INTRODUCTION

Animals live and move in heterogeneous environments [Johnson et al., 1992]. This heterogeneity affects not only resources such as food, shelter, breeding sites and partners, but also the impact of climate change [Rai et al., 2012]. Given this heterogeneity, the distribution of organisms is often non-random, resulting from the habitat selection processes that are almost universal in the animal kingdom. Understanding the habitat selection process and its structuring (spatial and temporal) is therefore essential, reflecting the structuring of potential population-limiting factors [Northrup et al., 2022]. The partridge is an emblematic bird species of agricultural heritage. It is one of the most common bird species found in agricultural environments [Emmerson et al., 2016]. Its importance is both cultural and socioeconomic [Chattopadhyay et al., 2021]. Today, it enjoys an unfavorable conservation status due to a marked decline in abundance throughout the area in which it is native, and the origins of this decline in the partridge have been extensively
Several studies have shown that the relationship between NDVI and LST can be used to detect signs of climate change, environmental degradation, exaggerated weather events, anthropogenic activities such as agricultural practices, and changes in terrestrial ecosystems [Sandholt et al., 2002; Fontanelli et al., 2012; Tariq et al., 2020; Allam et al., 2021; Ullah et al., 2023]. On the other hand, the images obtained from satellites can be used to map LST and NDVI on a large scale, allowing analysis of long-term trends and changes in the land cover and land surface temperature [Li et al., 2019; Parmar et al., 2022]. Several techniques can be used to estimate land surface temperature from remote sensing data. One of these is the brightness temperature (BT) method, which represents the temperature at which a surface would emit thermal energy if it behaved like a perfect black body. To apply this method [Nguyen et al., 2019; Xing et al., 2021; Nasiri et al., 2022], the data from the thermal infrared bands of satellite images is required [Sajib and Wang, 2020].

The conceptualization of the ecological niche and its subsequent modeling constitute the foundational underpinning for the majority of methodologies crafted to prognosticate the spatial distribution of species [Fabri-ruiz 2019; Brier and lia-dwi, 2020]. The species niche modeling is essential for biodiversity conservation, particularly for endemic and rare species. It is particularly important in the context of environmental change [Toffa et al., 2022]. Maxent (maximum entropy) is an ecological niche modeling model widely used to predict the geographic distribution of species as a function of presence data and environmental variables [Urbani et al., 2017]. It has gained popularity in recent years due to its power and ease of use. One of Maxent’s key features is its ability to project and generate the probability maps showing how the potential distribution of a species would change under different scenarios of climate change or changes in environmental variables [Chikerema et al., 2013]. This capability makes it a valuable tool for assessing how species’ habitats might evolve in the present and future [Tang et al., 2021].

This research focused on the multi-temporal relationship LULC, NDVI and LST in the areas influenced by climate change with so many droughts on the one hand and anthropogenic effects on the other, knowing that this region is characterized by a specific geographical space and a very fragile natural environment [Karnieli et al., 2010; Ogunjobi et al., 2018; Gogoi et al., 2019]. During the study period, the land cover map of study area was obtained by the supervised likelihood classification method, while the LST and NDVI calculations are based on the data collected by the Landsat sensors in addition; this manuscript has a triple objective. Firstly, the aim of the project was to analyze the spatial and temporal distribution patterns of surface temperature in the study area. Secondly, it sought to examine the correlation between surface temperature and its determinants in various land use categories. Thirdly, it aimed to establish a correlation...
between ground surface temperature and the normalized difference vegetation index, with a view to predicting the impact of this temperature on the current and future geographical distribution of partridge ecological niches. This study represents the first initiative to assess the consistency of the relationship between LST and NDVI on the one hand and to collect the data on the spatio-temporal evolution of these variables in the city of Meknes (Morocco) on the other hand, with the aim of building a database that can be used in current and future modeling of the ecological niches of different species.

MATERIALS AND METHODS

Description of the study area

According to the latest administrative division of 2015, the prefecture of Meknes is part of the Fez-Meknes region; it covers an area of 1786 km², occupies a strategic geographical position, is located on the Saïs plateau between two sets of mountains of the Pre Rif and the Western Middle Atlas, and its territory is crossed by the valley of the Oued Boufakrane (Figure 1). According to the most recent data from the 2014 general population and housing census, the legal population of the prefecture in the majority urban area reached 835,695 inhabitants in 2014 with a density of 468 inhabitants per km², among whom 82.3% live in urban areas [Ayanlade et al., 2021]. The region is the second-largest regional metropolis and occupies a very strategic position. In addition to this geographical location, the region offers important economic potential; the fertile plains of Saïs, coupled with abundant water resources, promote human habitation and the establishment of extensive communication networks [Mohajane et al., 2018; Ayanlade et al., 2021].

Data

The USGS Earth Explorer website is a platform used to access a variety of geospatial data; it comprises satellite imagery from a variety of sensors, including Landsat 7 (ETM+) and Landsat 8 (OLI/TIRS). For the research area, this was taken between May 2000 and 2021. Each dataset was pre-processed and projected using the universal projection technique (UTM). The characteristics of the satellite data are presented in Table 1 [USGS 2022]. For this study, all bioclimatic and elevation variable layers were obtained from the WorldClim database at the highest spatial resolution (30 arc seconds (~1 km)). All these layers were processed using QGIS 3.26.3. Partridge distribution data for the study area was gathered through a combination of information sourced from the Global biodiversity information facility (GBIF) at https://www.gbif.org and in situ data in the study area. The application of the Maxent model was employed to ascertain the environmental factors shaping the distribution of partridge and to model the current geographic distribution zones of the species.

Methods

To achieve the study objectives, three fundamental measures were implemented. The initial step involved the identification of LULC types within the research area. The second step was to
Table 1. Characteristics of the primary/satellite data used in the present study

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Date</th>
<th>Resolution</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat-7 ETM+</td>
<td>May 2000</td>
<td>30 m</td>
<td>USGS Earth Explorer</td>
</tr>
<tr>
<td>Landsat-7 ETM+</td>
<td>May 2010</td>
<td>30 m</td>
<td>USGS Earth Explorer</td>
</tr>
<tr>
<td>Landsat-8 OLI/TIRS</td>
<td>May 2021</td>
<td>30 m</td>
<td>USGS Earth Explorer</td>
</tr>
</tbody>
</table>

extract the NDVI for analysis. The third step entailed the extraction of LST from thermal band images of Landsat 7 ETM+ and Landsat 8 OLI/TIRS [Chen et al., 2013]. A statistical analysis of NDVI in conjunction with LST was subsequently employed to assess the changes in LST in correlation with NDVI and, ultimately, to examine its relationship with the different LULC classes [Alademomi et al., 2022]. Figure 2 displays all of the specific methodologies employed in the study.

All acquired images were selected for processing using QGIS 3.26 software. These images were subjected to a supervised classification process by means of the maximum likelihood classification (MLC) method. This process was used for the classification and identification of different types of land use and land cover (LULC) in the study area during the specified period [Viana et al., 2019].

The Landsat 7 ETM+ thermal band 6 and Landsat 8 TIRS bands 10 and 11 were used to determine LST. The four processes listed above must be followed in order to determine the LST using these bands (Table 2) [USGS 2022].

Transforming DN into Spectral Radiance involves applying specific equations provided by the satellite sensor’s calibration coefficients. These coefficients vary depending on the sensor and band being used. The equations typically include such factors as gain, offset, and radiometric rescaling parameters [Mujabar 2019]. The pixels of the images are transformed into absolute radiance units according to equation 1 [Ogunjibi et al., 2018].

$$[L_x = \text{Grescale} \times QCAL + \text{Brescale}] \quad (1)$$

The equivalent equation was used for the calculation according to the following formula:

$$L_x = ([LMAX_x - LMIN_x] / [QCALMAX - QCALMIN]) \times [QCAL - QCALMIN] - LMIN_x) \quad (2)$$

where: $L_x$ – spectral radiance at the sensor aperture (W/(m²·sr·μm)); QCAL – quantized calibrated pixel value (DN); LMINX – Spectral radiance scaled to QCALMIN (W/(m²·sr·μm)), and represented the

Figure 2. The specific methodologies of the study
Table 2. Description of Landsat 7 (ETM+) and Landsat 8 (OLI & TIRS)

<table>
<thead>
<tr>
<th>No</th>
<th>Band Name</th>
<th>Resolution (m)</th>
<th>Wavelength (Micrometers)</th>
<th>Band Name</th>
<th>Resolution (m)</th>
<th>Wavelength (Micrometers)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Blue</td>
<td>30</td>
<td>0.435–0.451</td>
<td>Ultra-Blue (coastal/aerosol)</td>
<td>30</td>
<td>0.435–0.451</td>
</tr>
<tr>
<td>2</td>
<td>Green</td>
<td>30</td>
<td>0.52–0.60</td>
<td>Blue</td>
<td>30</td>
<td>0.452–0.512</td>
</tr>
<tr>
<td>3</td>
<td>Red</td>
<td>30</td>
<td>0.63–0.69</td>
<td>Green</td>
<td>30</td>
<td>0.533–0.590</td>
</tr>
<tr>
<td>4</td>
<td>NIR</td>
<td>30</td>
<td>0.77–0.90</td>
<td>Red</td>
<td>30</td>
<td>0.636–0.673</td>
</tr>
<tr>
<td>5</td>
<td>SWIR1</td>
<td>30</td>
<td>1.55–1.75</td>
<td>NIR</td>
<td>30</td>
<td>0.851–0.879</td>
</tr>
<tr>
<td>6</td>
<td>Thermal</td>
<td>60°(30)</td>
<td>10.40–12.50</td>
<td>SWIR1</td>
<td>30</td>
<td>1.566–1.651</td>
</tr>
<tr>
<td>7</td>
<td>SWIR2</td>
<td>30</td>
<td>2.09–2.35</td>
<td>SWIR2</td>
<td>30</td>
<td>2.107–2.294</td>
</tr>
<tr>
<td>8</td>
<td>Panchromatic</td>
<td>15</td>
<td>0.52–0.90</td>
<td>Panchromatic</td>
<td>15</td>
<td>0.503–0.676</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td></td>
<td></td>
<td>Cirrus</td>
<td>30</td>
<td>1.363–1.384</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td>TIRS1</td>
<td>100°(30)</td>
<td>10.60–11.19</td>
</tr>
<tr>
<td>11</td>
<td></td>
<td></td>
<td></td>
<td>TIRS2</td>
<td>100°(30)</td>
<td>11.50–12.51</td>
</tr>
</tbody>
</table>

The picture pixels are transformed into absolute radiance units [Bodart et al., 2011]. Formula 3 can be expressed as follows:

\[ L_\lambda = ML \times \text{QCAL} + AL \] (3)

where: \( L_\lambda \) – represents the spectral radiance at a given wavelength \( \lambda \), expressed in \( \text{W/} \) \( \text{m}^2 \cdot \text{sr} \cdot \mu\text{m} \); \( ML \) – the slope coefficient, also known as the radiometric calibration slope. It represents the linear relationship between the quantized pixel values (QCAL) and the spectral radiance. The slope coefficient is expressed in \( \text{W/} \) \( \text{m}^2 \cdot \text{sr} \cdot \mu\text{m} \)/DN; \( \text{QCAL} \) – this is the quantized pixel value, expressed in digital numbers (DN). It is a discrete measurement that represents the intensity of light captured by the sensor for a specific pixel. \( AL \) – this is the offset or intercept of the radiometric calibration. It represents a constant shift that is added to the QCAL value to obtain the corresponding spectral radiance. This is expressed in \( \text{W/} \) \( \text{m}^2 \cdot \text{sr} \cdot \mu\text{m} \).

To calculate the absolute radiance of a specific pixel, the calibrated pixel value \( Q_{\text{CAL}} \) is multiplied by the multiplicative gain factor \( M_1 \) and then the additive offset \( A_1 \) is added. These specific values \( M_1 \) and \( A_1 \) depend on the calibration process and the imaging system used. Absolute radiance calculation allows quantitative analysis and interpretation of the image data in terms of radiometric measurements [Mohajane et al., 2018].

**Estimation of land surface emissivity**

Land surface pixels in satellite pictures are frequently mixed pixels, which means they contain elements of several surface types, including water, plants, and soil. The NDVI threshold approach was used to determine the emissivity of the land surface. This was done using satellite thermal band data. NDVI is used to assess the degree of vegetation cover by analyzing red and near-infrared (NIR) reflectance values to distinguish between the vegetated and non-vegetated areas. The NDVI can be calculated according to equation 4, with the utilization of bands 3 and 4 for the Landsat 7 imagery and bands 4 and 5 for the Landsat 8 imagery [Ayanlade et al., 2021].

\[ \text{NDVI} = (\lambda_{\text{NIR}} - \lambda_{\text{RED}})/(\lambda_{\text{NIR}} + \lambda_{\text{RED}}) \] (4)

\( \lambda_{\text{NIR}} \) and \( \lambda_{\text{RED}} \) represent the reflectance values in the near-infrared (NIR) and red bands, respectively. The NDVI measurements were used to calculate the proportion of vegetation (PV) in accordance with equation 5 [Yue et al., 2007]:

\[ \text{PV} = (\text{NDVI} - \text{NDVimin})/(\text{NDVimax} - \text{NDVimin})^2 \] (5)
NDVI<sub>max</sub> represents the NDVI value for densely vegetated land cover, whereas NDVI<sub>min</sub> corresponds to the NDVI value for non-vegetated land cover. The resulting PV values range from 0 to 1, with 0 corresponding to no vegetation and 1 to complete vegetation cover (Table 3). These values can be used to estimate the emissivity value of the land surface under the following conditions (Eq. (6)).

\[ \varepsilon = \begin{cases} 
\varepsilon_v \cdot PV + \varepsilon_s (1 - PV) + C_s \cdot 0.2 \leq \text{NDVI} \leq 0.5 \quad (6) \\
\varepsilon_v + C_s \cdot \text{NDVI} > 0.5 \end{cases} \]

where: \( \varepsilon_v \) – the emissivity of the vegetation component. It represents the emissivity of the vegetation cover; \( \varepsilon_s \) – the emissivity of the non-vegetated (soil) component. It represents the emissivity of the bare ground or non-vegetated surface; \( PV \) – the vegetation cover fraction or vegetation proportion. It represents the proportion of an area that is covered by vegetation. It ranges from 0 to 1, where 0 indicates no vegetation and 1 indicates full vegetation cover; \( C_s \) – the emissivity constant or offset, \( C_s = (1 - \varepsilon_v) (1 - \varepsilon_s) \).

Emissivity values can vary depending on many factors, such as vegetation type, soil composition, wavelength, temperature, and environmental conditions. Table 3 shows some typical emissivity values for vegetation and bare soil.

### Brightness temperature calculation

The brightness temperature (BT) is an approximation of the actual temperature that is measured by a satellite sensor. The Planck equation is commonly used, which relates the spectral radiance (\( L_\lambda \)) of a surface at a given wavelength to the brightness temperature [BT; Qin and Karmeli, 1999]. It is expressed as follows (Eq. (7)).

\[ BT = ((K_2 / (\ln((K_1/L_\lambda) + 1)) – 273.15 \quad (7) \]

where: \( BT \) – is the actual sensor brightness temperature; \( K_1 \) – calibrating constant 1; \( K_2 \) – calibrating constant 2; \( L_\lambda \) – the spectral radiance.

To obtain results in Celsius, the radiation temperature is corrected by adding absolute zero (-273.15°C) (Table 4) [Qin and Karmeli, 1999].

### Estimation of LST

Equation 8 is one of the common methods for estimating land surface temperature from brightness temperature (BT) [Sajib and Wang, 2020].

\[ \text{LST} = \frac{BT}{(1 + \lambda \cdot (BT/\rho) \cdot \ln(\varepsilon_\lambda))} \quad (8) \]

where: \( \text{LST} \) – represents the land surface temperature; \( BT \) – represents the brightness temperature in Celsius (°C); \( \lambda \) – the wavelength at which the measurement is made, usually expressed in (μm); \( \rho \) – the spectral density of the radiation emitted by the blackbody at temperature BT, expressed in (W/(m²-sr-μm)); \( \ln \) – the neperian logarithm function; \( \varepsilon_\lambda \) – the spectral emissivity, which represents the ability of an object or surface to emit thermal radiation at a given wavelength.

This equation takes into account the influence of surface emissivity and atmospheric effects on the brightness temperature-land temperature relationship.

### Table 3. Land surface emissivity of Landsat 7 and 8 thermal bands

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Bands</th>
<th>Vegetation</th>
<th>Soil</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat 7 ETM +</td>
<td>Band 6</td>
<td>0.99</td>
<td>0.973</td>
</tr>
<tr>
<td>Landsat 8 Oli/TIRS</td>
<td>Band 10</td>
<td>0.984</td>
<td>0.97</td>
</tr>
</tbody>
</table>

### Table 4. K1 and K2 value for Landsat 7 ETM+ and Landsat 8 TIRS bands

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Landsat 7 ETM+</th>
<th>Landsat 8 TIRS bands</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band</td>
<td>Band 6</td>
<td>Band 10</td>
</tr>
<tr>
<td>K1</td>
<td>666.09</td>
<td>1321.08</td>
</tr>
<tr>
<td>K2</td>
<td>1282.71</td>
<td>777.89</td>
</tr>
</tbody>
</table>
Statistical analysis

To assess the most significant variables, statistical analysis is crucial. The NDVI and LST were subjected to statistical methods for evaluation by extracting data points from the pixel values of the LST and NDVI images in this study. In total, 1200 sample points were chosen for each study period. The outcomes of the linear regression analysis were then used to create the scatterplots.

RESULTS AND DISCUSSION

LULC mapping

Using the Landsat images from the USGS archive, variation in the different land use and land cover classes was detected throughout the study period (2000, 2010 and 2021). The application of the maximum likelihood supervised classification algorithm on Landsat imagery facilitated the identification and mapping of distinct LULC classes and detection of the changes that have

Figure 3. Land use land cover classification map for the year 2000, 2010 and 2021 and percentage of change statistics
occurred in space and time. The results obtained are shown in Figure 3.

According to the statistical analysis carried out, the LULC classes that showed the majority of changes are as follows: there was a reduction in the areas covered by the dense vegetation (-0.46%), sparse/shrubby vegetation (-1.48%), plantations (-1.05%), barren/rocky land (-3.12%), and barren land (-3.15%) classes. In contrast, there was an increase in the areas devoted to agriculture (0.71%), moderately dense forest (0.78%), and built-up areas (7.67%) (Table 5).

The results obtained indicate significant changes in LULC classes over the study period. These changes can be explained by various environmental, socio-economic, and anthropogenic factors, further studies, such as field surveys and socio-economic analyses, were carried out for a more in-depth understanding of the factors responsible for the observed variations.

The decline observed in the Dense Forest, Sparse/scrub, Plantation, Barren/Rocky and Barren classes can be attributed to such processes as climate change, deforestation, urbanization, and the conversion of natural land into barren or artificial areas.

The increase in agricultural, medium-density forest and built-up classes can be explained by such factors as agricultural expansion, population growth and urbanization, while the increase in agricultural land can be due to the conversion of forest land, the introduction of new agricultural practices or the expansion of cash crops. The increase in built-up and urban areas can be due to rapid urbanization, industrial and residential development as well as infrastructure expansion.

### Effects of LULC change on NDVI

Figure 4 presents the NDVI images of the Meknes watershed for the years 2001, 2010 and 2021. The obtained NDVI values vary from -0.5 to 0.48 in 2001, -0.65 to 0.55 in 2010 and -0.20 to 0.65 in 2021 (Table 6). Negative to near-zero values generally indicate low vegetation density, while values near 1 indicate high vegetation density and healthier vegetation. These NDVI readings make it possible to compare the vegetation cover in the Meknes catchment over time and to detect possible changes or variations in vegetation density between the different years studied.

### Spatio-temporal patterns in LST dynamics

Land surface temperature derivation from the studied region showed substantial spatial and temporal variation. The maps in Figure 5 show that the temperature range from 15.85 to 36.20°C in 2000, 12.76 to 38.24°C in 2010 and 25.73 to 47.79°C in 2021 (Table 7). In turn, the areas with increasing temperatures were indicated in red, the regions with dense plant cover were highlighted in blue as having lower temperatures. The results were in line with the regression analysis, which showed that the surface temperatures of populated areas and arid terrain were higher than those of regions with bodies of water and vegetation.

### Exploring the correlation between NDVI dynamics and LST

Scatterplots show an inverse correlation ($R^2$) between LST and NDVI (Figure 6), which was 0.3682 in 2000, 0.2812 in 2010 and 0.2133 in

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**Table 5. Land uses Land cover area and change statistics**

<table>
<thead>
<tr>
<th>Land use class</th>
<th>2000 (%)</th>
<th>2010 (%)</th>
<th>2021 (%)</th>
<th>Change in area (%) 2000-2010</th>
<th>Change in area (%) 2010-2021</th>
<th>Change in area (%) 2000-2021</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water bodies</td>
<td>0.11</td>
<td>0.22</td>
<td>0.11</td>
<td>0.11</td>
<td>-0.11</td>
<td>0</td>
</tr>
<tr>
<td>Dense Forest</td>
<td>0.79</td>
<td>0.35</td>
<td>0.33</td>
<td>-0.44</td>
<td>-0.02</td>
<td>-0.46</td>
</tr>
<tr>
<td>Moderately dense Forest</td>
<td>1.75</td>
<td>1.57</td>
<td>2.53</td>
<td>-0.18</td>
<td>0.96</td>
<td>0.78</td>
</tr>
<tr>
<td>Sparse/Scrub</td>
<td>27.41</td>
<td>21.49</td>
<td>25.93</td>
<td>-5.92</td>
<td>4.44</td>
<td>-1.48</td>
</tr>
<tr>
<td>Agriculture</td>
<td>7.41</td>
<td>3.92</td>
<td>8.12</td>
<td>-3.49</td>
<td>4.2</td>
<td>0.71</td>
</tr>
<tr>
<td>Plantation</td>
<td>8.84</td>
<td>9.17</td>
<td>7.79</td>
<td>0.33</td>
<td>-1.38</td>
<td>-1.05</td>
</tr>
<tr>
<td>Barren/Rocky</td>
<td>40.43</td>
<td>46.59</td>
<td>37.31</td>
<td>6.16</td>
<td>-9.28</td>
<td>-3.12</td>
</tr>
<tr>
<td>Barren</td>
<td>9.66</td>
<td>12.31</td>
<td>6.51</td>
<td>2.65</td>
<td>-5.8</td>
<td>-3.15</td>
</tr>
<tr>
<td>Built-up</td>
<td>3.60</td>
<td>4.38</td>
<td>11.27</td>
<td>0.78</td>
<td>6.89</td>
<td>7.67</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
Figure 4. Normalized differential vegetation index maps for the years 2000, 2010 and 2021

Table 6. Statistical summary of NDVI values in Meknes City and its surroundings (2000–2021)

<table>
<thead>
<tr>
<th>Year</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Mean NDVI difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2000-2010</td>
</tr>
<tr>
<td>May 2000</td>
<td>-0.5</td>
<td>0.48</td>
<td>-0.10</td>
<td>-0.03</td>
</tr>
<tr>
<td>May 2010</td>
<td>-0.65</td>
<td>0.55</td>
<td>-0.13</td>
<td></td>
</tr>
<tr>
<td>May 2021</td>
<td>-0.20</td>
<td>0.65</td>
<td>-0.26</td>
<td></td>
</tr>
</tbody>
</table>
Table 7. Statistical summary of LST (°C) values in Meknes City and its surroundings (2000–2021)

<table>
<thead>
<tr>
<th>Year</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Mean LST difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2000-2010</td>
</tr>
<tr>
<td>May 2000</td>
<td>15.85</td>
<td>36.20</td>
<td>27.28</td>
<td>2.55</td>
</tr>
<tr>
<td>May 2010</td>
<td>12.76</td>
<td>38.24</td>
<td>29.83</td>
<td>12.28</td>
</tr>
<tr>
<td>May 2021</td>
<td>25.73</td>
<td>47.79</td>
<td>39.93</td>
<td></td>
</tr>
</tbody>
</table>

Figure 5. Land surface temperature maps for 2000, 2010 and 2021
Table 8. Linear regression data between NDVI and LTS for the years 2000, 2010 and 2021

<table>
<thead>
<tr>
<th>Year</th>
<th>Parameter</th>
<th>Value</th>
<th>Error</th>
<th>R</th>
<th>SD</th>
<th>N</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>A</td>
<td>24.59841</td>
<td>0.12547</td>
<td>0.60679</td>
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Figure 6. Spatially scattered plots of LST and NDVI of Meknes city and its surrounding for the years 2000, 2010 and 2021
271 (Table 8). Similar results have been reported by Naikoo et al. (2020), who revealed that there is an inverse trend between these two variables, where an increase in surface temperature is associated with a decline in NDVI and vice versa. This relationship can be explained by several factors. When the surface temperature increases, it can lead to unfavorable environmental conditions for vegetation. Periods of intense heat can induce heat stress on plants, which can affect their growth and health. As a result, plant density may decrease, reflected in a decrease in NDVI [Allam et al., 2021]. In addition, an increase in surface temperature can lead to an increase in evapotranspiration, the loss of water through evaporation from the soil and plant transpiration. Increased evapotranspiration can reduce water availability for plants, which can also contribute to a decrease in NDVI [Li et al., 2021].

Model evaluations and critical environmental variables

The results obtained by the maximum entropy model for predicting potential habitats for partridges were excellent. The mean AUC value of 0.959 was significantly higher compared to random prediction value (0.5) (Figure 7); this confirms that the predictions were very accurate, suggesting that the potential distribution area results obtained from MaxEnt were reliable and robust [Qin et al., 2017; Jain et al., 2021].

Potential distribution of partridges in the study area

The results obtained are promising for predicting the distribution of partridges in the study area. On the basis of this data, it can be anticipated where these birds are most likely to be found. The geographical distribution map, shown in Figure 8, clearly visualizes these predictions. It should provide a visual overview of the likely distribution of partridges throughout the region.

The escalation in surface temperature has emerged as a pivotal factor exerting discernible impacts on ecological dynamics, particularly manifest in the alteration of normalized difference vegetation indices and subsequent ramifications for the distribution patterns of avian species, exemplified by the partridge in the Moroccan context. In relation to these results, Stralberg et al. (2020) reported that elevated temperatures induce shifts in vegetation characteristics, thereby influencing the availability of suitable habitats for various species. Similar results were revealed by Kaluskar et al. (2020) who showed the intricate interplay between temperature fluctuations and vegetation dynamics as well as underscored the indispensability of a comprehensive understanding of these ecological relationships between the environmental conditions and the potential distribution of some species under the African climatic conditions. The decline in NDVI, as a proxy for vegetation health and vigor, emerges as a crucial link in this causal chain, delineating a trajectory wherein the temperature-induced
alterations reverberate through trophic levels, ultimately impacting the distributional ecology of species, such as the Partridge in the Moroccan landscape. This intricate nexus demands further exploration, with implications for both fundamental ecological theory and applied conservation practices in the face of ongoing climatic perturbations.

CONCLUSIONS

The present study delved into an examination of spatial and temporal dynamics of temperature, land use, and land cover within the Moroccan region, spanning the temporal epochs of 2000, 2010, and 2021. The deduced spatial distribution of land surface temperature, contingent upon the normalized difference vegetation index, was predicated upon multispectral remote sensing data. The obtained results can be used to understand the various environmental changes occurring over the period studied and their impact on terrestrial ecosystems and consequently, on changes in the distribution of partridge ecological niches. Significant changes in land use and land cover classes over time, clearly show that these changes are not uniform, as some classes have regressed, such as Dense Forest, Sparse/Scrub, Plantation, Barren/Rocky and Barren, while others have increased, such as Agriculture, Moderately Dense Forest and Built up. The quantitative analysis between NDVI and LST indicates that there is a negative correlation between the density of the vegetation and the recorded surface temperatures. This finding highlights the beneficial influence of vegetation on the thermal regulation of the environment, where the presence of vegetation helps to reduce local temperatures. These data were used to model the distribution of ecological niches for partridges. This modeling provides an understanding of the environmental conditions that are favorable to the partridge’s habitat, as well as the factors that influence its presence or absence in the study region. The present work provides the first map of partridge potential range in the context of current climatic data. This original study for this emblematic species will serve as the basis for any strategic planning for biodiversity conservation and sustainable management of the partridge in Morocco.

Acknowledgements

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REFERENCES


