



QGIS-based modeling and analysis of urban dynamics affecting land surface temperature towards climate hazards in coastal zones of Portugal

Oznur Isinkaralar¹

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Abstract

Climate risk creates considerable concern due to the density of natural and socio-economic assets in coastal areas. Monitoring land use/cover changes, detecting population growth, and analyzing their impact on land surface temperature (LST) are necessary for effective urban management. In this study, land use/land cover (LULC), population, and LST changes in coastal regions of Portugal. Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imagery was examined using World Bank population and CORINE data. Changes in land use types and LST values from 1990 to 2018 were analyzed. At the same time, LULC predictions were made using the Modules for Land Use Change Simulation (MOLUSCE) plug-in included in the QGIS software, and population projections were analyzed with LULC predictions in 2046. The results show the significant impact of land use on temperatures. It has been demonstrated that green and water areas can effectively cool cities. In the LULC changes between 1990 and 2018, the Leiria region stands out, with an annual increase of 4.04% in built areas from 121.58 to 259.06 km². According to the simulations between 2018 and 2046, it was predicted that 18.74% of agricultural areas and 14.43% of forest areas would be transformed into built environments. The study is also essential as it confirms that the MOLUSCE plug-in can be effectively applied to land cover simulation on a large regional scale.

Keywords Climate change mitigation · Climate policy · Geographical information science · Land surface temperature · Land use/cover simulation

1 Introduction

Urbanization dynamics put pressure on limited natural resources, increasing greenhouse gas emissions, deforestation, loss of ecosystems, and biodiversity threaten human life, especially in cities (Orimoloye et al. 2019; Matloob et al. 2021). This process leads to land degradation, soil quality, and loss of green–blue cover (Sarif and Gupta 2021; Kadaverugu

✉ Oznur Isinkaralar
obulan@kastamonu.edu.tr

¹ Department of Landscape Architecture, Faculty of Engineering and Architecture, Kastamonu University, 37150 Kastamonu, Türkiye

2023). It also affects climate, soil, vegetation, water resources, and biodiversity (Gao et al. 2022). Many studies have stated that climatic parameters change spatiotemporally (Isinkaralar 2023). The frequency and scale of disasters caused by climate change will be predicted to increase gradually. It is known that natural disasters cause severe material damage and loss of life (Rekapalli and Gupta 2023). The United Nations report on disaster risk reduction emphasizes that climate-related disasters may increase to approximately 560 events per year, or 1.5 events per day, by 2030 (UNDRR 2022). The Intergovernmental Panel on Climate Change (IPCC) Third Assessment Report (TAR) predicts a sea level rise of up to 88 cm by the end of the twenty-first century (Church et al. 2001; Nicholls and Lowe 2004). The most tangible consequences of human-induced global warming are rising temperatures (Cui and Zhong 2024; Isinkaralar and Isinkaralar 2023; Semenova 2024), an increase in extreme events (Calabrese et al. 2024; Iyke 2024) and sea level rise (Ciccarelli and Moratta 2024; Tol 2024).

The rising sea level creates serious concern due to the density of settlements and investments in coastal areas. The rising sea level is a critical threat to countries with fragile economies, especially tourism, and trade on the oceanside coastline, such as Portugal. Portuguese economy in terms of income in 2022, the European Commission has positioned Portugal as the European country with the highest growth. Lisbon, the locomotive of Portugal's tourism sector economy, the city of Porto, which UNESCO protects as a World Heritage Site, and the cities at the heart of trade and culture, are located on the coastline, which are the strengths of Portugal's economic development. While the temperature increase caused by the changing climate creates changes in bioclimatic comfort, environmental risks threaten the country's wealth. The essential possible dangers include destruction due to natural disasters such as floods, storm surges, and erosion. This study uses Quantum GIS (QGIS) software to estimate the impact of population, land use, and Normalised Difference Vegetation Index (NDVI) changes on future LST under a current and simulated 2046 scenario in the context of climate change. It will provide a scientific perspective revealing the dynamics of effective mitigation and adaptation policies and risk management.

2 Literature review

Due to its ability to combine surface-atmosphere interactions and energy flows between the atmosphere and the land surface, it is used for many different environmental applications, especially climate change and land use/land cover (Sinha et al. 2015; Zhang et al. 2017; He et al. 2020; Jamali et al. 2022). Analyzing and planning LULC changes as a whole with climatic parameters and population will help to understand environmental changes better and prevent different adverse developments (Wu et al. 2015; Wang and Murayama 2020). Many studies have concluded that there is a high correlation between land surface temperature (LST) and LULC (Feizizadeh et al. 2013; Bokaie et al. 2016; Wang and Murayama 2018). Remote sensing and GIS-based studies are quite common in the literature on predictive urban growth and land use change monitoring in Fig. 1.

It has been determined that there is an inverse relationship between the normalized difference vegetation index (NDVI) variable and LST, representing the vegetation model from the 1960s to the present (Yuan and Bauer 2007; Garcia et al. 2019; Jamali et al. 2022). In this context, spatial-temporal LULC changes in the Portuguese coastal regions from 1990 to 2018 were correlated with LST, NDVI, and population in three periods (1990–2012, 2012–2018, 1990–2018) and included in the QGIS software for the year 2046. LULC estimation was made

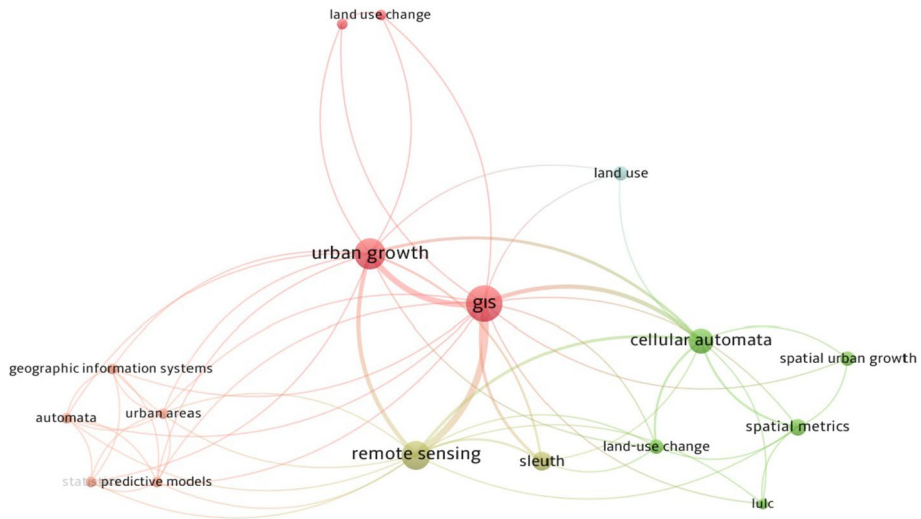


Fig. 1 Vosviewer software bibliographic analysis between GIS, urban growth and land use articles

by the Modules for Land Use Change Simulation (MOLUSCE) plug-in in the study. By also foreseeing the relationship between LULC and population in 2046, predictions have been made for future LST distribution for sustainable development. This literature approaches the climate crisis from two different perspectives. (i) To determine the factors that trigger climate change. Current studies focusing on explaining the potential for global warming from the perspective of greenhouse gases and climate, based on carbon sequestration and nature-based solutions, bear this concern (Don et al. 2024). (ii) To identify the trend of the climate crisis and develop the necessary research for the measures that can be taken. There are studies analyzing the issue of food security at risk in the changing process (Lee et al. 2024) and associating it with land use/cover change (Dessu et al. 2020). One of the most prominent indicators that reveal the trend of climate change is ground surface temperature (LST). Urban activities held responsible for the changing climate cause urban heat island formation (Wang et al. 2018). As a result, LST values increase over time. The unique aspect of this research is to reveal the impact of the current population, land use/cover (LULC), and normalized difference vegetation index (NDVI) on current LST values based on correlation while also predicting how all elements will be practical in the future. In this context, the main research aims of the study are:

RA¹: To determine the population, LST, LULC, and NDVI changes between 1990 and 2018 in Portugal's coast districts.

RA²: To identify the predicted factors: population, LST, LULC and NDVI for 2046.

RA³: To analyze the correlation of the factors that affect LST in the present and future.

3 Methodology

A series of stages was completed in a step-by-step workflow pattern in Fig. 2. First, the 1990, 2012, and 2018 datasets were created using remote sensing and geographic information systems (GIS). Then, the model's suitability was tested, and a prediction of 2046 was made. The correlation of estimated LST and urban dynamics was analyzed statistically.

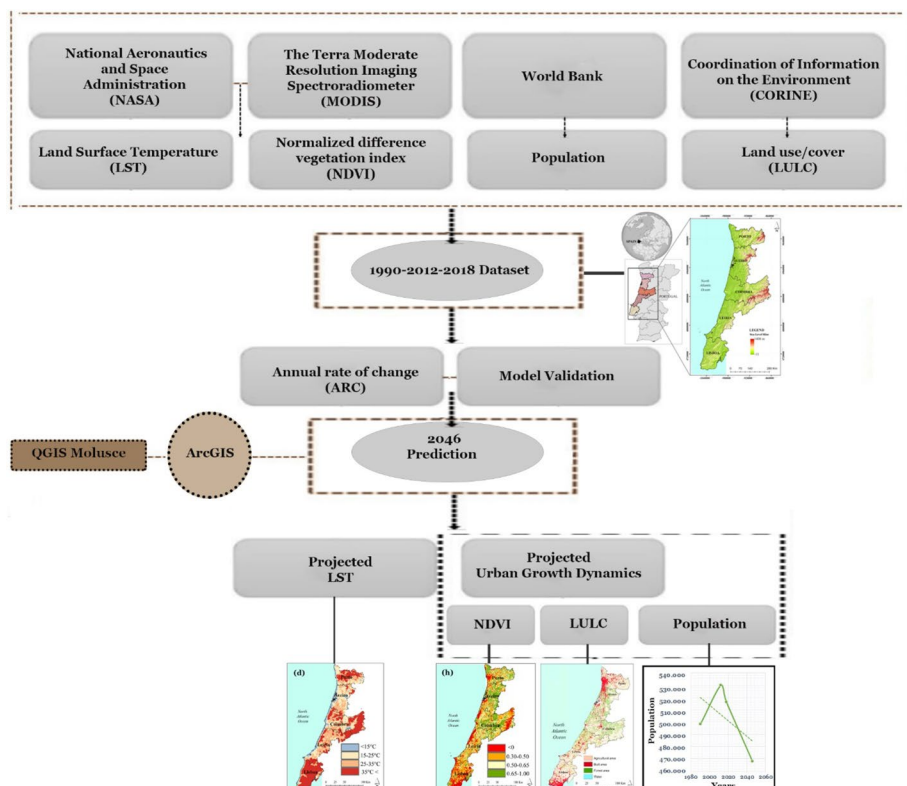


Fig. 2 Methodology flowchart of this study

3.1 Study area and data preparation

Portugal, located between latitudes 30°–42° N and longitudes 32°–6° W, constitutes Spain's two archipelagos in the Atlantic Ocean. Five regions of the seven regions bordering the ocean, namely Lisboa/Lisbon, Leiria, Coimbra, Aveiro, and Porto, were selected as the study area. These coastal areas consist of highly variable altitudes. Moving towards the east, the rugged terrain increases, and the altitudes are relatively lower in the interior and near the coast in Fig. 3. A temperate maritime climate prevails in northern Portugal, where mostly Mediterranean characteristics are observed. The spatial representation of the Köppen climate classification reveals two climate types from 1990–2019. According to this classification, the city's south is classified as Csa (hot summer), and the north is as Csb (warm summer).

3.2 LST and NDVI mapping

LST and NDVI data were obtained in vector format from the National Aeronautics and Space Administration (NASA) database. In line with Portugal's meteorological data, MODIS satellite images were obtained, taking into account the hottest month of August. The MODIS Land Surface Temperature/Emissivity 8-Day (MOD11A2) Version 6.1

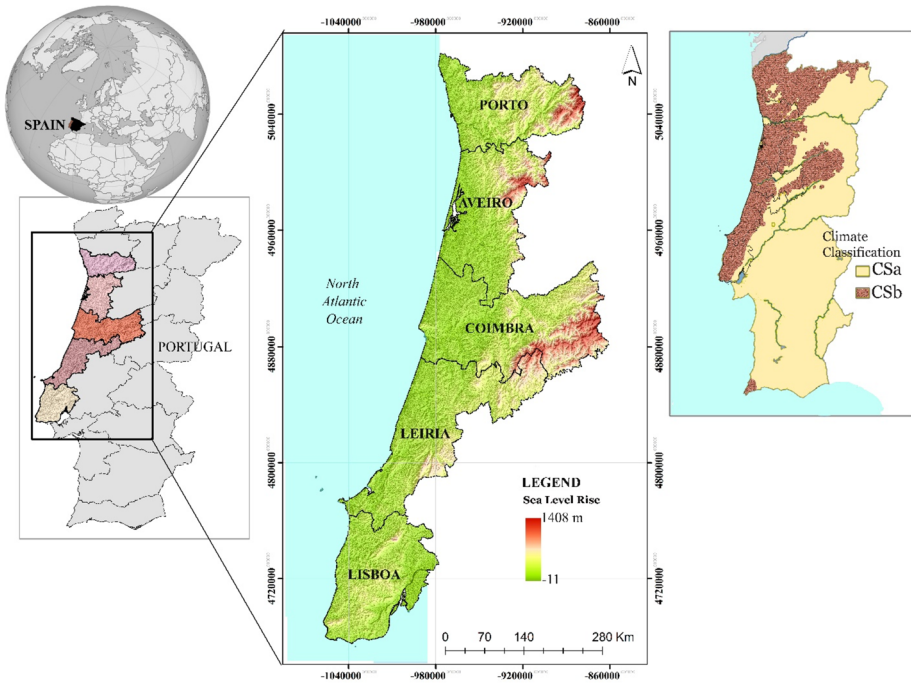


Fig. 3 Location, sea level rise and climate classification of the area

product provides an average 8-day per-pixel Land Surface Temperature and Emissivity (LST&E) with a 1 km (km) spatial resolution in a 1.200 by 1.200 km grid. Each pixel value in the MOD11A2 is a simple average of all the corresponding MOD11A1 LST pixels collected within those eight days. Satellite image obtained in vector format. Edited in ArcGIS 10.4 program. LST map Eq. Obtained using Eq. (1):

$$LST(^{\circ}C) = (MD * SF) - 273.15 \quad (1)$$

Where LST ($^{\circ}C$): the Land Surface Temperature in Celsius. MD: MODIS data. SF: MOD11A2 represents the satellite image scale factor (0.02). MODIS MOD13Q1 data was used for NDVI values. The satellite image of NDVI data obtained in vector format was edited in the ArcGIS 10.4 program. The NDVI map is Eq. obtained using Eq. (2):

$$NDVI = MD * SF \quad (2)$$

Where NDVI: the Normalized Difference Vegetation Index. SF: MOD13Q1 represents the satellite image scale factor (0.0001).

3.3 LULC mapping and prediction

LULC, covering the coastal regions of Portugal, was obtained in vector format from the CORINE layers of the Copernicus Land Monitoring Service database. For the LULC of 2006, 2012, and 2018, the study area is divided into four classes (built area, agricultural

area, forest area, and water). LULC maps were created using the maximum likelihood classification technique in the ArcGIS 10.4 program. Temporal and spatial changes between years were revealed by analyzing LULC changes. The difference between the final year and the initial year, representing the magnitude of change between corresponding years, was divided by the initial year and period to obtain the annual rate of change for each land use type. We used Eq. (3) to assess the spatiotemporal magnitude and rate of change in LULC categories (Muhammad et al.2022):

$$\text{ARC}(\%) = [(F_y - I_y) / (I_y * t)] * 100 \quad (3)$$

Where ARC: the Annual Rate of Change in LULC categories, I_y and F_y : the initial and final year areas, respectively, and t : the time interval.

3.4 Estimated population growth

Population data for Lisboa, Leiria, Coimbra, Aveiro, and Porto were obtained from the World Bank database in Table 1. Since population and urban growth are directly linked, the relationship between 2046 LULC and population was evaluated by creating Scatterplot graphics using 1990, 2012, and 2018 population data and 2046 projection data in Fig. 4.

4 Results

4.1 Model validation

The obtained LULC data was cut into the ArcGIS program in line with the boundaries of the work area. It is classified into four groups in the classification process. Maximum likelihood classification technique was used to correct spatial resolution differences with LULC data. QGIS 2.0.1 Land-Use Change Simulation (MOLUSCE) plugin was used to calculate the LULC transition between years (1990–2012, 2012–2018, 1990–2018) to detect spatial and temporal changes. LULC was estimated for 2046 using the 1990 and 2018 CORINE LULC maps, which were the most prominent and changing. It has projected LULC for 2018 using the years 1990 and 2012. It was validated by calculating the kappa statistic. The observed and simulated LULC were validated using multi-resolution in Fig. 5.

The Kappa results in Table 2 show that the maximum Kappa coefficient value is 0.93 across the study area, and the maximum accuracy percentage is 96%. Many researchers

Table 1 Portugal districts population (1990–2046)

Districts	1990	2012	2018	2046
Lisboa	498.342	530.117	516.514	467.854
Leiria	425.652	470.377	458.307	415.131
Coimbra	424.662	451.739	440.147	398.682
Aveiro	52.126	55.450	54.027	48.937
Porto	240.251	255.570	249.012	225.553

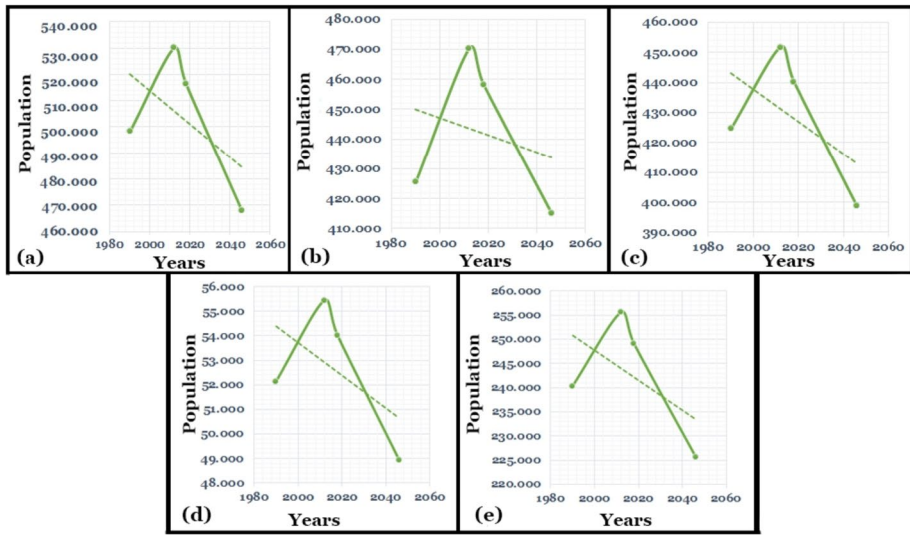


Fig. 4 Portugal districts population graph (1990–2046) **a:** Lisboa, **b:** Leiria, **c:** Coimbra, **d:** Aveiro, **e:** Porto

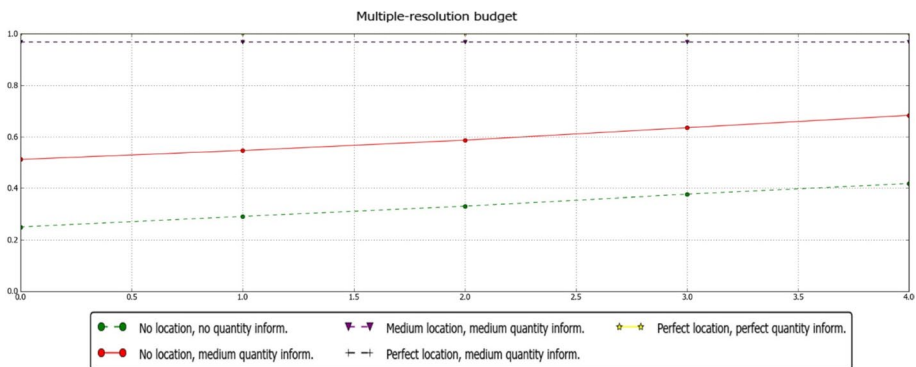


Fig. 5 Comparison of the 2018 LULC observed data with the 2018 predicted data

Table 2 Different combinations of explanatory maps and Kappa coefficients

	Percentage of Kappa correctness (%)	Kappa coefficient
LULC	96.86	0.93

consider a maximum Kappa value of 0.93 excellent (Isinkaralar and Varol 2023). Therefore, it reveals the accuracy of the model created in estimating the LULC map of the study area.

4.2 LULC and annual rate of change (ARC) analysis

LULC maps change statistics, and annual change rates are given in Table 3. There is an irregular change in land use due to urban expansion. There has been a continuous increase in built environments between 1990 and 2018. Regarding the increase in built

Table 3 LULC 1990–2018 and annual rate of change (ARC)

	LULC TYPE	1990		2012		2018		ARC (%)
		km ²	%	km ²	%	km ²	%	
LISBOA	Built area	373.06	13.51	604.92	21.9	607.32	21.99	2.24
	Agricultural	2037.51	73.77	1802.97	65.27	1826.2	66.12	−0.37
	Forest area	332.6	12.04	334.53	12.11	308.9	11.18	−0.25
	Water	18.82	0.68	19.62	0.71	19.62	0.71	0.15
LEIRIA	Built area	121.58	3.48	254.41	7.28	259.06	7.41	4.04
	Agricultural	1984.77	56.76	1886.25	53.94	2136.85	61.11	0.27
	Forest area	1383.22	39.56	1348.13	38.55	1092.88	31.25	−0.75
	Water	7.24	0.21	8.02	0.23	8.02	0.23	0.38
COIMBRA	Built area	79.47	2.00	150.27	3.78	150.67	3.79	3.20
	Agricultural	2147.24	54.05	2000.19	50.35	2301.41	57.93	0.26
	Forest area	1717.95	43.24	1791.63	45.10	1490.01	37.51	−0.47
	Water	28.04	0.71	30.61	0.77	30.61	0.77	0.33
AVEIRO	Built area	165.41	6.00	328.01	11.89	331.94	12.04	3.60
	Agricultural	1204.36	43.67	1196.65	43.39	1461.54	52.99	0.76
	Forest area	1381.04	50.08	1223.58	44.37	952.78	34.55	−1.11
	Water	7.09	0.26	9.66	0.35	11.64	0.42	2.29
PORTO	Built area	233.6	10.03	466.27	20.01	468.98	20.13	3.60
	Agricultural	1467.12	62.97	1420.51	60.97	1521.01	65.29	0.13
	Forest area	611.94	26.27	420.62	18.05	317.41	13.62	−1.72
	Water	17.12	0.73	22.38	0.96	22.38	0.96	1.10

environments, the Leiria region stands out with an annual increase of 4.04%, from 121.58 to 259.06 km². It has built areas in the Lisboa and Porto regions, which form the central structure of the city of Portugal, with an annual increase of 2.24% and 3.60%. In contrast, it increased from 373.06 to 607.32 km² in the Lisbon region. In the Porto region, it increased from 233.60 to 468.98 km². While there is an uncertain increase and decrease in agricultural areas throughout the region, there are apparent decreases in forest areas. The Lisbon region comes to the fore with an annual decrease of −0.25% in forest areas, from 332.60 to 308.9 km². Similarly in the same region. −0.37% annually agricultural areas also decreased from 2037.51 to 1826 km². On the other hand, the Aveiro region attracts attention with a 2.29% increase in water areas, from 7.09 to 11.64 km². 1990–2018 LULC change analysis results show significant expansion in built environments. It shows that there is a contraction in agricultural and forest areas. The most significant change occurred in the 1990–2018 period.

According to this period, the highest change in built environments was calculated as 235.38 km² in the Porto region and 234.26 km² in the Lisboa region. Table 4 is given that the Portuguese regions saw the most change between 1990 and 2018 and the transition and contribution between LULC types in Portugal regions from 1990 to 2018. There is a continuous decrease in forest areas. In the regions respectively: −23.7 km² in the Lisbon region, −227.94 km² in the Coimbra region, −290.34 km² in the Leiria region. It was determined that there was a decrease of −294.53 km² in the Porto region and −428.26 km² in the Aveiro region.

Table 4 Contribution of LULC types to change 1990–2018

LULC TYPE		1990–2012		2012–2018		1990–2018	
		km ²	%	km ²	%	km ²	%
LISBOA	Built area	231.86	62.15	2.4	0.39	234.26	62.79
	Agricultural	234.54	11.51	23.23	1.28	−211.31	10.37
	Forest area	1.93	10.25	−25.63	7.66	−23.7	7.12
	Water	0.8	4.25	0	0	0.8	4.25
LEIRIA	Built area	132.83	109.25	4.65	1.83	137.48	113.08
	Agricultural	−98.52	−4.96	250.6	13.29	152.08	7.66
	Forest area	−35.09	−2.54	−255.25	−18.93	−290.34	−20.99
	Water	0.78	10.77	0	0.00	0.78	10.77
COIMBRA	Built area	70.8	89.09	0.4	2.26	71.2	89.59
	Agricultural	−147.05	−6.85	301.22	15.06	154.17	7.18
	Forest area	73.68	4.29	−301.62	−16.83	−227.94	−13.27
	Water	2.57	9.17	0	0.00	2.57	9.17
AVEIRO	Built area	162.6	98.30	3.93	1.20	166.53	100.68
	Agricultural	−7.71	−0.64	264.89	22.14	257.18	21.35
	Forest area	−157.46	−11.40	−270.80	−22.13	−428.26	−31.01
	Water	2.57	36.25	1.98	20.50	4.55	64.17
PORTO	Built area	232.67	99.60	2.71	0.58	235.38	100.76
	Agricultural	−46.61	−3.18	100.5	7.07	53.89	3.67
	Forest area	−191.32	−31.26	−103.21	−24.54	−294.53	−48.13
	Water	5.26	30.72	0	0.00	5.26	30.72

4.3 Spatiotemporal changes of LST and NDVI

Figure 6 shows the study areas' LST and NDVI change maps for 1990, 2012, 2018, and 2046. LST values vary between 12.03 and 42.77 °C. While the lowest LST values were 12.03 °C in 1990, it increased by 7.02 to 19.05 °C in 2012, and by 2018 it increased by 7.64 to 19.67 °C. The highest LST values were 38.13 °C in 1990, increased by 3.34 to 47.48 °C in 2012, and increased by 4.64 to 42.77 °C in 2018. High LST values are primarily concentrated in the central region of Lisbon. Moving towards the interior, the increase in LST values is noticeable. While low LST values were observed in areas close to the coast in 1990, LST values increased in 2018. NDVI values vary between −0.1975 and 0.9856. While low NDVI values are seen in areas with high LST values, high NDVI values are seen in areas with low LST values. It has been determined that high NDVI and low LST values are seen mainly in dense green vegetation, such as forest areas.

4.4 2046 Estimation of LULC

The transformation from agricultural and forest area to built environment between 2018 and 2046 is noticeable mainly in Fig. 7. After obtaining an "excellent" result from model validation, the LULC of 2046 was predicted. The transformation from other types of LULC to built environments is noticeable every period. The highest conversion to built

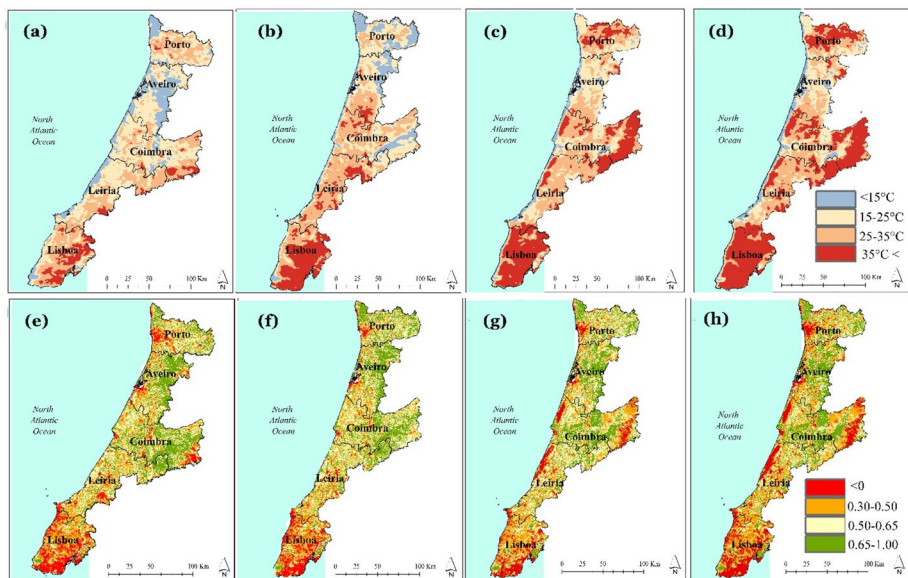


Fig. 6 Changing Trend of LST **a:** 1990, **b:** 2012, **c:** 2018, **d:** 2046 and NDVI **e:** 1990, **f:** 2012, **g:** 2018, **h:** 2046 in Portugal Districts

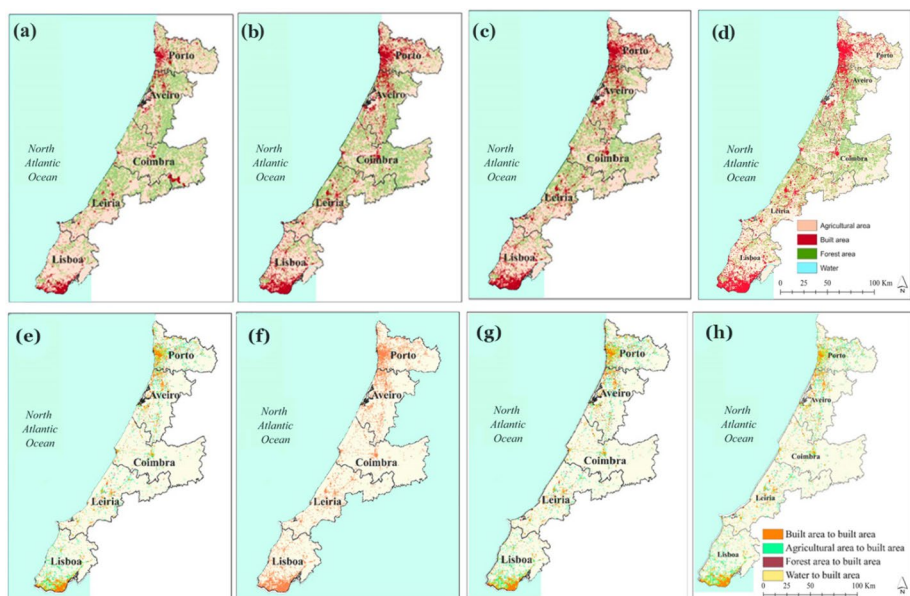


Fig. 7 LULC maps **a:** 1990, **b:** 2012, **c:** 2018, **d:** 2046 and transition maps to built area **a:** 1990–2012, **b:** 2012–2018, **c:** 1990–2018, **d:** 2018–2046

environments was 17.67% from forest areas and 16.84% from agricultural areas. Water areas contribute very little to these rates of change. It is anticipated that there will be a significant expansion in built areas.

In the ARC rates for 2046, the most significant increases in built areas are in the Coimbra region, with 11.85% annually. Leiria follows Coimbra with an annual rate of 1.38%, Lisboa with 1.18%, Aveiro with 0.79%, and Porto with 0.76%. Table 5 observes that the water surfaces in the Leiria region, which were 8.02 km² in 2018, will decrease by −3.57% and disappear entirely in 2046.

The highest conversion to built environments was 18.74% from agricultural areas and 14.43% from forest areas in Table 6. Water areas do not contribute to these rates of change.

Table 5 LULC 2018–2046 and annual rate of change (ARC)

		2018		2046		ARC (%)
		km ²	%	km ²	%	%
Lisboa	Built area	607.32	21.99	807.64	28.23	1.18
	Agricultural	1826.2	66.12	1824.84	63.79	0.00
	Forest area	308.9	11.18	208.01	7.27	−1.17
	Water	19.62	0.71	19.96	0.69	0.06
Leiria	Built area	259.06	7.41	359.15	10	1.38
	Agricultural	2136.85	61.11	2136.85	59.54	0.00
	Forest area	1092.88	31.25	1092.79	30.45	0.00
	Water	8.02	0.23	0	0	−3.57
Coimbra	Built area	150.67	3.79	650.651	14.54	11.85
	Agricultural	2301.41	57.93	2299.36	51.40	0.00
	Forest area	1490.01	37.51	1494.98	33.42	0.01
	Water	30.61	0.77	27.85	0.62	−0.32
Aveiro	Built area	331.94	12.04	405.74	14.19	0.79
	Agricultural	1461.54	52.99	1457.85	51.01	−0.01
	Forest area	952.78	34.55	981.19	34.33	0.11
	Water	11.64	0.42	13.12	0.45	0.45
Porto	Built area	468.98	20.13	568.94	23.41	0.76
	Agricultural	1521.01	65.29	1522.07	62.63	0.00
	Forest area	317.41	13.62	319.46	13.14	0.02
	Water	22.38	0.96	19.41	0.79	−0.47

Table 6 Contribution of LULC types to change 2018–2046 (%)

LULC	Built area	Agricultural	Forest area	Water
Built area	22.96	0.02	0.06	0.00
Agricultural	18.74	0.83	0.08	0.1
Forest area	14.43	0.32	0.63	0.00
Water	0.04	0.08	0.00	0.91

4.5 LST and urban growth dynamics scatterplots

Figure 8 depicts an analysis of the relationship between LST and urban parameters from 1990 to 2018 and projected for 2046. The parameters' correlation coefficients were calculated. The highest LST values in 1990, 2012, and 2018 were seen in built-up areas. LST values decrease as you move to agricultural, forest, and water areas. A negative correlation exists between LST LULC and NDVI, and a positive correlation between LST and population. In particular, the increase in population and built environments causes LST values to increase. However, increasing the density of green vegetation is also very effective in decreasing LST values.

5 Discussion

Especially in recent years, urbanization and climate change have begun to be felt more intensely in all cities (Qiu et al. 2020; Atisa and Racelis 2022). As a result of these two parameters, significant decreases occur in agricultural and forest areas (Raihan and Tuspekova 2022). This situation also causes economic problems in Portuguese cities, which is essential in agricultural production. For this reason, the coastal regions of Portugal were examined in the study, and spatial–temporal LULC changes from 1990 to 2018 were examined and correlated with LST, NDVI, and population (Huang et al. 2020). Our findings show that LULC types, population, and NDVI significantly impact LST. LST values are generally high in areas where built environments are dense and low in areas where green vegetation is dense, such as forests and agriculture. Many research studies ultimately show the effect of green vegetation on reducing temperature values by Cao et al. (2020), Olokeogun and Kumar (2020), and Anand and Oinam (2020). LULC map was predicted for 2046. As a result of the prediction, the intense pressure of built areas on other LULC types comes to the fore. This situation shows that the effect of urbanization will be felt more intensely in coastal regions in 2046. In a study conducted in Portugal on a similar subject, a trend projection was developed for 2040 by considering the significant changes in the agricultural landscape (Viana and Rocha 2020; Yonaba et al. 2021). Considering changes in land use/land cover and urbanization, Kadaverugu (2023) found that the compatibility between the Weather Research and Forecasting (WRF) model simulated surface skin temperature and MODIS satellite-derived land surface temperature (LST) is heterogeneous. They have examined through LULC (established crop). Gao et al. (2023) used the MOLUSCE plug-in of QGIS software for spatio-temporal change analysis and prediction of land cover. In addition, natural disasters and different population characteristics can be used as parameters in future studies.

6 Conclusion, limitations and prospects

The study revealed a strong relationship between LULC distribution and LST, opening research avenues for future LULC predictions. The research contains important LULC predictions that will contribute not only to urban health but also to the field of sustainable development. In this study, the coastal regions of Portugal were chosen as the research area. Focusing on the relationship between LULC and LST in these regions, a prediction of future land cover was carried out. The study is essential as it confirms that the MOLUSCE

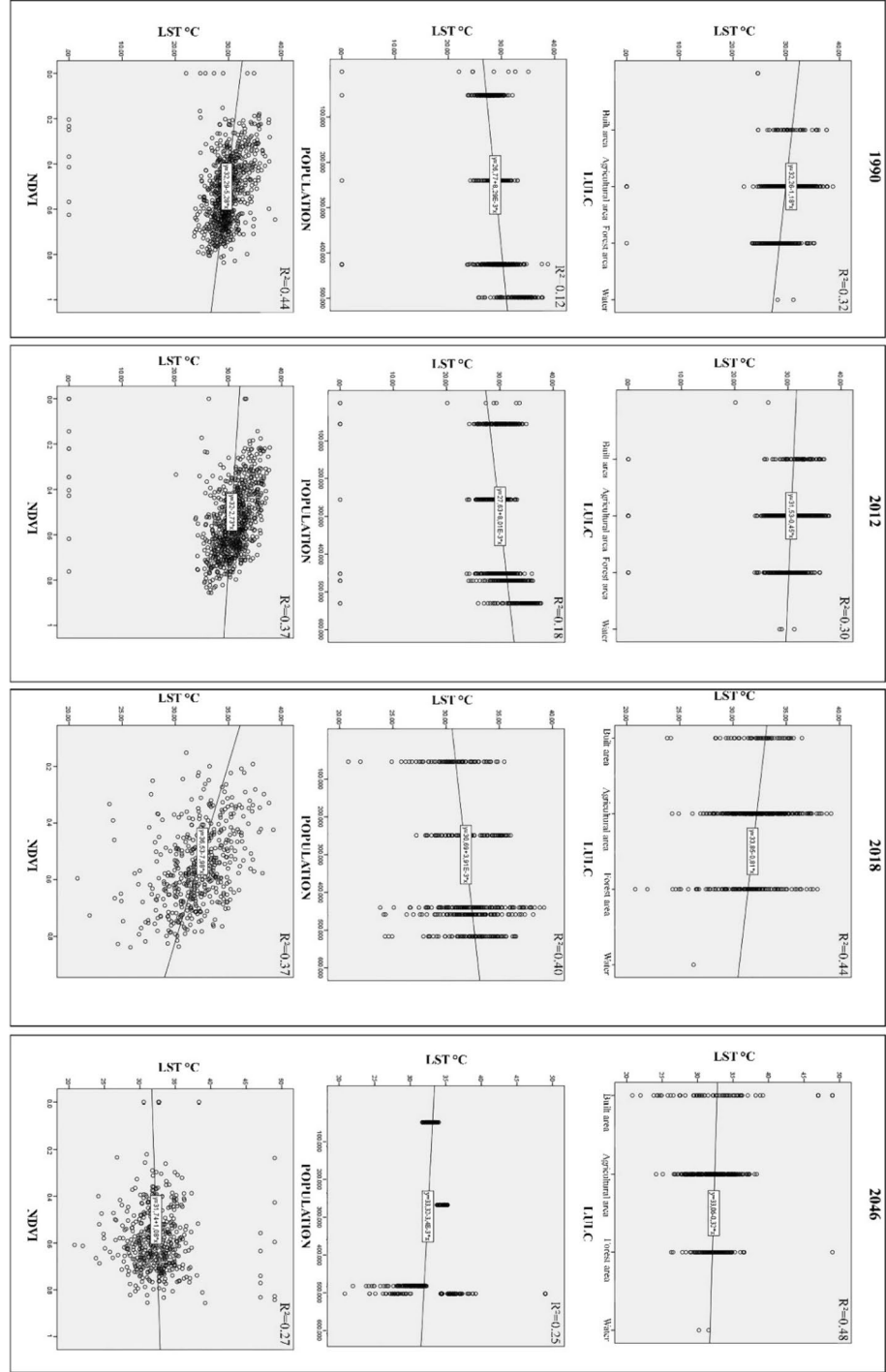


Fig. 8 The correlation analysis of LST, NDVI, and urban growth dynamics

plug-in can be effectively applied to land cover simulation on a large regional scale. Based on the method followed and the study's analysis, logistic regression, and CA model in the MOLUSCE plug-in in QGIS software, the LULC simulation 2046 was used. This paper can provide a reference source for future research on similar topics, especially for sizeable regional-scale land cover simulations. According to the simulation and prediction results regarding land cover, agricultural and forest lands will decrease in 2046. The increase in land cover in residential areas, which shows the continuous development of urbanization, cannot be ignored. Regional climate models must be further developed to accurately reproduce the dynamic urban phenomenon, especially in dense urban centers such as Lisboa and Porto. The results may assist in land use planning and quantifying the impact of urban growth on surface meteorology. With advances in geospatial analytics, numerical models, earth observations complemented by sensor-based observation networks, and climate modeling applications, we can help accurately predict the probabilities of extreme natural events at multiple spatial scales. In this way, it will be possible to slow down the rate of disasters.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

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