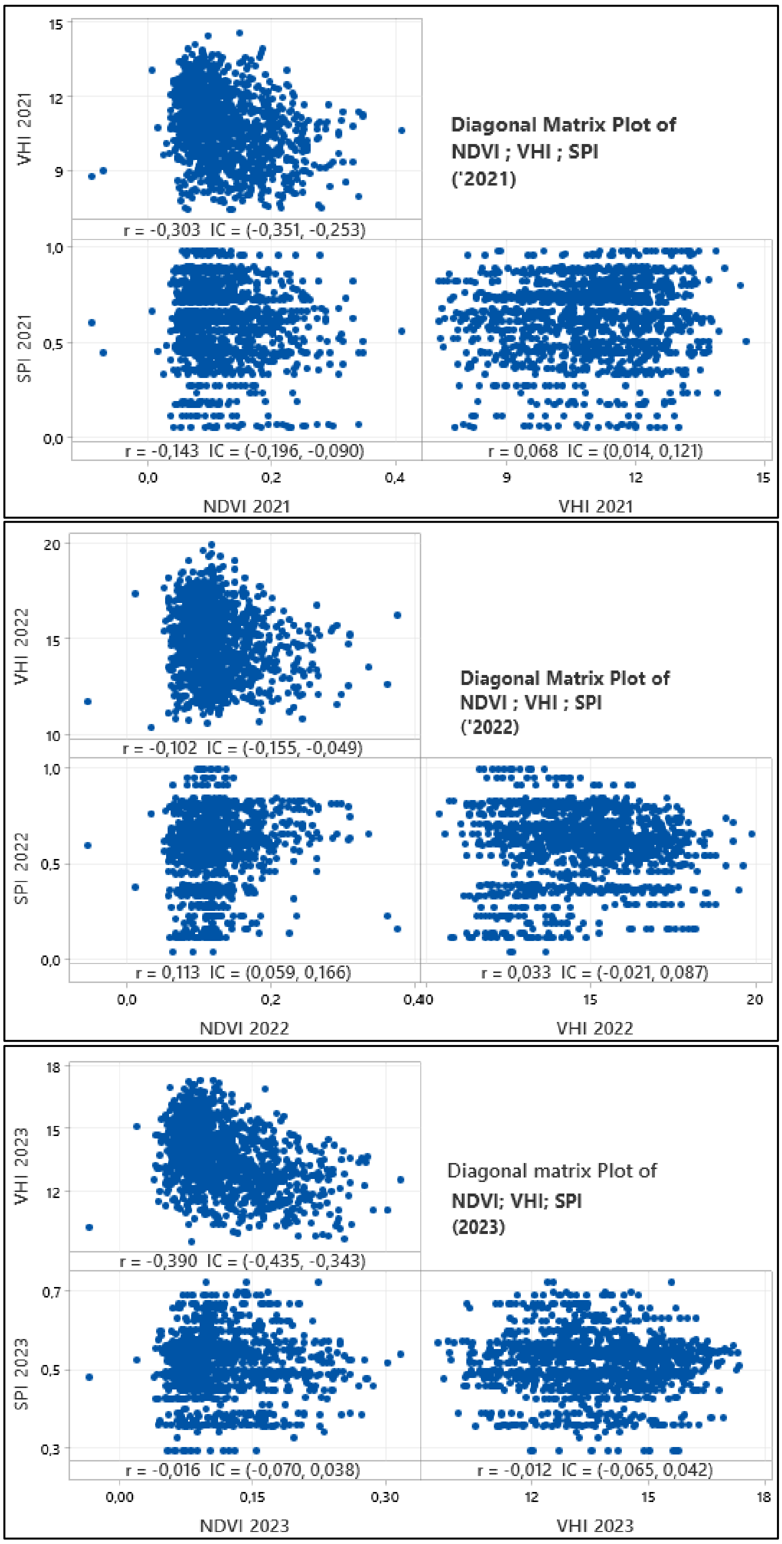


Figure 9 NDVI, VHI and SPI pearson correlation

The strength of the correlation between NDVI and VHI varies throughout different seasons within the same year, as evidenced by 2021, where the coefficient reaches -0.4 in summer but only -0.29 in winter. This seasonal disparity suggests that factors beyond water availability, such as temperature and sunlight, also influence the NDVI/VHI relationship.

Spatially, the correlation between NDVI and VHI is more pronounced in arid regions (south of the study area) compared to the relatively more humid northern areas. The heightened link between vegetation status and water availability in drier regions implies that water stress amplifies the relationship between these two factors.

Our spatial analysis, demonstrating the strengthening of the NDVI/VHI correlation in the arid southern regions, aligns with findings from prior research (Acharki et al., 2023). This supports the idea of a significant association between water availability and vegetation condition in arid or semi-arid landscapes 5 (A landscape is a visible area of land that includes various physical features, such as terrain, vegetation, water bodies, and human structures, shaped by natural and environmental processes, contributing to its aesthetic and ecological character).

The combined outcomes of the NDVI, VHI, and SPI indices signal a gradual decline in climatic conditions and vegetation health in the Constantine region between 2021 and 2023 (Figure 10).

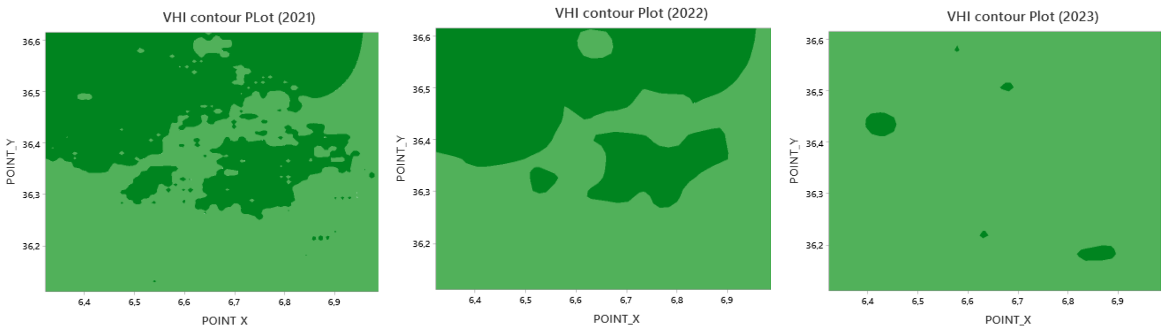


Figure 10 VHI contour plot (2021, 2022, 2023) in order

4. Conclusion

In essence, the research on remote sensing indices (NDVI, VHI, SPI) reveals a degradation in climatic conditions and vegetation health in the Constantine region from 2021 to 2023. The diminishing NDVI indicates a decline in photosynthetic activity and plant biomass, while the increasing VHI signals heightened water stress on vegetation. Concurrently, the SPI data illustrates a downward trajectory in rainfall over this period, consistent with trends in similar semi-arid zones and indicative of larger-scale global climate change impacts. These results emphasize the pivotal role of remote sensing in monitoring biophysical shifts that signal environmental decline.

The persistent negative correlation between NDVI and VHI, both spatially and temporally, underscores the robust link between water availability and chlorophyll activity in semi-arid settings, albeit influenced by seasonal variations and other factors.

This study unveils prospects for further exploration of climate change effects through the integration of additional indices, weather data, and field measurements. Leveraging high-resolution satellite monitoring stands as a critical tool for forecasting agricultural implications and enacting effective adaptation measures in response to evolving environmental dynamics.

References

Acharki, S., Singh, S. K., do Couto, E. V., Arjdal, Y., & Elbeltagi, A. (2023). Spatio-temporal distribution and prediction of agricultural and meteorological drought in a Mediterranean coastal watershed via GIS and machine learning. Physics and Chemistry of the Earth, Parts A/B/C, 103425. https://doi.org/https://doi.org/10.1016/j.pce.2023.103425.

Andrieu, J. (2008). Cartographie Par Télédétection Végétale Sur La Bande Littorale Ouest-Africaine : Exemple Des Rivières Du Sud Du Delta Du Saloum (Sénégal) Au Rio Geba (Guinée-Bissau). Revue Télédetection, *8*(2), 93-118. https://shs.hal.science/halshs-00388170.

Bento, V. A., Gouveia, C. M., DaCamara, C. C., & Trigo, I. F. (2018). A climatological assessment of drought impact on vegetation health index. *Agricultural and forest meteorology*, *259*, 286-295. https://doi.org/10.1016/j.agrformet.2018.05.014.

Clarke, K. R., Chapman, M. G., Somerfield, P. J., & Needham, H. R. (2006). Dispersion-based weighting of species counts in assemblage analyses. *Marine Ecology Progress Series*, *320*, 11-27. https://www.int-res.com/abstracts/meps/v320/p11-27/.

Diédhiou, I., Mering, C., Sy, O., & Sané, T. (2020). Cartographier par télédétection l'occupation du sol et ses changements. *EchoGéo*, (54), 0-41. https://doi.org/10.4000/echogeo.20510.

Gidey, E., Mhangara, P., Gebregergs, T., Zeweld, W., Gebretsadik, H., Dikinya, O. & Fisseha, G. (2023). Analysis of drought coping strategies in northern Ethiopian highlands. *SN Applied Sciences*, *5*(7), 195. https://doi.org/10.1007/s42452-023-05409-5.

Gomes, A. C. C., Bernardo, N., & Alcântara, E. (2017). Accessing the southeastern Brazil 2014 drought severity on the vegetation health by satellite image. *Natural Hazards*, *89*, 1401-1420. https://doi.org/10.1007/s11069-017-3029-6.

Mälicke, M. (2022). SciKit-GStat 1.0: a SciPy-flavored geostatistical variogram estimation toolbox written in Python. *Geoscientific Model Development*, *15*(6), 2505-2532. https://doi.org/10.5194/gmd-15-2505-2022.

Mostafa, A.-M. (2023). An update on Egypt climate change policies post-coronavirus. *Journal of Legal and Economic Research*, *13*, 101-186. https://mjle.journals.ekb.eg/article_315095.html.

Ramo, R., García, M., Rodríguez, D., & Chuvieco, E. (2018). A data mining approach for global burned area mapping. *International journal of applied earth observation and geoinformation*, *73*, 39-51.

Thomke, S. H. (2003). *Experimentation matters: unlocking the potential of new technologies for innovation*. (S.l.): Harvard Business Press.

Tsiros, E., Domenikiotis, C., Spiliotopoulos, M., & Dalezios, N. R. (2004). Use of NOAA/AVHRR-based vegetation condition index (VCI) and temperature condition index (TCI) for drought monitoring in Thessaly, Greece. Dans *EWRA Symposium on water resources management: risks and challenges for the 21st century, Izmir, Turkey* (pp. 2-4).

Unganai, L. S., & Kogan, F. N. (1998). Southern Africa's recent droughts from space. *Advances in Space Research*, *21*(3), 507-511.

Wang, S., Chen, H., & Yao, X. (2010). Negative correlation learning for classification ensembles. Dans *The 2010 international joint conference on neural networks (IJCNN)* (pp. 1-8). IEEE. DOI: 10.1109/IJCNN.2010.5596702.

Yengoh, G. T., Dent, D., Olsson, L., Tengberg, A. E., & Tucker III, C. J. (2015). *Use of the Normalized Difference Vegetation Index (NDVI) to assess Land degradation at multiple scales: current status, future trends, and practical considerations*. (S.l.): Springer.

Zambrano, F., Lillo-Saavedra, M., Verbist, K., & Lagos, O. (2016). Sixteen years of agricultural drought assessment of the BioBío region in Chile using a 250 m resolution Vegetation Condition Index (VCI). *Remote Sensing*, *8*(6), 530.

Zhou, X., Wang, P., Tansey, K., Zhang, S., Li, H., & Wang, L. (2020). Developing a fused vegetation temperature condition index for drought monitoring at field scales using Sentinel-2 and MODIS imagery. *Computers and electronics in agriculture*, *168*, 105144.

Zhu, Y., Wang, W., Singh, V. P., & Liu, Y. (2016). Combined use of meteorological drought indices at multi-time scales for improving hydrological drought detection. *Science of the Total Environment*, *571*, 1058-1068.

Resume

Maya Benoumeldjadj is a teaching researcher and assistant professor B. After obtaining her State Architect diploma from the University of Constantine (Algeria), she worked for eighteen years in private study offices as well as within local communities. She earned her Master's degree in 2014 from Salah Boubnider University, Constantine 3, and was recruited as an assistant professor B at Larbi Ben Mhidi University, Oum El Bouaghi, in 2015. In 2023, she defended her PhD in urban planning with a focus on urban projects and earned the title of assistant professor B.

Malika Rached Kanouni is a teacher researcher at at Larbi Ben Mhidi University, Oum El Bouaghi, Algeria, where she works a professor specialist in the development of natural environments for academic ecology and environment training.

Abdelouahab Bouchareb is a lecturer and researcher at the University of Constantine 3, affiliated with the AUTES laboratory. Professor, holder of adoctorate in urban planning 2006. Area of interest; urban heritage, projects and actions.