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Spatio-Temporal Analysis of the Remote Sensing Ecological Index – A Case Study of the Favorable Agro-Ecological Zone in Northwest Morocco

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ABSTRACT

Agriculture has traditionally been one of Morocco's most important industries, providing the largest percentage of the nation's GDP (Gross Domestic Product). However, over the past two decades, the frequency and severity of Morocco's droughts have grown. These climate changes have a direct impact on essential crops in the country. Exploring the geographical and temporal evolution of the ecological quality is thus critical for the conservation of the natural environment. To achieve this, the present study attempted to evaluate seasonally the environmental quality in the most favorable agro-ecologic zone in Morocco, using remote sensing data, in the years 2001, 2011, and 2021. An index was created, called Remote Sensing Ecological Index (RSEI), which combines four ecological indicators, related to vegetation, humidity, heat, and dryness aspects. The results indicate that from 2011 to 2021, the RSEI values deteriorated the greatest, particularly during the winter months. In addition, vegetation and humidity were the parameters most affecting the RSEI index. Thus, the key drivers of the improvement in the environmental quality are the establishment of ecological policies, rules, and actions to maintain a sustainable environmental development.

Keywords: remote sensing ecological index, GIS, remote sensing, principal components analysis, statistical methods, agro-ecologic zone, environmental sustainability.

INTRODUCTION

Since the previous decades, the growing urbanization and overuse of resources have caused a number of ecological issues on environmental components, such as lack of water, deforestation, insufficient green space, a rise in urban heat islands, etc. (Bahi et al., 2016; Yang et al., 2021). These anthropogenic impacts, combined with climate change might endanger the achievement of environmental sustainability.

The African continent with its countries (such as Morocco) remains environmentally the most vulnerable one, with mainly rain-fed agriculture (World Wildlife Fund, 2002). This makes Africa extremely sensitive to changes in climatic variability, seasonal shifts, and rainfall patterns. Therefore, it is critical to employ accessible approaches and techniques to evaluate environmental quality in an African context.

Since data acquisition for ecological monitoring is complex and difficult on large scales, remote sensing technology combined with the Google Earth Engine platform became an efficient and accessible way used to assess the quality of the natural environment (Liu et al., 2021; Wang et al., 2023).

Due to its Mediterranean and Atlantic coastlines as well as its proximity to Europe, Morocco is in an exceptional geostrategic position. However, as a result of its dependency on natural resources, Morocco is particularly vulnerable to the effects of climate change. Flooding, droughts, desertification, coastline erosion, etc. are all rising issues in the country (World Bank, 2022). Thus, according to the Ministry of Agriculture, Maritime Fisheries, Rural Development, Water, and Forests, several agro ecological zones (AEZ) were defined in Morocco to describe the country's current agricultural and ecological conditions (Gommes et al., 2009). These AEZ are: favorable, intermediate, mountainous, unfavorable oriental, unfavorable south, and saharian zone.

The objective of this study was to evaluate (for the first time) the environmental quality of the favorable agro-ecological zone in Morocco, through a satellite index combining greenness, humidity, heat, and dryness factors. This index, called Remote Sensing Ecological Index (RSEI), was analyzed seasonally, in the years 2001, 2011, and 2021. Thus, the purpose of this research was to respond to the following scientific questions: How environmental quality in the study area has varied by season over the three years? What regions are the most impacted by quality changes? Which environmental indicators studied have the greatest impact on the RSEI model?

STUDY AREA

In this research, the favorable agro-ecological zone, selected as the study area, is located in the northwest of Morocco (Fig. 1). Its topography ranges from -38 m to 3300 m in elevation, where low altitudes are located in the Rharb plain (center and west of the area), the middle altitudes (up to 1000 m) are in the Meseta zone (southwestern part), while the high altitudes are both in the Rif Mountains (northern Morocco) and the Middle Atlas Mountains (south and southeast side of the study area). On the basis on the World Bank Group's Climate Change Knowledge Portal (CCKP), the annual precipitation in this geographic zone (especially the Rif mountains) reaches up to 800 mm/year, from 1991 to 2020 (World Bank, 2021). In addition, according to the Ministry of Agriculture, Maritime Fisheries, Rural Development, Water, and Forests data, this AEZ has the greatest contribution to national cereal production (the Rharb plain holds an important irrigation network) (Gommes et al., 2009 and references therein). The study area also includes the largest Moroccan economic cities, namely Casablanca, Rabat (the capital), Tangier, Kenitra, and Fez.

METHODOLOGY

Satellite data

As seen in the methodology flowchart (Fig. 2), remote sensing data were used to assess seasonally the ecological quality index RSEI in the study for the years 2001, 2011 and 2021. MODIS data, which is freely available, is an efficient tool to detect and evaluate ecological quality on a large scale. In this study, the three datasets (MOD11A2, MOD09A1, and MOD13A1) collected by Terra sensor were used to calculate the four necessary indicators that synthesize the RSEI index per season, for the years 2001, 2011, and 2021 (Table 1). All the MODIS images were extracted from the Google Earth Engine platform, after cloud

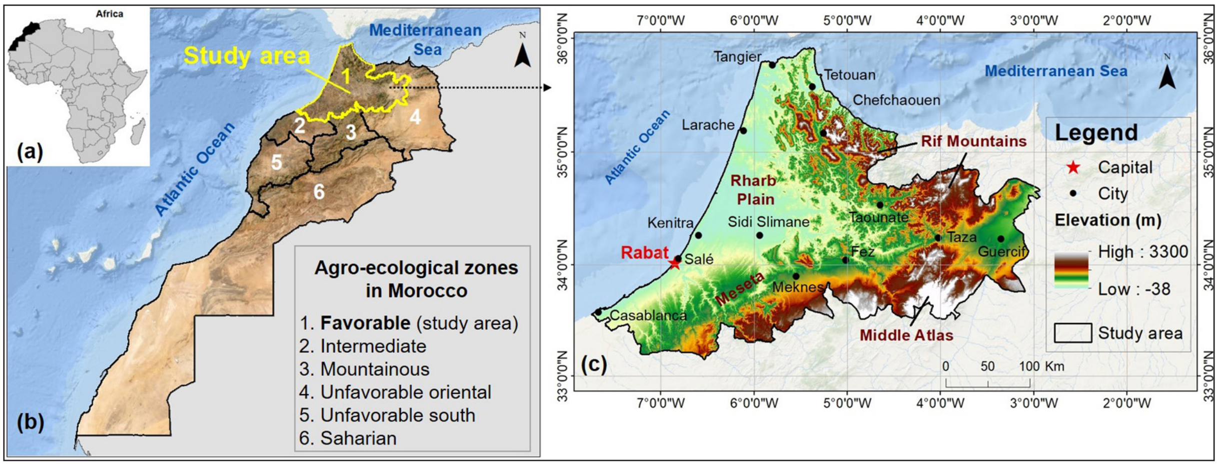

Figure 1. Location of the study area: a) Situation in the northwest of Africa, b) Location of the favorable agro-ecological zone (adapted from Gommes et al., 2009), c) Topographic map of the study area

Table 1. MODIS data products used in the study

MODIS product	Description	Temporal resolution	Spatial resolution	Index calculated
MOD11A2	A product of land surface temperature	8-Day	1 km (resampled to 500 m)	Land Surface Temperature (LST)
MOD13A1	A product of vegetation indices	16-Day	500 m	Normalized Difference Vegetation Index (NDVI)
MOD09A1	A product of surface reflectance of MODIS bands 1–7	8-Day	500 m	Normalized Difference Bare Soil Index (NDBSI)
				Wetness (WET)

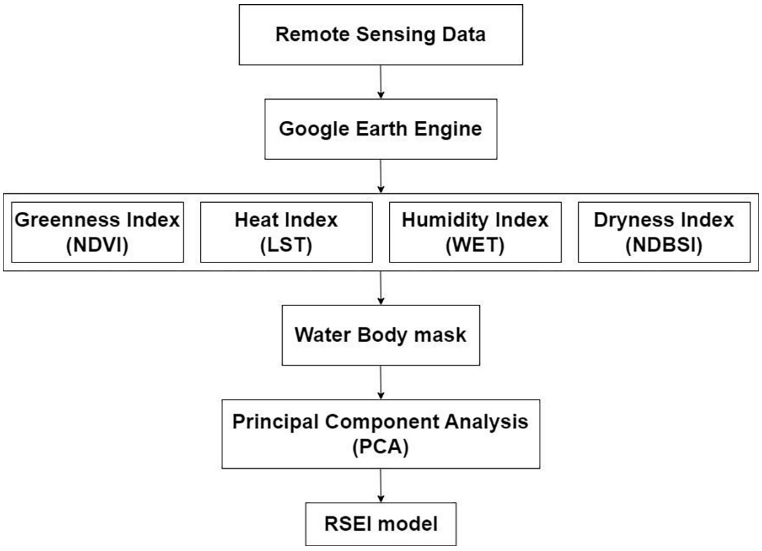

Figure 2. Methodology flowchart

removing, radiometric calibration and atmospheric correction. The seasonal images of 2001, 2011, and 2021 were selected according to the meteorological seasons (Winter: 1 December of the previous year to 28/29 February of the following year, Spring: 1 March to 31 May, Summer: 1 June to 31 August, Autumn: 1 September to 30 November). The MOD11A2, which provides an average 8 days of land surface temperature (LST) at 1000 m resolution, was resampled to 500 m, such as MOD09A1 and MOD13A1 resolution.

Construction of RSEI

In this research, the RSEI model was used to assess the environmental ecological status in the favorable agro-ecological zone of Morocco, using remote sensing data. This model, as proposed by (Xu, 2013), is based on four indicators related to greenness (vegetation), wetness (soil moisture), heat (temperature), and dryness (built-up area). These environmental indicators are directly associated with the ecological quality (Xiong et al, 2021) (Eq 1):

$$\mathrm{RSEI} = \mathrm{f(Greenness, Wetness, Heat, Dryness)} \quad (1)$$

Indicators used in RSEI

The four spatial indices used to assess the RSEI model are Normalized Difference Vegetation Index (NDVI), Wetness (WET), Land Surface Temperature (LST), and Normalized Difference Bare Soil Index (NDBSI). Water bodies extraction was applied to the four indicators before computing the RSEI model, using the Modified Normalized Difference Water Index (MNDWI). This water clipping ensures that the wetness component of the model accurately reflects the wetness in the study area (Xu, 2005). NDVI and LST extracted from MOD11A2 and MOD13A1 products are ready to be used (except for the LST resampling to 500 m resolution). The formulas of the calculated indicators are presented in Table 2.

Integration of the indicators

The RSEI was developed using GIS as a spatial tools and Principal Component Analysis

Table 2. Formulas of the used indicators in the RSEI model

Indicator	Formula	References
Wetness (WET)	$WET = \rho_{blue} * \beta_1 + \rho_{green} * \beta_2 + \rho_{red} * \beta_3 + + \rho_{NIR} * \beta_4 + \rho_{SWIR1} * \beta_5 + \rho_{SWIR2} * \beta_6$	(Lobser et al. 2007)
Normalized Difference Bare Soil Index (NDBSI)	$NDBSI = \frac{IBI + SI}{2}$ where $IBI = \frac{\frac{2\rho_{SWIR1}}{\rho_{SWIR1} + \rho_{NIR}} - \frac{\rho_{NIR}}{\rho_{NIR} + \rho_{Red}} - \frac{\rho_{Green}}{\rho_{Green} + \rho_{SWIR1}}}{\frac{2\rho_{SWIR1}}{\rho_{SWIR1} + \rho_{NIR}} + \frac{\rho_{NIR}}{\rho_{NIR} + \rho_{Red}} + \frac{\rho_{Green}}{\rho_{Green} + \rho_{SWIR1}}}$ and $SI = \frac{(\rho_{SWIR1} + \rho_{Red}) - (\rho_{NIR} + \rho_{Blue})}{(\rho_{SWIR1} + \rho_{Red}) + (\rho_{NIR} + \rho_{Blue})}$	(Mfondoum et al., 2016)
Modified Normalized Difference Water Index (MNDWI)	$MNDWI = \frac{\rho_{Green} - \rho_{SWIR}}{\rho_{Green} + \rho_{SWIR}}$	(Xu, 2005)

Note: ρ – the spectral reflectance of the corresponding MODIS band, β_i – the parameters of MODIS bands.

(PCA) as a statistical method, instead of the standard weighted sum techniques. Since the units and data ranges of indicators differ (e.g., LST in Celsius), it is important to normalize the values of all four indicators within [0,1] before using PCA. RSEI is generally represented by the first component of PCA (PC1), because this component explains generally most of the total dataset variation (Eq 2):

$$\text{RSEI} = \\ = \text{PC1 (Greenness, Wetness, Heat, Dryness)} \quad (2)$$

To unify the range of data, the RSEI values must be normalized and rescaled between 0 and 1, with 0 representing very poor environmental quality, and 1 an excellent environmental quality. The RSEI normalized values were then classified into 5 classes: Very poor: 0-0.2; Poor: 0.2, 0.4; Moderate: 0.4, 0.6; Good: 0.6, 0.8; Excellent:0.8,1 (Song et al., 2016). Then, the spatial distribution of RSEI results was performed by season, for the years 2001, 2011, and 2021.

RESULTS

RSEI indicators

Taking the year 2021 as an example, a spatial distribution of the four normalized indicators was realized before the RSEI calculation, to better understand indicators changing through the seasons (Fig. 3). The results show that the areas corresponding to high altitudes maintain low surface temperatures all year long. In summer, the Atlantic and Mediterranean coastal areas experience a thermal freshness due to their proximity to the sea. The west side of the agro-ecological zone keeps low values of vegetation and moisture, mainly due to the lack of greenness in these areas. The low values of NDBSI, corresponding to agricultural soil, became higher in summer and autumn. In general, this change in dryness indicates the end of the harvest season.

PCA results

The primary components' contribution rates resulting from the PCA calculation in 2001, 2011, and 2021 during the 4 seasons, are shown in Table 3. During all the dates, PC1 has a percent of eigenvalues larger than 71.32 (autumn 2011), which confirms that this component concentrated most of the characteristic information of the four indicators, compared to PC2, PC3, and PC4. Also, the contribution rate of PC1 is higher in spring than in the other seasons, which confirms that vegetation is an important component of RSEI (Xu & Deng, 2022).

In PC1 (Fig. 4), according to the indicator loadings in wet seasons (winter and spring) and dry seasons (summer and autumn), the four indicators can be classified into two categories: NDVI and WET in the first category, LST and NDBSI in the second. Vegetation indices contribution is negative in dry seasons, and positive in wet seasons. This is why PC1 in dry seasons (for the three years) was multiplied by (-1) to invert the scores.

Spatio-seasonal distribution of RSEI

On the basis of the spatio-seasonal distribution of RSEI during the studied three years (Figure 5), the results show that the western part of

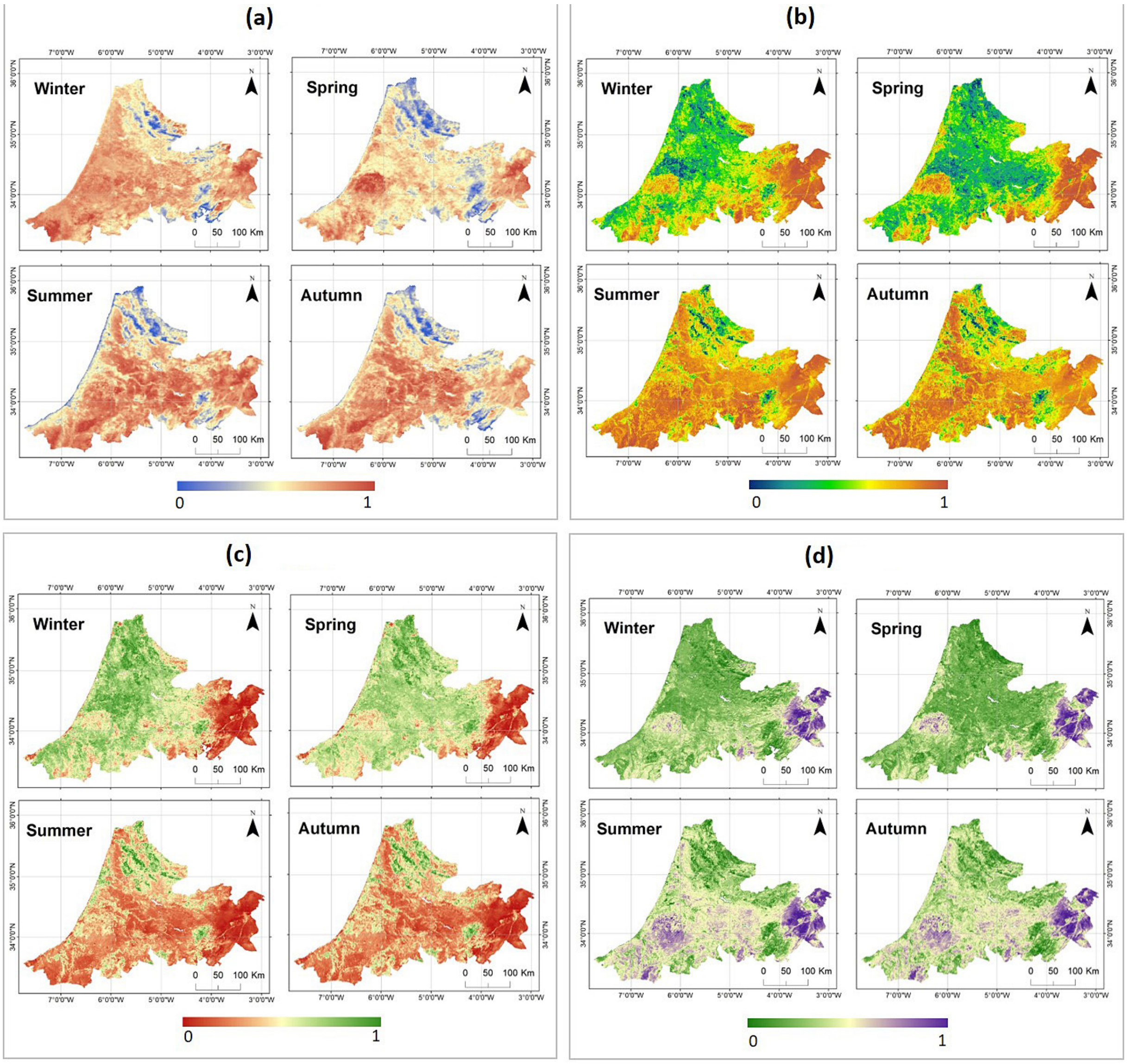

Figure 3. Spatial distribution of the normalized indicators; (a) nLST, (b) nNDBSI, (c) nNDVI and (d) nWET

Table 3. Principal component analysis results of RSEI in 2001, 2011, and 2021

Year	Season	Percent of EigenValues (%)			
		PC1	PC2	PC3	PC4
2001	Winter	77.7941	12.7047	6.2003	3.3008
	Spring	79.8314	10.9977	6.0360	3.1349
	Summer	75.1766	13.3391	7.9915	3.4928
	Autumn	71.3272	14.9235	10.5026	3.2468
2011	Winter	80.2140	12.1423	5.2822	2.3615
	Spring	82.5048	9.4781	5.4203	2.5968
	Summer	79.8532	9.2218	8.3910	2.5340
	Autumn	72.7641	14.3158	9.8880	3.0320
2021	Winter	79.5633	11.2562	5.1531	3.0274
	Spring	80.2478	12.0338	5.7050	3.0134
	Summer	78.6776	11.4479	7.4511	2.4233
	Autumn	72.9082	13.7434	10.1325	3.2159

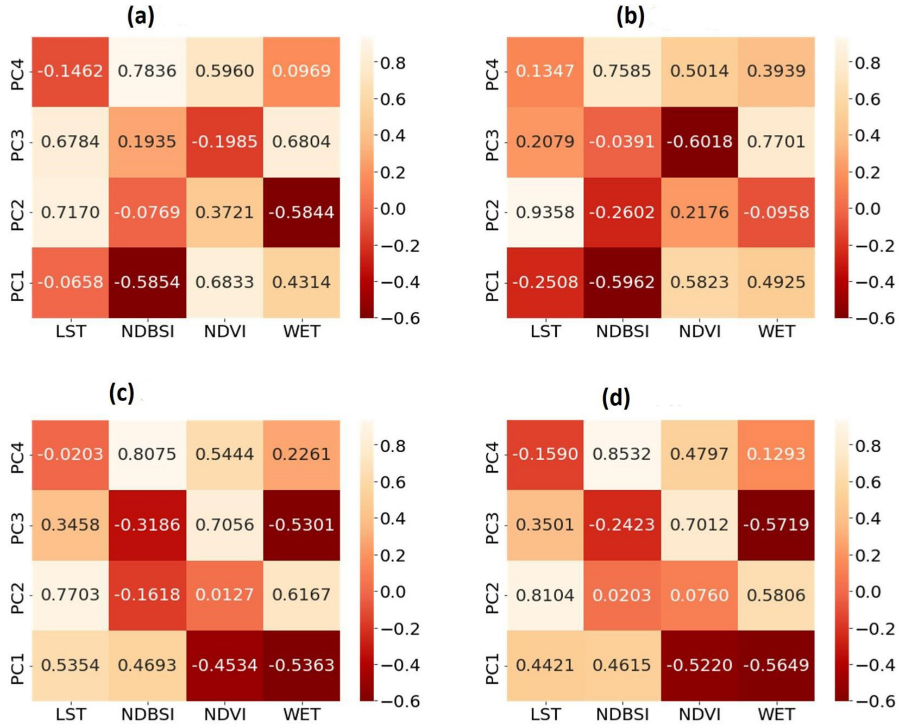

Figure 4. Indicator loadings on the 4 components; (a) winter, (b) spring, (c) summer, (d) autumn

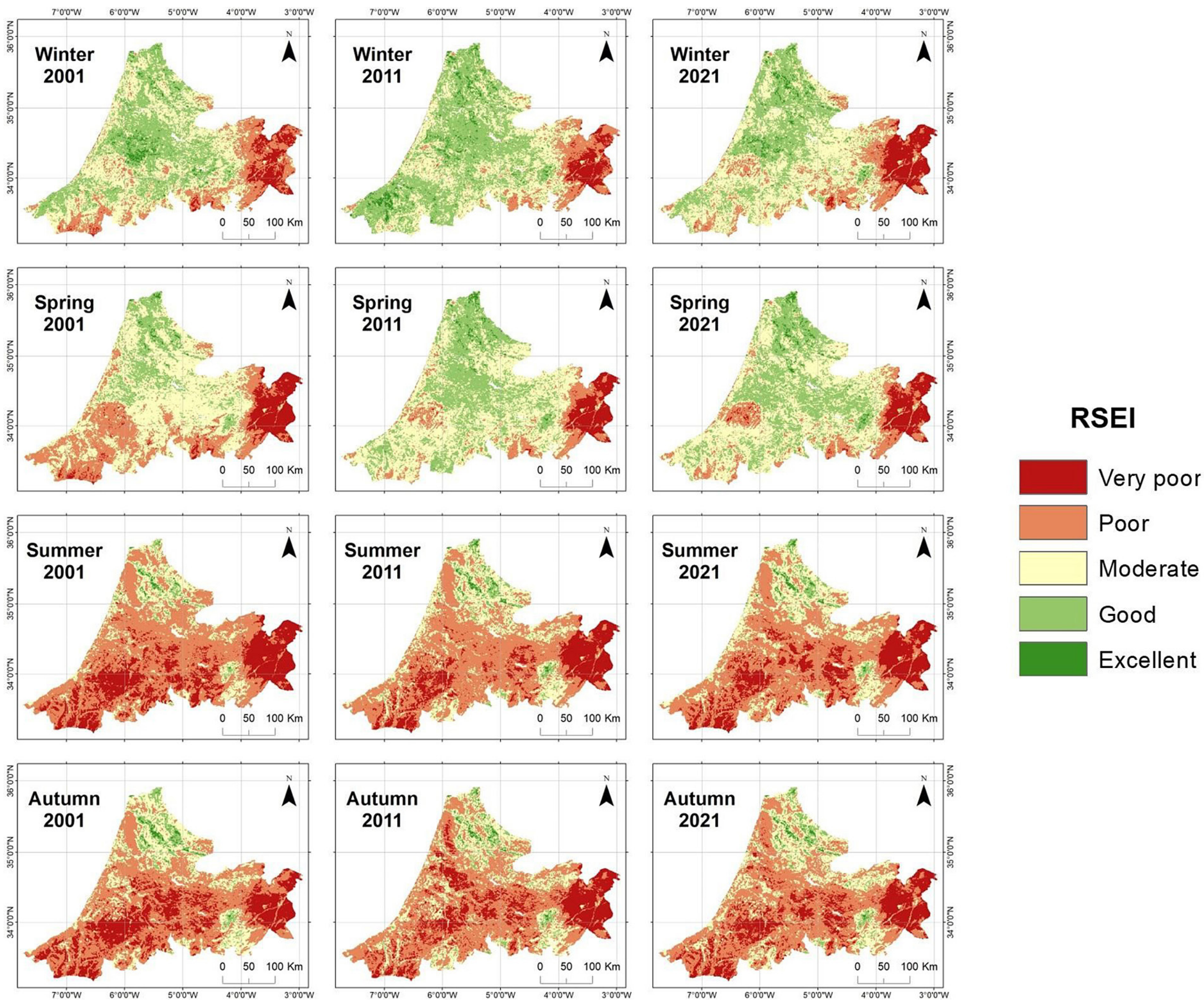

Figure 5. Spatio-seasonal distribution of the RSEI index for the years 2001, 2011, and 2021

the favorable agro-ecological zone maintained a poor environmental quality, during all the seasons. This base status is mainly due to the lack of vegetation in this area. The northern zones, corresponding to the high altitudes of the study area with an abundance of vegetation, maintained a good environmental quality, all season and year combined. Regarding the central and southern parts of the area, which is mainly agricultural, the environmental status changes according to the seasons; during wet seasons, they keep good quality. However, once the agricultural harvest period

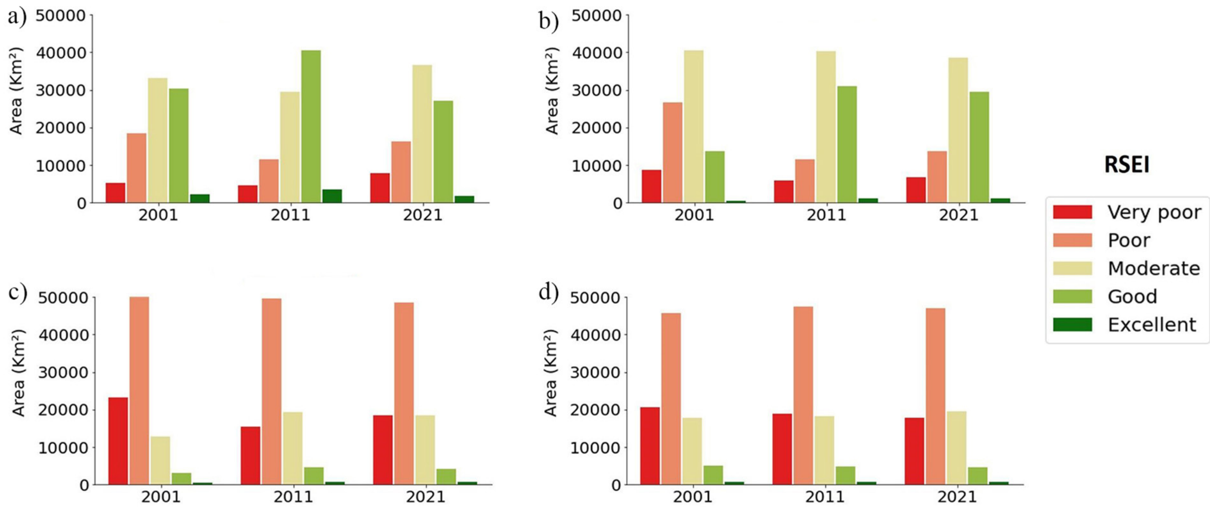

Figure 6. Area of each RSEI class per season in the 3 years of study; (a) winter, (b) spring, (c) summer, (d) autumn

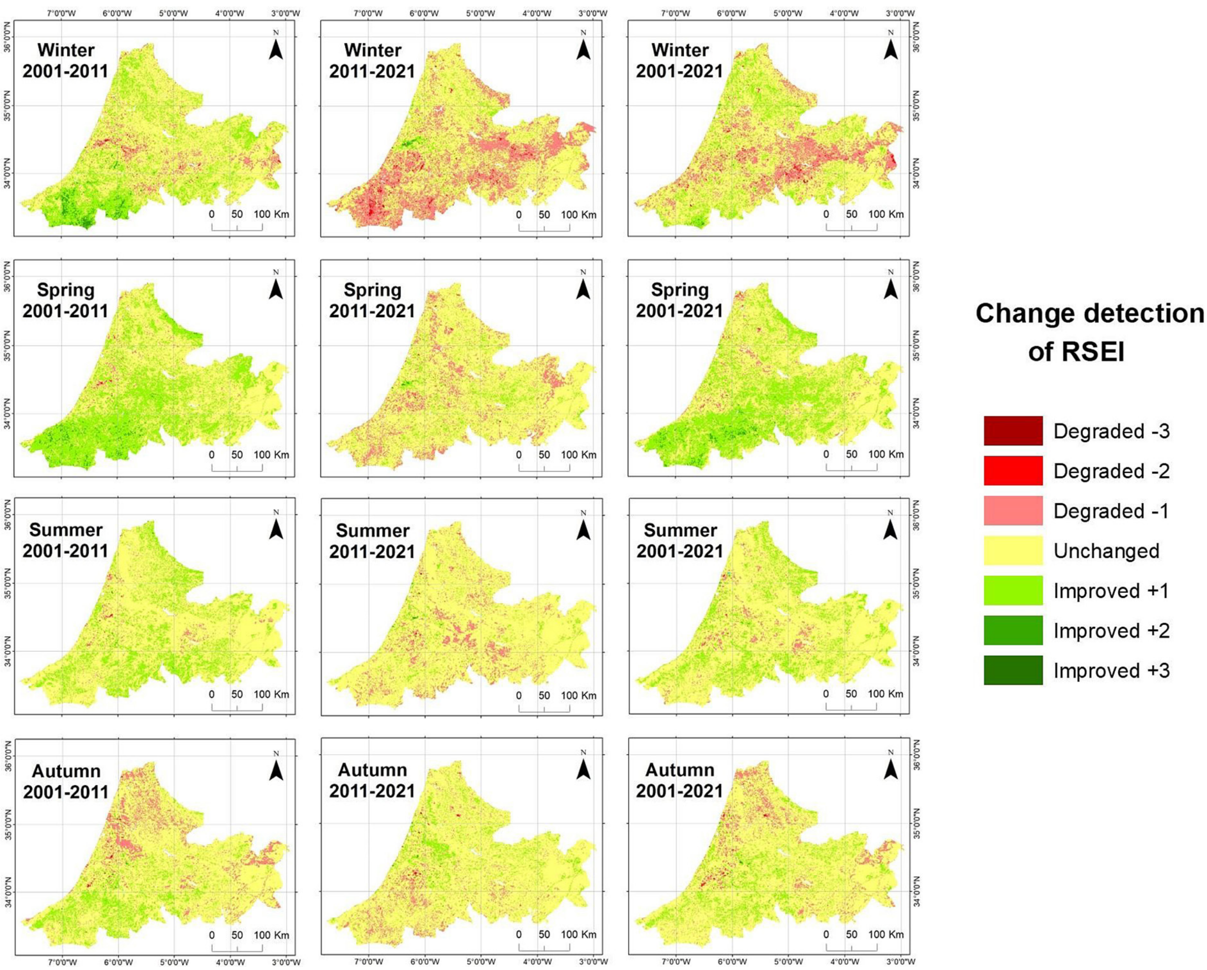

Figure 7. Spatio-seasonal distribution of the RSEI change detection

ends towards the end of spring, RSEI values become bad, because of the appearance of already cultivated soils considered bare soils.

Furthermore, the outcomes (Figure 6) demonstrate that wet seasons (winter and spring) correspond to periods of the year with the largest areas of good RSEI values. This is due to the positive impact of rainfall on vegetation and irrigation in agricultural areas. The year 2021 relates to the largest good RSEI superficies. However, the lack of precipitation in dry seasons and the end of agricultural seasons causes the lowest RSEI value, indicating a bad environmental quality.

Dynamic change analysis of RSEI

Figure 7 and Table 4 illustrate the spatio-seasonal change detection of RSEI in the favorable agro-ecological zone, and the season percent change of RSEI level in the 3 years. From 2001 to 2011, especially in winter, spring, and autumn, an improvement in the RSEI values was identified, mainly in the southwestern part of the area. In summer, the enhancement concerned dispersed zones throughout the whole area. However, the most degradation change located in the north, northeast, and west sides was noticed in the autumn season.

The change detection in winter from 2011 to 2021 was the most degraded, compared to the other years and seasons, with 35.598% of degradation percent change. This deterioration concerned almost 80% of the total study area. The other seasons also notice degradation changes in the RSEI values, ranging from 8.822% to 15.019% of degradation percent change, scattered throughout the favorable agro-ecological. From 2001 to 2021,

Table 4. Change seasonal detection of RSEI class from 2001 to 2021

Season	Class change	Level	2001–2011		2011–2021		2001–2021	
			Percent change %	Total percent change	Percent change %	Total percent change	Percent change %	Total percent change
Autumn	Degraded	-3	0.002	12.574	0.007	8.822	0.004	9.642
		-2	0.140		0.130		0.183	
		-1	12.432		8.685		9.455	
	Unchanged	0	72.816	-	80.195	-	76.579	-
	Improved	+1	14.495	14.610	10.888	10.983	13.618	13.778
		+2	0.113		0.091		0.160	
		+3	0.002		0.004		0.000	
Winter	Degraded	-3	0.009	8.066	0.028	35.598	0.016	22.068
		-2	0.274		1.328		0.806	
		-1	7.783		34.242		21.246	
	Unchanged	0	61.991	-	58.782	-	62.681	-
	Improved	+1	27.750	29.943	5.395	5.621	14.947	15.250
		+2	2.151		0.220		0.295	
		+3	0.042		0.006		0.008	
Spring	Degraded	-3	0.000	2.118	0.000	15.019	0.000	3.395
		-2	0.061		0.105		0.053	
		-1	2.057		14.914		3.342	
	Unchanged	0	53.787		75.727		56.807	
	Improved	+1	42.470	44.095	9.128	9.251	38.379	39.792
		+2	1.620		0.123		1.413	
		+3	0.005		0.004		0.007	
Summer	Degraded	-3	0.001	2.412	0.006	11.235	0.004	4,255
		-2	0.050		0.047		0.050	
		-1	2.362		11.182		4.201	
	Unchanged	0	74.382		83.587		76.767	
	Improved	+1	23.128	23.205	5.106	5.177	18.876	18,978
		+2	0.077		0.070		0.098	
		+3	0.000		0.001		0.005	

winter was the season the most affected by RSEI degradation, with 22.068% of deterioration percent. However, almost 40% of the RSEI values were improved in spring, mainly located in the south and the east-south part of the study area.

DISCUSSION

In order to study the relationships between the RSEI model and the four indicators (NDVI, WET, LST, and NDBSI), a 1 km x 1 km unit grid was created to secure the integrity of the scale information and to explore the final RSEI representation. A total of 88906 points were generated through this grid. These points were used in a stepwise regression to assess the quantitative correlation of the RSEI index with the four indicators. Also, a three-dimensional scatter plot of the year 2021 showing the relationships between RSEI and each indicator was produced (Fig. 8). The green areas with the highest ecological quality are represented at the top of the scatter plot. However, the red parts of the 3D scatter plot are related to the zones with poor environmental quality. The results show that, on one hand, NDVI and WET indices are positively correlated to the environmental quality of the study area for all the seasons. On the other hand, the increase of LST and NDBSI values decreases the ecological quality, even in wet or dry seasons. This indicates that LST and NDBSI are negatively correlated with environmental quality.

According to the regression coefficients for the absolute value of each indicator (Table 5), the ecological quality of the study area was, in wet seasons, mostly influenced by NDVI, followed by WET, NDBSI and LST. In dry seasons, the ecological quality is affected first by WET index, then NDVI, NDBSI and LST. In general, vegetation indices are predominant in the environmental quality of the study area. Thus, in order to better face climate change impacts, the environmental decision-makers should consider expanding more green areas, protecting wetlands and water resources, and promoting ecologic agriculture as a perspective to maintain a sustainable environmental quality in the favorable agro-ecological zone in Morocco.

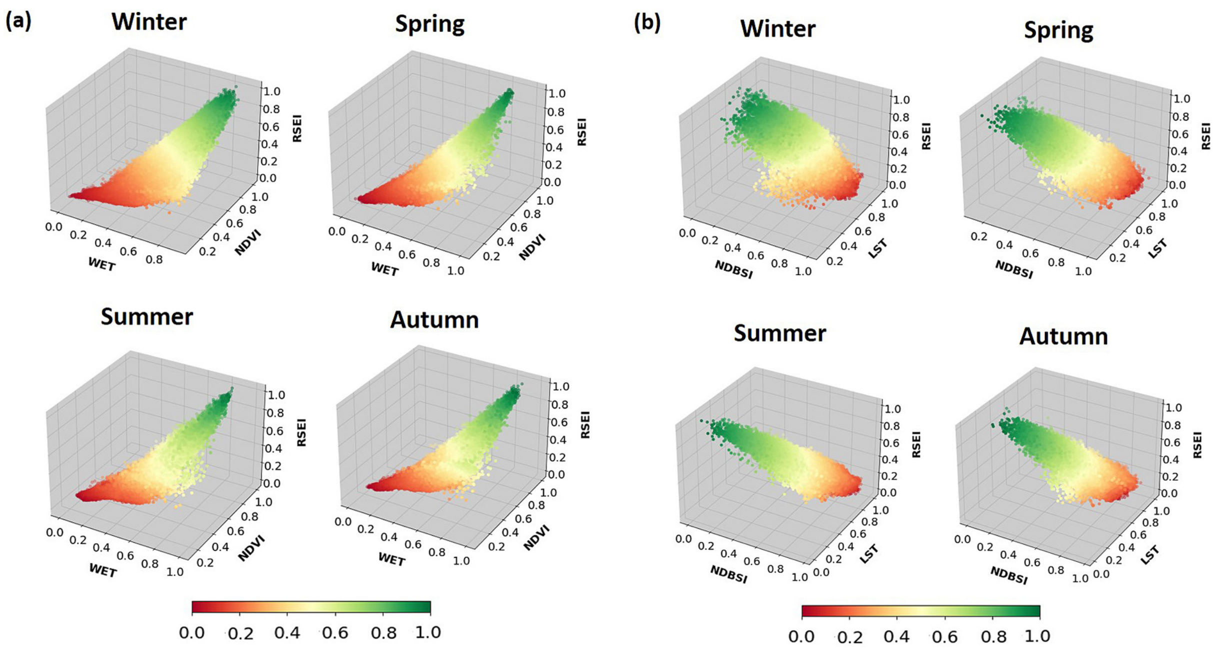

Figure 8. Seasonal 3D scatterplots of the relationship between the RSEI index and the four indicators for the year 2021; (a) RSEI, NDVI and WET, (b) RSEI, LST and NDBSI

Table 5. Regression model equations by season for the year 2021

Season	Regression model equation
Winter	RSEI = 0.466 NDVI + 0.294 WET – 0.044 LST – 0.399 NDBSI + 0.329
Spring	RSEI = 0.384 NDVI + 0.324 WET – 0.165 LST – 0.393 NDBSI + 0.420
Summer	RSEI = 0.286 NDVI + 0.338 WET – 0.337 LST – 0.296 NDBSI + 0.484
Autumn	RSEI = 0.360 NDVI + 0.389 WET – 0.305 LST – 0.318 NDBSI + 0.402

CONCLUSIONS

To assess the environmental quality of the favorable Moroccan agro-ecological zone, the RSEI model was adopted by combining four indicators related to greenness, wetness, heat, and dryness. Remote sensing technology, especially MODIS products, was used to extract the satellite indicators. Spatio-temporal prospection of the RSEI index was employed for the years 2001, 2011, and 2021 for all the seasons. According to the results, the RSEI values degraded the most from 2011 to 2021, especially in the winter season. This may be mainly due to climate change impacts, principally the rarity of precipitation that Morocco is facing this last decade. In addition, the findings of this research indicate that vegetation and wetness are the ecological parameters influencing greatly the environmental quality of the study area. For those reasons, in order to maintain a good environmental quality of the study area which is the most favorable agro-ecological of the country, ecological sustainability plans should focus on more green planning practices. Decision-planner policies must also aim to protect wetlands and water sources in strategic areas, to face the potential impact of climate change as much as possible.

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