

Article

Cooling of Maximum Temperatures in Six Saudi Arabian Cities (1994–2024)—Reversal of Urban Heat Islands

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Abstract

Urban heat islands (UHIs) intensify thermal stress in cities, particularly in arid and semi-arid regions undergoing rapid urban expansion. The main objectives of this study are to quantify and compare UHI intensity in six major Saudi Arabian cities (Dammam, Makkah, Madinah, Jeddah, Riyadh, and Abha) representing diverse climatic zones and to examine how UHI patterns vary between urban, suburban, and rural zones over a 30-year period. Understanding the magnitude and spatial variability of UHIs across different climatic settings is crucial for developing effective urban planning and climate adaptation strategies in Saudi Arabia's rapidly expanding cities. Except for Abha, these cities are the five most populous cities in the Kingdom. Each city was categorized into urban (>1500 people km^{-2}), suburban ($300\text{--}1500$ people km^{-2}), and rural (<300 people km^{-2}) zones using high-resolution population density data. Two independent temperature datasets (ERA5-land and CHIRTS-ERA5) were analyzed for the years 1994, 2004, 2014, and 2024. Both datasets revealed consistent spatial patterns and a general warming trend across all zones and cities over the 30-year period. The UHI effect was most pronounced for minimum temperatures, with urban zones warmer than rural zones by 0.85 °C (ERA5-land) and 1.10 °C (CHIRTS-ERA5), likely due to greater heat retention and slower cooling rates in built-up areas. Mean temperature differences were smaller but still indicated positive UHI. Conversely, both datasets exhibited a reversed UHI pattern for maximum temperatures, with rural zones warmer than urban zones by 1.73 °C (ERA5-land) and 1.52 °C (CHIRTS-ERA5). This reversed pattern is attributed to the surrounding desert landscapes with minimal vegetation, indicated by low normalized difference vegetation index (NDVI), while urban areas have increasingly benefited from greening and landscaping initiatives. City-level analysis showed the strongest reversed UHI in maximum temperatures in Abha, while Jeddah exhibited the weakest. These findings highlight the need for localized urban planning strategies, particularly the expansion of vegetation cover and sustainable land use, to mitigate extreme thermal conditions in Saudi Arabia.

Keywords: normalized difference vegetation index; reversed urban heat island; ERA5-land; CHIRTS-ERA5; temperature trend; arid and semi-arid climate



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1. Introduction

Urban areas are experiencing accelerating growth as increasing numbers of people migrate from rural to urban environments in search of better job opportunities and improved quality of life [1,2]. Urban environments differ markedly from rural ones in terms of land cover, pollutant and greenhouse gas emissions, and energy usage. These differences influence the exchange of heat between the land surface and the atmosphere, disrupting the surface energy balance and typically making urban areas warmer than their rural surroundings, a phenomenon known as the Urban Heat Island (UHI) effect [3,4]. The UHI effect is of particular concern because it can exacerbate heat stress in human populations, affect vegetation health, alter energy demand patterns, and interact with broader climate change processes [5,6]. Given the rapid pace of urbanization, it is essential to understand the spatial and temporal dynamics of UHI, as well as its driving mechanisms and potential mitigation strategies [7,8].

Numerous studies have investigated UHI characteristics in cities worldwide [9], including in desert and arid environments [10,11]. In Saudi Arabia, several researchers have examined UHI intensity and its characteristics in cities such as Riyadh [6,12], Jeddah [13], and Al Ahsa Oasis [14]. These studies generally found a negative association between UHI and vegetation, and a positive association with built surfaces and anthropogenic heat emissions. Interestingly, Alghamdi and Moore [12] reported a reversed UHI in Riyadh, which they attributed to the relatively greater presence of vegetation in urban areas. Broader Gulf-region analyses have also highlighted the influence of sandy deserts and bare soils on daily temperature inversions and the weakening or reversal of daytime UHI in arid settings [10].

Saudi Arabia's unique geographical and climatic context, characterized by extreme summer temperatures often exceeding 50 °C [15] and rapid economic development, makes it an important case study for UHI research. While numerous studies have examined UHI phenomenon in Saudi Arabia, most of them have focused on single cities, most notably Riyadh, the capital city of Saudi Arabia. Their findings have been inconsistent: some identify a pronounced UHI effect, whereas others report reversed UHI patterns. Such variability highlights the need for a comprehensive, multi-city comparison based on robust, long-term datasets. Therefore, quantifying UHI intensity and understanding its drivers in major cities such as Dammam, Jeddah, Madinah, Makkah, and Riyadh, as well as high-altitude cities like Abha, is essential for informing climate adaptation strategies, urban design, and public health planning. The main objectives of this study are to: (a) Quantify UHI intensity by calculating the temperature differences between urban, suburban and rural zones in Saudi Arabia. (b) Compare UHI magnitudes across several major cities with varying size of population, geographic settings, and climatic conditions. (c) Assess how UHI intensity varies across minimum, mean, and maximum temperatures, and (d) how UHI has been evolving over time (1994–2024).

The main strengths of this study are:

- I The use of two independent and high-resolution datasets, ERA5-Land and CHIRTS-ERA5, to cross-validate UHI estimates, enhancing the robustness of the results.
- II A multi-city approach encompassing six major Saudi cities (Dammam, Jeddah, Makkah, Madinah, Riyadh, and Abha), in contrast to most previous UHI studies in the Kingdom that have focused on a single city.
- III Assessing the UHI across urban, suburban, and rural zones to provide a continuous perspective from city centers to rural landscapes.
- IV The comparative analysis of coastal cities (Dammam and Jeddah) and inland cities (e.g., Riyadh), allowing for the examination of the role of maritime influence on UHI intensity.

- V The inclusion of high-altitude cities such as Abha, enabling an evaluation of how elevation and mountainous terrain affect UHI patterns.
- VI A spatiotemporal perspective that assesses UHI changes over a 30-year period (1994–2024), providing insights into both long-term climate variability and the impacts of rapid urbanization.

The rest of the paper is organized as follows: Section 2 outlines the methodology of the study, including the criteria for city selection, temperature data, Normalized Difference Vegetation Index (NDVI), and the software employed. Section 3 presents the main findings and interprets the underlying reasoning. Finally, Section 4 concludes the study and provides recommendations for future research and strategies to address the issue of UHI in urban areas.

2. Methodology

This study focuses on UHI analysis in six Saudi Arabian cities: Abha, Dammam, Makkah, Madinah, Jeddah, and Riyadh, by quantifying temperature differences across urban, suburban and rural areas.

2.1. City Selection

The main aim of this study was to quantify and compare the UHI effect in six large cities of Saudi Arabia (Table 1), a country situated in an arid to semi-arid climatic zone and undergoing rapid urban expansion. Based on national population statistics, the five most populous cities, Dammam, Makkah, Madinah, Jeddah, and Riyadh, were selected as primary study sites. In addition, the city of Abha was included to represent high-altitude and topographically complex urban environments, characteristic of hilly regions in the Asir Mountains. The six selected cities represent diverse climatic zones, population densities, and urbanization levels in Saudi Arabia, including coastal, inland, and elevated areas. The northwestern and southeastern regions were not included primarily due to their low population density and limited urban development, which would not allow meaningful UHI analysis. This combination of cities captures a range of climatic, geographic, and urbanization contexts, allowing for a more comprehensive assessment of UHI dynamics. Table 1 presents city names, latitude, longitude, elevation, total population and annual mean temperature in 2024. Figure 1 illustrates the spatial distribution of the six selected cities, showing their geographic locations within Saudi Arabia, while Figure 2 presents the population densities of Saudi Arabia, which clearly shows that northwestern and southeastern regions have low population density, compared to the regions selected for this study.

Table 1. Characteristics of the six cities analyzed for urban heat island (UHI) effect.

City Name	Latitude (°N)	Longitude (°E)	Elevation (m)	Population (Residents)	Mean Temperature (2024) (°C)
Abha	18.2465	42.5117	1700	334,290	23.23
Dammam	26.4257	50.05516	13	1,386,166	28.59
Jeddah	21.4925	39.17757	35	3,712,917	32.40
Madinah	24.4709	39.61224	852	1,411,599	28.17
Makkah	21.42251	39.82617	577	2,385,509	30.50
Riyadh	24.77427	46.73859	606	6,924,566	26.90

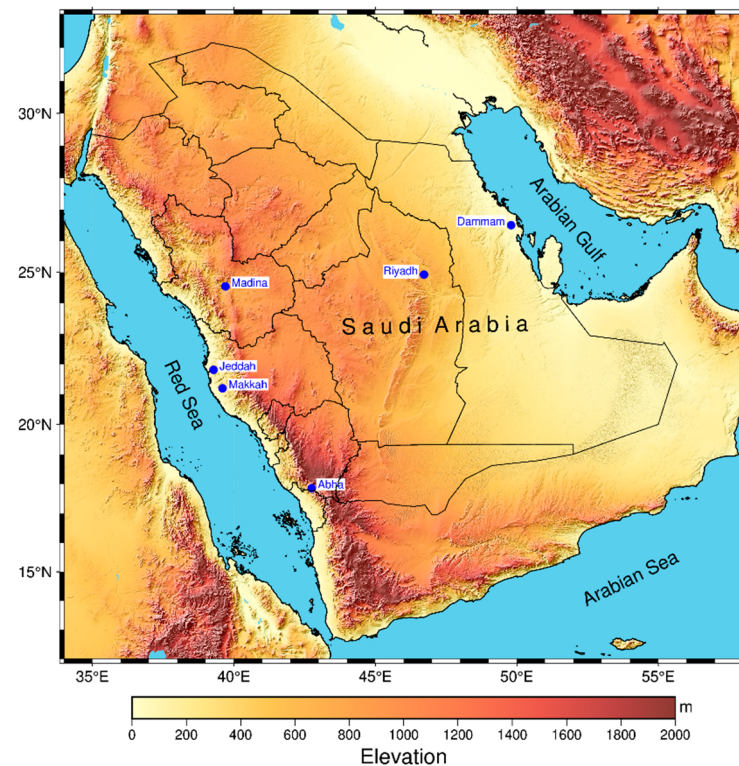


Figure 1. Geographical locations of the six cities, analyzed for urban heat island (UHI) effect. The legend shows the elevation (m) of Saudi Arabia. The selected six cities are highlighted as blue points.

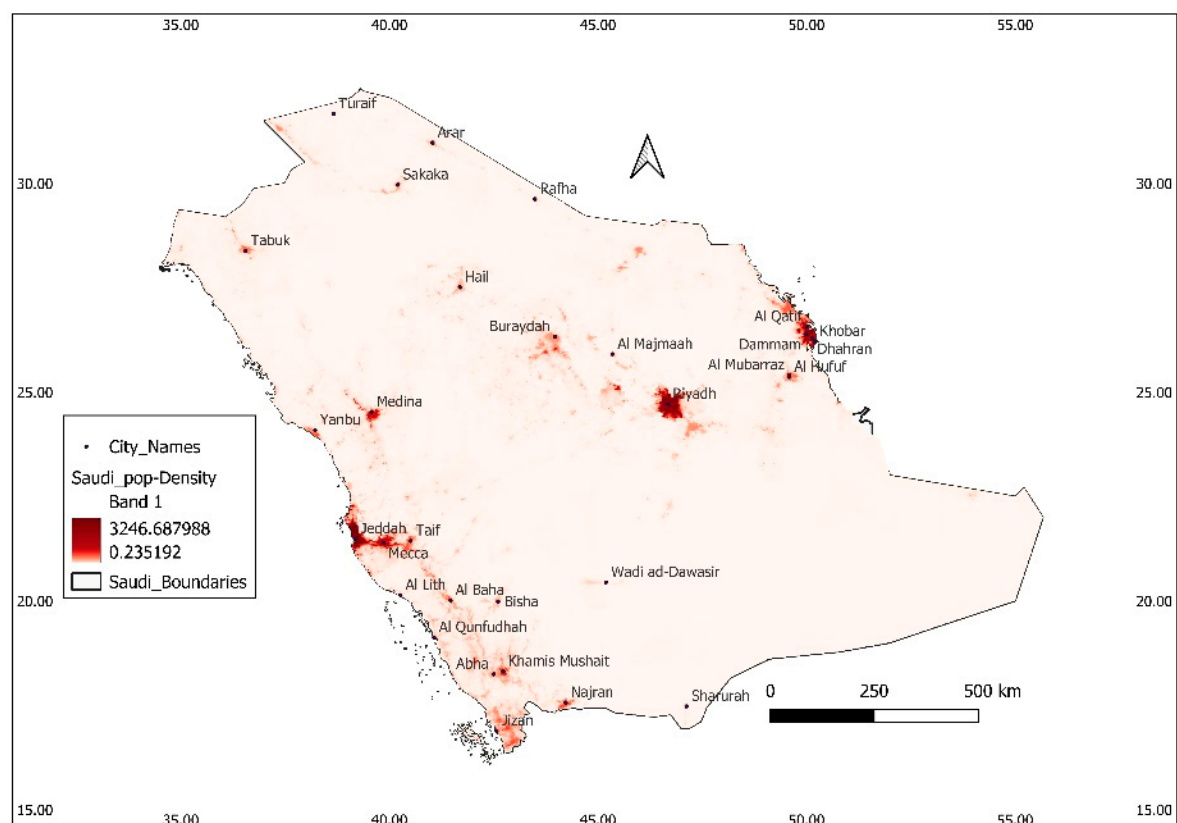


Figure 2. Population density per km square (pop/km²) in Saudi Arabia 2020 [16], used to classify the six cities into urban, suburban and rural zones.

2.2. Zonal Classification

To enable a detailed comparison of temperature patterns across varying degrees of urbanization, each of the six cities was subdivided into three distinct zones, urban, suburban, and rural, based on population density thresholds of Eurostat [17]. Areas with a population density greater than 1500 people km⁻² were classified as urban, zones with a population density between 300 and 1500 people km⁻² were designated as suburban, and regions with a population density of less than 300 people km⁻² were considered rural. This classification allowed for a systematic evaluation of the UHI effect across gradients of population density, providing insights into how urban form and human activity influence local thermal environments. While a formal sensitivity analysis of these thresholds was not performed, the observed temperature differences between urban, suburban, and rural zones are consistent with expected UHI patterns, supporting the validity of this approach. Moreover, this represents the first study to classify Saudi cities based on population density, offering a novel methodology in a region where such basic urban classification data are largely unavailable and highlighting the need for further research in this area.

2.3. Temperature Data

Temperature data were obtained from two online sources: The ERA5-Land (v1, there is only one major version, which is periodically updated and extended) and CHIRTS_ERA5 (v2.0, released in 2024, with improvements in bias correction and temporal consistency) datasets, which are described below. The datasets ERA5-Land and CHIRTS-ERA5 were selected based on their high spatial resolution, long-term coverage, and independent data sources, which allow for robust quantification of temperature trends and UHI intensity. ERA5-Land provides globally consistent land-surface temperature data with fine temporal and spatial resolution, while CHIRTS-ERA5 combines satellite observations with reanalysis data to improve accuracy in regions with sparse ground stations. Using both datasets allows cross-validation of results and increases confidence in the observed UHI patterns.

2.3.1. The ERA5-Land Dataset

ERA5-Land is a reanalysis dataset that provides a consistent and long-term representation of land variables at a spatial resolution enhanced relative to ERA5 [18,19]. ERA5-Land is provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) via Copernicus Climate Data Store (CDS). It is generated by replaying the land component of the ECMWF ERA5 climate reanalysis, which combines model simulations with observations from around the globe to produce a physically consistent, spatially complete dataset. In the case of air temperature, ERA5-Land provides the temperature of air at 2 m above the land surface, including inland water bodies such as lakes and rivers, but excluding seas and oceans. The 2 m temperature is derived by interpolating between the lowest model level and the Earth's surface, accounting for atmospheric conditions [18]. Temperatures are reported in kelvin, which were converted to degrees Celsius (°C) for further analysis. ERA5-Land offers a high-resolution land surface reanalysis at ~9 km native resolution, typically provided on a 0.1° × 0.1° regular latitude–longitude grid (~9 km) for data access purposes.

ERA5-Land uses atmospheric variables from ERA5, such as air temperature and humidity, to constrain the simulated land fields, a process known as atmospheric forcing. While observations are not directly assimilated into ERA5-Land, they exert an indirect influence through the ERA5 driving variables. Furthermore, ERA5-Land applies a lapse-rate correction to account for elevation differences between the forcing grid and the finer-resolution ERA5-Land grid. As with any simulation, ERA5-Land estimates carry a degree of uncertainty, which can be assessed in conjunction with the uncertainty estimates of the equivalent ERA5 fields.

In this study, we utilised ERA5-Land to obtain 2 m air temperature data for Saudi Arabia for the years 1994, 2004, 2014, and 2024. Annual minimum (Tmin) and maximum (Tmax) temperatures were calculated from the hourly temperature fields using standard aggregation procedures. The native 9 km spatial resolution was resampled to 1 km using the bilinear interpolation method. These data were analysed to assess temporal and spatial changes in temperature patterns to quantify the intensity of UHI effect. For each study year, temperature values were extracted for six major Saudi cities, and each city was classified into urban, suburban, and rural zones to enable comparative analysis.

2.3.2. CHIRTS-ERA5

The Climate Hazards Center (CHC), University of California, produces the Climate Hazards Infrared Temperature with Stations (CHIRTS-ERA5) temperature dataset, a quasi-global product covering latitudes from 60° S to 70° N at a spatial resolution of $0.05^\circ \times 0.05^\circ$ (approximately 5 km). The dataset provides daily maximum and minimum air temperature at 2 m height, derived by merging satellite observations, in situ station measurements, and reanalysis outputs. ERA5 has demonstrated robust performance in representing spatial covariance and daily anomalies; however, it exhibits a global cool bias, particularly in Africa, leading to an underestimation of extreme hot days [20]. The CHIRTS-ERA5 v2.0 framework applies bias correction to address this cooling bias.

CHIRTS-ERA5 extends the CHIRTS-daily record beyond 2016 by leveraging ERA5's low-latency data to fill gaps in station-based temperature reporting. The methodology exploits the complementary strengths of both datasets: CHIRTSmax provides reliable monthly climatology, particularly in data-sparse regions [21], while ERA5 supplies dynamically consistent and accurate day-to-day temperature anomalies. In this approach, CHIRTSmax monthly climatology represents the underlying climate signal, and ERA5 daily fields capture short-term weather variability. The result is a bias-corrected and downscaled ERA5 product harmonized with the CHIRTS framework, which aligns with the CHIRTS climatology on monthly timescales while preserving the temporal variability of ERA5.

In this study, we used CHIRTS-ERA5 v2.0 to obtain daily 2 m air temperature for Saudi Arabia for the years 1994, 2004, 2014, and 2024. The daily data were aggregated to annual means for analysis, and the native 5 km resolution was resampled to 1 km using the bilinear interpolation method to match the spatial scale of the other datasets. Although the resampling increases the apparent spatial resolution, it does not add new information, and some fine-scale urban temperature variations may remain unresolved due to the coarser native resolution of the source data. The processed data were used to investigate temporal and spatial changes in temperature patterns and quantify the UHI effect. For each target year, temperatures were extracted for six major Saudi cities, which were further classified into urban, suburban, and rural zones for comparative analysis.

Figure 3 presents an example of the spatial distribution of temperature across Saudi Arabia for the year 2024, revealing a pronounced positive gradient from north to south. The highest temperatures are observed in the southeastern part of the country, predominantly within the Rub' al Khali (Empty Quarter) desert. This pattern reflects the combined influence of latitude, arid climatic conditions, and the absence of moderating topographic or coastal effects in the interior desert regions.

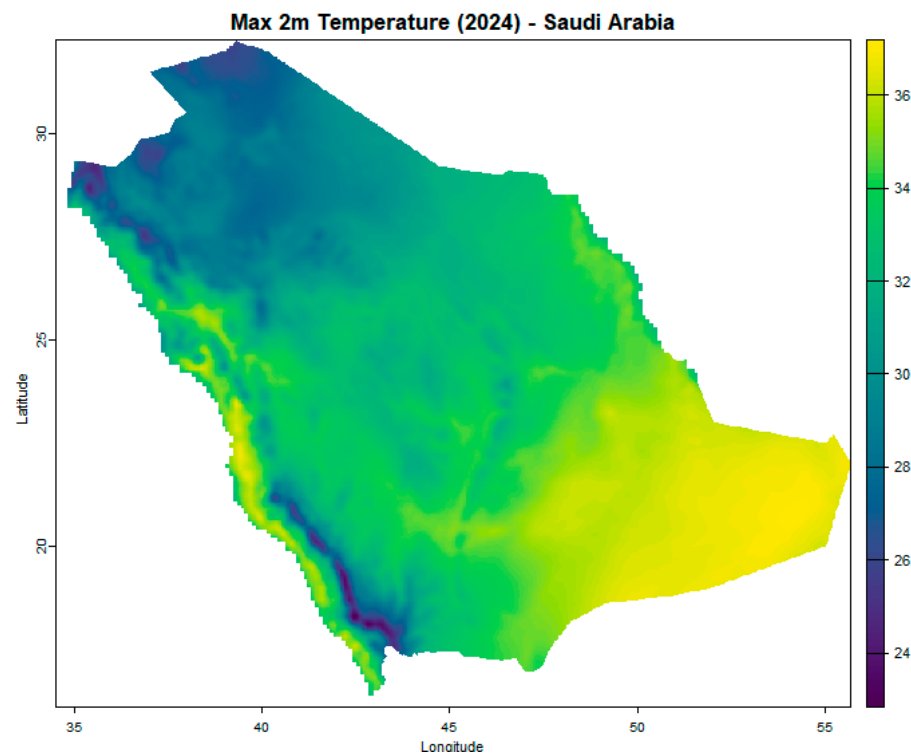


Figure 3. CHIRTS–ERA5 maximum 2 m annual air temperature for 2024 Saudi Arabia.

2.4. Normalized Difference Vegetation Index (NDVI) Data

For this study, NDVI data were derived from the Sentinel-2 Surface Reflectance Harmonized (S2_SR_HARMONIZED) Image Collection from Google Earth Engine (GEE). Sentinel-2 provides multispectral imagery at 10–20 m spatial resolution, enabling detailed assessment of vegetation cover in urban and surrounding areas. Vegetation cover is considered to be a controlling factor of temperature in urban areas [9,12].

NDVI data were obtained for 2024 for six Saudi Arabian cities (Abha, Dammam, Jeddah, Makkah, Madinah, and Riyadh). The NDVI images were filtered by city boundaries using shapefiles for each city. The images were limited to those with <20% cloud cover to reduce atmospheric interference.

NDVIs were calculated using Equation (1):

$$\text{NDVI} = \frac{(\text{NIR (B8)} - \text{RED (B4)})}{(\text{NIR (B8)} + \text{RED (B4)})} \quad (1)$$

where

NIR (B8) represents near-infrared reflectance measured in band 8 (~842 nm), and RED (B4) represents red reflectance measured in band 4 (~665 nm). Vegetation strongly reflects NIR light, making this band sensitive to plant biomass and vigor, while chlorophyll absorbs red light, so the RED band captures photosynthetic activity. The NDVI ratio exploits the contrast between high NIR reflectance and low RED reflectance in healthy vegetation, producing values that indicate vegetation density and condition. All filtered images were averaged to produce annual mean NDVI for each city, and the resulting rasters were clipped to city boundaries to focus the analysis on urban and peri-urban areas. The data were processed at 100 m spatial resolution, resampled from the original 10 m bands for computational efficiency, and exported as GeoTIFF files via Google Earth Engine to Google Drive for subsequent analysis. NDVI values range from −1 to +1, where positive values indicate vegetation cover and negative values typically correspond to water, snow,

or highly reflective non-vegetated surfaces. For this study, only positive NDVI values were considered to quantify urban and peri-urban vegetation in relation to temperature patterns.

2.5. Software, Mapping and Analysis

All data analysis was carried out using the R programming language [22] together with a set of specialized packages designed for statistical computing, spatial data processing, and visualization. Data manipulation was primarily performed using dplyr [23] and tidyr [24], both of which are part of the tidyverse collection [25]. The stringr package [26] was employed for efficient and consistent handling of string operations, while readr [27] facilitated fast and reliable import of tabular data. For data visualization, we used ggplot2 [28], a grammar-of-graphics-based plotting system, which allows for flexible and publication-quality figure generation. Spatial data handling and analysis were performed with several packages: sf [29] for vector data in simple features format, stars [30] for handling raster and spatiotemporal arrays, and terra [31] for raster and vector spatial analysis with efficient memory handling. NetCDF climate data were accessed using the ncdf4 package [32].

The mapping and data analysis were conducted through the following ten sequential steps (Figure 4):

- ✓ Selection of study cities: Six cities were selected for UHI analysis. These cities represent the five most populated cities in Saudi Arabia (Dammam, Makkah, Madinah, Jeddah, and Riyadh) and Abha, representing a high-altitude, hilly region.
- ✓ Acquisition of population density data: A high-resolution population density map of Saudi Arabia was obtained and used as the basis for spatial classification.
- ✓ Extraction of city boundaries: Administrative boundary outlines for the six selected cities were sourced and prepared for spatial analysis.
- ✓ Derivation of population density values for each city: Population density data were spatially intersected with the city boundaries to extract population density values specific to each urban area.
- ✓ Zonal classification: Based on established thresholds, each city was subdivided into three zones: urban (>1500 people km^{-2}), suburban ($300 - 1500$ people km^{-2}), and rural (<300 people km^{-2}).
- ✓ Acquisition of temperature datasets: Two independent gridded climate datasets were downloaded for the entire Kingdom of Saudi Arabia: (i) ERA5-Land and (ii) CHIRTS-ERA5.
- ✓ City-level temperature extraction: For each dataset, temperature values corresponding to the spatial extent of each city and its zonal subdivisions (urban, suburban, rural) were extracted for the years 1994, 2004, 2014, and 2024.
- ✓ Temperature estimation for each zone: For each study year, mean, minimum, and maximum annual air temperature values were calculated for the urban, suburban, and rural zones within each city.
- ✓ Computation of annual temperature differences: The annual temperature differences between urban–suburban, urban–rural, and suburban–rural zones were calculated to quantify the magnitude of the UHI effect.
- ✓ Visualization and comparative analysis: The results were visualized using graphical methods to facilitate both temporal and spatial comparison of UHI intensity across the selected cities and zones.

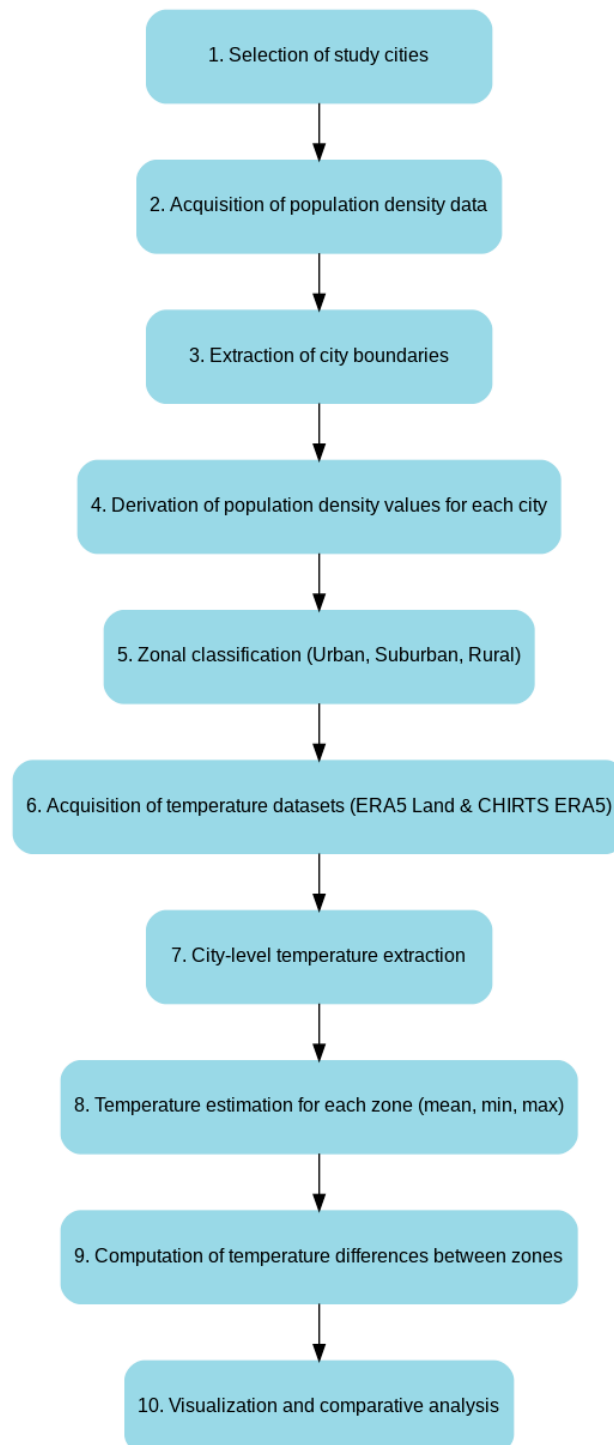


Figure 4. Linear flowchart of the ten sequential steps used for mapping and data analysis.

3. Results and Discussion

3.1. Comparing CHIRTS-ERA5 and ERA5-Land Datasets

To make sure the data utilized in this analysis was reliable, the two datasets CHIRTS-ERA5 and ERA5-Land were compared to quantify their differences. The comparison revealed consistent differences between the two datasets across the study years (Table 2 and Figure 5). On average, CHIRTS-ERA5 reported slightly higher minimum, mean and maximum temperatures than ERA5-Land, with an absolute difference of 1.60 °C for minimum, 1.55 °C for mean, and 0.44 °C for maximum temperatures (Table 2). These

discrepancies slightly increased over time, particularly in minimum temperatures, which exhibited a rise in absolute difference from 1.52 °C in 1994 to 1.86 °C in 2024, corresponding to a percentage increase from 8.72% to 9.85%, respectively. However, the increase in difference was relatively less in maximum temperature, averaging only 1.28% and highest of 1.55% in 2004 (Table 2). This implied greater consistency between the two datasets in capturing temperature extremes. Overall, the CHIRTS-ERA5 dataset tended to produce warmer temperature estimates, especially for minimum and mean values, which might have implications for UHI analyses and related climate impact assessments. The percent (%) differences ranged from 7.57 to 9.85, 5.67 to 6.23, and 1.06 to 1.55 for minimum, mean and maximum temperatures, respectively. To further quantify the relationship between the two datasets, we calculated the correlation coefficient and root mean squared error (RMSE). The correlation coefficients were 0.97, 0.93, and 0.94, while the RMSE values were 1.85, 1.87, and 0.90 for minimum, mean, and maximum temperatures, respectively, indicating a strong correlation and minimal error between CHIRTS-ERA5 and ERA5-Land. Figure 5a depicts further details by comparing minimum, mean and maximum temperatures in various zones (rural, suburban and urban) and their trends. In mean temperature the difference is slightly greater in urban areas than in rural areas. The differences seem to be widening over time, especially in minimum and mean temperature. CHIRTS-ERA5 was bias-adjusted and is considered suitable for this analysis; however, using both ERA5-Land and CHIRTS-ERA5 datasets simultaneously provides greater confidence in the robustness of the results. It is reported that, in the earlier part of the ERA5-Land record, uncertainties were larger due to the limited availability of assimilated observations and the dependence on ERA5 atmospheric forcing fields [18,19]. The forcing data before the 2000s were constrained by a sparser global observing system, particularly over regions such as the Middle East, which increases the risk of artificial biases in surface temperature estimates [18,19]. A further source of discontinuity arises around the late 1990s and early 2000s, when major changes in the assimilated satellite observations occurred. In particular, the introduction of advanced microwave sounding instruments (AMSU) after 1998 substantially altered the observational constraint of the reanalysis, leading to detectable step changes in temperature and humidity fields that propagate into ERA5-Land surface products [17]; however, these reported changes are not clearly observable as compared to CHIRTS-ERA5 in Figure 5.

Table 2. Absolute (Abs) and percent (%) temperature differences (Diff) between CHIRTS-ERA5 and land-ERA5 datasets. The differences were estimated by subtracting Land-ERA5 from CHIRTS-ERA5.

Year	AbsDiff_Min	AbsDiff_Mean	AbsDiff_Max	%Diff_Min	%Diff_Mean	%Diff_Max
1994	1.52	1.44	0.36	8.72	5.67	1.06
2004	1.34	1.51	0.53	7.57	5.87	1.55
2014	1.70	1.58	0.45	9.50	6.07	1.30
2024	1.86	1.66	0.42	9.85	6.23	1.21
Average	1.60	1.55	0.44	8.91	5.96	1.28

3.2. City-Level Results: ERA5-Land Data

Figure 6 presents Makkah as a representative example of the six cities, illustrating city-level population density, zonal classification, and spatial temperature patterns. The same procedure was followed for all six cities. High-density urban areas, depicted in dark red (Figure 6a), are encircled by medium-density suburban zones and then low-density rural areas. This classification is further clarified in Figure 6b, where urban, suburban, and rural zones are shown in red, green, and blue, respectively. However, the spatial distribution of temperature (Figure 6c–e) does not mirror this population density pattern.

Instead, temperature maps for 2024 (Figure 6c–e) reveal a clear northeast-to-southwest gradient across Makkah.

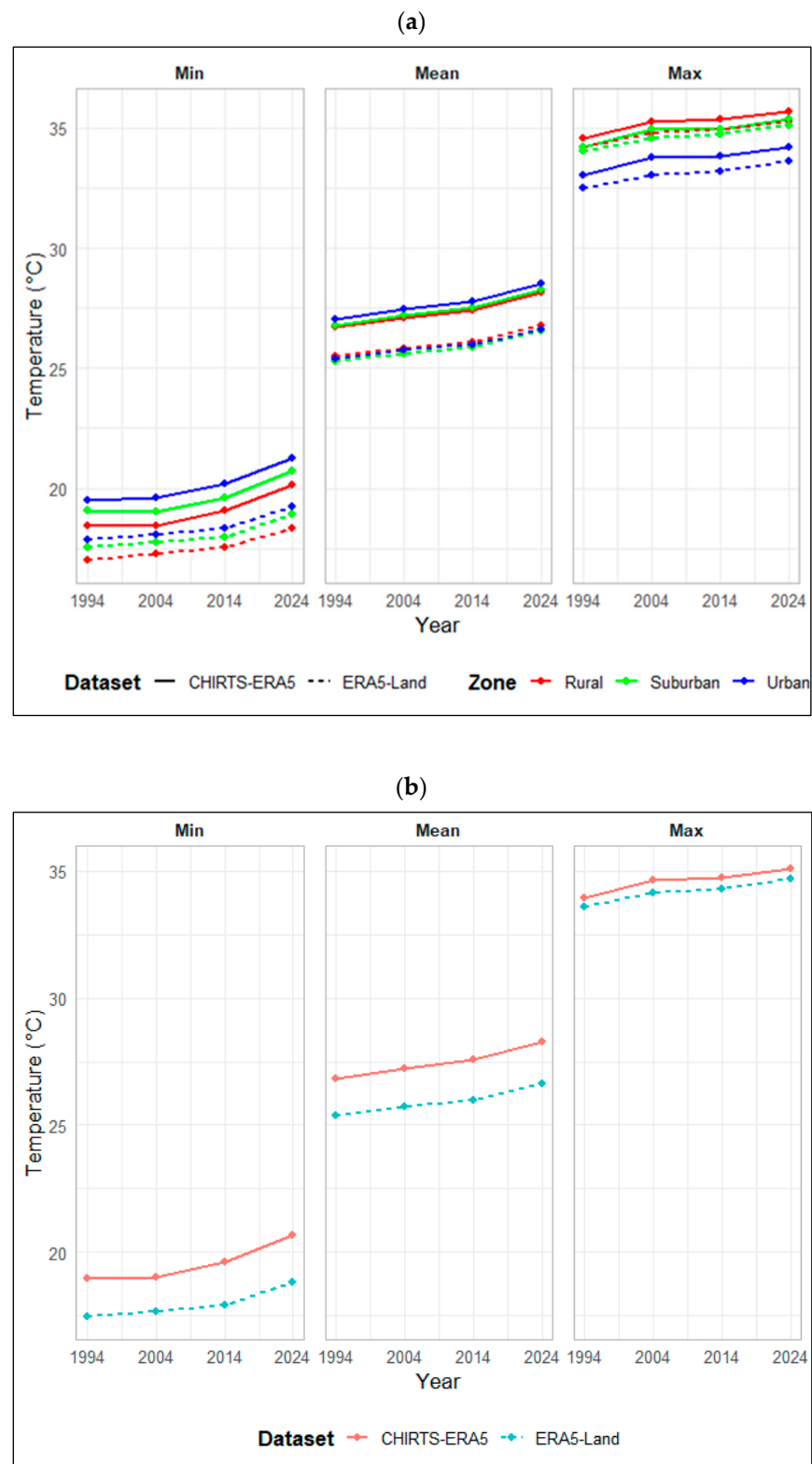


Figure 5. Comparing minimum, mean and maximum CHIRTS-ERA5 and ERA5-land temperatures for different zones (a) and the corresponding zonal averages (b).

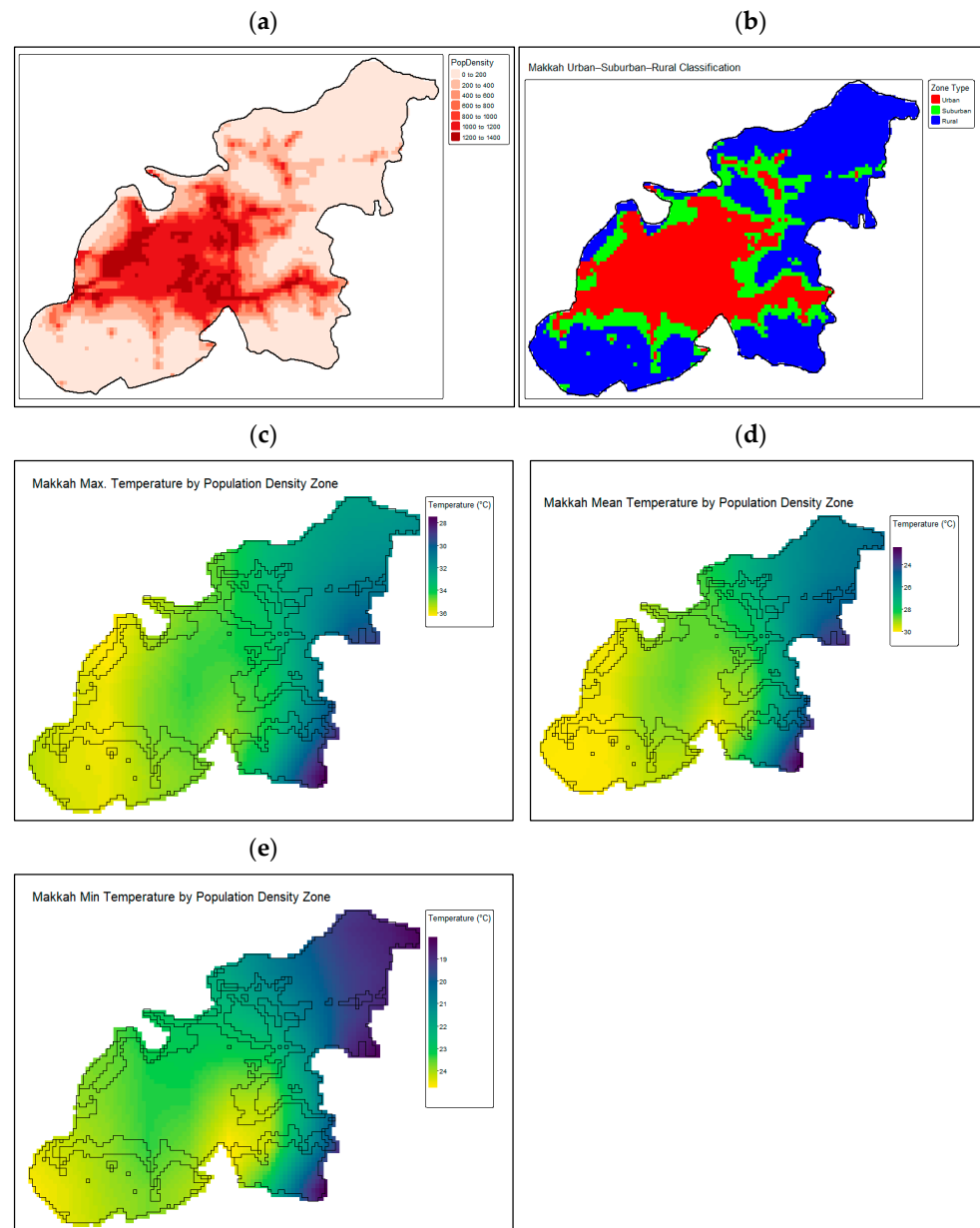


Figure 6. Makkah population density (a), classification into urban, suburban and rural zones (b), and maps of 2 m annual air temperature for 2024 maximum (c), mean (d), and minimum (e). Note black lines in panels c, d and e separate urban, suburban and rural areas.

Figure 7 visualizes temperature levels and their trends in the six cities in Saudi Arabia. For more detailed statistics see Table S1 in the Supplementary Materials, which presents ERA5-Land temperature data in different zones of the six cities. The analysis of temperature patterns across rural, suburban, and urban zones in six major cities reveals consistent urban–rural gradients, particularly for minimum and mean temperature. Urban zones generally exhibit the highest temperature, followed by suburban and then rural zones. This pattern is especially prominent in minimum temperature in all cities, particularly in Dammam, Madinah and Makkah, suggesting stronger heat retention during the cooling process in urban areas, consistent with the expected UHI effect. The average minimum temperature across all cities is 18.38 °C in urban areas compared to 17.53 °C in rural zones, indicating an average urban–rural difference of approximately 0.85 °C (Table S1). In contrast, average maximum temperature in rural and urban areas across all cities was 34.80 and 33.07, respectively, indicating an urban–rural difference of 1.73 °C. This is a

clear example of a reversed UHI in maximum temperature, where rural areas experience higher maximum temperatures than urban areas. Over the study period (1994–2024), the temperature differences between zones have either persisted or slightly increased, particularly for minimum temperature, highlighting an intensifying UHI signal. This is evident in cities like Abha and Makkah, where the minimum temperature difference between rural and urban zones grew by more than 1 °C over 30 years. In contrast, maximum temperature shows minimal spatial variability across zones, with overlapping values and minor differences. Overall, the results confirm that UHI effects are more pronounced in minimum temperature and are becoming more distinct over time in several Saudi Arabian cities, likely due to continued urbanization and land-use intensification. Every city has experienced the same trend showing higher maximum temperature in rural areas than urban areas, especially Abha, Dammam, Jeddah, and Madinah.

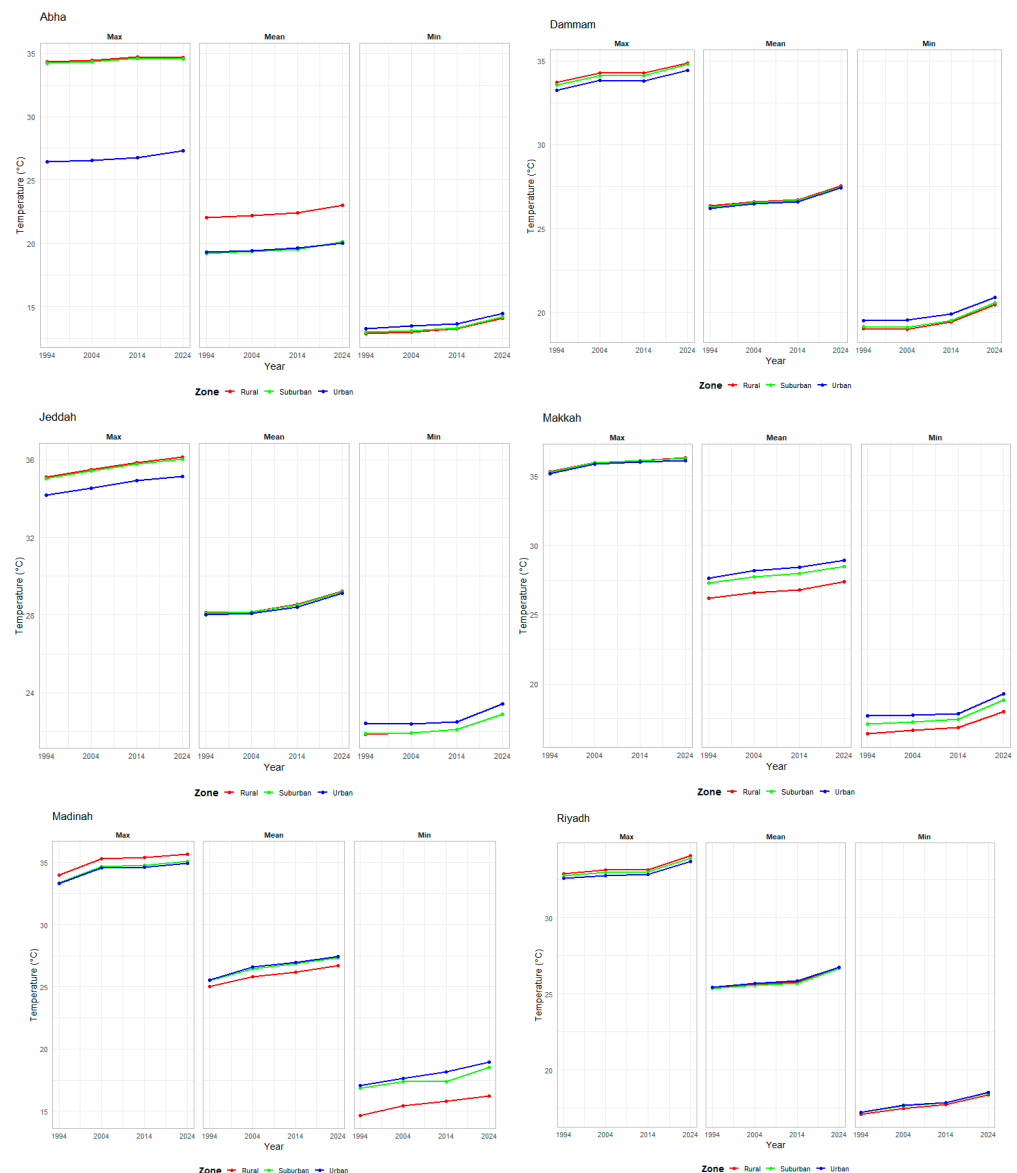


Figure 7. Minimum, mean and maximum temperature in various zones and temperature trends by urbanization level from 1994 to 2024 in the six cities using ERA5-Land data. In case of mean and minimum temperatures, overall the levels are highest at urban areas (blue lines) and lowest in rural areas (red lines), while in case of maximum temperature the levels are highest in rural areas and lowest in urban areas.

3.3. City-Level Results: CHIRTS-ERA5 Data

Figure 8 presents CHIRTS-derived minimum, mean, and maximum temperatures for rural, suburban, and urban zones across six major Saudi Arabian cities for the study period. The data clearly indicates a consistent UHI signal, especially in minimum and mean temperatures, where urban zones are persistently warmer than their suburban and rural counterparts. On average, urban areas are 1.1 °C warmer than rural zones in minimum temperature and 0.35 °C warmer in mean temperature. This difference is most pronounced in cities like Makkah and Jeddah, where urban zones consistently exhibit higher temperatures throughout the study period. However, maximum temperature showed the opposite results, where rural zones demonstrated higher temperature than the urban zones, especially in Abha, Madinah and Riyadh. On average, maximum temperature in rural zones was higher by 1.52 °C than the urban zones and by 0.38 °C than the suburban zones (for detailed statistics see Table S2 in the Supplementary Materials).

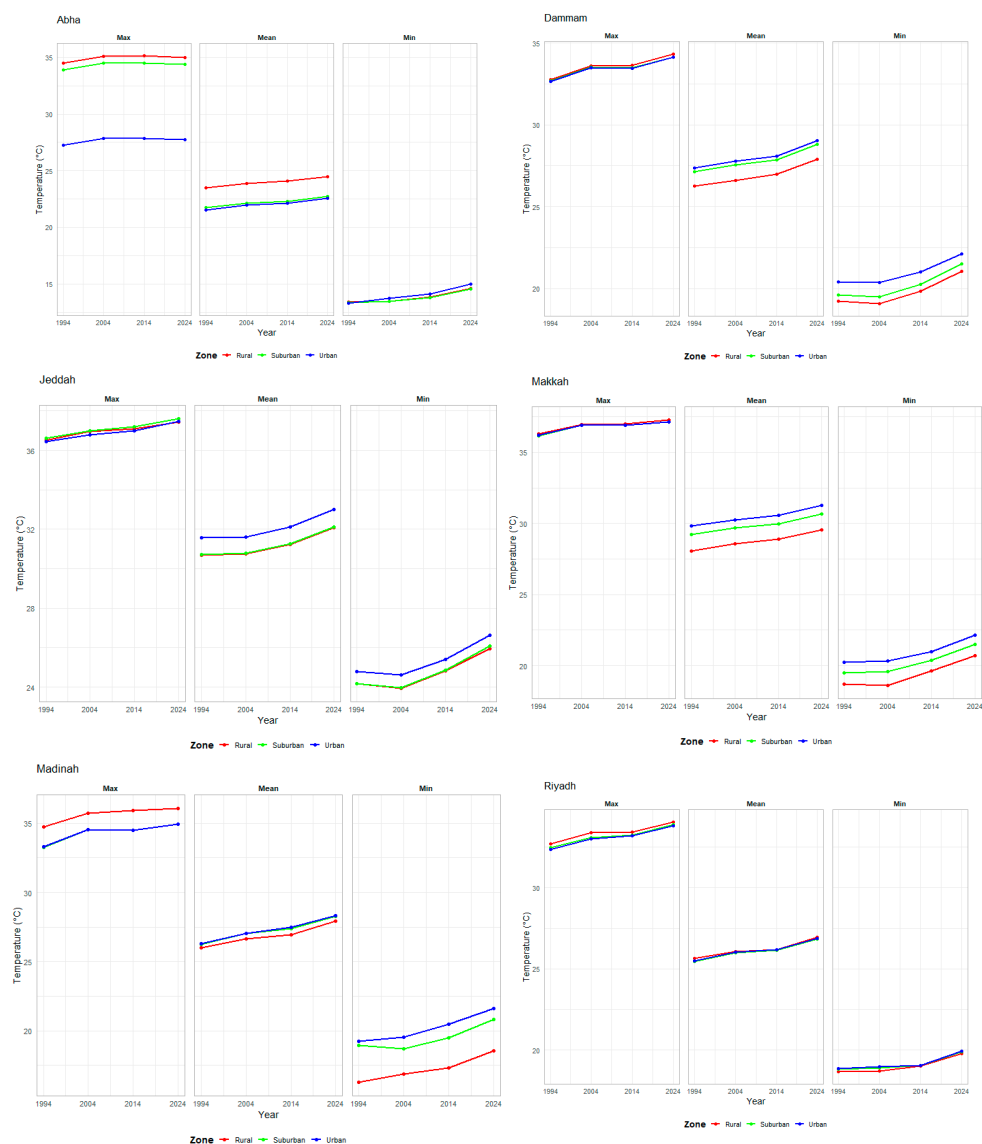


Figure 8. Spatial and temporal variations in minimum, mean, and maximum temperatures in different zones of six Saudi cities from 1994 to 2024, derived from CHIRTS-ERA5 data.

Over time, the urban–rural temperature gap appears to have increased, particularly for minimum temperatures, suggesting an intensification of heat retention in urban envi-

ronments. For example, in Dammam minimum temperature increased from 20.41 °C to 22.12 °C in urban areas, and from 19.22 °C to 21.06 °C in rural areas during the study period. Likewise, minimum temperature in rural areas rose from 24.16 °C to 25.94 °C in Jeddah and from 16.29 °C to 18.52 °C in Madinah during the study period. The temporal progression across all cities confirms a steady warming trend in minimum temperature in all zones. These trends showed that city-level temperature is not only affected by regional and global scale factors of climate change but also by local-level factors including urbanization and tree plantations, which reaffirms the need for city-level urban climate management strategies.

3.4. Discussion

Analysis of 2 m air temperature derived from two different datasets revealed consistent spatial patterns in rural, suburban, and urban zones across six major Saudi Arabian cities between 1994 and 2024. Both datasets indicated general warming trends over the 30-year period for all cities and land use zones. However, CHIRTS-ERA5 consistently reported higher absolute temperature values for minimum, mean, and maximum temperatures compared to ERA5-Land dataset. These differences are likely attributable to methodological contrasts and biased adjustment of CHIRTS-ERA5 datasets.

The UHI effect was most apparent in minimum temperature. At the national scale, urban zones were warmer than rural zones. This elevated minimum temperature in urban areas is consistent with established UHI theory, reflecting reduced radiative cooling due to the thermal properties of built environments and anthropogenic heat release. The UHI effect in mean temperatures was weaker but still positive. Interestingly, both datasets recorded a reversed UHI signal for maximum temperatures, with rural zones being warmer than urban zones. This pattern suggests stronger heating in rural areas, potentially due to lower shading, higher surface albedo in desert environments, and greater solar exposure compared to urban cores. Such reversed UHI patterns have been reported previously [12] in Riyadh, where rural surfaces can heat more rapidly under intense insolation.

At the city level, consistent patterns were observed. Overall, the agreement in the direction of rural–urban temperature differences between datasets, despite absolute value differences, supports the robustness of the observed spatial temperature gradients. The stronger UHI effect in minimum temperatures and the reversed signal in maximum temperatures highlight the complex interaction between urban form, land cover, and atmospheric processes in the hot desert climate of Saudi Arabia. These findings have implications for urban climate adaptation strategies, emphasizing the need to address heat retention issues in cities while also considering rural heat stress of maximum temperature.

By integrating Landsat remote sensing data with long-term air temperature records spanning from 1985 to 2010, Alghamdi and Moore [12] investigated the UHI effect in Riyadh City, Saudi Arabia. They found that rural areas exhibited higher land surface temperatures (LSTs) than urban areas, a finding that aligns with the results of the present study. Similarly, Almazroui et al. [33] examined the potential influence of urbanization on increasing air temperatures in Saudi Arabia for the period 1981–2010 and concluded that no clear correlation existed between temperature increases and urban population growth. This lack of correlation can be explained by the counterbalancing role of vegetation: while urban areas generally have higher population densities, in cities such as Riyadh they also contain more managed vegetation and landscaping compared to surrounding rural zones. The cooling influence of vegetation appears to outweigh the warming effect of population growth, thereby masking a direct link between urban population and rising temperatures. Aina et al. [6] assessed the impact of land use on surface temperature in Riyadh and reported that industrial zones recorded the highest temperature, while vegetated areas experienced the lowest. More recently, Hassaballa and Salih [34], in

their study of surface temperatures in the city of Al-Ahsa, found that the warmest zones corresponded to built-up areas, whereas zones characterized by dense palm tree coverage exhibited cooler temperatures, forming spatial clusters of low land surface temperature (LST). Furthermore, their analysis revealed a strong and consistent association between LST and the Normalized Difference Built-up Index (NDBI), reinforcing the role of built-up surfaces in driving temperature increases. Similarly, Halder et al. [35] confirmed that built-up areas were positively correlated with LST, while vegetated areas were negatively correlated, further supporting the inverse relationship between vegetation and surface temperature. Munir et al. [36] reported that tree plantation in Arafat had helped keep temperature lower in the area than the urban area. Deng et al. [9] reported that in arid cities vegetation contributed to cooling surface urban heat island by up to 61%; however, the effect was related to city size.

Spatial analyses of thermal conditions revealed that UHI intensity was substantially lower within cities and towns compared to surrounding rural areas, exhibiting a reversed UHI effect relative to typical urban microclimates [37]. De Razza et al. [37] reported that in Lecce, thermal intensity varied from -11°C to 5.6°C and that the reflective properties of building materials in historical urban areas may play a key role in this reversed UHI phenomenon. Urban green infrastructure has been shown to mitigate UHI across European cities, reducing temperatures by an average of 1.07°C and up to 2.9°C in some areas [38]. However, achieving a 1°C reduction typically requires at least 16% tree cover in urban areas [38]. Therefore, widespread implementation of urban green infrastructure, particularly in arid regions and cities with low vegetation cover, is essential to promote healthier urban living environments.

A study by Abulibdeh [10] analyzed UHI characteristics across eight arid and semi-arid Gulf region cities using land cover classification to differentiate between urban, green, and bare areas. The findings revealed that bare surfaces exhibited the highest mean land surface temperature values, exceeding those of urban areas by $1\text{--}2^{\circ}\text{C}$ and green areas by $1\text{--}7^{\circ}\text{C}$, while urban areas were $1\text{--}5^{\circ}\text{C}$ warmer than green zones. These results underscore the critical role of vegetation in moderating surface temperature variations in arid environments. Similar reversed UHI effects have been reported in other arid regions. For instance, in Abu Dhabi, urban centers were found to be cooler than their suburban surroundings, challenging the conventional understanding of urban microclimates [39]. This reversal was primarily attributed to factors such as increased vegetation and moisture within the city, wind-optimized building layouts that enhance ventilation, and extensive shading from tall buildings. Moreover, the use of reflective construction materials, such as marble and stone, further contributes to lowering downtown temperatures by approximately $4\text{--}6^{\circ}\text{C}$ compared to the suburbs [39].

The collective findings from the literature clearly demonstrate a negative correlation between vegetation cover and land surface temperature. This relationship is often used to explain the commonly observed pattern where urban areas, typically less vegetated than their rural counterparts, exhibit higher surface temperatures. However, this pattern does not hold uniformly in the context of Saudi Arabia. Unlike temperate regions where rural landscapes are often rich in vegetation, much of Saudi Arabia's rural and remote areas are characterized by hyper-arid conditions, with limited or no vegetation due to minimal rainfall, extreme temperatures, and dominant sandy desert terrain. Consequently, rural areas tend to exhibit higher temperatures compared to urban zones. In contrast, many Saudi cities have undergone extensive greening efforts, including large-scale tree plantations and the development of irrigated green spaces, as part of government-led environmental initiatives and urban beautification programs. These initiatives, particularly under the Vision 2030 framework, have significantly increased vegetation cover within

urban boundaries, leading to cooler microclimates in specific city zones during extreme summer temperatures. As a result, in Saudi Arabia, urban areas can paradoxically appear greener and cooler than the surrounding rural landscape, reversing the conventional UHI pattern observed in other global contexts.

3.5. Analysis of NDVI

Normalized Difference Vegetation Index (NDVI) maps were generated for the six Saudi cities using Sentinel-2 data, which provide high spatial resolution (10–20 m). NDVI is a widely used vegetation indicator, with higher values (closer to 1) representing denser and healthier vegetation, and lower or negative values indicating bare soil, built-up areas, or water.

Figure 9 presents NDVI distributions for three representative cities: Riyadh, Dammam, and Jeddah (only three cities are shown for brevity) in Saudi Arabia. For comparison, classification maps (urban, suburban, and rural zones) of these cities are also shown. Overall, the NDVI maps reveal that vegetation in Saudi cities is highly fragmented and unevenly distributed. In Riyadh, for example, most vegetation patches are concentrated in the western and central urban zones, often associated with irrigated landscapes such as parks, farms, and roadside plantings. By contrast, the eastern and peripheral rural areas show almost no vegetation, with NDVI values near zero. This pattern highlights the strong dependence of vegetation in Riyadh on urban planning and irrigation, rather than natural growth. A similar spatial contrast is observed in Dammam and Jeddah, where green cover is largely confined to localized urban green spaces, while surrounding rural landscapes remain barren. These findings are consistent with the arid climatic conditions across most of Saudi Arabia, where vegetation is primarily sustained through artificial irrigation within cities.

In contrast, rural zones surrounding the cities consistently exhibit very low NDVI values, reflecting sparse or absent vegetation cover. Taken together, the NDVI analysis underscores the limited but spatially concentrated vegetation within Saudi cities, strongly linked to human intervention. These spatial patterns of greenness are important for urban climate regulation, as vegetation can help mitigate heat stress, enhance evapotranspiration, and contribute to overall urban livability. Comparing NDVI across cities further indicates that even suburban areas often host relatively higher NDVI values than the rural areas due to the availability of irrigation water.

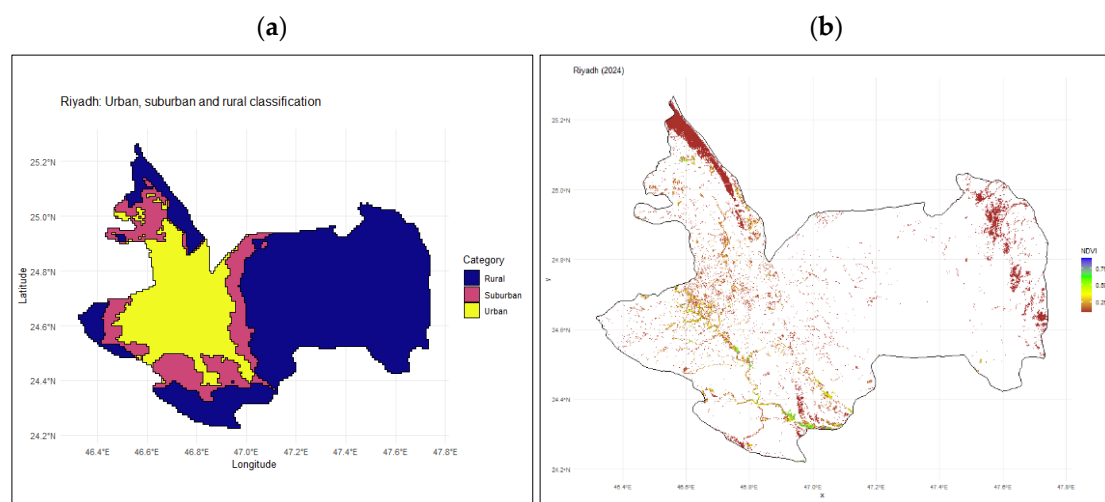


Figure 9. Cont.

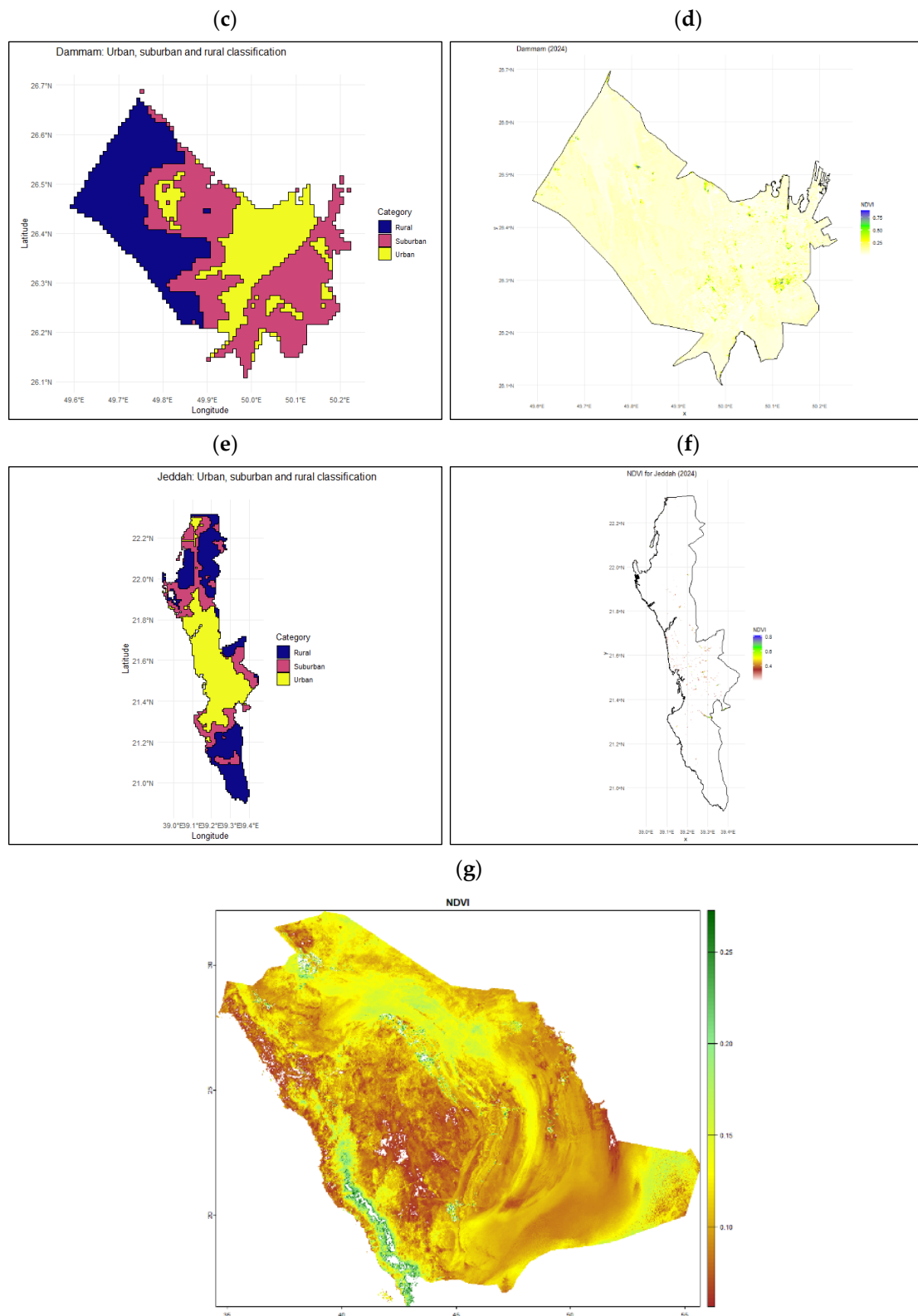


Figure 9. Urban, suburban, and rural classification compared to the NDVI values (representing vegetation) in several cities, namely, Riyadh (a,b), Dammam (c,d), Jeddah (e,f) and Saudi Arabia (g).

It is important to note that, in addition to vegetation, local temperatures are also influenced by broader geographical factors such as altitude, proximity to large water bodies, and regional topography. These factors largely explain the inter-city variability in temperature across Saudi Arabia (Figure 3), rather than the differences between urban and rural areas

within a single city. For example, Abha, situated in the elevated Asir Mountains, is considerably cooler than Riyadh or Dammam, regardless of its vegetation cover (Table 1). Annual temperature in Abha for the year 2024 was 23 °C, whereas it was about 32 °C in Jeddah. Air temperature generally decreases with altitude due to the reduction in atmospheric pressure. On average, the temperature drops by approximately 0.65 °C for every 100 m of elevation increase [40]. In dry atmospheric conditions, such as under high-pressure systems, this lapse rate can approach 1 °C per 100 m. The rate of temperature decrease is influenced by factors including air pressure, radiative heat exchange, and the water vapour content of the atmosphere [40]. Consequently, the highest temperatures are typically recorded at sea level, where atmospheric pressure is greatest, while temperature decreases progressively with increasing elevation under comparable meteorological conditions. Similarly, Navarro-Serrano et al. [41] demonstrated that elevation exerts a significant influence on air temperature in regions with complex terrain. In a study conducted in a mountain valley of the Spanish Pyrenees, they found that night-time lapse rates ranged between -4 and -2 °C km⁻¹, while daytime lapse rates varied from -6 to -4 °C km⁻¹, primarily due to temperature inversions and topographic effects. In addition to altitude, the presence of water bodies also contributes to moderating urban temperatures. Water features, especially when integrated with green spaces and supported by thoughtful urban design, can significantly reduce heat accumulation in cities [42]. Their cooling efficiency depends on factors such as size, shape, surrounding land use, local climate, and associated vegetation. Larger and well-designed water bodies are particularly effective due to enhanced evaporation and heat storage capacity, while the combination of water and vegetation further amplifies cooling through evapotranspiration and shading [42]. Within cities, however, vegetation plays a more direct role in moderating local temperatures. Although urban areas typically generate higher anthropogenic heat flux due to dense built-up surfaces, energy use, and traffic emissions, the presence of irrigated green spaces appears to partially mask these heat contributions by enhancing cooling through evapotranspiration and shading. This interplay highlights the importance of vegetation as a mitigating factor in the urban thermal environment, even in regions where natural climatic drivers dominate larger-scale temperature patterns.

4. Conclusions and Recommendations

In this study, we analyzed the UHI phenomenon across six large Saudi cities, Abha, Dammam, Jeddah, Madinah, Makkah, and Riyadh, over a 30-year period (1994–2024), utilizing two reliable gridded datasets: ERA5-Land and CHIRTS-ERA5. Urban areas consistently exhibited higher minimum and mean temperatures than suburban and rural zones, indicating a positive UHI effect. Conversely, maximum temperatures were generally higher in rural areas, suggesting a reversed UHI effect in urban areas.

Importantly, this study revealed meaningful differences in UHI intensity among urban areas themselves. For example, Madinah (2.40 °C) and Makkah (1.16 °C) displayed stronger positive UHI effects in minimum temperatures than Riyadh (0.16 °C) and Abha (0.40 °C), while maximum temperature suppression was more pronounced in Abha (-7.78 °C) and Jeddah (-0.94 °C), where Abha is the city with highest altitude and Jeddah is a coastal city. In contrast, UHI in mean temperature was positive and highest in Makkah (1.56 °C) and negative in Abha (-2.82 °C). These inter-urban variations highlight the role of local urban morphology, surface materials, and green infrastructure in modulating thermal behavior. NDVI comparisons confirmed that urban vegetation contributes to mitigating daytime extremes, particularly in cities with active greening programs. The findings emphasize the dual role of urbanization: while urban areas amplify minimum temperature warming due to heat retention, they can mitigate maximum temperature extremes through vegetation and

land management. Moreover, differences between urban centers underscore the importance of city-specific interventions to manage UHI impacts effectively.

The observed positive UHI in minimum and mean temperatures may be attributed to the higher thermal inertia and heat retention capacity of built-up urban surfaces, which maintain elevated temperatures relative to the surrounding rural areas that cool more rapidly due to sparse development and lower surface heat storage. In contrast, lower maximum temperatures in urban zones may be due to recent afforestation efforts and green initiatives led by government campaigns, whereas surrounding rural and desert areas remain largely barren due to limited rainfall and extreme climate conditions. As evidence, NDVI maps were compared in rural, suburban and urban areas, which indicated that NDVI values were greater in urban areas.

While this study provides a comprehensive analysis of UHI intensity across six Saudi Arabian cities, several limitations should be acknowledged. First, the analysis focuses solely on the effect of vegetation cover (NDVI); other important factors influencing UHI, such as population density, traffic, and anthropogenic emissions, were not considered and could be explored in future research. Second, the study does not employ advanced statistical or machine learning techniques, which may provide deeper insights into the complex interactions driving UHI patterns. Third, we did not incorporate data from the ground-based monitoring network, as most meteorological stations are located at airports and are therefore not fully representative of urban thermal conditions. Fourth, NDVI was calculated only for the year 2024; long-term analysis could be conducted using data from diverse regions across the Middle East. Therefore, these results are indicative and intended to illustrate general spatial patterns. Longer-term NDVI datasets are needed in future studies to more robustly assess the influence of vegetation on UHI dynamics over time. Despite these limitations, the study offers valuable baseline information for urban planning and climate adaptation strategies in Saudi Arabia.

Considering these findings the following recommendations are provided for mitigating UHI effects in urban areas of Saudi Arabia:

1. Integrate UHI monitoring into national climate adaptation frameworks, particularly in arid and semi-arid regions, where the effects of urbanization differ from temperate climates, especially considering minimum and maximum temperature.
2. Encourage the use of high-resolution gridded datasets (e.g., ERA5-Land, CHIRTS-ERA5) for climate diagnostics and urban climate modeling in data-sparse regions.
3. Foster regional collaborations among Middle Eastern countries to study UHI dynamics in similar desert environments, enabling more unified mitigation strategies.
4. Promote climate-informed urban growth policies at both national and regional levels to ensure sustainable development while minimizing heat-related risks.
5. Develop an integrated regional–global climate strategy to reduce greenhouse gas emissions and lower the carbon footprint, aligning with international climate commitments.
6. Develop city-specific UHI mitigation strategies that prioritize increasing green cover, especially in highly built-up zones, through sustainable landscaping and urban forestry.
7. Encourage urban greening programs and heat-resilient infrastructure, such as cool roofs, reflective surfaces, and water-sensitive urban design.
8. Implement detailed zoning policies that consider thermal comfort and heat exposure, especially in new urban developments.
9. Increase community awareness and stakeholder engagement regarding the UHI effect and its health, energy, and environmental implications.
10. Expand the existing monitoring networks to include ground-based sensors that complement satellite data and enable real-time climate risk assessments.

11. Employing machine learning and artificial intelligence tools, future research should aim to estimate the relative contributions of key driving factors such as land-use and land-cover changes, population density, vehicular traffic, and vegetation cover in shaping the intensity and spatial distribution of UHI effects.

The current meteorological monitoring network in Saudi Arabia is primarily concentrated in airports, resulting in a spatial bias that limits its suitability for UHI analysis, particularly when comparing urban and rural areas. The lack of monitoring stations in rural and remote regions hinders comprehensive assessment of spatial temperature gradients. Therefore, it is strongly recommended to establish a dedicated, purpose-built observational network that is spatially representative and designed specifically for capturing UHI dynamics.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/urbansci9110445/s1>, Table S1: Showing maximum, minimum, and mean temperatures in various zones (urban, suburban and rural) in different years and cities using ERA5_Land data.; Table S2: Showing maximum, minimum, and mean of CHIRTS temperatures for various zones (urban, suburban and rural) in different years and cities.

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