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Harvesting Insights: A Comprehensive Analysis of Agricultural Lands using Remote Sensing

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***Abstract*— Climate change has emerged as a critical global challenge, with far-reaching consequences for our planet's ecosystems, weather patterns, and human societies. With the advancement in technology today, decision-makers have begun to move away from costly and traditional monitoring methods to leveraging advanced techniques such as remote sensing for agricultural monitoring. Traditional methods of assessing agricultural lands often involve time-consuming and costly field surveys. However, with recent advancements in remote sensing technology, and with the availability of satellite imagery, it has become possible to utilize remote sensing indices to assess agricultural lands more efficiently and accurately. This study focuses on utilizing Sentinel-2 and Landsat-8 satellite images to provide spatiotemporal insights on a seasonal basis. The primary objective of this study is to assess the agricultural lands in the Northern Governorate of the Kingdom of Bahrain by analysing the potential of remote sensing indices in characterizing and quantifying key agricultural parameters such as vegetation health, water stress, temperature levels and soil conditions. To extract meaningful geospatial insights from satellite imagery, various remote sensing indices have been applied such as the Normalized Difference Chlorophyll Index (NDCI), Normalized Difference Moisture Index (NDMI), Soil Moisture Index (SMI), Soil Salinity Index (SSI) and Land Surface Temperature (LST). The comparative analysis reveals key spatial and temporal dynamics between all indices. Correlation coefficient (r) highlights relationships between NDCI, SMI, and NDMI, showing notable interdependence in agricultural parameters with r values ranging from 0.623 to 0.783 across summer and winter seasons.**

Keywords—Agriculture, Soil Moisture and Salinity, Leaf Water Content, Land Surface Temperature, Chlorophyll Content

I. INTRODUCTION

Agriculture is commonly recognized as an essential sector to sustain global food security. Presently, there are high demands expected from this sector as a response to the expected increase of global population which has placed an amplified pressure for enhanced global food production [1]. The need to increase food supply, coupled with the unstable environmental conditions due to climate change, is causing the development of agriculture to be in a vulnerable and difficult state to accommodate to global food security requirements [2].

Since economic and political elements come into play with land distribution, such as population increase, climate change, land-use, urbanization and water scarcity; the availability of arable lands for agricultural production is also limited [3]. By 2050, arable lands are expected to decrease by approximately 50 million hectares and food production by 20% whereas global population is expected to increase by 9.2 billion, global greenhouse emissions to rise by 50% and food demand to increase between 59 to 98% [4]. These factors present an evident dissonance between potential demand and supply of agriculture in the future.

To respond to these challenges, the agricultural industry is observing a transformation from traditional agricultural methods to smart agriculture, also known as the 'Digital Agricultural Revolution' or Agriculture 4.0 [5]. Agriculture 4.0 involves enhancement of agricultural outcomes through the integration of various dimensions such as Industry 4.0, precision farming, digital technologies, food value chain and sustainability [6]. Through these advancements, agriculture is aiming to achieve a productivity increase, efficient resource allocation, climate change adaptation and minimization of food waste [7].

A core technology that feeds the usage of data analytics and artificial intelligence in these dimensions is remote sensing. Remote sensing has had an increasing usage trend over the past 20 years and has played a huge role in providing crop production and environment analytical tools [8]. This technology refers to the employment of sensors or instruments on a platform such as a satellite or an aircraft to gather information about spatial phenomena [9]. With the various remote sensing systems available and the geographical coverage that remote sensing offers, applications ranging from land use mapping to crop classification to biophysical parameter identification can be conducted [10].

The vegetation & agricultural sector in the Kingdom of Bahrain, has undergone tremendous developments in recent years to ensure sustainability in the country. With major goals set to double the tree coverage and quadruple the mangrove coverage as initiatives to reach Net Zero by 2060 [11], the focus on innovative agricultural technologies such as remote sensing to drive these changes and assist in data-driven decision making is rising [12, 13]. A notable project is the Botanical Atlas, which highlights the diverse vegetation in the Kingdom of Bahrain. It utilizes satellite imagery and remote sensing, to showcase a variety of plant life across various landscapes [11]. The analysis of the vegetation has shown five main classes which are grass/ornaments, cultivation, palm trees, deciduous trees, and mangroves/halophytes [14].

Thus, this paper aims to uncover agricultural parameters such as soil moisture, soil salinity, chlorophyll content, leaf water content and Land Surface Temperature (LST) to provide a comprehensive land assessment through remote sensing techniques and to assist national goals in agricultural sustainability.

II. Literature Review

Numerous scientific papers have been published to derive agricultural analytics based on remote sensing. Some notable ones where they assessed agricultural lands suitability through Geographical Information Systems (GIS) and remote sensing is on the Ma'an Governorate in Jordan [15]. The assessment is based on rainfall, temperature, slope percentage, soil types and water wells distribution. They have uncovered low levels of suitability due to water scarcity and low soil fertility.

In terms of assessing individual components, chlorophyll content is considerably investigated as it plays a critical role in crop health and photosynthesis monitoring. Another study utilized hyperspectral data to estimate soybean chlorophyll content at different growth stages [16]. The final growth stage demonstrates that the first-order differential spectral index has strong predictive capability with a correlation coefficient of 0.854. Similarly, a study explored leaf chlorophyll estimation using Sentinel-2 data, finding a high correlation between satellite and ground-measured chlorophyll content ($r = 0.77$) [17]. Both studies underscore the efficacy of remote sensing for accurate chlorophyll monitoring in crops across different stages of growth.

Regarding the exploration of agriculture through vegetation water content and stress, a study examined different remote sensing technologies for assessing crop water stress [18]. Their review highlights the suitability of the integration remote sensing for crop water stress and its capabilities in providing accurate and reproducible analytical frameworks. A vegetation water content assessment on the central of Iowa in the United States has been performed [19]. This has been done through the fusion of calculated indices from Landsat and the Moderate Resolution Imaging Spectroradiometer (MODIS). The analysis showcases the significance of crop type when considering vegetation water content.

Another study inspected the possibility of mapping soil moisture in agricultural lands using multi-temporal Landsat images [20]. The study illustrates the successful application of remote sensing in developing a Soil Moisture Index (SMI) that depends on Normalized Difference Vegetation Index (NDVI) and LST parameters. This study was undertaken in the Mandri River watershed situated in the Kanker district of Chhattisgarh. The study's findings indicate that 50% of the targeted area is experiencing extreme drought conditions. To address this issue, they suggest reforestation and enhancing moisture levels in the area. It was determined that the SMI effectively monitors agricultural drought and flood disaster assessment.

Soil salinity is another component that facilitates agricultural analysis. Research has demonstrated that there are various indicators for determining soil salinity, and each one is sensitive to a particular reflection in the electromagnetic spectrum. A study in Portugal explores the utilization of Sentinel-2 for soil salinity assessment in irrigated rice fields using various types of multispectral-based indices for the period from 2017 to 2018 for the Spring and Autumn seasons [21]. The Salinity Index ASTER (SI-ASTER) demonstrated a sharper response to soil surface salinity among various salinity indices. Computing SI-ASTER requires using the Short-Wave Infrared (SWIR) bands to distinguish the differences between soil salinity contents and map the targeted area spatially and temporally. Using the SI-ASTER index ultimately led to the development of a valuable soil salinity assessment tool.

It is also evident that surface temperature alterations caused by environmental and climate changes negatively affect crop health. Variations in LST significantly impact the vegetation cover worldwide, with a firm reliance on factors such as vegetation degradation, drought, and moisture levels. Landsat-8 satellite imagery uses thermal ultraviolet bands to estimate LST across broad areas. A study presented the relationship of LST with different vegetation indices using multi-temporal satellite data in the Sahiwal region, Pakistan [22]. The results indicate a strong relationship between NDVI and LST with a 0.83 kappa coefficient value. Thus, remote sensing technology and thermal satellite missions provide valuable information for sustainable land use and agriculture management.

III. Study Area And Data Used

A. Study Area

The area chosen for this study is the Northern Governorate of the Kingdom of Bahrain. This selection is based on the presence of the most agricultural areas in the Kingdom, to maximize the applications of the outcomes of this study. The study examines overall agricultural health in the region, irrespective of crop type. The Northern Governorate has an area of almost 170 km^2. Fig 1 marks the chosen area on the map.

Fig. 1. Northern Governorate of the Kingdom of Bahrain

B. Dataset Used

For this study, Landsat-8 and Sentinel-2 satellite images with spatial resolutions of between 10 and 30 meters were acquired from the USGS Earth Explorer and Copernicus Browser, respectively, for the year 2023. To assess the changes on a seasonal basis, images from January to March were utilized for the winter. Accordingly, images from June to August were used for the summer.

IV. Methodology

The methodology followed a data preprocessing step, the calculation of four remote sensing indices and modelling LST.

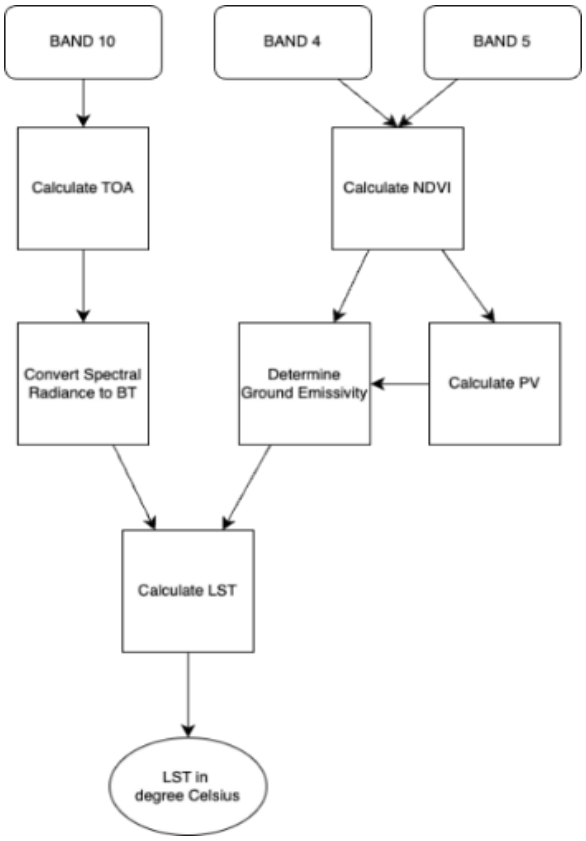

Fig 2. LST Workflow

A. Data Preprocessing

1) *Landsat-8:* Image is geoprojected to Ain el Abd (2019) – European Petroleum Survey Group (EPSG) Code 20439 and clipped to the Northern Governorate region

2) *Sentinel-2:* The Northern Governorate spans two image scenes; hence the image is mosaicked, geoprojected to Ain el Abd (2019) – EPSG Code 20439 and then clipped to the Northern Governorate region

3) *Sensor Resolution Conflict:* Due to the differences in sensor resolution, and the requirements of different bands from each sensor to calculate the indices, the study results are organized as follows:

a) Individual Analysis: Each index is examined indvidually in terms of its distribution in winter and summer months according to native resolution

b) Correlation Analysis: Each index results are downsampled to 100 m by taking the mean of that area. This then allows looking at the average correlation values of the indices.

B. Chlorophyll Content

The Normalized Difference Chlorophyll Index (NDCI) is influenced by two primary spectral bands, the red and red-edge bands, which are highly sensitive to chlorophyll. Sentinel-2 satellite imagery is used for this computation, incorporating the red and red-edge1 bands to monitor chlorophyll levels as an indicator of vegetation health and photosynthetic activity.

For this study, the red and red-edge reflectance values are retrieved from Sentinel-2 satellite images to compute NDCI as follows:

$$\mathrm{NDCI} = \frac{(\mathrm{RE1}-\mathrm{R})}{(\mathrm{RE1}+\mathrm{R})} \quad (1)$$

Where

RE1 = Red-Edge 1 Band
R = Red Band

Similar to other vegetation indices, the higher the NDCI value, the greater the chlorophyll concentration, which signifies healthier vegetation. This index has been successfully applied in numerous studies to assess crop productivity and monitor plant stress. The red-edge band specifically captures subtle changes in chlorophyll content, making it a valuable tool for precise agricultural and ecological assessments.

C. Leaf Water Content

The Normalized Difference Moisture Index (NDMI) is used to calculate vegetation water content in this study. This index has been effectively utilised in many applications as an indicator of vegetation water content. The following is the NDMI calculation using Sentinel-2:

$$\mathrm{NDMI} = \frac{(\mathrm{NIR}-\mathrm{SWIR})}{(\mathrm{NIR}+\mathrm{SWIR})} \quad (2)$$

Where

NIR = Near-Infrared Band

SWIR = Short-Wave Infrared Band

D. Soil Moisture

The Soil Moisture Index (SMI) is influenced by two main empirical factors which are the land surface temperature and vegetation indices. To compute the factors, Landsat-8 satellite imagery is used including red, near-infrared (NIR) bands, and thermal infrared (TIR) bands. The red and NIR are used to compute NDVI values and TIR bands are used for LST estimation in degree Celsius. For this study, the emissivity (ε) value is determined to be 0.95 [23].

$$\mathrm{SMI} = \frac{(\mathrm{LST_{max}}-\mathrm{LST})}{(\mathrm{LST_{max}}-\mathrm{LST_{min}})} \quad (3)$$

Where

$\mathrm{LST_{max}}$= Season Maximum Value of LST
$\mathrm{LST_{min}}$= Season Minimum Value of LST
LST= LST Raster

E. Soil Salinity

The SI-ASTER is based on the principle that the thermal properties of soil are affected by soil moisture and salinity. Saline soils have a higher thermal inertia than non-saline soils, meaning they take longer to heat up and cool down. As a result, saline soils have a lower temperature contrast between the TIR11 and TIR10 bands compared to non-saline soils. The SI-ASTER takes advantage of this difference to estimate soil salinity, using Sentinel-2.

$$\mathrm{SI\ ASTER} = \frac{(\mathrm{SWIR\ 1}-\mathrm{SWIR\ 2})}{(\mathrm{SWIR\ 1}+\mathrm{SWIR\ 2})} \quad (4)$$

Where

SWIR 1 = Short-Wave Infrared 1 Band

SWIR 2 = Short-Wave Infrared 2 Band

F. Land Surface Temperature

Computing the LST values relies on Level 1 (L1) products from the Landsat-8 satellite mission. It uses the thermal band (TIRS 1), red, and NIR bands. The metadata file is used to obtain the thermal constant values to estimate brightness temperature by calculating the Top of Atmospheric (TOA) spectral radiance and converting it to Brightness Temperature (BT). Calculating other values such as NDVI and the proportion of vegetation and determining the ground emissivity is essential to retrieve the LST values measured in degrees Celsius. Similar to SMI, the common value of 0.95 is used for ground emissivity.

V. Indices Results

The following sections demonstrate the maps & classification results for the indices. Since the study examines results obtained from remote sensing data solely, the four indices have been classified using the Geometric Interval Classifier, which adjusts for the right-skewed distribution of the data [24]. Additionally, table results have been rounded up from many significant figures; hence, 100% addition of all area values is not demonstrated here.

A. Chlorophyll Content

Fig. 3 presents the NDCI classification across the Northern Governorate, while TABLE I. summarizes the NDCI value ranges observed during the summer and winter of 2023. It also details the percentage distribution of chlorophyll content across the governorate for both seasons.

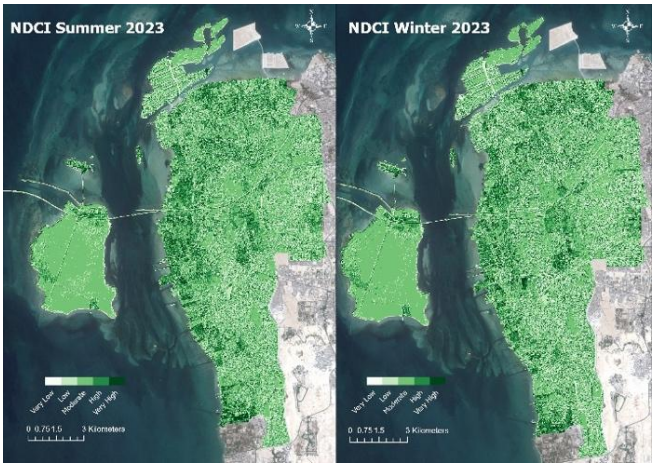

Fig. 2. NDCI Classification Map for Summer & Winter 2023

TABLE I. NDCI Classification Values for Summer & Winter 2023

Class	Season					
	Summer 2023			Winter 2023		
	NDCI		*Area (%)*	*NDCI*		*Area (%)*
	From	*To*		*From*	*To*	
Very Low	-0.08	0.0004	6.01	-0.09	0.006	7.0
Low	0.0004	0.0074	20.2	0.006	0.01	21.0
Moderate	0.0074	0.02	44.9	0.01	0.02	42.9
High	0.02	0.03	21.6	0.02	0.03	21.1
Very High	0.03	0.12	7.2	0.03	0.14	7.9

B. Leaf Water Content

Fig. 4 illustrates the NDMI classification on the Northern Governorate. TABLE. II highlights the values range achieved from implementing the NDMI during the summer and winter as well as their water content classification.

Fig. 3. NDMI Classification Map for Summer & Winter 2023

TABLE II. NDMI Classification Values for Summer & Winter 2023

Class	Season					
	Summer 2023			Winter 2023		
	NDMI		*Area (%)*	*NDMI*		*Area (%)*
	From	*To*		*From*	*To*	
Very Low	-0.34	-0.06	40.4	-0.24	-0.03	43.5
Low	-0.06	0.0003	42.8	-0.03	0.07	50.7
Moderate	0.0003	0.01	3.8	0.07	0.12	3.8
High	0.01	0.07	9.6	0.12	0.22	1.8
Very High	0.07	0.35	3.4	0.22	0.43	0.1

C. Soil Moisture

The results in Fig. 5 and Table III. show the percentage of soil moisture classification seasonal distribution over the northern governorates.

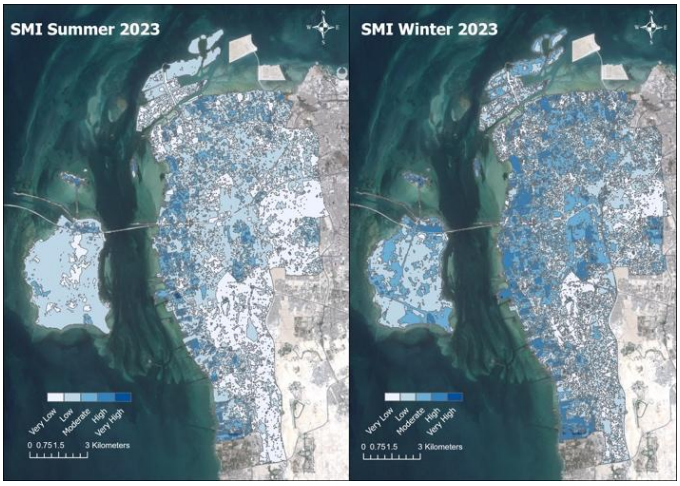

Fig. 4. SMI Classification Map for Summer & Winter 2023

TABLE III: SMI Classification Values for Summer & Winter 2023

Class	Season					
	Summer 2023			Winter 2023		
	SMI		*Area (%)*	*SMI*		*Area (%)*
	From	*To*		*From*	*To*	
Very Low	0.05	0.17	27.7	0.03	0.07	13.9
Low	0.17	0.24	45.1	0.07	0.09	36.9
Moderate	0.24	0.36	11.3	0.09	0.13	27.2
High	0.36	0.56	3	0.13	0.22	8.8
Very High	0.56	0.91	0.2	0.22	0.41	0.5

D. Soil Salinity

The results in Fig. 6 and TABLE. IV show the percentage of soil salinity classification seasonal distribution over the northern governorates.

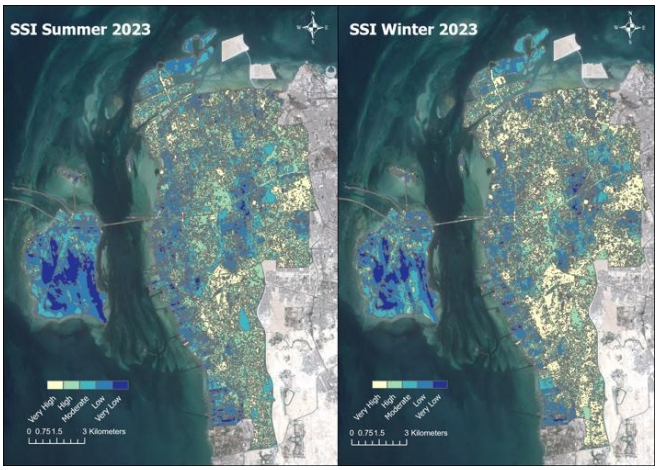

Fig. 5. SSI Classification Map for Summer & Winter 2023

TABLE IV: SSI Classification Values for Summer & Winter 2023

Class	Season					
	Summer 2023			Winter 2023		
	SSI		*Area (%)*	*SSI*		*Area (%)*
	From	*To*		*From*	*To*	
Very Low	0.16	0.27	5.2	0.18	0.33	3.2
Low	0.12	0.16	16.4	0.14	0.18	13.5
Moderate	0.09	0.12	23.9	0.11	0.14	19.7
High	0.06	0.09	29.7	0.08	0.10	27.8
Very High	-0.36	0.06	12.3	-0.11	0.08	23.1

E. Land Surface Temperature

The results in Fig. 7 and TABLE. V show the percentage of land surface temperature classification seasonal distribution over the northern governorates based on a manual classification that accounts for the seasonal variation of land temperature in Bahrain retrieved from the Meteorological Directorate datasets.

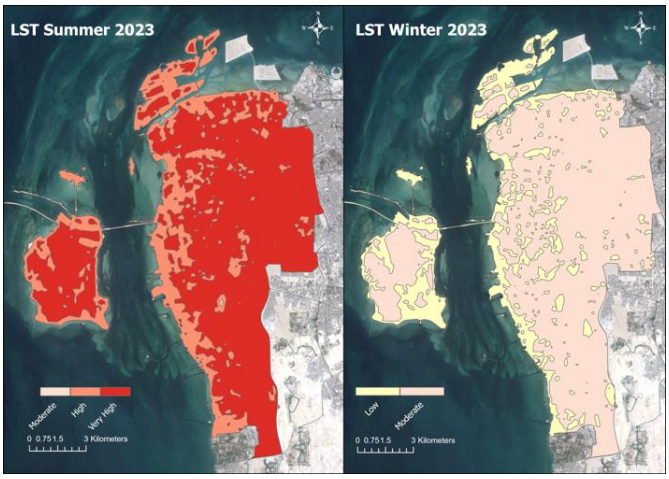

Fig 6. LST Classification Map for Summer & Winter 2023

TABLE V: LST Classification Values for Summer & Winter 2023

Class	LST Range		Summer 2023	Winter 2023
	From	*To*	*Area %*	
Low	18.52	22.92		21.5
Moderate	22.92	40	65.8	0.7
High	40.1	50	22.8	
Very High	50.1	57	63.9	

VI. Interpretation & Discussion

The four indices applied as well as the LST calculated provides insights on the distribution of agricultural-related qualities in the area. In terms of chlorophyll content, the NDCI analysis reveals seasonal variations in chlorophyll content, with lower values in summer ranging from -0.08 to 0.12 due to extreme heat and water stress [25]. In winter, NDCI values cover a broader range from -0.09 to 0.14, indicating improved vegetation health under cooler, less arid conditions, as vegetation can more effectively utilize available resources to support photosynthesis [26, 27]. However, persistent vegetation stress in both seasons underscores the challenges posed by Bahrain's arid climate, highlighting the need for seasonal monitoring and adaptive agricultural practices to optimize crop performance [28].

Vegetation water content in the form of NDMI index is consistent within both winter and summer season. Only a minor decrease is observed in NDMI maximum value where it dropped from 0.43 to 0.35 in winter and summer seasons, respectively. This is attributed to the fact that Bahrain is in an arid region with minimal rainfall per year [29], causing the average results of both seasons to be within a similar range.

Moving to soil moisture and salinity assessment in both seasons, comparing the highest values in winter and summer. The maximum SMI value increased from 0.413 in winter to 0.905 in summer. According to the UK Centre for Ecology & Hydrology and the Natural Environment Research Council, in cold climates, the infiltration process is reduced or stopped due to frozen soil [30].

According to [31], Bahrain's soil has been impacted by saline groundwater in the past and water pollutants, which based on the Supreme Council for Environment (SCE) in Bahrain. increases soil salinity [32]. Analysis shows that

TABLE VI: Correlation Coefficient (r) between indices for Summer and Winter 2023

Summer 2023		NDCI	NDMI	SMI	SSI	LST
	NDCI	X				
	NDMI	0.356	X			
	SMI	0.783	0.667	X		
	SSI	0.299	0.104	0.394	X	
	LST	-0.098	-0.349	-0.277	-0.022	X

Winter 2023		NDCI	NDMI	SMI	SSI	LST
	NDCI	X				
	NDMI	0.455	X			
	SMI	0.754	0.623	X		
	SSI	0.339	0.143	0.456	X	
	LST	-0.090	-0.323	-0.076	-0.046	X

salinity level increases when the SSI value decreases [21]. The highest salinity level value in winter is 0.076, compared to summer, which is 0.063. The results indicate an increase in salinity levels in winter by 17.1%. According to the FAO, regular and adequate irrigation removes salt particles in the soil [33].

The LST analysis demonstrates the average highest LST value starts at 50.1°C and the average lowest LST value starts at 18.5°C. According to the SCE, the climate in the summer season is very hot and humid, and it starts from July to September with an average temperature of 36°C [34]. In the winter, the climate varies from cool to mild with irregular rainfall with an average temperature of 10°C - 20°C; the seasons start from December to February [34]. The remaining months are warm, with an average temperature of 20°C - 30°C [34].

The correlation coefficient, Pearson (r), has been derived for all agricultural examined elements to provide further context into their relationships for agricultural purposes as seen in Table 6. The two parameters with the highest correlation identified is between NDCI and SMI in which they have an r of 0.783 for summer and 0.754 for winter, respectively. With this information derived, we can assess agricultural health dependencies with further in-situ measurement of soil moisture, land surface temperature, and chlorophyll content properties [35].

Another above moderate correlation identified is between SMI and NDMI with 0.667 at summer and 0.623 at winter, highlighting an interrelationship between moisture in the plant biomass and the soil [36]. Hence, it can be deduced that the usage of water resources for agriculture can be assessed based on either the vegetation biomass or soil moisture [37], facilitated by ground truth measurements to achieve so.

VII. Conclusion

This study highlights the potential of remote sensing technology, specifically with the use of Sentinel-2 and Landsat-8, to assess agricultural lands in Bahrain's Northern Governorate. Through the application of key remote sensing indices—NDCI, NDMI, SMI, and SSI—alongside LST, the seasonal dynamics of chlorophyll content in vegetation, leaf water content, soil moisture, and soil salinity were effectively monitored. The analysis of seasonal variations in chlorophyll content revealed lower NDCI values during the summer, whereas winter exhibited a broader range of NDCI values. The consistency in NDMI values between winter and summer emphasizes Bahrain's arid climate. The study also revealed a significant increase in soil moisture during the summer, despite the high temperatures, likely due to reduced evaporation during the cooler winter months. Soil salinity, conversely, showed a noticeable rise in the winter season. The LST analysis further provided valuable insights into the extreme temperatures experienced in the region. The correlation analysis demonstrated strong relationships between key indices, particularly between NDCI and SMI, offering a more integrated understanding of vegetation health and soil moisture dynamics. The findings of this study contribute to the ongoing efforts to enhance agricultural productivity in Bahrain, aligning with national goals for sustainability and food security. The study would benefit from future work that incorporates more extensive in-situ validation to strengthen the correlations observed, enhanced multi-sensor data calibration as well as advanced data modelling techniques.

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