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Research Paper

Assessment of agricultural suitability through remote sensing: A Google Earth Engine and GIS-based approach for integrated urban planning

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ABSTRACT

This study utilizes remote sensing (Sentinel-2 images via Google Earth Engine) to analyze maize growth in the El Meniaa region, Algeria, and assess agricultural land suitability. Using vegetation indices (NDVI, EVI, NDPI), growth cycles were characterized, showing a cyclical NDVI evolution (0.51 at the start, peaking at 0.71, and dropping to 0.06-0.09 at season end). A multi-criteria approach (AHP method) revealed that the topographic criterion (weight 0.413, notably aspect) is the most influential for agricultural suitability, followed by climatic data (weight 0.327, including temperature) and vegetation indices (weight 0.216, including NDVI). This research demonstrates the effectiveness of integrating remote sensing and multi-criteria analysis to accurately model crop phenology and map areas of high agricultural suitability, offering a transferable methodological framework for arid regions of Algeria.

***Keywords**: Google earth engine, Crop phenology, AHP, Sentinel-2, Maize.*

Vegetation in the Algerian Sahara, particularly in El Meniaa, is undergoing significant changes. Remote sensing observations are now used for the spatial and temporal evolution of vegetation at a regional scale (Wang *et al.*, 2023) which allows for a dynamic and comprehensive analysis of plant transformations over vast territories (Helman, 2018). The land surface phenology (LSP) metrics allow for precise mapping of vegetation dynamics from remote sensing data. The key indicators are the start of the season (SOS), the length of the growing season, the peak of growth (POS), and the end of the season (EOS) (De Beurs *et al.*, 2010) besides the maturity and senescence. These measures are calculated using the Normalized Difference Vegetation Index (NDVI) or other common vegetation indices and are expressed in days and years (Alemayehu *et al.,* 2023).

Satellite phenological study is an emerging field focused on cereal and market garden crops (Benaouf *et al.*, 2015; Pokhariyal *et al*., 2024; Patel *et al.*, 2023). Processing data from multiple remote sensing sources and scales is a major technological challenge today. Faced with the growing complexity of spatial data analysis, Google Earth Engine (GEE) has become a revolutionary computing solution. This gigantic intensive processing platform offers remarkable computational capabilities that enable addressing the algorithmic challenges related to the analysis and global simulation of satellite data (Louati *et al.*, 2023). Moreover, integrating Analytical Hierarchy Process (AHP) with GIS improves decision-making processes through effective mapping and visualization capabilities. This facilitates the creation of land-use suitability maps and optimizes land-use planning (Kayal *et al.*, 2025).

Saharan areas are sensitive indicators of climate change, and it is therefore crucial to monitor them to develop effective adaptation and mitigation policies. This study aims to estimate corn phenological parameters in this region, using high-resolution

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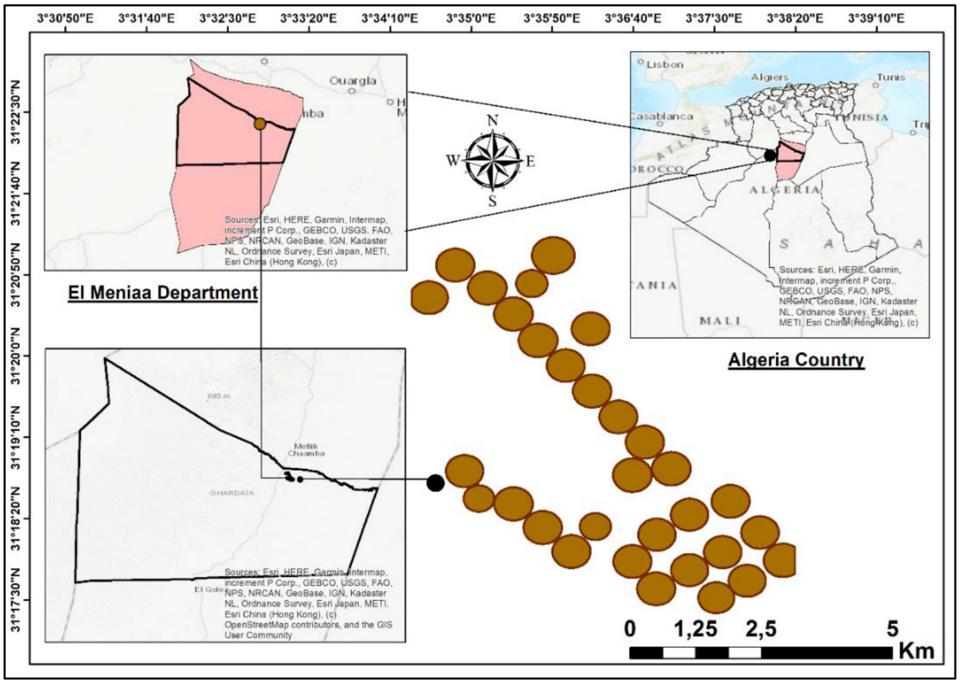

Fig. 1: Study area map

satellite images via Google Earth Engine to obtain phenological metrics from various vegetation indices.

MATERIAL AND METHODS

Study area

The study area is located in the region of El Meniaa, Algeria. It is bordered to the north by wilaya of Ghardaïa to the south, wilaya of Ain Saleh to the east, wilaya of Ouargla to the west, wilaya of Timimoun (Fig. 1). It has hot desert climate, with long and extremely hot summers and short and hot winters. There is very little rain throughout the year and summers are particularly dry. For cultivation in this region and apart from the Oases, wheat and corn are the main crops of this region and constitute the backbone of its economy. Other crops include potatoes, tomatoes, peas and other plantations.

Satellite data

Sentinel-2 satellite data were used in this study to calculate phenological parameters. These metrics were derived using vegetation indices such as Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Difference Phenological Index (NDPI). Satellite data preparation and phenological modeling were carried out on Google Earth Engine (GEE) platform. The formulas used are:

$$NDVI = \frac{NIR_{Band} - Red_{Band}}{NIR_{Band} + Red_{Band}}$$

$$NDPI = \frac{(NIR - (alpha * RED + (1 - \alpha) * SWIR)}{(NIR + (alpha * RED + (1 - \alpha) * SWIR)}$$

$$EVI = \frac{2.5 * (NIR - RED)}{(NIR + 6 * RED - 7.5 * BLUE + 1)}$$

Here, NIR (band 8), RED (band 4), BUE (band 2) and SWIR (band 11) were obtained from Sentinel 2. The value of α was set to 0.51, as it was considered the most effective value to suppress soil background variability (Varghese, 2017).

Data processing

The experimental site is located in the eastern part of the commune of El Meniaa (3.59 °N °٣١,٣٢E), representing a maize cropping system. The beginning and end of the growing season were also recorded at the experimental site. In October ٢٠٢٤, a field campaign was conducted in the study area to measure crop yield. A total of 31 pivots or plots were selected in the study area for this purpose. Plot size varied between 29 and 31 hectares, and information on transplanting date (DOT) and harvesting date (DOH) was collected from farmers as secondary data. The corn plowing season runs August 15 to September 15, and the harvest season runs from November 15 to December 15.

Methodology

In this study, a method based on the analysis of vegetation indices was applied. This approach allows identifying the start and end dates of the growing season respectively the SOS (Start of Season) and the EOS (End of Season) as being the first and last day on which a specified threshold value is exceeded. The length of the growing season is then calculated as the period separating SOS and EOS. In our study the threshold value, noted τ, was defined dynamically, according to the characteristics of each pixel of the NDVI and EVI indices (Koutsoumanis *et al*., 2020) in order to take into account local variations linked to the type of land cover and climatic conditions.

Table 1 : Criteria and sub-criteria weights and consistency ratios from AHP analysis

Main criteria	Weight	Sub criteria	Weight	Consistency ratio
Climatic	0.327	Relative humidity	0.206	0.06
		Air temperature	0.270	
		NDSI	0.216	
		LST	0.242	
		UTFVI	0.067	
Topographic	0.413	Appearance	0.499	0.05
		Slope	0.396	
		DEM	0.105	
Vegetation indices	0.216	NDVI	0.436	0.01
		EVI	0.413	
		NDPI	0.081	
		SPI	0.070	

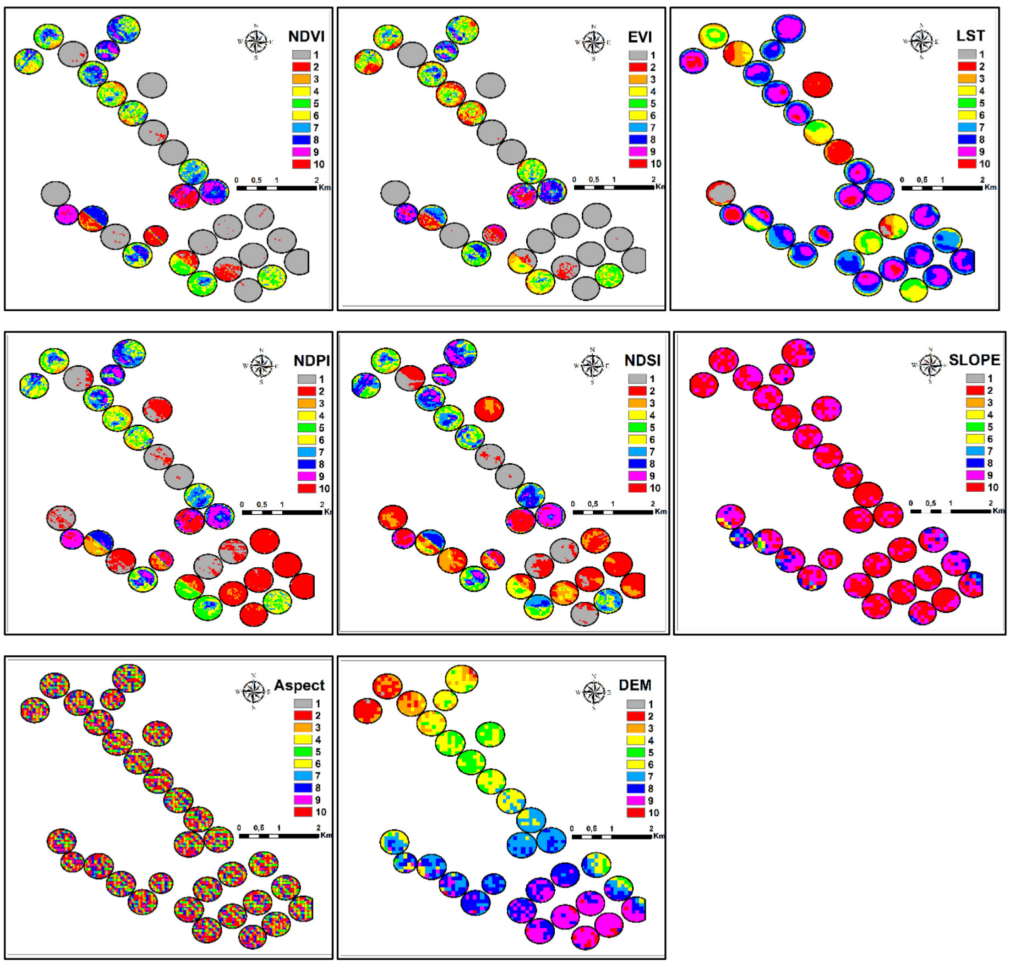

Fig. 2: The reclassification of indices using AHP_GIS

Where τ is the dynamic threshold value, which depends on the annual amplitude of the time series; minVi and maxVi, represent the minimum and maximum values of the vegetation index during the crop-growing season, respectively. The value φ was calculated and set to 0.33 which represents the mid-green and mid-green of the crop growth cycle (Pokhariyal *et al.*, 2024).

Executing multi- criteria evaluation using AHP techniques

The Analytical Hierarchy Method (AHP), is a widely used multi-criteria approach to address complex decision-making problems (Saaty and Vargas, 2006). It prioritizes and assigns weights to the various factors involved, based on pairwise comparisons on a numerical scale from 1 to 9. This method is based on a hierarchical structure that facilitates the analysis of relationships between the main criteria and their sub-criteria. In this study, five main criteria influencing maize growth were identified, each of which is broken down into several sub-criteria. Using the AHP approach, we constructed the judgment matrices, calculated the respective weights

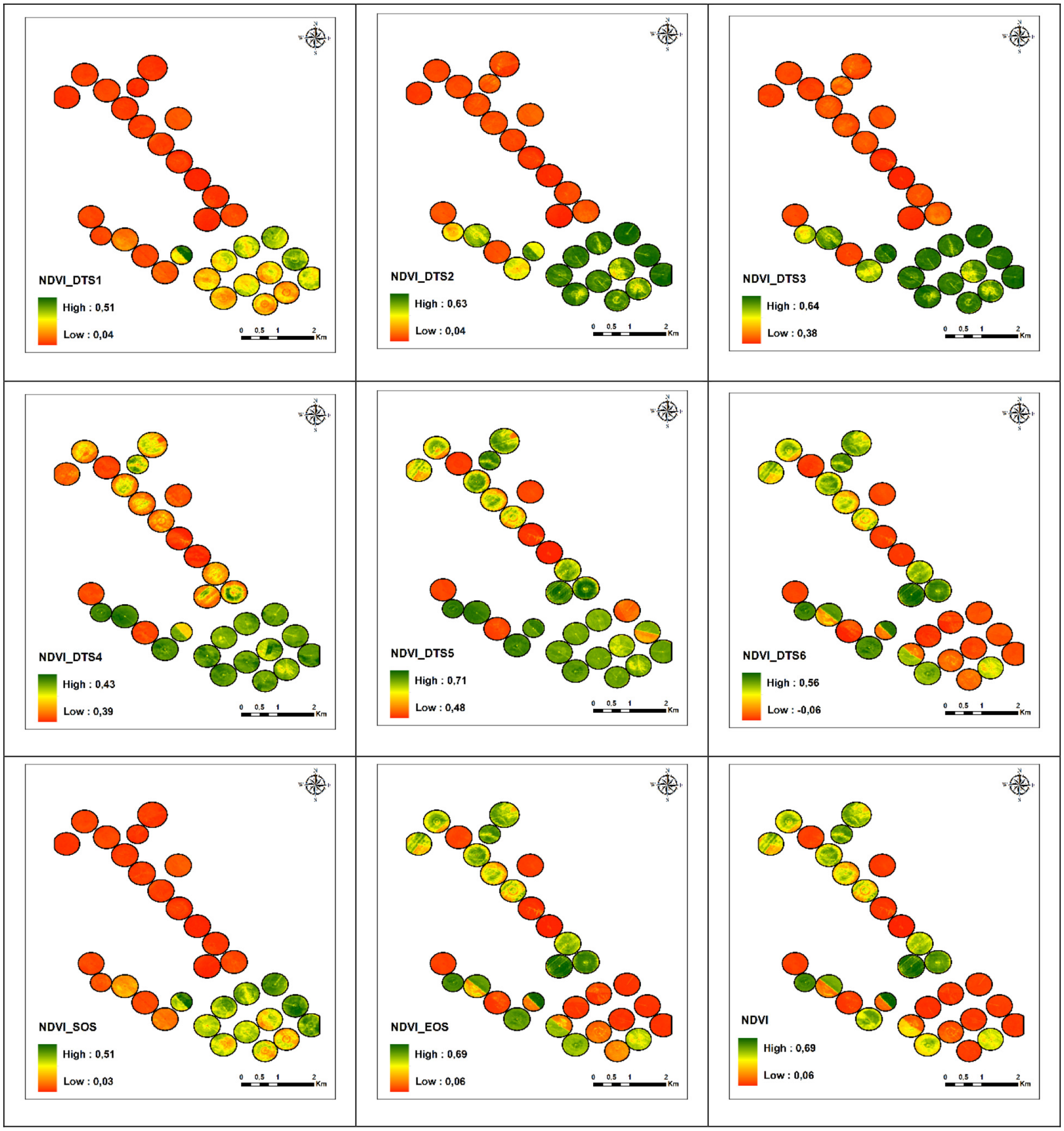

Fig. 3: Temporal variation of NDVI during maize crop seasons

of each element, and verified the consistency of the judgments using the consistency ratio (CR). A matrix is considered consistent when the CR is less than 0.1 (Saaty and Vargas, 2006). The weights thus obtained were then integrated into a geographic information system (GIS), more precisely with the ArcGIS 10.4 software, to produce a multi-criteria spatial analysis (Saaty *et al.*, 2022). Finally, a field study was carried out to collect accurate data and validate reliability. The index weight was determined by the analytical hierarchy process in this study and, we used expert choice.11 software to measure the consistency index and weight value. The result shows that CR = 0.06 < 0.1, which means that the consistency ratio is acceptable (Table 1). All raster data were resampled according to the classification criteria of all factors. The spatial resolution of all factors was unified at a scale of 30 m × 30 m, and all data used in the study were projected into the WGS1984 projection system.

RESULTS AND DISCUSSION

Fig. 2 illustrates the reclassification of the different environmental and topographic indices, expressed on a scale of 1 to 10, where 1 corresponds to the least favorable values (poor) and 10 to the most favorable values (excellent). These indices were reclassified for use in a multi-criteria analysis based on the AHP method, in order to assess the pivot's suitability. We combined a phenological index (NDPI), vegetation indices (NDVI, EVI) and texture features (DEM) (Yu *et al.*, 2013), temperature indices (LST) and Urban Thermal Field Variance Index (UTFVI), humidity and salinity (NDSI), orientation indices (Aspect) and slope to classification model.

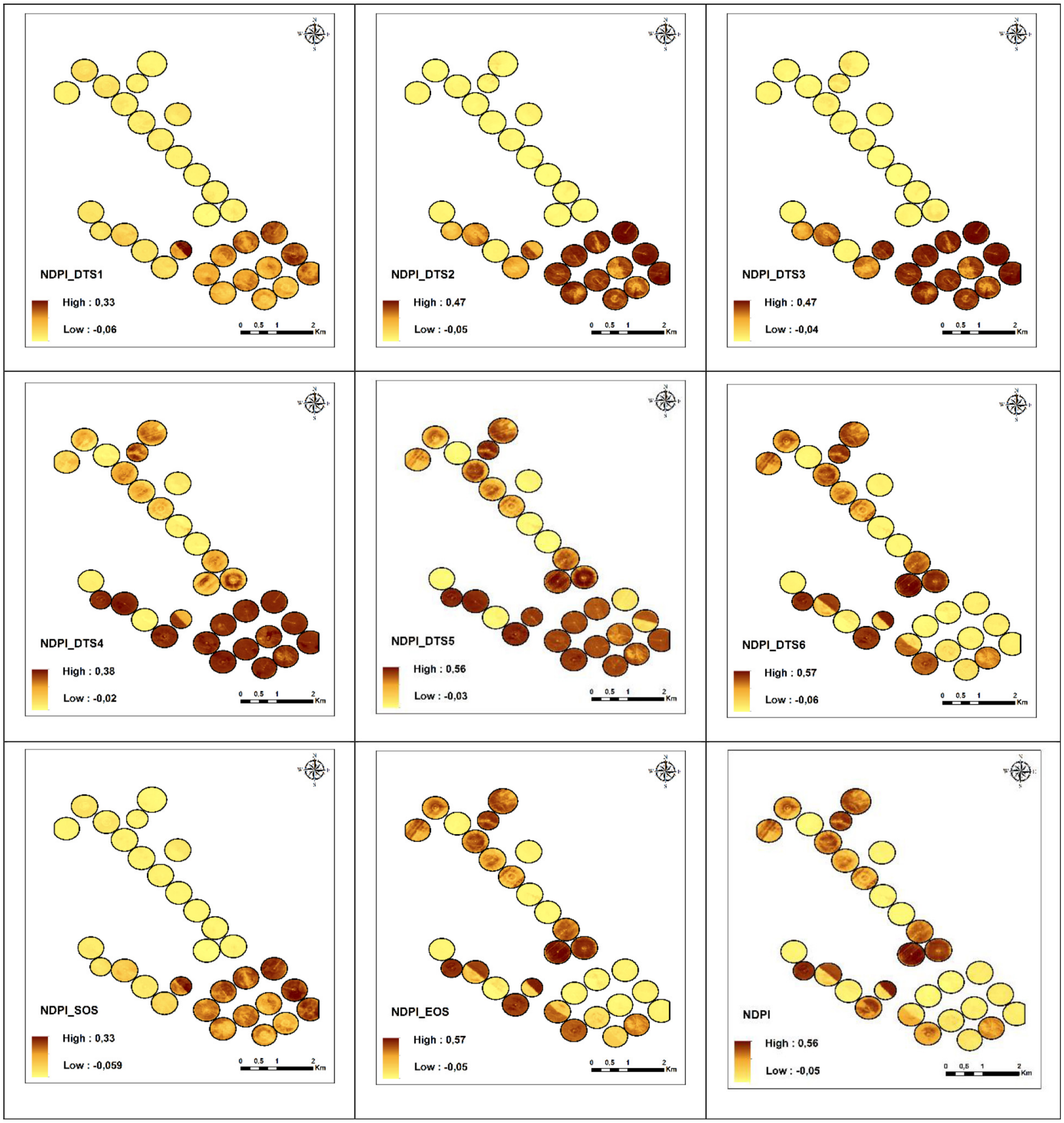

Fig. 4: Temporal variation of NDPI during maize crop seasons

Temporal profile of NDVI during the crop growth cycle

Fig. 3 presents the time series of the NDVI index of the experimental site, with the Start of Season (SOS) during the growing season (for each week/days) (DTS1, DTS2, DTS3 DTS4 DTS5 DTS6) and the End of Season (EOS) based on satellite data phenology observations during the 2024 agricultural season (Fig. 3). It also illustrates the dates of start (SOS) and end of growing season (EOS), calculated for each vegetation index used in this study.

Analysis of NDVI images (Fig 3) clearly shows a cyclical evolution of vegetation over the season, reflecting different phases of growth, stagnation, and decline. NDVI index values vary significantly across seasons and spatial regions, highlighting the influence of local environmental conditions and cardinal directions. From the beginning of the season (SOS), NDVI values are relatively high with a maximum of 0.51, indicating good initial vegetation cover, particularly in the areas shown in red and orange. During the season (DTS), the index shows a marked fluctuation: a peak in plant vigor is observed at NDVI_DTS2 with a maximum value of 0.63, followed by a period of stagnation or stress at NDVI_DTS4 where values drop to 0.43. A new peak is recorded at NDVI_DTS5 with a maximum value of 0.71, reflecting a notable recovery in plant growth. These variations illustrate natural cycles influenced by climatic conditions and available resources. At the end of the season (EOS), the values drop sharply with a maximum of 0.09 and a minimum of 0.06, marking the end of the growing cycle and the transition to a phase of decline or inactivity. Spatial analysis of NDVI values reveals marked regional differences. The north shows high NDVI (0.51 to 0.71) but strong degradation at the end of the

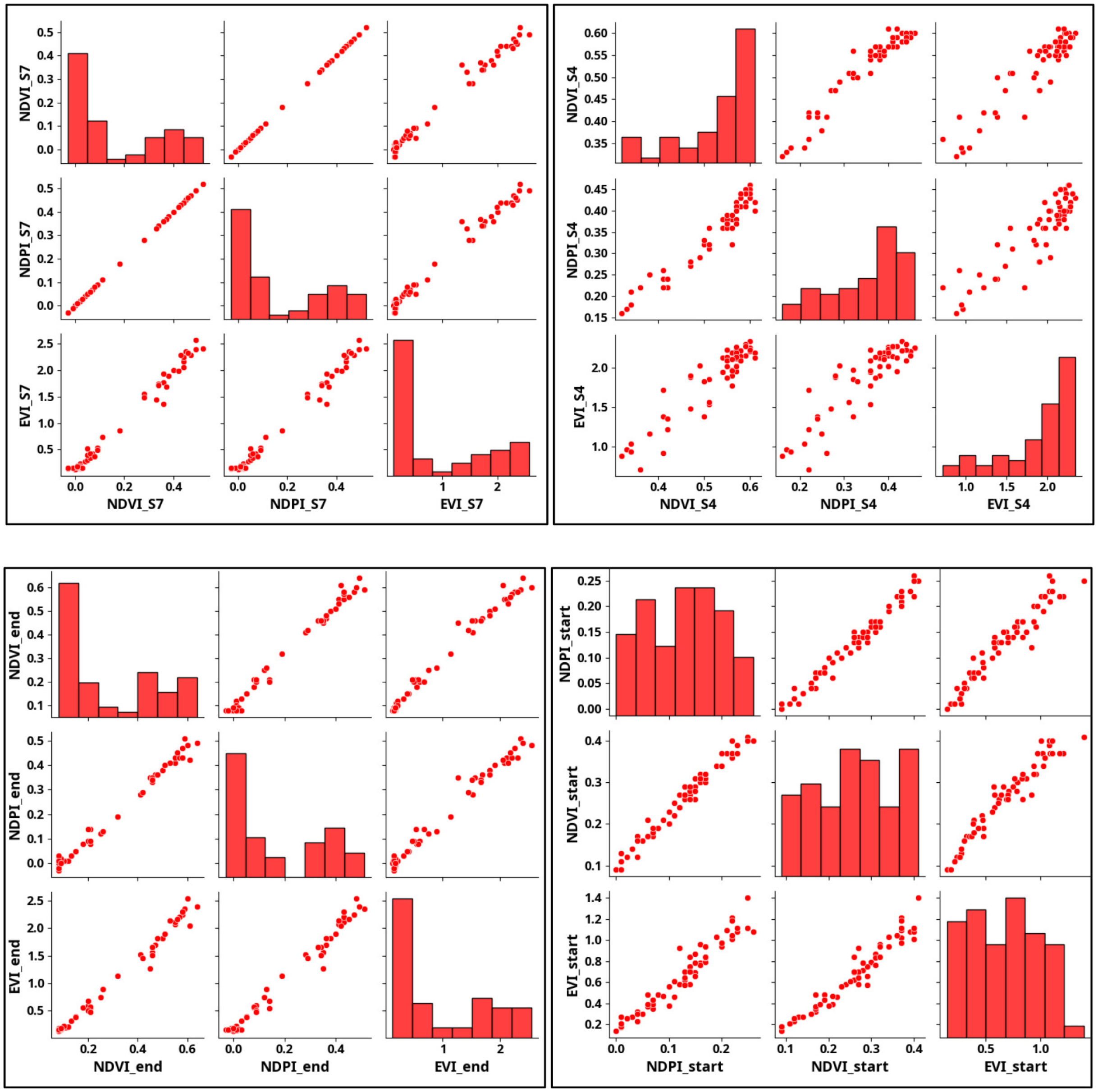

Fig. 5: Correlation between the indices

season due to intensive resource use. The south exhibits low values (0.09 to 0.06), indicating low plant density due to unfavorable conditions. The east and west display heterogeneity (0.43 to 0.71), reflecting local variations in nutrient availability, soil moisture, or climatic exposure. These observations highlight the importance of geographical and environmental factors for understanding vegetation dynamics and optimizing agricultural and ecological management.

Temporal profile of NDPI during the crop growth cycle

Fig. 4 shows NDPI data for periods similar to NDVI. Analysis of NDPI images, used here as a phenology indicator, reveals a clear cyclical evolution of plant development over the season, allowing the identification of different phases of plant growth, maturity and decline: positive values indicate significant plant activity, while values close to zero or negative correspond to areas with little vegetation or in a resting phase.

From the beginning of the season (SOS), the values are relatively low with a maximum of 0.33 and a minimum of -0.09, reflecting a slow start of phenology across the entire territory. As the season progresses (DTS), the index shows a characteristic fluctuation; after a slight improvement with a peak at 0.47 during NDPI_DTS2, the values stabilize around 0.47 before temporarily dropping to 0.38 during NDPI_DTS4, indicating stress or stagnation. A notable recovery then occurs with a peak at 0.56 during NDPI_DTS5, followed by a stabilization at 0.57 at the end of the season (NDPI_DTS6). These variations illustrate the natural cycles of crop development, influenced by climatic conditions and water availability. In terms of spatial distribution, the differences according to cardinal orientations are well marked: the northern region, although timidly demarcating, follows an active cyclical dynamic with significant peaks, while the southern region shows a gradual but constant improvement. The eastern and western zones, on the other hand, present a more heterogeneous distribution, probably reflecting local differences in soil, exposure and access to water. At the end of the season (EOS), the values reach a maximum of 0.57, with a dominance of orange and red colors, showing that the plants have reached their optimal maturity. Thus, the NDPI index asserts itself as a relevant tool to precisely monitor the key stages of the phrenological cycle of crops and adapt agricultural practices to the spatio-temporal needs of the plots (Wang *et al.*, 2017).

Correlations among different indices

The pair plots for both sets of indices (NDPI, NDVI, EVI during, start and end seasons)) consistently demonstrate strong positive correlations among all three indices within each set, indicating that they measure similar aspects of vegetation or surface characteristics and tend to increase or decrease together (Fig. 5). Specifically, a very strong positive linear relationship is observed between NDPI_start and NDVI_start in the first set, and between NDVI_S4 and NDPI_S4 in the second set. While the distributions of the 'start' indices are multimodal, the 'S4' indices generally exhibit unimodal distributions, suggesting different value concentrations across the datasets (Fig. 5). The central areas, rich in vegetation and benefiting from favorable climatic conditions, appear to be the most promising. On the other hand, the peripheral areas, marked by steep slopes and low plant density, require special attention to optimize their exploitation.

CONCLUSION

This study successfully demonstrates the effectiveness of integrating remote sensing (Sentinel-2, GEE) and multi-criteria analysis (AHP) for precise maize crop monitoring and rigorous agricultural suitability assessment in the El Meniaa region of Algeria. The results confirm the predominant influence of topography, climatic data, and vegetation indices on crop productivity. This robust and transferable methodological framework offers a promising solution to address the challenges of food security and sustainable resource management in the face of climate change in similar regions

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