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**Research Article**

# Assessing the Impact of Urbanization on Mangrove Cover, Shoreline Dynamics, and Land Surface Temperature Changes in Qatar

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**ABSTRACT**

This study investigates the relationship between mangrove cover changes, shoreline dynamics, and urban development from 2014 to 2022 in a designated coastal area. Utilizing satellite imagery and GIS analysis, the research maps and quantifies shifts in mangrove distribution and shoreline erosion and accretion patterns. Additionally, changes in Land Surface Temperature (LST) are analyzed to understand their correlation with mangrove health and urbanization trends. Ground-truthing is conducted through strategically chosen sample points, some located within mangrove ecosystems and others along the urbanized shoreline, to assess environmental impacts accurately. The research reveals a notable increase in mangrove cover, rising from 4.9 $km^2$ to 12.9 $km^2$, highlighting the effectiveness of conservation efforts. In contrast, urban land expanded dramatically from 140 $km^2$ to 396 $km^2$, presenting significant environmental challenges. Analysis of LST showed a maximum decrease from 54°C in 2014 to 45°C in 2022, suggesting potential cooling effects linked to increased mangrove cover. Correlation analyses indicated a weak positive relationship between LST and the normalized difference built-up index (NDBI) and a negligible relationship with the normalized difference vegetation index (NDVI). These findings underscore the need for sustainable urban planning that prioritizes ecological integrity while accommodating rapid urban development. Further research is essential to explore these dynamics and inform effective environmental policies.

**Keywords:** Mangrove, Urbanization, LST, Shoreline, GIS, Remote Sensing.

## INTRODUCTION

Mangrove forests provide essential ecosystem services to humans and environment sustainability. Mangroves protect coastlines from natural events coastal flooding and control soil erosion (Bunting et al., 2022). Provision of habitats and livelihoods and mitigate climate through carbon sequestration (Hagger et al., 2022). Despite harsh desert conditions in Qatar, continuous efforts have been made by the governments, to implement mangrove expansion, restoration and conservation programs (Milani, 2018). Although ongoing restoration in recent years, a marina along the Qatar coastline (at Al Thakhir, Simaisma, Al Khor and Fuwairit) are threatened due to climate change and an expanding tourism industry and the escalating scale of coastal development (Al-Khayat and Balakrishnan, 2014; Burt et al., 2017). Sea-level rise, a shortage of fresh water recurrent hypoxia, increasing wave energy, extreme storm, drought and erosion are some examples of environmental hazard are exacerbated by climate change (Melville-Rea et al., 2021, Lincoln et al., 2021; Lachkar et al., 2022). Monitoring cover changes in mangrove ecosystems is essential for understanding the future challenges and current risks they face, as well as for implementing effective conservation policies. Remote sensing technology is particularly well-suited for tracking these changes, and when combined with geographic information systems (GIS), it provides powerful tools for the quantitative analysis of mangrove cover extent and changes over time (Elmahdy & Ali, 2022). This paper aims to model current and historical changes in mangrove distribution in Qatar using remote sensing and GIS technologies. This comparative study helps identify patterns of mangrove degradation, restoration, and expansion in response to urbanization pressures and explore the change affect to shoreline change is also, coastal areas experiencing increased urbanization may see a decline in

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mangrove cover, while regions undergoing reforestation efforts may show positive trends. Many studies indicate a strong correlation between the presence of mangroves and improved shoreline stability, reinforcing the need for conservation and restoration efforts, especially in vulnerable regions like Qatar (Costanza., 2008; Duarte et al., 2013)

## MATERIAL AND STUDY AREA

### Study Area:

Al Khor and Al Thakhira, lies in northeastern Qatar. Its located on the northeast coast of Qatar encompassing site of mangrove tree planting. This region is renowned for its abundant fisheries, ports, and beaches, but it also faces challenges such as land subsidence, coastal erosion, and dissolution processes. According to 2020 data from the National Planning Council, the population of the Al Khor and Al Thakhira Municipality was approximately 140,453 residents. The geographical boundaries of the area are defined by Al Shamal Municipality to the north, Al Daayen Municipality to the south, the Arabian Gulf to the east, and Al Sheehaniya Municipality to the west. Central, as illustrated in Figure 1. In Qatar, mangroves are predominantly found along the eastern coastline, with Al Thakhira representing the largest mangrove area in the country. Among the various species present, the Grey Mangrove (Avicennia marina) is notable (Al-Thani, & Yasseen, 2024). These unique plants thrive in highly saline waters, thanks to their specialized root systems that allow them to absorb oxygen, even in sediments that are low in oxygen and heavily laden. The complex network of mangrove roots provides a vital habitat and food source for fish, migratory birds, marine life, and insects, thereby enhancing the region's biodiversity. According to Nature Qatar, mangroves are classified as viviparous plants. This means their seeds germinate while still attached to the parent tree, allowing them to disperse and grow into new trees along coastal areas, which facilitates ongoing reproduction and expansion (Hogarth, 2015). Mangroves play a vital role in environmental health by effectively capturing and storing harmful carbon in their leaves and roots while producing oxygen. According to the Food and Agriculture Organization (FAO), studies indicate that mangroves sequester over 6.23 gigatons of carbon globally, making a significant contribution to mitigating global warming and reducing harmful carbon emissions (FAO, 2020).


**Figure 1.** Study Area (ALkhour and Al Thakhira)

### Data Collection:

The study utilized satellite imagery from Landsat-8, provided by the United States Geological Survey (USGS). The images were downloaded in the Universal Transverse Mercator (UTM) projection system, specifically within Zone

39N, and referenced to the World Geodetic System 1984 (WGS 1984). To minimize cloud cover, two Landsat-8 images were selected:

First image: Captured on June 1, 2014 Second image: Captured on June 1, 2022

The Center for Geographic Information Systems (CGIS).

Landsat-8 imagery contains spectral bands with a spatial resolution of 30 meters, while the panchromatic band has a resolution of 15 meters, which enhances classification accuracy.

## METHOD

### A. NDVI Calculation:

The first step in our analysis was to calculate the Normalized Difference Vegetation Index (NDVI) from the satellite imagery (Figure 2). NDVI is a valuable metric for assessing vegetation health and density, calculated using the following formula:

NDVI = (NIR – Red) \ (NIR+ Red) (1)

Where:

NIR represents the near-infrared band of the satellite imagery.

Red represents the red band of the satellite imagery.

By calculating NDVI, we can effectively distinguish between vegetated and non-vegetated areas (Mehmood et al., 2024). This index highlights areas with healthy vegetation while minimizing the impact of noise from other spectral bands, thereby refining our classification boundaries.

The NDVI values can be categorized into different thresholds to identify various land cover types, such as forests, grasslands, and agricultural fields. This preliminary analysis of vegetation health sets the stage for more detailed land cover classification, as it provides critical information that enhances the accuracy of subsequent classification algorithms.

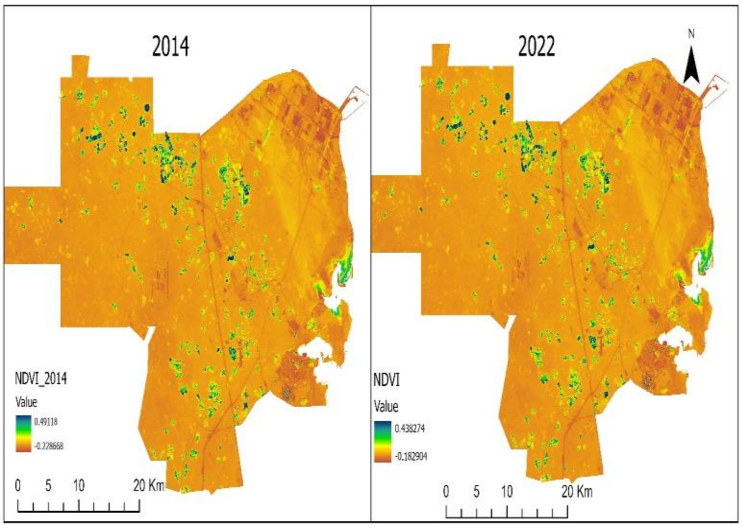


**Figure 2**. NDVI for two different periods in ALkhour and Al Thakhira

### Supervised Classification:

Following the NDVI calculation, a supervised classification of satellite imagery from 2014 and 2022 was conducted. NDVI was utilized as a key feature, and various classification algorithms were employed to categorize different land cover types based on their spectral characteristics and corresponding NDVI values. This integration of NDVI into the

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classification process significantly improved accuracy, allowing for the effective detection and quantification of changes in urban areas over the two time periods. Consequently, valuable insights into land cover dynamics and the impact of urbanization on the landscape were provided by the analysis. The results of the classification revealed trends in urban expansion or contraction, contributing to a deeper understanding of how the urban landscape has evolved. This comprehensive analysis is visually represented in Figure 3. The Normalized Difference Built-up Index (NDBI) uses the NIR and SWIR bands to indicate built-up areas (Varshney, 2013). The Normalized Difference Built-up Index (NDBI) can significantly enhance supervised classification, particularly in urban areas where distinguishing built-up regions from vegetation and water bodies is crucial. By effectively highlighting built-up areas, NDBI improves spectral separation, making it easier to differentiate urban land cover from other types.

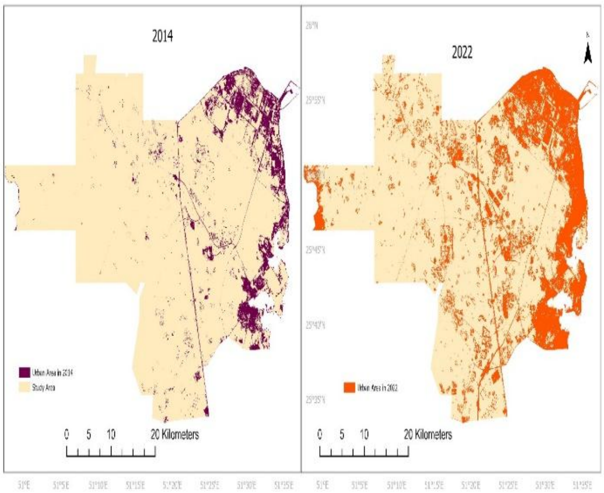


**Figure 3.** Urban Area in two different periods

**Calculate Land Surface Temperature (LST):**

To analyze Land Surface Temperature (LST) from Landsat Level 1 data for the years 2014 and 2022, along with its relationship to NDVI (Normalized Difference Vegetation Index) and mangrove cover, preprocessing steps were undertaken, including radiometric calibration to convert digital numbers to reflectance and atmospheric correction as needed

$$L = (\text{Lmin} - \text{Lmax})\, DN + \text{Lmin} \,/ DNmax \qquad (2)$$

Where L is the spectral radiance received at the sensor;

Lmin and Lmax are the minimum and the maximum spectral radiance for the sensor respectively (Chander et al., 2009)

DNmax is the maximum DN.

Radiant temperature calculation: The thermal band derived radiance images is key factor in calculating radiant temperature based on the formula below (Chander et al., 2009)

$$T = K2/ln\,(K1/L + 1) \qquad (3)$$

Where T = radiant temperature (in Kelvin); K1 and K2 = pre-launched calibration constants; L = spectral radiance.

NDVI was calculated for LST, the top-of-atmosphere brightness temperature from the thermal band was converted to surface temperature using a formulated approach that considered emissivity.

Emissivity was calculated based on (Sobrino et al., 2004) from the equation

$$\varepsilon = 0.004\, Pv + 0.986 \qquad (4)$$

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Where Pv = vegetation proportion; NDVI image was used to extract Pv with reference to (Carlson and Ripley, 1997) was calculated from equation below:

$$Pv = [NDVI - NDVImin/NDVImax - NDVImin]\ 2 \quad (5)$$

Subsequent statistical analyses were conducted to examine correlations between LST and NDVI, as well as between LST and urban cover, utilizing Arc pro. LST was calculated and the result provided in Figure 4.

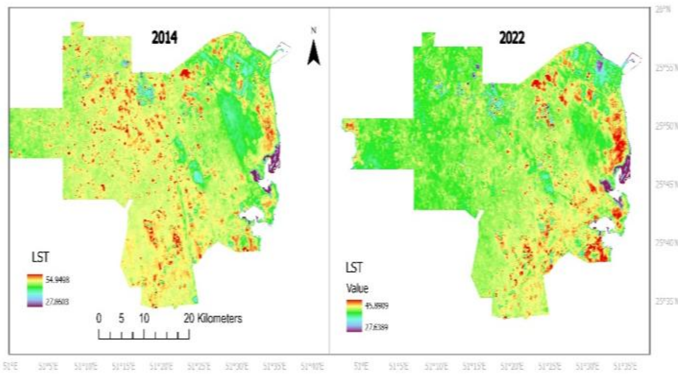


**Figure 4.** LST in two different periods

**Extraction of Mangrove Area:**

For the extraction of mangrove areas, two methodologies were utilized for the years 2014 and 2022. The mangrove area for 2014 was sourced from the Geographic Information System (GIS) department of the Ministry of Municipality. In contrast, for the year 2022, we employed a deep learning model designed for the classification of mangroves using Landsat 8 imagery from the Living Atlas (Figure 5). The deep learning approach allows for more sophisticated analysis of remote sensing data, improving the classification accuracy of mangroves compared to traditional methods (Xu et al., 2023; Hong et al., 2024). The initial NDVI analysis facilitated this process by enhancing the accuracy of distinguishing mangrove areas from other land cover types. The variation function was used to calculate the change in the mangrove cover within the two period.

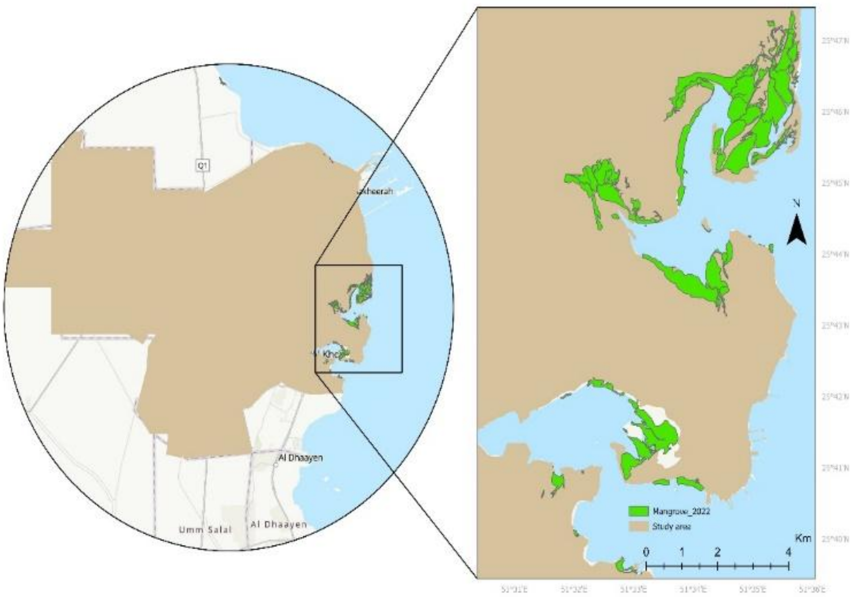


**Figure 5**. Extract Mangrove cover from Landsat 8 by using deep learning model

**Sample Point Selection:**

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To explore the stability of the shoreline and the influence of mangroves and urbanization, 30 sample points along the shoreline was selected, focusing on areas with and without mangrove presence. The shoreline was digitized for both 2014 and 2022 specific focus on areas containing mangrove ecosystems to analyze erosion and accretion dynamics. The distance between each line was determined by establishing an offshore baseline and creating intersections based on sample points. The selected sample points captured a representative cross-section of the shoreline, enabling us to assess how mangrove presence and urban development interact to impact shoreline stability. This comprehensive analysis provides valuable insights into the role of mangroves in coastal protection and their potential contributions to mitigating the effects of urbanization on shoreline dynamics.

## RESULT AND DISCUSSION

### Urbanization

The total urban area experienced significant growth between 2014 and 2022, increasing from 139.7 square kilometers to 396.2 square kilometers. This represents an increase by a factor of approximately 1.8, indicating a rapid expansion of urban development during this period. Such growth can be attributed to various factors, including population growth, economic development, and ongoing urbanization trends in the region. The substantial rise in urban area reflects the changing landscape and the increasing demand for residential, commercial, and infrastructure development.

### Mangrove Change

The total mangrove area was recorded at 4.9 square kilometers. This baseline figure 6 reflects the extent of mangrove (green color) cover prior to any significant restoration efforts. The total area of mangroves had increased to 12.9 square kilometers. This change represents a significant increase in mangrove cover over the eight-year period (Figure. 6).

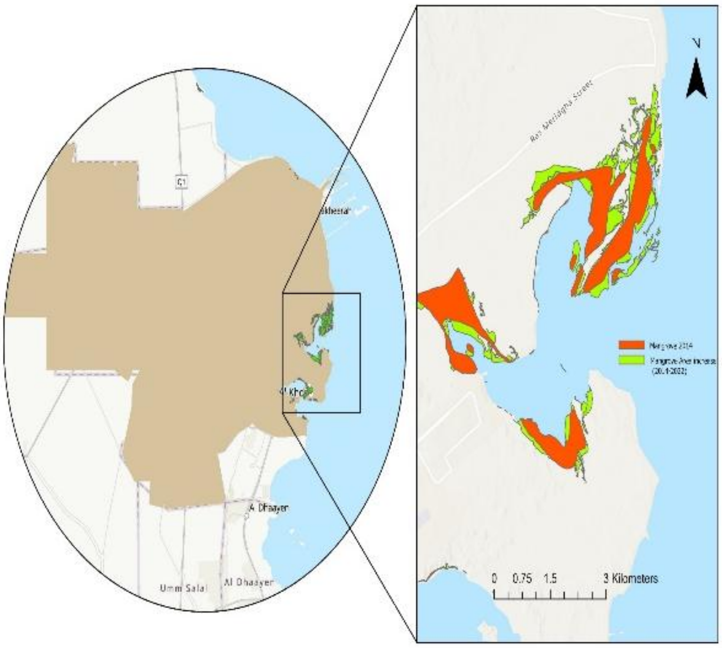


**Figure 6.** Change in Mangrove cover

### Land Surface Temperature

The analysis of LST revealed a minimum temperature of 27°C and a maximum of 54°C in 2014. By 2022, the maximum temperature decreased to 45°C, while the minimum remained constant at 27°C. This reduction in the maximum LST may suggest a cooling effect attributed to the increasing mangrove cover, which can mitigate urban

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heat effects. This reduction in the maximum LST may suggest a cooling effect attributed to the increasing mangrove cover, which can mitigate urban heat effects.

**Shoreline Stability**

When examining the green-colored sectors at the sample points, the shoreline change (erosion) rate in these areas is 50 meters or less. This is due to the presence of mangrove trees, which are indicated by the vegetation density index in these sectors (Figure 7). Conversely, areas with fewer or no mangrove trees exhibited noticeably higher erosion rates. Figure 7 illustrates the extent of shoreline change, highlighting regions that experienced the most significant erosion, including a retreat of 557 meters between 2014 and 2022. This considerable shift is largely attributed to human activity and urbanization. Analysis of satellite imagery confirmed that this area lacks mangrove trees, making it more vulnerable to tidal waves and erosion compared to other parts of the study area.

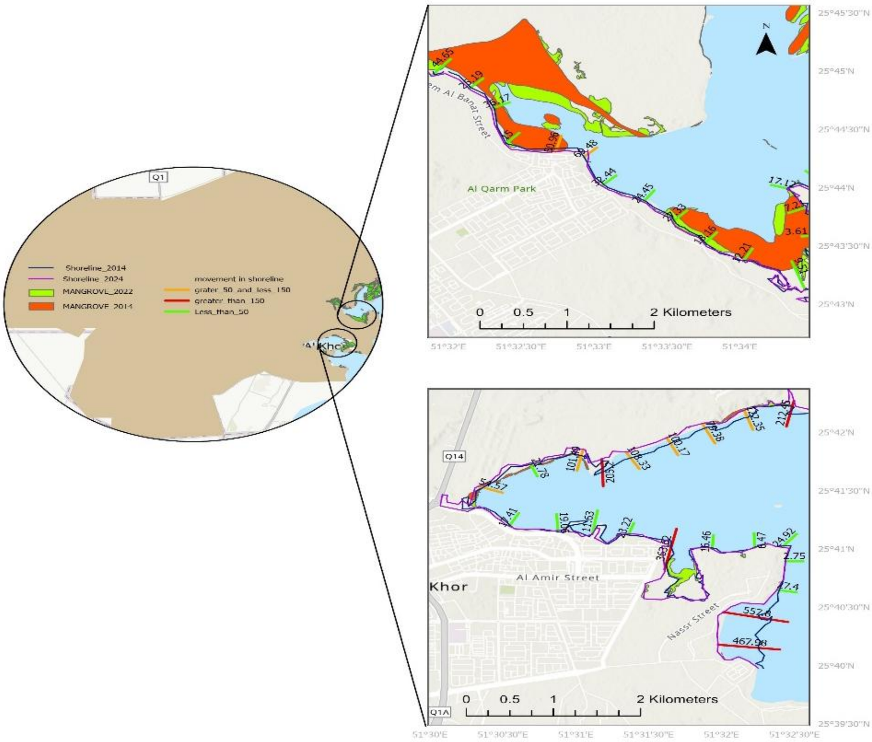


**Figure 7**. Shoreline change and erosion rates (2014-2022)

**Regression Analysis of Land Surface Temperature, Urbanization, and Vegetation Dynamics**

The regression analysis revealed important insights into the relationships between land surface temperature (LST), urbanization (measured by the normalized difference built-up index, or NDBI (Figure 8), and vegetation cover (represented by the normalized difference vegetation index, or NDVI). The correlation coefficient between LST and NDBI was found to be 0.14 and .0.11, indicating a weak positive relationship; this suggests that as urbanization increases, there is a slight tendency for land surface temperatures to rise. However, this relationship is not strong enough to imply direct causation, highlighting the influence of other factors on temperature changes.

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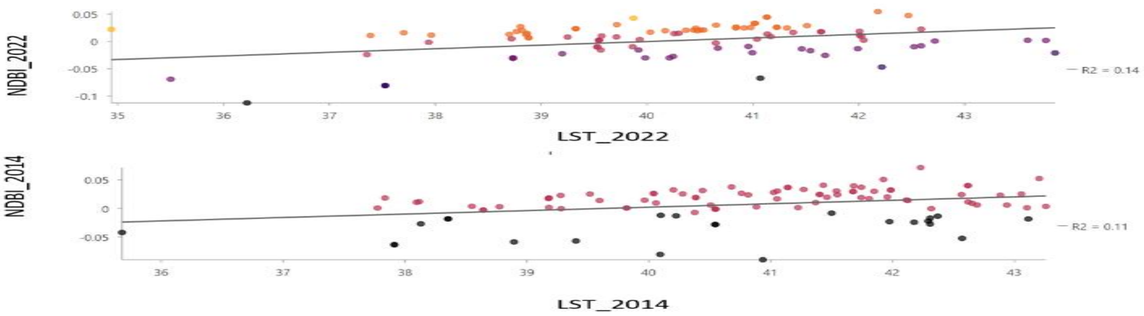


**Figure 8.** Regression Analysis (LST & NDBI)

In contrast, the correlation between LST and NDVI was -0.05, indicating a negligible negative relationship (Figure 9), suggesting that increased vegetation cover does not significantly reduce land surface temperatures. This weak correlation may reflect the counteracting effects of urban development and heat retention in built-up areas. Overall, these findings underscore the complexity of interactions among urbanization, vegetation, and temperature in Qatar, emphasizing the need for a multifaceted approach to understanding environmental dynamics. While the increasing mangrove cover may contribute to shoreline stability and potentially moderate temperature extremes, the rapid expansion of urban areas presents challenges that can diminish these ecological benefits. Further research is essential to explore these relationships in greater depth and to identify effective urban planning strategies that balance development with environmental sustainability.

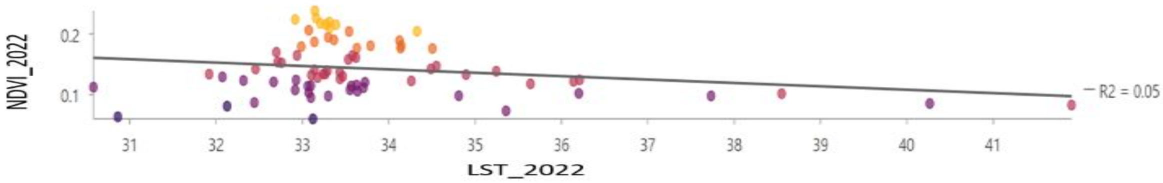


**Figure 9.** Regression Analysis (LST & NDVI)

Urbanization growth underscores the rapid development in the region and its implications for the surrounding ecosystem stabilizing and contribute to instability. Additionally, mangroves may influence local weather patterns, adding another layer of ecological significance. Overall, the results emphasize the need for integrated urban planning that prioritizes ecological sustainability and the preservation of mangrove ecosystems to ensure long-term shoreline stability and environmental health.

## CONCLUSION

This study highlights the intricate relationships between urbanization, mangrove cover, and land surface temperature dynamics in Qatar. The significant increase in mangrove cover underscores the effectiveness of conservation efforts, demonstrating that mangroves play a crucial role in stabilizing shorelines and reducing erosion, particularly in the face of climate impacts. However, rapid urban expansion presents significant environmental challenges and can adversely affect shoreline stability. The findings indicate that while mangroves help mitigate erosion and enhance resilience to climate change, urbanization can counteract these benefits and contribute to instability. Additionally, mangroves may influence local weather patterns, adding another layer of ecological significance. Overall, the results emphasize the need for integrated urban planning that prioritizes ecological sustainability and the preservation of mangrove ecosystems to ensure long-term shoreline stability and environmental health.

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