

MSC

2.º
CICLO

FCUP
2021

U.PORTO

Remote Sensing Image-Based Analysis of the Urban
Heat Island Effect in Bragança, Portugal

Cátia Rodrigues de Almeida

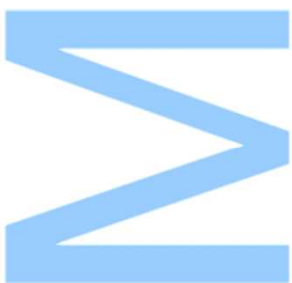
FC

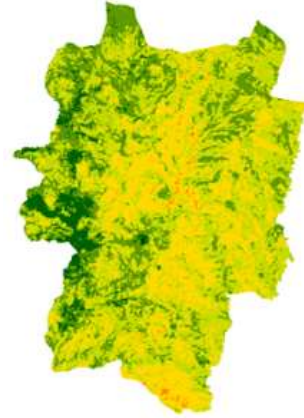
U.PORTO
FACULDADE DE CIÊNCIAS
UNIVERSIDADE DO PORTO

Remote Sensing Image-Based Analysis of the Urban Heat Island Effect in Bragança, Portugal

Cátia Rodrigues de Almeida
Dissertação de Mestrado apresentada à
Faculdade de Ciências da Universidade do Porto em
Área Científica
2021

U.PORTO
FACULDADE DE CIÊNCIAS
UNIVERSIDADE DO PORTO





Remote Sensing Image-Based Analysis of the Urban Heat Island Effect in Bragança, Portugal

Cátia Rodrigues de Almeida

Mestrado em Detecção Remota

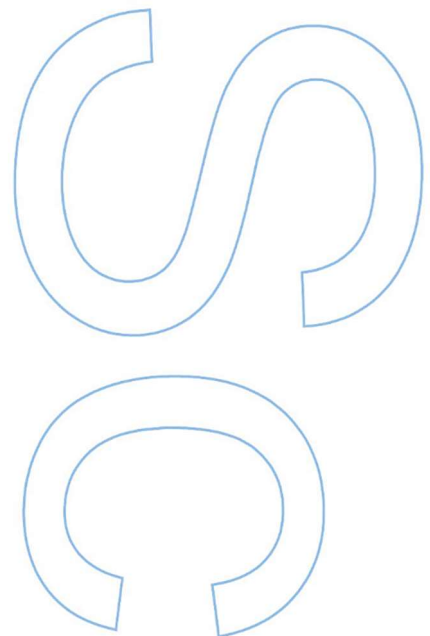
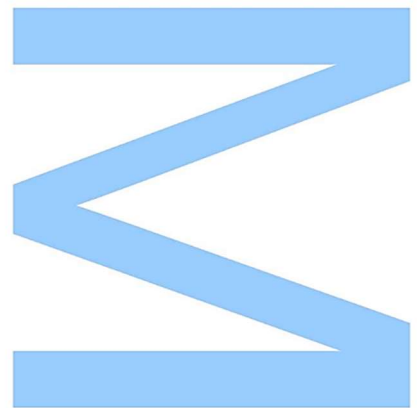
Departamento de Geociências, Ambiente e Ordenamento do Território
2021

Orientadora

Ana Cláudia Moreira Teodoro, Professora Associada com Agregação, FCUP

Coorientador

Dr. Artur Gonçalves, Professor Adjunto, Instituto Politécnico de Bragança

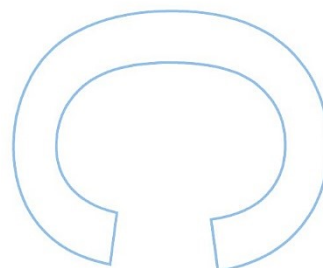
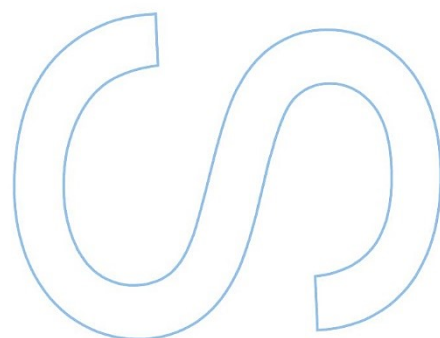
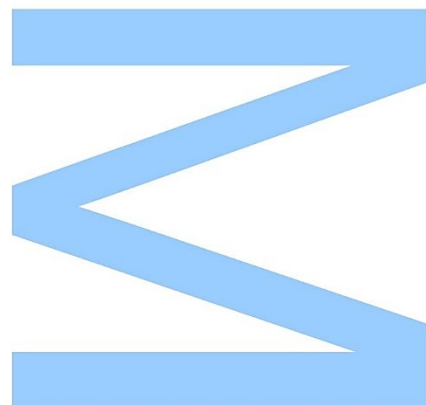




Todas as correções determinadas
pelo júri, e só essas, foram efetuadas.

O Presidente do Júri,

Porto, ____/____/____



Agradecimentos

Quando iniciei mestrado em Portugal, não imaginava o quão transformador seria esse processo. A escolha do curso de Detecção Remota foi motivada pela intenção de estudar o efeito de Ilhas de Calor, tema previamente analisado durante meu curso de Engenharia Ambiental, no Brasil. O Dr. Benjamin Capellari, meu orientador na ocasião, foi um dos grandes incentivadores e responsáveis pela minha vontade de seguir na carreira de pesquisadora.

Minha jornada em Portugal transcendeu o desafio do afastamento físico de familiares e amigos do Brasil, e incluiu o conceito da “convivência virtual” entre as pessoas queridas que conheci, em meio à pandemia da COVID-19. Entre ressignificações a respeito da limitação humana perante um momento desafiador, o carinho e incentivo de tantas pessoas em relação ao meu trabalho, foi extremamente importante!

Agradeço o apoio da Professora Ana Cláudia Teodoro e do Professor Artur Gonçalves, que me orientaram, compartilharam ensinamentos e me deram total liberdade para conduzir meu processo de ensino-aprendizagem. Obrigada pelas horas dedicadas às reuniões de orientação, às coletas de campo, às discussões sobre os resultados e pela confiança.

Obrigada Leonardo e todos os colaboradores do CIMO: o auxílio nas medições de campo, sempre com muito bom humor e motivação, fez toda a diferença nesse processo!

Agradeço à coordenadora Professora Joana Fernandes, pelo apoio e comprometimento com a qualidade do curso, desde meu primeiro contato do Brasil. A empatia e dedicação foram fundamentais no meu processo.

Finalmente, agradeço e dedico esse trabalho à minha avó Alexandrina, que sempre será uma das figuras mais importantes na minha vida. Aos meus pais Miranda e Maria, pelo afeto e incentivo ao longo da minha formação. Aos meus irmãos Fernando e Lúcia, que me acolheram sempre que as saudades apertaram. Aos meus sobrinhos Ana Júlia, Luiz Felipe e Bianca, que exercem um papel importante no meu processo. Aos meus tios, tias e primos, especialmente à Thayrine e ao Tiago. Eu amo vocês.

Agradeço aos meus amigos, em especial ao Angelo, Anna Land, Anderson, Bernard, Carolina Andriola, Clareana, Igor, Joelen, Luciano, Luisa, Mariana Visone, Mariana Galera, Monica, Monique, Nicole, Paula, Pedro e tantas outras pessoas que auxiliaram nesse processo. Gratidão pelos conselhos, ideias, suporte e amizade.

Resumo

A Agenda para o Desenvolvimento Sustentável de 2030 prevê uma série de ações para garantir a prosperidade e paz do planeta e das pessoas, incluindo a sustentabilidade. Para garantir o equilíbrio entre o desenvolvimento económico, ambiental e social é importante compreender os impactos relacionados às ações antrópicas, como a urbanização e eventuais modificações nos materiais de superfície, que culminam na supressão de vegetação, variação do albedo e impermeabilização do solo. O efeito de Ilhas de Calor Urbano (ICU), potencializado por estas mudanças, especialmente após o por-do-sol, resulta em uma maior absorção de energia eletromagnética e arrefecimento lento nos edifícios das cidades em comparação com as áreas rurais, contribuindo para o aumento da temperatura da superfície e para os impactos na saúde e bem estar da população. Este trabalho teve como objetivo analisar o comportamento sazonal do ICU nas diferentes Zonas Climáticas Urbanas (ZCU) em Bragança – Portugal, integrando parâmetros diversos, como dados de temperatura do ar provenientes de sensores térmicos da rede meteorológica fixa, imagens de satélite (Landsat 8) e dados adquiridos em campo por câmeras térmicas e estações meteorológicas portáteis. A metodologia proposta integrou dados de diferentes escalas (espaciais, radiométricas e espectrais) e, apesar de ser pouco aplicada (especialmente em função da necessidade de investimento para implementação de estações meteorológicas fixas, por exemplo), possibilita obter níveis de detalhe complementares em estudos de ICU. O processamento dos dados do Landsat 8 foi realizado no Google Earth Engine (GEE). A partir do tratamento de cada dado, considerando suas especificidades, foram realizadas uma série de análises qualitativas e quantitativas e avaliou-se o comportamento térmico das ZCUs, incluindo uma abordagem sazonal (inverno e verão). Como resultado, a integração de dados com diferentes escalas corroborou para complementação da informação e análise, tornando um método relevante para o estudo do ICU. O uso do GEE no tratamento dos dados do Landsat 8, otimizou o tempo de processamento e exigência computacional. A identificação do ICU foi comprometida, devido ao horário da passagem do Landsat 8 (11h15 – Tempo Universal Coordenado (UTC)). Entretanto, foi identificado o efeito de Ilha de Frio em ZCUs com presença de construção civil, que é um oposto complementar e característico de locais com ICU: nas primeiras horas do dia houve equivalência entre a Intensidade da Ilha de Calor Urbana (UHI_{Int}) tanto da temperatura do ar quanto do Land Surface Temperature (LST) calculado a partir dos dados de Detecção Remota (DR) (Landsat 8) e as áreas vegetadas apresentaram

valores próximos ou ligeiramente superiores às antropicamente alteradas. Os dados de LST (medidos pela câmera térmica portátil) apresentaram valores maiores de temperatura em ZCUs com alterações antrópicas, característica de locais com ICU. Foram identificadas correlações “forte” e “muito forte” entre os dados de temperatura do ar (medidos pelos sensores fixos) e o LST (Landsat 8), especialmente ao utilizar todos os dados (sem separação por estação) e os específicos do inverno. O modelo de regressão linear, aplicado com o objetivo de prever os dados de temperatura do ar (sensores fixos) a partir dos dados de LST (Landsat 8), apontaram maior explicabilidade quando se considerou os dados de todos os dias e os de inverno, similar ao teste de correlação. A equivalência obtida nos resultados das análise entre a temperatura do ar (obtido pela rede meteorológica fixa e que registra o comportamento a nível de microescala) e o LST (calculado a partir dos dados do Landsat 8, a nível de zona climática urbana) ratifica a coerência e aplicabilidade da DR para análise de comportamento térmico de um local, como estudos de ICU. Espera-se que este estudo possa contribuir para que outros locais sejam estudados, incluindo dados de diferentes escalas, inclusive os montanhosos, cuja complexidade morfológica configura um desafio na análise do efeito local.

Palavras-chave: Mudança climática, Temperatura da Superfície Terrestre, Landsat, Google Earth Engine, Correlação, Regressão.

Abstract

The 2030 Agenda for Sustainable Development envisions a series of actions to ensure prosperity and peace for the planet and the people, including sustainability. To ensure the balance between economic, environmental, and social development, it is important to understand the impacts related to anthropic actions, such as urbanization and any modifications to the surface materials, which culminate in vegetation suppression, albedo variation, and soil sealing. The Urban Heat Island (UHI) effect, potentiated by these changes especially after sunset, results in greater absorption of electromagnetic energy in city buildings and slow cooling when compared with rural areas, contributing to increased surface temperatures and health impacts and well-being of the population. This work aimed to analyze the seasonal behavior of UHI in different Urban Climate Zones (UCZ) in Bragança – Portugal, integrating diverse parameters, such as air temperature data from thermal sensors of the fixed meteorological network, satellite images (Landsat 8), and data acquired in the field by the thermal camera and portable monitoring equipment. The proposed methodology integrated data from different scales (spatial, radiometric, and spectral) and, despite being little applied (especially due to the need for investment to implement fixed meteorological stations, for example), it allows obtaining complementary levels of detail in UHI studies. The processing of the Landsat 8 data was done in Google Earth Engine (GEE). From the treatment of each data, considering its specificities, a series of qualitative and quantitative analyses were performed and the thermal behavior of the UCZs was evaluated, including a seasonal approach (winter and summer). As a result, the integration of data with different scales corroborated the complementation of information and analysis, making it a relevant method for the study of UHI. The use of GEE in the treatment of Landsat 8 data, optimized the processing time and computation requirement. The identification of the UHI was compromised, due to the time of the passage of Landsat 8 (11h15 - Universal Time Coordinated (UTC)). However, it was identified the Cool Island effect in UCZs with the presence of civil construction, which is a complementary opposite and characteristic of places with UHI: in the first hours of the day there was equivalence between the Urban Heat Island Intensity (UHI_{int}) of both air temperature and Land Surface Temperature (LST) calculated from Remote Sensing (RS) data (Landsat 8) and the vegetated areas presented values close or slightly higher than the anthropically altered ones. The LST data (measured by the handheld thermal camera) showed higher temperature values in anthropically altered UCZs, characteristic of UHI sites. "Strong" and "very strong" correlations were identified between air temperature data (measured by the fixed sensors) and LST (Landsat 8), especially when using all data

(without separation by station) and winter-specific ones. The linear regression model, applied to predict the air temperature data (fixed sensors) from the LST data (Landsat 8), pointed out higher explainability when considering the data of all days and those of winter, like the correlation test. The equivalence obtained in the results of the analysis between air temperature (obtained by the fixed meteorological network and that records the behavior at the micro-scale level) and the LST (calculated from Landsat 8 data, at the urban climate zone level) ratifies the coherence and applicability of RS for analyzing the thermal behavior of a location, such as UHI studies. It is hoped that this study can contribute to other sites being studied, including data from different scales, including mountainous ones, whose morphological complexity sets up a challenge in the analysis of the local effect.

Keywords: Climate change, Land surface temperature, Landsat, Google Earth Engine, Correlation, Regression.

Contents

Agradecimentos	i
Resumo	ii
Abstract.....	iv
List of Tables	ix
List of Figures	x
List of Equations	xiv
List of Abbreviations.....	xv
1. Introduction.....	20
1.1. Objectives.....	22
1.2. Work Structure.....	23
2. Background	25
2.1. Climate	25
2.1.1. Solar Radiation	25
2.1.2. The Urban Climate in Mountain Regions	26
2.1.3. Climate Scales.....	27
2.2. UHI effect.....	29
2.2.1. Causes for UHI Formation	30
Urban Morphology.....	31
Albedo.....	32
Width (W) / Height (H) / Length (L) and Urban Canyons.....	33
SVF	33
Urban Densification	34
Rugosity	34
Porosity.....	34
Anthropogenic Heat.....	35
Energy Balance in a Building and Between Buildings.....	35
2.2.2. UHI Impacts.....	37
2.3. Use of RS for UHI Studies	38
2.3.1. Landsat Mission.....	40
2.3.2. RS products.....	41
LST	41
VI	42
2.4. UCZ in UHI studies	43
2.4.1. UCZ in UHI study in Bragança.....	45
2.4.2. RS in UHI assessment in different UCZs	45

3.	Methodology	47
3.1.	Study Area.....	48
3.2.	Dates for Data Collection	49
3.3.	Research Data.....	50
3.3.1.	Meteorological Network Data	50
3.3.2.	LST Estimation Using the Thermal Camera.....	53
3.3.3.	Local Microclimate Measurements	55
3.3.4.	Satellite Data.....	56
3.4.	Data Processing	56
3.4.1.	Meteorological Network Data Processing	56
3.4.2.	LST Processing Using the Thermal Camera.....	58
3.4.3.	Processing of Data from Portable Meteorological Stations and the Landsat 8	59
	i) LST Calculation in ArcGIS	60
	ii) LST Calculation in GEE	63
	iii) Using ArcGIS to Extract Temperature data from the LST.....	65
3.5.	Statistics Analysis	66
3.5.1.	Descriptive Data Analysis.....	66
	LST Maps.....	66
	Boxplot.....	66
	Air Temperature variation versus Landsat 8 LST.....	67
	UHI _{Int} analysis	67
3.5.2.	Quantitative Data Analysis	68
	Shapiro Test.....	68
	Pearson's Correlation	69
	Spearman's Correlation	70
	Correlations.....	71
3.5.3.	Validation	71
3.5.4.	Linear Regression	72
4.	Results and Discussion	73
4.1.	Descriptive Analysis.....	75
	LST Maps.....	75
	Boxplot.....	76
	Temperature difference between air temperature (fixed weather station) and LST (Landsat 8)	80
	UHI _{Int}	83
4.2.	Analytical Statistics	88

Shapiro's Test.....	88
Correlation Between Air Temperature (Fixed Weather Station) and LST (Landsat 8)	90
Correlation between $\overline{LST_{ZRE}}$ and LST_{UCZ}	94
4.3. Field Data for Validation.....	96
Classification of the Surfaces Sampled by the Thermal Camera Portable.....	96
Analysis of the LST on the various sampled surfaces (LST obtained by Landsat 8 and the manual thermal camera).....	97
Analysis of LST (handheld thermal camera) differences between morning and afternoon collections.....	104
Analysis of air temperature differences (fixed meteorological station) between morning and afternoon collections	109
Wind Speed analysis (Portable Monitoring Equipment)	112
Tr analysis (Portable Monitoring Equipment).....	113
4.4. Linear Regression between Air Temperature (Fixed Weather Station) and LST (Landsat 8).....	114
4.5. Coefficient of Determination (r^2).....	115
5. Conclusion	119
5.1. Limitations and Future Research	122
Reference.....	125
Appendix I	141
Appendix II	180
Appendix III	193
Appendix IV	198
Appendix V	199
Appendix VI	200
Appendix VII	215
Appendix VIII	216
Appendix IX	228
Appendix X	231
Appendix XI	232

List of Tables

Table 1. Summary of the causes of the UHI.....	31
Table 2. A proposed classification for UCZ	44
Table 3. Planning of field visits in Bragança.....	50
Table 4. Classification and Coordinates of the 23 sensors.....	52
Table 5. Climate zones and indicators of characterization of urban morphology in the city of Bragança	53
Table 6. Missing values for Air Temperature (° C) after the SPSS processing, in all dates.....	57
Table 7. Missing values for Air Temperature (° C) after the SPSS processing (coincident with the passage of Landsat 8).	58
Table 8. Constants for LST generation.....	61
Table 9. List of the sensors, per UCZs, and the respective percentages of representativeness about the 23 sensors.....	80
Table 10. Results obtained in the Shapiro test using all dates, with 95% confidence level (p-value data greater than 0.05 are highlighted in red).....	88
Table 11. Results obtained in the Shapiro test, using the summer dates, with 95% confidence level (p-value data greater than 0.05 are highlighted in red).....	89
Table 12. Results obtained in the Shapiro-Wilk test, using the winter dates, with 95% confidence level (p-value data greater than 0.05 are highlighted in red).....	90
Table 13. Scale for data correlation analysis.....	91
Table 14. Classification of the points sampled with the thermal camera. Where: i) Asphalt (As); ii) Sidewalk (S); iii) Vegetation (V); iv) Vegetation with exposed Soil (Vs); v) Dry Vegetation (DV), and vi) Dry Vegetation and Rock (DVSt).....	96
Table 15. P-values obtained in the linear regression model.	114

List of Figures

Figure 1. The 17 SDGs set by the United Nations.....	21
Figure 2. Earth's Energy Budget.....	26
Figure 3. UHI: Vertical and Horizontal Scale Schematic – Microscale.....	28
Figure 4. UHI: Local Scale Scheme	28
Figure 5. Mesoscale Scheme.....	28
Figure 6. Profile of the urban UHI about suburban.	30
Figure 7. The albedo of urban materials.....	32
Figure 8. Relation between the height (H) and the spaces among the edifications (W)	33
Figure 9. Energy balance scheme in a building.....	36
Figure 10. Electromagnetic Spectrum	38
Figure 11. RS process	39
Figure 12. Landsat timeline.....	40
Figure 13. Summary of Methodological Procedures.....	47
Figure 14. Identification of the study area, with the sensor delimitation in red	48
Figure 15. Meteorological network installation site (23 sensors).	51
Figure 16. Example of an installed sensor	51
Figure 17. Identification of the 10 areas in which the thermal measurements of the different surfaces were carried out.	54
Figure 18. Identification of the four portable monitoring equipment measurement areas with different UCZ classification.	55
Figure 19. Example of LST Collection with the Thermal Camera and its sampled point image (point 1, surface B (Vs), collection on 08/03/2020, M).	59
Figure 20 Tabulated data of the surfaces sampled with the thermal camera.....	59
Figure 21. Data Organization Model - Portable Meteorological (with the parameters used highlighted).	59
Figure 22. Steps for generating the LST map.	61
Figure 23. Exemplification of the calculation applied to the pixels (in gray) contained in the buffer (in yellow), generated from the sensor (in green).	65
Figure 24. Example LST maps, calculated/generated in GEE, with the area delimitation of the 23 fixed sensors (black square) and the respective sensors plotted (black dots).	75
Figure 25. Number of observations between air temperature (fixed weather station) and LST (Landsat 8), used in the boxplot for the sensors that did not present the complete data, on all analyzed dates.	77

Figure 26. Boxplot of sensor 4, representing the distribution of air temperature data (fixed weather station) and the LST (Landsat 8), split across all analyzed dates, the summer and winter dates, respectively.	79
Figure 27. Boxplot of sensor 19, representing the distribution of air temperature data (fixed weather station) and the LST (Landsat 8), split across all analyzed dates, the summer and winter dates, respectively.	79
Figure 28. Absolute temperature difference between air temperature and Landsat 8 LST in all dates.	80
Figure 29. Absolute temperature difference between air temperature and Landsat 8 LST in summer.	81
Figure 30. Absolute temperature difference between air temperature and Landsat 8 LST in winter.	81
Figure 31. Boxplot with the Air temperature UHI_{int} , calculated for summer and winter, at each sensor and its respective UCZ.	86
Figure 32. Boxplot with the LST UHI_{int} , calculated for summer and winter, at each sensor and its respective UCZ.	87
Figure 33. Statistical values were obtained from the correlation between air temperature, measured by the fixed weather station and the LST, estimated from Landsat 8 data (absolute values).	93
Figure 34. Statistical values were obtained from the correlation between LST UHI_{int} LST <i>versus</i> LST of other UCZs (Landsat 8).	95
Figure 35. Analysis of the temperatures on the various sampled surfaces at point 1 (ZRE).	98
Figure 36. Analysis of the temperatures on the various sampled surfaces at point 3 (ZCS).	99
Figure 37. Analysis of the temperatures on the various sampled surfaces at point 6 (ZCS).	99
Figure 38. Analysis of the temperatures on the various sampled surfaces at point 4 (TUR).	100
Figure 39. Analysis of the temperatures on the various sampled surfaces at point 9 (TUR).	100
Figure 40. Analysis of the temperatures on the various sampled surfaces at point 5 (EVU).	101
Figure 41. Analysis of the temperatures on the various sampled surfaces at point 7 (BDT).	101
Figure 42. Analysis of the temperatures on the various sampled surfaces at point 8 (PMA).	102

Figure 43. Analysis of the temperatures on the various sampled surfaces at point 2 (UMR).....	103
Figure 44. Analysis of the temperatures on the various sampled surfaces at point 10 (UMR).....	103
Figure 45. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P1 (ZRE).....	104
Figure 46. Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P3 (ZCS).	105
Figure 47. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P6 (ZCS).....	105
Figure 48. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P4 (TUR).....	106
Figure 49. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P9 (TUR).....	106
Figure 50. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P5 (EVU).....	107
Figure 51. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P7 (BDT).....	107
Figure 52. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P8 (PMA).	108
Figure 53. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P2 (UMR).....	108
Figure 54. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P10 (UMR).....	109
Figure 55. Analysis of the air temperature data collected in the morning and afternoon of collection 1 (08/03/2020 - Summer).	110
Figure 56. Analysis of the air temperature data collected in the morning and afternoon of collection 2 (04/09/2020 - Summer).	110
Figure 57. Analysis of the air temperature data collected in the morning and afternoon of collection 3 (04/16/2021 - Spring).	111
Figure 58. Analysis of the air temperature data collected in the morning and afternoon of collection 4 (07/05/2021 - Summer).	111
Figure 59. Comparison of wind speed at each portable monitoring equipment, per collection day.....	112
Figure 60. Comparison of Tr at each portable monitoring equipment, per collection day.	114

Figure 61. R^2 refers to the linear regression model between air temperature (measured at the fixed meteorological network) and the LST (Landsat 8)..... 117

Figure 62. R^2 adjusted referring to the linear regression model between air temperature (measured at the fixed meteorological network) and the LST (Landsat 8)..... 117

Figure 63. R^2 refers to the linear regression model between air temperature (measured at the fixed meteorological network) and the LST (Landsat 8) – Seasonality. 118

Figure 64. R^2 adjusted referring to the linear regression model between air temperature (measured at the fixed meteorological network) and the LST (Landsat 8) – Seasonality. 118

List of Equations

$Q^* + Q_F = Q_H + Q_E + Q_G + \Delta Q_S$	35
$Q^* + Q_F = Q_H + Q_E + \Delta Q_S + \Delta Q_A$	36
$p^* + F + I = E + \Delta r + \Delta S + \Delta A$	36
$\alpha + \rho + \pi = 1$	37
$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$	42
$L\lambda = MLQ_{cal} + AL$	62
$TK = K_2 / (\ln(K_1 / L\lambda) + 1)$	62
$TC = TK - 273.15$	62
$PV = \sqrt{\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}}$	62
$E = 0.004 \times PV + 0.986$	63
$LST = \frac{TB}{(1 + (L\lambda \times \frac{TB}{P}) \times \ln(E))}$	63
$P = h \times c / \sigma (1.438 \times 10^{-2} \text{ mk})$	63
$\Delta t = LST_{RS} - T_{air}$	67
$UHI_{Int} = LST_{UCZ} - \overline{LST_{ZRE}}$	68
$UHI_{Int} = AirT_{UCZ} - \overline{AirT_{ZRE}}$	68
$W = \frac{(\sum_{i=1}^n a_i x_{(i)})^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$	68
$\rho = \frac{\sum_{i=1}^n (x_i - \bar{x}) \times (y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \times \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} = \frac{cov(X,Y)}{\sqrt{var(X) \times var(Y)}}$	69
$\bar{x} = \frac{1}{n} \times \sum_{i=1}^n x_i$	69
$\bar{y} = \frac{1}{n} \times \sum_{i=1}^n y_i$	69
$r_s = \rho_{rgx,rgy} = \frac{cov(rg_x,rg_y)}{\sigma_{rg_x}\sigma_{rg_y}}$	70
$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2-1)}$	70
$y_i = \alpha + \beta X_i + \varepsilon_i$	72

List of Abbreviations

AI	Artificial Intelligence
As	Asphalt
COG	Cloud Optimized Georeferenced
DEM	Digital Elevation Models
DN	Digital Number
DR	Deteção Remota
DV	Dry Vegetation
DVSt	Dry Vegetation and Rock
E	Emissivity
ESA	European Space Agency
ETM+	Enhanced Thematic Mapper Plus ETM+
FOV	Field of View
GCPs	Ground Control Points
GEE	Google Earth Engine
GIS	Geographic Information System
GLS DEM	Global Land Survey Digital Elevation Model
GRI	Global Reference Image
H	Height
HWs	Heat Waves
ICU	Ilhas de Calor Urbano
IFOV	Instantaneous Field Of View
IPB	Polytechnic Institute of Bragança
IQR	Interquartile Range
VI	Vegetation Index
JPL	Jet Propulsion Laboratory
L	Length
LAI	Leaf Area Index
LaSRC	Land Surface Reflectance Code
LST	Land Surface Temperature
LULC	Land Use and Land Cover
ML	Machine Learning
NASA	National Aeronautics and Space Administration
NASADEM	NASA Shuttle Radar Topography Mission
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared

OLI	Operational Land Imager
PMV	Expected Average Rating
PPD	Unsatisfied Percentage
Pr	Atmospheric Pressure
PV	Vegetation Proportion
Q1	Quantile 1
Q2	Quantile 1
Q3	Quantile 3
QA	Quality Assessment Bands
RH	Relative Humidity
RIT	Rochester Institute of Technology
RS	Remote Sensing
S	Sidewalk
SDGs	Sustainable Development Goals
shp	Shapefile
SLC	Scan Line Corrector
SR	Surface Reflectance
SUHI	Surface Urban Heat Island
SVF	Sky View Factor
SWIR	Short-Wave Infrared
Ta	Ambient Temperature
Tg	Globe Temperature
TIR	Thermal Infrared
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TOA	Top of Atmosphere
Tr	Average Radiation Temperature
UAV	Unmanned Aerial Vehicles
UBL	Urban Boundary Layer
UCL	Urban Canopy Layer
UCZ	Urban Climate Zones
UHI	Urban Heat Island
UHIInt	Urban Heat Island Intensity
UTC	Tempo Universal Coordinado/Coordinated Universal Time
UTM	Universal Transverse Mercator
USGS	United States Geological Survey
V	Vegetation

Va	Wind Speed
VNIR	Visible and Near-Infrared
Vs	Vegetation with Soil
VSt	Vegetation and Rock
W	Width
ZCU	Zonas Climáticas Urbanas

CHAPTER 1

1. Introduction

The 2030 Agenda for Sustainable Development proposes a reflection on actions that prioritize the balance between economy, environment, and society. Studies focused on understanding this dynamic and interrelationship can contribute to analyzing and supporting mitigating measures, minimizing long-term impacts [1].

The agenda adopted in 2015, under the leadership of the United Nations Member States aimed to promote peace and prosperity for the planet and its people, both now and in the future. The agenda provides 17 Sustainable Development Goals (SDGs) at a global level, which should be considered in the actions of developed and developing countries, focusing on actions such as reducing inequalities, strategies to improve health and education, stimulating economic growth, combating climate change, and encouraging the preservation of oceans and forests [1].

This dissertation directly addresses three SDG goals, namely: i) Goal 3. Ensure healthy lives and promote well-being for all at all ages (since UHI impacts can promote thermal discomfort and human health impacts); ii) Goal 11. Make cities and human settlements inclusive, safe, resilient, and sustainable (microclimatic changes from Urban Heat Island (UHI) can compromise local biomes and natural specificities, regulate prevailing property values, and access to restrictive means of regulating thermal comforts, such as air conditioners and heaters); and iii) Goal 13. Take urgent action to combat climate change and its impacts (as in the identification of UHI and mitigation proposals on a local scale, such as prioritizing the maintenance and expansion of local vegetation areas and adoption of more sustainable technologies/materials). Figure 1 presents the 17 SDGs, highlighting in red the three mentioned above and related to this research.

In this sense, for human life to be viable in a place, it is necessary to make anthropogenic adaptations, which suppress the vegetation, increase the unsealed areas and corroborate the increase of civil construction [2]. However, all these changes can culminate in socio-environmental impacts and influence on local climate characteristics, generating microclimates. As a consequence, surface temperature increases, changes in the displacement of air masses, precipitation, thermal discomfort, etc. may occur, in addition, to contribute the contrast between urban and surrounding areas with the presence of vegetation, favoring the formation of the effect known as UHI [3–8].



Figure 1. The 17 SDGs set by the United Nations (adapted from [1,9]).

Voogt & Oke (2003) [10] suggested a sub-classification analogous to UHI, called Surface Urban Heat Island (SUHI) that, in addition to studying surface temperature differences between urban and rural areas, also addresses temporal variability [11]. Despite this concept, UHI is understood in the broad sense, which will occur during this thesis.

The effect can be studied considering the use of several methodologies, such as Remote Sensing (RS), which comprises a set of data and techniques to obtain information about targets without direct physical contact. The electromagnetic radiation emitted or reflected by the analyzed surfaces is recorded by sensors on-board of different platforms (satellites, aircraft, balloons, motor vehicles) and converted into a signal that consequently allows the generation of images [12].

This process is possible due to the emission of electromagnetic radiation by the Sun to the Earth's surface (which absorbs one part and reflects another) and from the Earth's surface, which also emits energy (thermal). Satellites equipped with thermal sensors operate in the atmospheric window of the Thermal Infrared (TIR) range (whose absorption rate is minimal) and measure, at the top of the atmosphere, the radiation emitted by the Earth's surface [13]. The recorded data vary according to the albedo of the analyzed surface, that is, the absorption or reflection of electromagnetic energy will depend on the constitution of the material, the density of construction, the heterogeneity of the material, etc. [14].

Employing RS data/techniques in the development of scientific investigations can be a great contribution, since it is possible to obtain information at different temporal and spatial scales of the same location (parameters intrinsically associated with the specificities of the sensors used in the collection), besides allowing the

identification of microclimatic changes and analyze their correlations with anthropic changes that occurred in the region [4].

One of the articles published during this thesis focused on reviewing articles on the study of UHI integrating RS data, (Appendix I) made it possible to identify that UHI is increasingly being evaluated, especially since 2016, with different approaches and study sites and has been integrated into public policies, aiming at the improvement and well-being of the population and the environment [15].

Following the methodology of using RS for Land Surface Temperature (LST) analysis, another paper was also published, which focused on the analysis of UHI in Brasilia - Brazil, and used RS techniques to obtain LST values and compare them with Land Use Land Cover (LULC) to assess whether anthropologically altered areas had higher temperatures [16] (Appendix II).

The city of Bragança, in Portugal, was chosen as the study area for this thesis because the methodology integrating RS to analyze LST has not been implemented yet, and this local presents characteristics that can corroborate the formation of the UHI effect: i) its mountainous configuration, which naturally influences the circulation and speed of winds; ii) the presence of centralized urban densification, and; iii) it has been the target of UHI studies, considering data collected by 23 meteorological stations [17–19], on different surfaces, at three meters above ground level and that can be used to validate the continuous data obtained in RS.

It is expected that the use of RS data associated with data obtained from meteorological stations in Bragança will be a scientific contribution and stimulate the expansion of UHI analysis in other cities and that it will corroborate discussions about the need to adopt a more sustainable urban planning (including the adoption of new surface materials, for example), and partially meet the proposals of the 2030 Agenda for Sustainable Development [1,20,21].

1.1. Objectives

This work hypothesizes that Bragança (Portugal) is a propitious region for the formation of UHI since it is anthropically altered and mountainous. These conditions corroborate the changes in the wind circulation patterns, the albedo of the materials, the heating and cooling pattern compared to surrounding areas with the presence of vegetation [5,22]. This dynamic can be directly associated with changes in LULC, considered in the previous classification of the city in Urban Climate Zones (UCZ), and can be statistically identified to understand the effect of Bragança's UHI.

The overall objective of this work is to analyze the seasonal behavior of UHI in Bragança (Portugal) and relate it to data collection *in situ*, to evaluate their possible correlations.

The specific objectives of this work are:

- i. Combine satellite data and *in situ* data to model the behavior of surface temperature in Bragança;
- ii. Use computational processing tools, to generate LST from satellite data;
- iii. Apply descriptive and quantitative statistical analyses (correlation and regression model), especially between air temperature and LST variables, to analyze the behavior of Bragança's UHI in each UCZ, in summer and winter (seasonality).

1.2. Work Structure

This work was structured by several subjects separated into chapters and, with their respective sub-themes, aggregated in sub-items.

Chapter 2 presents the background, with pertinent subjects for the understanding of the proposed discussions, among them: i) the functioning of solar radiation and heat exchange in a place; ii) the description of urban climate in mountainous regions; iii) how the climatic scales are separated and classified; iv) the definition of UHI and causes for its formation; v) the composition of urban morphology, albedo, and others characteristics; vi) UHI impacts; vii) the application of RS to identify the characteristics of UHI; and viii) presentation of some studies that analyzed this effect in different ways, to highlight the relevance of research in this area.

Chapter 3 presents the methodology adopted in this work, considering the description of the study area, with the details of the field data collection stage (including the definition of dates, the material, human resources required, and the techniques adopted in each stage), the processes of tabulation, processing, and proposal of analysis of the data obtained.

Chapter 4 discussed the results obtained in each objective of the work, including qualitative and quantitative analyses.

Chapter 5 presents the main conclusions, limitations of the work, and suggestions for further studies.

Finally, the bibliographical references that supported the study were highlighted, as well as the appendices, including: i) the scientific review article published in the journal *Environments* (MDPI), during the development of this thesis; ii) the paper published in SPIE Europe Remote Sensing Conference, prepared during the writing of

the thesis; iii) the photographs identifying the sampled surfaces; iv) the portable monitoring equipment and the surroundings involved; v) the code used for LST processing in Google Earth Engine (GEE); vi) the LST maps; vii) the list of dates related to the passage of Landsat 8; viii) boxplot generated; ix) maximum, minimum, average and standard deviation values of UHI_{int} (LST (Landsat 8) and air temperature (fixed weather station)); x) correlation values and p-value between air temperature (fixed weather station) and LST (Landsat 8); xi) linear regression model, between air temperature (fixed weather station) and LST (Landsat 8), of each sensor.

CHAPTER 2

2. Background

This chapter presents the main concepts related to this thesis, separated into subchapters due to its multidisciplinary nature. First, the concepts on urban climate, especially in mountainous regions, and the parameters needed to classify a region are addressed. Subsequently, issues pertinent to the RS are described, such as data recording procedure, spatial missions, data processing techniques, and an overview of the tools and software used in this investigation. Finally, studies that have applied monitoring techniques like those applied in this research are presented.

2.1. Climate

The study of climate refers to the understanding of temperature, humidity, local biome, atmospheric pressure, and other environmental factors [4]. In this context, solar energy is one of the most important components and influences, directly or indirectly, all these climatic elements. This sub-item is intended to conceptualize the solar radiation, urban climate, its specificities in mountainous regions, and its scales, the UHI effect, its formation, impacts, and methodologies that apply to study, including the state of art, and highlighting some applications to identify, monitoring and propose mitigation the effect.

2.1.1. Solar Radiation

The solar radiation incident on the Earth's surface can be divided into direct and diffuse, and its decomposition results in an electromagnetic spectrum, with differentiated (but continuous) wavelengths. The Sun is a body with high temperatures and emits thermal radiation in short waves. About 6% of the radiation that hits the planet is reflected by the atmosphere, 20% is reflected by the clouds, 4% is reflected by the Earth's surface, 16% is absorbed by the atmosphere, and 3% is absorbed by the clouds [23]. The remaining part (about 51%) reaches the Earth's surface (including oceans) and is partially re-emitted into the atmosphere as longwave radiation. The shortwave solar radiation absorbed by the atmosphere and clouds is emitted as longwave radiation partly to the Earth and partly to space (Figure 2) [23].

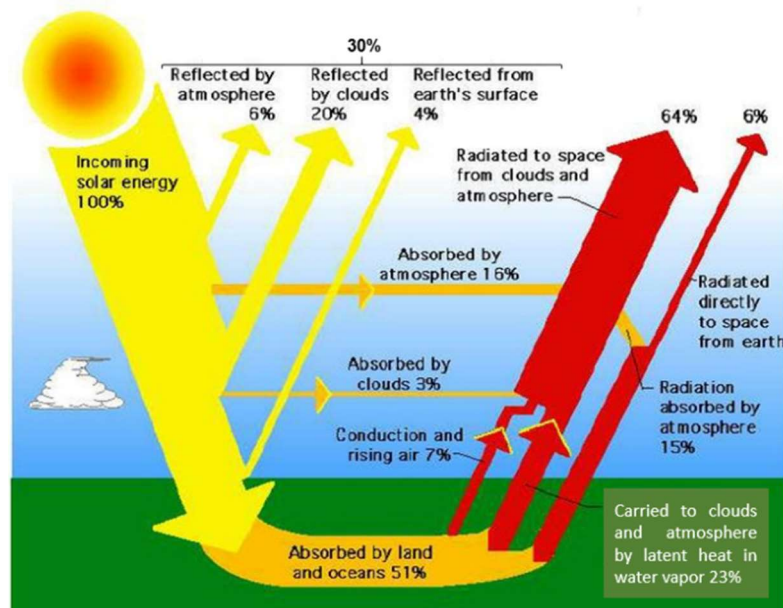


Figure 2. Earth's Energy Budget (adapted from [23]).

This dynamic provides heat exchange between the surface compositional materials and interferes in the temperature, pressure, Relative Humidity (RH), wind direction, etc., promoting specificities in the climate of a location [14,24].

2.1.2. The Urban Climate in Mountain Regions

The formation of the topography of mountainous regions is due to the movement of tectonic plates and erosion processes (which depend on other factors, such as climate) [17,25]. The specific climate is one of the parameters used to distinguish from other systems, such as valley and lowland zone, and is associated with three effects¹: i) synoptic weather systems or air flows that alter dynamic and thermodynamic processes; ii) differences generated in regional conditions (cloudiness, precipitation regimes, dynamic and thermal winds, etc.); and iii) terrain morphologies and slopes [17,25].

Altitude and relief can change the influence of latitude, sea, or land and corroborate local variabilities, which can be considered contradictory, such as torrid and dry heat on slopes that are exposed to the sun, sweltering heat in enclosed valleys, cold in these same valleys, both at night and in the winter, including fog and intense sun, considerable aridity and torrential rain [26].

Due to the variability of some environmental parameters (such as temperature, radiation, precipitation, etc.) in a short period, the high daily and annual temperature

¹ Two of which are related to the annual modeling of the mountain climate (although they occur in a particular synoptic situation).

range, lower mean annual temperatures, extreme winter behavior, interannual climate variability, and snow cover during the year or in some months [25,27], mountains can be considered complex for UHI studies, as there is a challenge in separating anthropogenic from natural influences for the formation of this effect. However, the scarcity of research considering this profile as a study area may compromise the scientific understanding of this effect in more complex locations and the stimulus in developing analytical methodologies that can even corroborate for research in other areas.

2.1.3. Climate Scales

To investigate the climate in mountainous regions it is necessary to define the vertical and horizontal analytical scales, since there are elements that can influence the results at a global or regional level, as in the case of the mountain orientation on the prevailing winds, the shape, the relief, the slope and the angle of the terrain [17,25].

There are three important levels in the horizontal climate scale: i) micro-scale: includes the typical scales from less than a meter to hundreds of meters, including trees, streets, roads, gardens, isolated buildings, etc. Considering that each object, surface, and its surroundings have a specific microclimate, there is no homogeneity in temperature, and variations of several degrees are possible over short distances (including millimeters). At this scale, airflow can be disturbed even by small objects. Due to the variability of temperature and for the data collected to be reliable, it is important to implement measurement equipment to avoid these effects, adopting a standardized measurement height and little obstruction of the horizon (Figure 3) [28,29]; ii) local scale: typically scales to one to several kilometers. Standardized weather stations are set up to monitor this scale. It excludes micro-scale effects and considers landscape features such as topography and similar structures of neighboring spaces (size, spacing of buildings, ground cover, etc.). There is an area of origin, which is usually the upstream part of the surface, that contributes to the main flow or meteorological properties (Figure 4) [28,29]; and iii) mesoscale: corresponds to a scale to tens of kilometers in length and consists of the influence of the city on its weather and climate, as well as on the surrounding regions. Monitoring with a single station is not representative (Figure 5) [28,29].

MICROSCALE

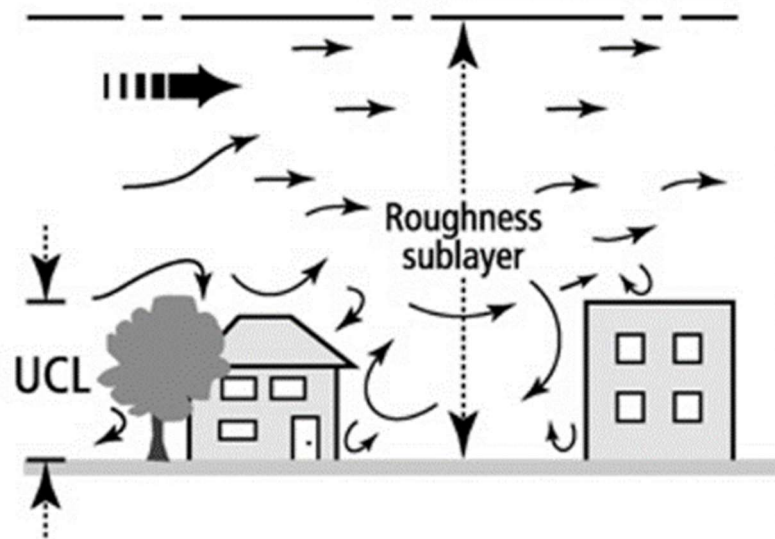


Figure 3. UHI: Vertical and Horizontal Scale Schematic – Microscale (adapted from [29]).

LOCAL SCALE

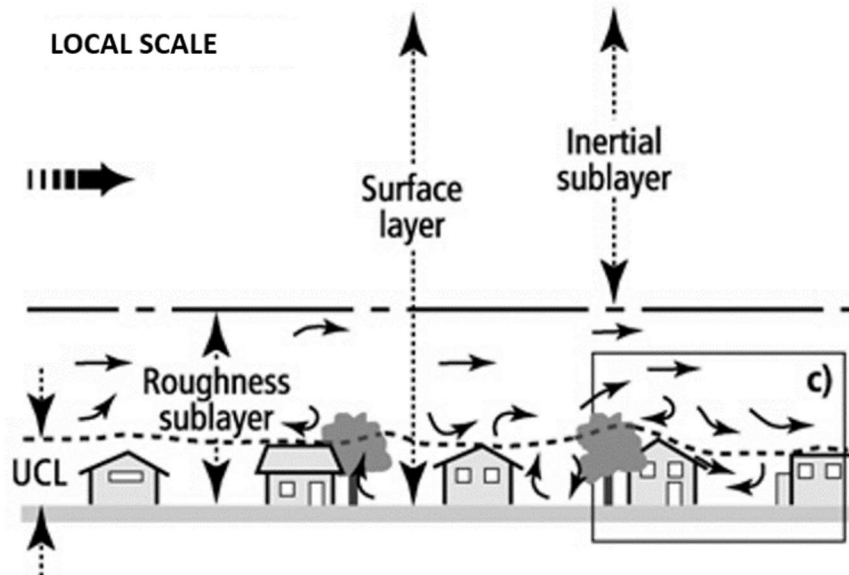


Figure 4. UHI: Local Scale Scheme (adapted from [29]).

MESOSCALE

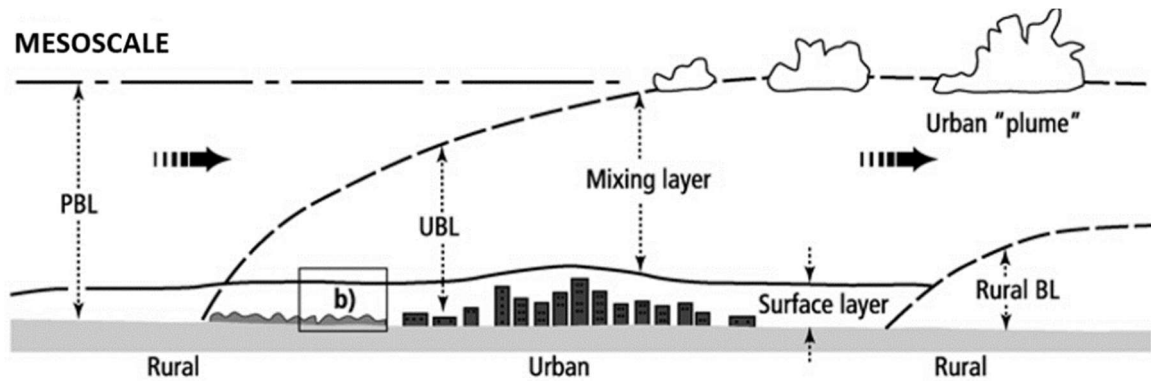


Figure 5. Mesoscale Scheme (adapted from [29]).

Related to the vertical climate scale, Oke (1984 and 1987) defined a concept that divided the urban atmosphere and is still used today [14,30]. The vertical structure is composed of horizontal layers, defined based on pressure, density, temperature, electric and magnetic molecular state, and chemical composition [17,31].

When comparing urban to rural or airport areas, a considerable difference can be observed in the vertical changes of momentum, humidity, and heat that occur in cities in the thick layer called Urban Canopy Layer (UCL) (Figure 3) and not in flat or almost flat surfaces. The diversity in the roughness of urban area conditions the height of the UCL, which is equivalent to the average height of these elements (buildings, trees, etc.). They are included in the UCL from the average level of the roofs to the zone of influence of the city in the atmosphere.

The Urban Boundary Layer (UBL) is where the effects of the Earth's surface are felt, through surface friction, heat transfer, and deviations in atmospheric circulation according to the topography (Figure 5). This layer has a defined daily cycle, which begins with the entry of energy and mixture of air in the morning and the decrease of its thickness at night once the surface air is cooled and turbulence is minimized. This layer occurs both horizontally and vertically [17,32]. Above the UBL to the top of the troposphere, there is the Free Layer, in which the geostrophic theory reigns, through the balance between the force of the pressure gradient and the force of Coriolis [14].

The amount of liquid radiation that reaches the surface influences the daily cycle of thickness and temperature in both UBL and UCL. This dependence can be evaluated through the energetic balance at the surface [32].

2.2. UHI effect

The urbanization of a site results in a series of modifications in the surface materials and corroborates vegetation suppression, soil sealing, albedo variation, etc. These anthropic changes influence the local energy balance and contribute to the formation of the UHI effect [3], which consists of greater absorption of electromagnetic energy and slower night cooling of urbanized surfaces when compared to surrounding areas with the presence of vegetation [5,22,33].

The UHI effect corroborates changes in the local microclimate, contributing to an increase in surface temperature, reducing RH and latent heat, and intensifying sensible heat. Figure 6 presents a scheme with the contrast between local and rural climate and illustrates the formation of UHI. As can be seen, the UHI effect is more present in urban centers because the latent heat flow is reduced and the sensitive heat is intensified [5,22].

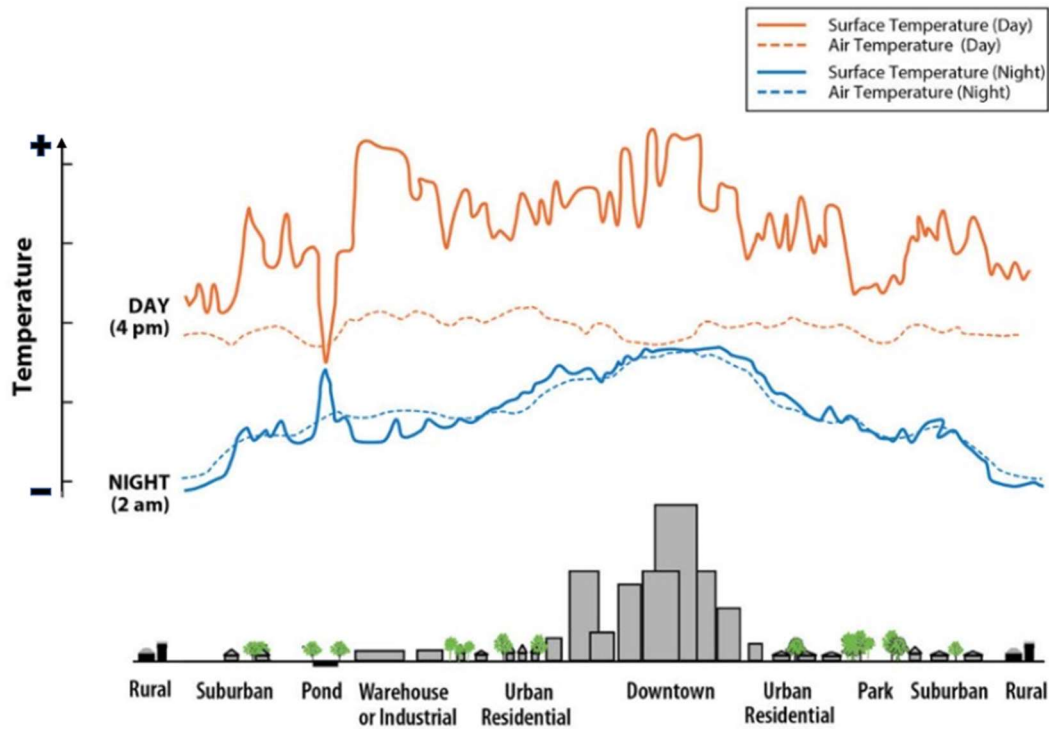


Figure 6. Profile of the urban UHI about suburban (adapted from [22]).

During the day, the SUHI shows variable behavior and considerable amplitude in urbanized areas, compared to areas with the presence of vegetation, whose temperature varies oppositely. Considering the concentration of construction, the greater the amount of mass per unit area and the larger the vertical and horizontal buildings, the more time is required for cooling [34–37]. SUHI gains intensity around noon in urban areas, and at night they retain more heat due to the thermal behavior of buildings, surface materials, and areas that have a reduced view of the skydome/hemisphere, as a function of the Sky View Factor (SVF) [34–37].

2.2.1. Causes for UHI Formation

The main causes for the formation of the UHI effect are: i) the heat storage capacity of building materials; ii) the anthropogenic heat produced in urban densification; iii) the change and influence on wind speed, depending on surface roughness; iv) the increased absorption of solar radiation, due to the albedo of some surfaces; and v) the surface constituent materials [38–41] among others. Table 1 presents the main causes of UHI.

Table 1. Summary of the causes of the UHI (adapted from [4]).

Cause	Effect
The higher absorption is not associated with the low albedo of the surface material.	Higher absorption of electromagnetic energy due to anthropic changes
Multiple reflections and trapping of radiation by the walls of buildings and vertical surfaces of the city.	
Restriction of the view of the sky due to increasing height and concentration of buildings and building surfaces.	Increased retention of infrared radiation in street canyons due to the restricted view of the "cold" hemisphere of the sky.
This effect is not only associated with the thermal properties of materials but also with the "trap" of solar and infrared radiation and the reduction of convective losses in the cover layer where the airflow is delayed.	Greater absorption and slower release of heat by buildings and paved surfaces in the city.
The replacement of wet soils and plants with paved and sealed surfaces.	Minimizing surface evaporation, greater absorption of absorbed solar radiation, and subsequently converting the energy into sensible rather than latent heat forms.
Although a minor component of the surface energy balance, heat and moisture are released from human metabolism and actions.	Increased release of sensible and latent heat due to urban transport fuels, industrial processing, and domestic space heating/cooling

The main characteristics associated with the formation of the UHI effect will be as follow.

Urban Morphology

The urban morphology, thermal properties of the constituent materials, and their layouts, all influence local heat exchange, as they can create shading zones, store heat, and corroborate the formation of UHI, as in the case of urban densifications. Understanding the factors related to urban morphology is critical for studies involving the thermal field [42].

There is a direct influence between urban geometry and ventilation flux, longwave radiation emission to the atmosphere, energy absorption, etc. [33,43]. The thermal properties of building materials influence the surface temperature of a place, such as solar factor², shading coefficient³, irradiance⁴, radiosity⁵, emissivity (E)⁶, absorptance⁷, reflectance⁸, and transmittance⁹. Urban geometry also interferes with the

² Percentage of solar energy that falls on the glass and is transferred (through the glass) directly or indirectly into the home (%).

³ Refers to the thermal performance of a glass unit (panel or window) in a building (values between 0 to 1).

⁴ It consists of the radiant flux (power) that is received by a surface, per unit area (W/m²).

⁵ Sum of the emitted and reflected radiation that leaves a surface (W/m²).

⁶ Ability to emit energy from surface radiation (values between 0 to 1).

⁷ It refers to the effectiveness of a surface in absorbing radiant energy and is calculated with the relationship between the absorbed radiant energy and the incident radiant energy (values between 0 to 1).

⁸ Relationship between the flow of the electromagnetic radiation incident on a surface and the flow that is reflected (%).

action of solar radiation, depending on the arrangement of buildings and the existence of shadows [44,45].

For the thermal interactions to occur, solar radiation is fundamental, since it promotes the heating of surfaces that, in turn, present a specific response. This operation results in different thermal behaviors, generating high and low-pressure zones, influencing air circulation and thermal amplitude [46].

Albedo

The reflective power of a surface or diffuse reflectivity is called albedo or reflection coefficient and is obtained through the ratio between the incoming and outgoing radiation. It is expressed as a percentage and it varies from zero to one, corresponding to no reflection (black surface) and perfect reflection (“pure” white surface), respectively. It is worth noting that the frequency and directional distribution of radiation influence the albedo, except for Lambertian surfaces, which by scattering the radiation in all directions and are independent of the incident distribution [47]. Figure 7 shows some of the materials used in construction, with their respective albedo rates.

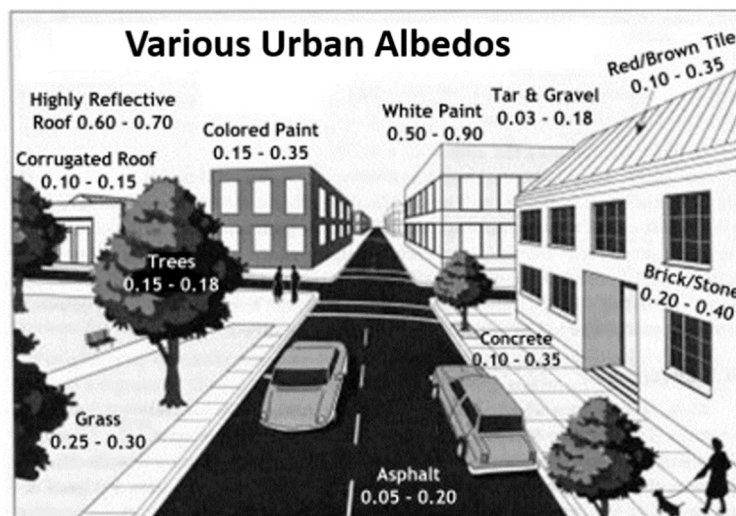


Figure 7. The albedo of urban materials (adapted from [33]).

The albedo of urban components presents high variability and, in its majority, absorbs more electromagnetic energy than the vegetation. As they take longer to cool down, they potentiate the formation of UHI, corroborating the increase in surface temperature, thermal discomfort, and the influence on the microclimate, such as the displacement of water masses due to the creation of low- and high-pressure zones and changes in local precipitation.

⁹ Fraction of the light incident with a certain wavelength, which passes through a sample of matter (values between 0 to 1).

Width (W) / Height (H) / Length (L) and Urban Canyons

The thermal performance and geometry of an urban area are calculated as the proportion between the W and H of its buildings. Oke (2006), Santamouris (2006), and Romero (2011) include L, which corresponds to the length of the Urban Canyon [29,38,39]. From this relationship, the concepts of densities, porosity, and roughness are derived, which will be discussed later. Romero (2011) and Oke and Stewart (2012) establish a classification of environments, based on this relationship, into three classes: i) claustrophobic spaces, ii) meeting spaces; and iii) expansive spaces [4,38]

Each type of space has its specificities regarding the influence on wind flow, sun, temperatures, shading, and thermal changes. According to Romero (2011), the urban canyon is formed when the H / W ratio is greater than 0.7 and has a strong influence on the urban climate [38].

SVF

Also known as the Horizon Obstruction Angle (ψ_s), the SVF is a dimensionless parameter that quantifies the amount of visible sky at a given location. It varies from zero to one, corresponding to an obstructed area and an area free of any obstacle between the chosen point of observation to the celestial vault, respectively. Figure 8 shows the relation between the H and the spaces among the edifications (W) [29,48–50].

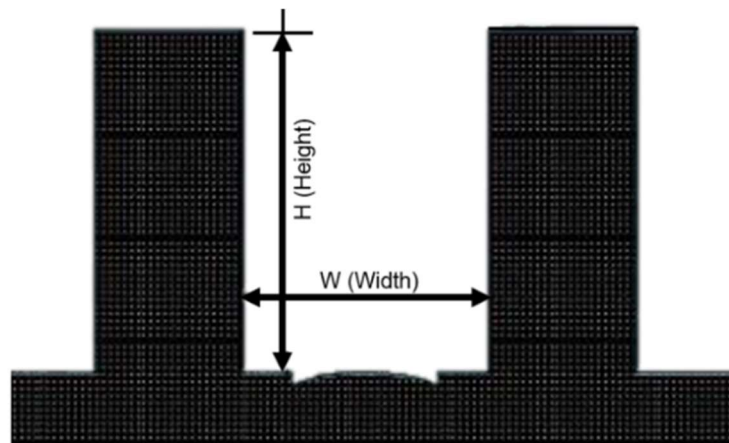


Figure 8. Relation between the height (H) and the spaces among the edifications (W) (adapted from [29]).

The more obstructed the view (SVF near zero), the more difficult it will be to disperse the stored thermal energy from the environment into the atmosphere. This occurs due to the vertical increase of the contact surface, which corroborates the

increased radiation absorption. Previous studies point to the influence of SVF in the UHI formation [48].

Urban Densification

Urban Densification corresponds to the ratio between the number of inhabitants in a region and the area available for occupation. In some cases, the greater concentration of population in each location is interesting because it centralizes the supply of services such as basic sanitation, transportation, health, school, employment, commerce, etc. However, the agglomeration of civil construction, vertical urban models, vegetation suppression, soil sealing, and anthropogenic changes may cause impacts on direct solar radiation and potentiate the formation of UHI [51,52].

Although some researchers advocate centralization, since it allows for greater control of these areas, it is relevant to evaluate ways to minimize impacts by choosing optimized building materials and layouts [51].

Rugosity

Urban density and changes in LULC can alter the wind circulation conditions and, consequently, the temperature distribution, such as roughness. This parameter consists of the difference between the heights of buildings and surrounding structures: comparing an area of flat vegetation with one with buildings, for example, it is possible to verify that the roughness of the former offers fewer obstacles to wind circulation. In regions with considerable altitude variation, as in the case of Bragança, part of this effect is inherent to the local geomorphology [17,20].

The high roughness in urban areas compared to rural areas corroborates the decrease of the SVF, minimizing the exchange of longwave radiation. This condition corroborates to more solar (shortwave) radiation being absorbed, and less longwave radiation being emitted, culminating in an increase in local average temperature. In addition, the warming may also be accentuated due to the reduction in average wind speed, which minimizes convective cooling [20].

Porosity

The concept is convergent with that of permeability and refers to the capacity of a material to be permeable to perforations, atmospheric manifestations, and levels of transparency. It is more related to the horizontal dimensions and their openings and,

eventually, to the vertical ones of buildings and their arrangement in urban densification [4,47].

Anthropogenic Heat

The definition of anthropogenic heat depends on the scale of analysis: when considering the building, it refers to the energy emitted by the human body in its activities inside the building (such as work, physical movements, etc.); when considering the urban scale, it refers to the heat generated in an anthropogenic way, from the most diverse sources (operation of buildings, companies, industry, means of transport) and which corroborate for the UHI [40].

Oke (1987) defines that the anthropogenic heat density is associated with the average energy use per inhabitant and varies, among several factors, with the population density of a city, economy, and local climate, since some regions will have higher energy consumption with heaters in winter and/or with air conditioners in summer [14].

Energy Balance in a Building and Between Buildings

The concept regarding the energy balance in a building can be compared to what occurs in an animal, and the energy flows are deducted from the spatial averages relative to the total external air volume of the building. Considering the energy conservation law, this estimation can be obtained according to Equation 1 [14].

$$Q^* + Q_F = Q_H + Q_E + Q_G + \Delta Q_S \quad (1) \quad [14].$$

The net radiation from all waves existing outside the building is represented by Q^* ; the total indoor anthropogenic heat density is Q_F ; the sensible and latent heat with the outside air is represented by Q_H and Q_E , respectively; the heat exchange between the building and the underlying ground is Q_G , and the net energy storage exchange by building materials as well as the enclosed air volume are represented by ΔQ_S [14].

Figure 9 presents an explanatory scheme about these constants. It is observed that due to the three-dimensional geometry of the house, the direct beam shortwave radiation input is uneven [14].

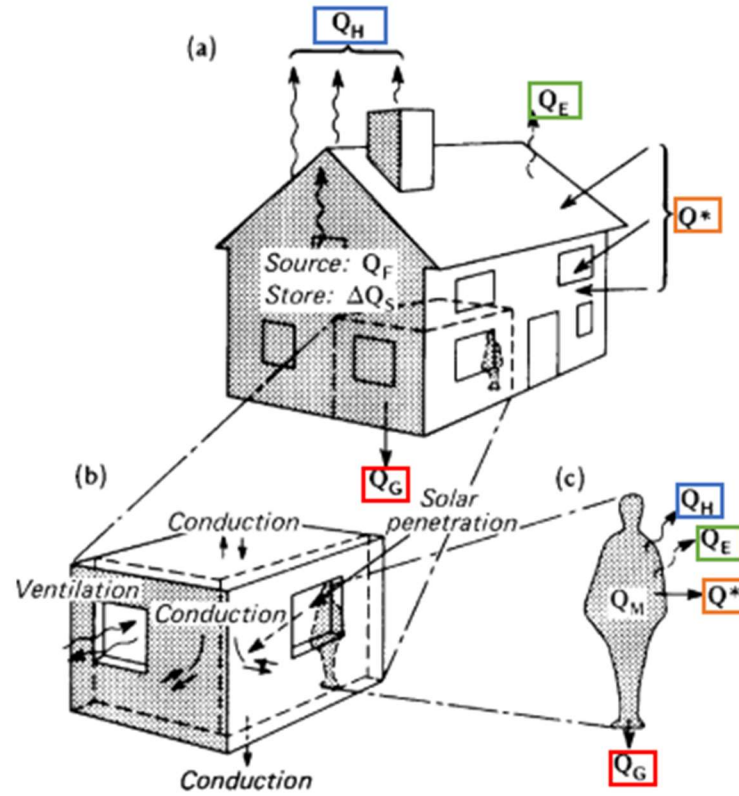


Figure 9. Energy balance scheme in a building (adapted from [14]).

Concerning the exchange of energy between buildings, the logic is the same, and the estimation can be made considering Equation 2:

$$Q^* + Q_F = Q_H + Q_E + \Delta Q_S + \Delta Q_A \quad (2) \quad [14].$$

Where, ΔQ_A represents the advective terms, as a function of net horizontal transfer of sensible and latent heat [14].

As for the water flow, it can be computed by Equation 3:

$$p^* + F + I = E + \Delta r + \Delta S + \Delta A \quad (3) \quad [14].$$

Precipitation is represented by p^* ; F consists of water released into the atmosphere due to combustion; urban water supply, channeled from rivers or reservoirs, is represented by I ; ΔA consists of the net moisture input to/from the city air volume (this balance is applied to volumes that expand in a condition sufficient for the vertical exchange (Q_H) of heat and water (f) to be negligible); the heat and water exchanges stored in buildings, internal air volumes (canyons) and on the ground are

represented by ΔQ_S and ΔS ; Q_F and F represent the sources of heat and water in the city, associated with combustion. It is emphasized that Q_F , F , and I are energy and mass fluxes controlled by human decisions and respond, indirectly, to activities related to the solar cycle. The other terms relate to the horizontal net transfer of sensible and latent heat (ΔQ_A), and water droplets (ΔA) [14,31].

Buildings have different characteristics concerning the thermal radiation incident on them, being able to transmit, reflect or absorb and re-emit the radiation to the interior, depending on the material, color, shape, etc. Considering the theory of energy conservation, it is possible to segregate the incident radiation according to Equation 4.

$$\alpha + \rho + \pi = 1(4) [14].$$

Where, absorptivity is represented by α ; the reflectivity is ρ , and the transmissivity is π . The sum of all parameters corresponds to 100%.

In addition, thermal exchanges in building materials can occur by: i) conduction: propagation of heat from a warmer body to a colder one, in a propitious environment for this thermal exchange, due to the transfer of energy between particles; or ii) convection: transport of energy by displacement of matter, in this way, thermal radiation is dissipated to the atmosphere in the form of heat, in a propitious environment [32,47,53].

In practice, the temperature of a surface rises when receiving direct radiation, allowing the flow of sensitive heat between the different surrounding surfaces or between air and a surface, due to the orientation about the path of the sun. As the surface temperature rise, there is an increase in the radiation emitted in the long-wave spectrum [54].

2.2.2. UHI Impacts

There are several impacts associated with UHI, the most recurrent are: i) influence on local microclimate; ii) public health impacts; iii) thermal discomfort, and iv) changes in hydrological behavior (such as displacement of water bodies) [38–41]. The effect of UHI and SUHI, when combined with natural phenomena such as Heat Waves (HWs), can directly impact human health, including, increasing mortalities [55].

Some studies discuss that climate change will potentiate the increase in air temperature and, consequently, the negative effects of UHI and SUHI, making urgent

the need for analysis and mitigating proposals of this effect, including in urban planning [56–59].

The capture of solar radiation and evapotranspiration are also processes that influence the energy balance and, in urbanized areas, can be suppressed due to LULC changes, such as soil sealing [2,38]. In this context, encouraging the maintenance and inclusion of vegetation in cities appears as an interesting mitigation alternative because, while acting in reducing the temperature, it can assist in the control of air pollution and wind humidification (urban microclimatic elements) [2,38].

2.3. Use of RS for UHI Studies

The electromagnetic spectrum includes both visible and non-visible bands (Figure 10), and each has different percentages of atmospheric transmission, *i.e.*, the amount of radiation recorded by the sensor depends on the associated wavelength.

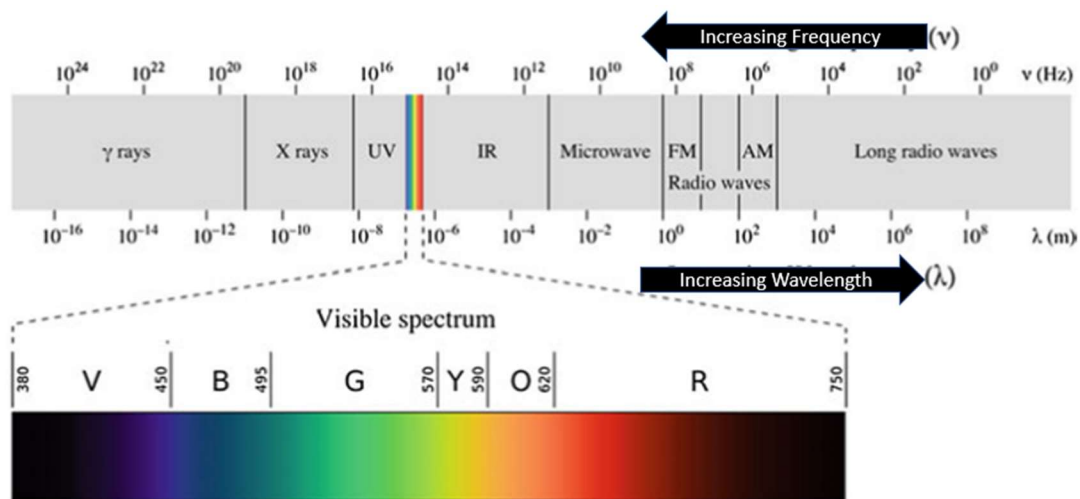


Figure 10. Electromagnetic Spectrum (adapted from [60]).

Each sensor has its operational specificities, such as spatial resolution (which refers to the pixel size, in meters), spectral resolution (is the measure of the width of the spectral bands: the more numerous and narrow the bands, the greater the spectral resolution and the sensor's sensitivity in distinguishing between two levels of intensity of the return signal, which contributes to the production of more accurate spectral signatures), radiometric resolution (which consists of the sensor's ability to discriminate small variations in energy, *i.e.* the higher the radiometric resolution, the more sensitive it is to detect small emitted/reflected differences) and temporal resolution (period between two consecutive observations of the same point) [61].

RS consists of a set of techniques to obtain information from targets, without the need to establish physical contact. Considering that all bodies with temperatures above absolute zero (0°K or -273°C) emit electromagnetic radiation, RS uses sensors available on-board of different platforms (such as satellites, airplanes, balloons, drones, etc.), to register the reflectance values at different wavelengths in the electromagnetic spectrum, convert them into a signal, and subsequently generate images from which information can be extracted [12] (Figure 11).

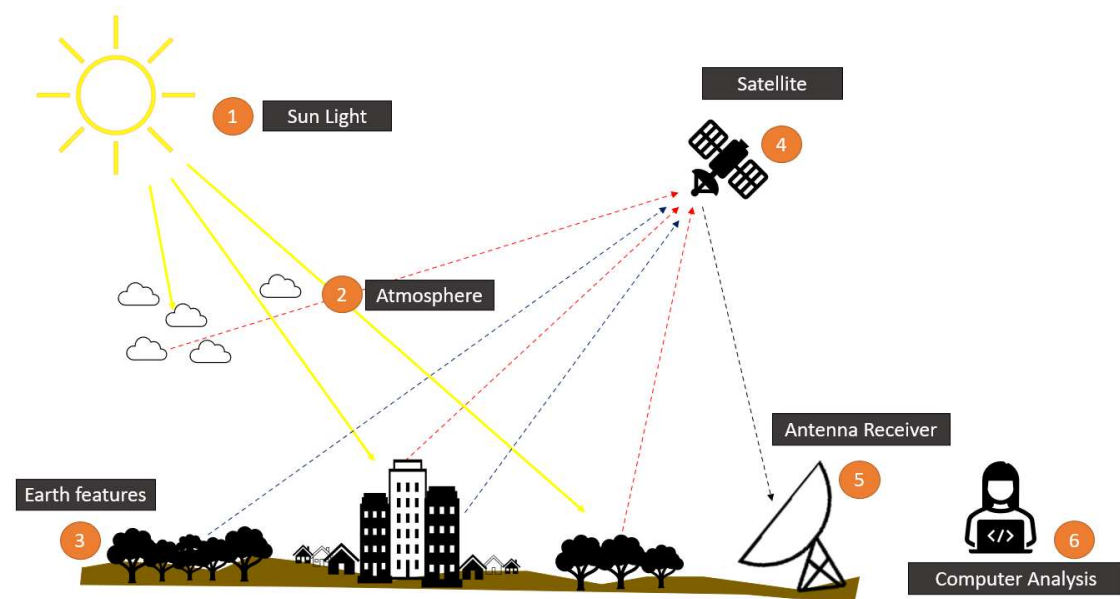


Figure 11. RS process (adapted from [62]).

For UHI studies, data from multispectral sensors are used, including the visible and infrared bands. Thermal sensors operate in the range of the atmospheric TIR window ($8 - 14\ \mu\text{m}$), which includes the emission portion of the Earth's spectrum and enables the detection of heat [12].

The thermal sensors are cooled to temperatures close to 0°K so that their eventual emissions do not influence the measurements and temperature data records of the targets. A comparison is made between the measured radiation temperature and the sensors' internal reference temperatures (related to the absolute radiation temperature) [5]. It is worth noting that there is proportionality between the values recorded by thermal sensors and the intensity of heat on the day of collection, so on days with higher intensities, targets will emit higher values of radiant energy [14].

2.3.1. Landsat Mission

Landsat mission has a long and uninterrupted observation program [63], since 1972. All satellites operate in the Earth in a sun-synchronous, near-polar orbit. The Landsat 1, 2 and 3 missions operated at a nominal altitude of 917 km, orbital inclination 99.2°, and a revisit period of 18 days. As of the Landsat 4 mission, the nominal altitude is 705 km, orbital inclination 98.2°, and with a revision time of 16 days, which makes temporal surveys of the same location interesting, since the same points are revisited at equal UTC times. The data are released free of charge by the United States Geological Survey (USGS), at levels 1 and 2 (without pre-processing and with processing, respectively) [64,65], Figure 12 shows all satellites launched and their respective years of operation.

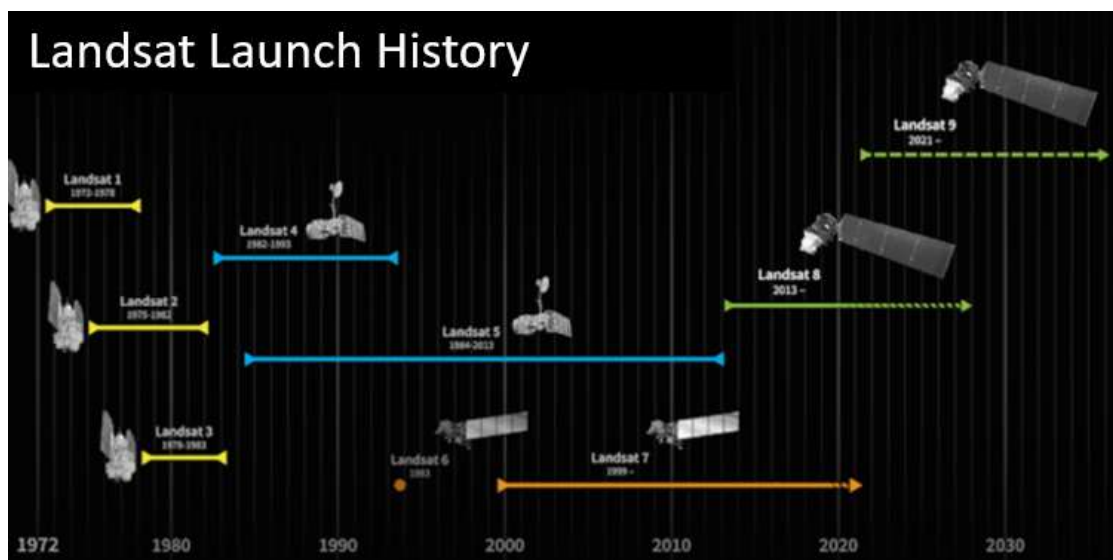


Figure 12. Landsat timeline (adapted from [66]).

Thermal data began to be collected starting at Landsat 4 by the Thematic Mapper (TM) sensor [64], also implemented at Landsat 5 [65], by the Enhanced Thematic Mapper Plus (ETM+) sensor at Landsat 7 [67]; and by the Thermal Infrared Sensor (TIRS) sensor at Landsat 8 [68].

It is important to mention that, in the first methodological approach in this thesis, the Landsat 7 data were also considered. However, as the Scan Line Corrector (SLC), used to compensate for the satellite's forward motion, presents flaws since May 31, 2003 [67], the use of these scenes was discarded in order not to add factors that could influence the results.

OLI sensor consists of a panchromatic band and eight multispectral bands, with a resolution of 15 and 30 meters, respectively. In the TIRS sensor, there are two thermal bands with a resolution of 100 meters, whose data are resampled to 30 m [68].

The band used in this work was band 10, relative to TIRS 1 (10.3 - 11.19 μm), with a radiometric resolution of 16 bits. The scanning system is a pushbroom scanner, which uses the satellite motion to scan several lines perpendicular to the line of flight, successively [61,68].

2.3.2. RS products

There are many products possible to obtain using RS data. For UHI studies, the most important information is LST (which, depending on the sensor and processing algorithm, will require correction of the emissivity (E) of the soil and vegetation, obtained from the Vegetation Index (VI).

In addition to these indices, it is common to use LULC data to analyze the land cover characteristics and understand their influence on the UHI. However, in this work the parameter used was the UCZ classification, identified in previous studies in Bragança and which considers the morphological aspects previously presented. In this subchapter, the LST, VI, and UCZ will be detailed.

LST

LST can be defined as a variable in the physics of local and global surface processes, linked to radiative, latent, and sensible heat fluxes at the surface. It is known as radiometric or "skin" temperature and consists of the direct measurement of the Earth's surface temperature [69].

Unlike measurements made by meteorological stations, which record the temperature close to the surface, the LST provides an analysis on a more detailed scale, for example, in places with dense vegetation, the LST will represent the temperature of the leaves in the canopy; regions with sparse vegetation, it will represent the temperature of the entire canopy, branches, etc. and include the ground surface; in bare ground, it will correspond to the temperature of the top of the ground surface (with a difference of a few micrometers) [69].

In RS, the LST will comprise the radiometric temperature aggregate of the set of components, including in the field of view of the sensor [12,61,69,70]. The value is recovered by estimating the emitted surface radiance (obtained by an atmospheric correction in the radiance sensor), and by inverse application of the Planck function, considering the effects of E variation [69].

Understanding the dynamics and modeling LST data can help to determine the radiative load of the Earth's surface, predict environmental changes, forecast warming trends, climate variability, among other applications. Some application examples are:

retrieving climate variables (such as soil moisture, evapotranspiration, vegetation water stress, and thermal inertia [71,72] global warming, cryosphere melting [73,74] insect infestation [75]; vector-borne diseases [76], UHI studies [70,77,78], (which will be the case of this thesis), etc.

VI

VI can be calculated from the combination of information from two or more bands obtained using RS data, considering or not the addition of constants to synthesize and improve the biophysical parameters of the vegetation [79]. Since there are several VIs, it is recommended that a specific analysis be performed on the objective of the study and what the spectral response of vegetation to solar radiation is like to adhere to the appropriate technique and equipment.

In general, the typical spectral behavior of healthy vegetation corresponds to the absorption of intense solar electromagnetic energy between 630 - 680 nm and high reflectance in the near-infrared region, between 760 - 900 nm [80]. The absorption is due to the presence of chlorophyll in the leaves [80], which uses radiant energy in the process of photosynthesis and converts and stores it as organic compounds [81]. The reflectance occurs due to the internal cellular structure of the leaves.

This behavior allows the linear combination of the data obtained in the red and near-infrared waves and the calculation of the amount of chlorophyll per unit area of a plant community, corresponding to a direct relationship with Leaf Area Index (LAI) and crop production, making it possible to monitor and compare both spatial and temporal photosynthetic activity and structural variations in vegetation [82].

In UHI studies, VIs can be added in the processing of the LST mapping to correct the radiative energy-emitting capacity of the soil surface and vegetation, *i.e.* E [83]. In standardized methods, the most widely used VI is the Normalized Difference Vegetation Index (NDVI) (Equation 5), first applied by Rouse *et al.* (1974).

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \quad (5) \quad [84,85].$$

Where, NIR is the Near-Infrared sensor band and RED is the red band.

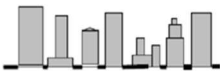
The result ranges from -1 to +1 and distinguishes between i) clouds, water, and snow with negative values; ii) bare ground or civil constructions with results close to zero; and iii) fully vegetated areas with positive results, respectively [84].

2.4. UCZ in UHI studies

Oke (2006), after 30 years of research, prepared a survey about the concepts pertinent to the study of UHI [29]. In the orientation material, the author addresses the locations for implementation of monitoring/measurement stations and their respective horizontal and vertical scales, equipment and methodologies for measuring parameters (such as temperature, solar radiation, wind, precipitation, humidity), the application of RS techniques for studies of UHI and definition of the concept of UCZ (Table 2) [4].

Oke and Stewart updated, in 2012, the methodological procedures for classifying UCZs. Still, the methodology is subjective and lacks specific knowledge of the site and its parameters [4]. Because it is a methodology widely applied in studies that require UCZ classifications, in Bragança this procedure was also adopted.

Table 2. A proposed classification for UCZ (adapted from [29]).

Urban Climate Zone (UCZ)	Number of the image	Example	Roughness class	Aspect ratio	% Built (impermeable)
Intense urban development, with high-rise buildings with cladding.		Downtown towers	8	> 2	> 90
Intense urban development, with 2 - 5 story buildings, attached or very close together, often of brick or rock.		Old city core.	7	1.0 – 2.5	> 85
Urban of high development, medium density with the presence of houses, stores, and apartments in a row or isolated, but closed set.		Urban housing.	7	0.5 – 1.5	70 - 85
Highly developed, low or medium-density urban with large low buildings and paved parking.		Shopping mall, warehouses.	5	0.05 – 0.2	70 - 95
Medium development, low-density suburban with 1 or 2 storey houses.		Suburban housing.	6	0.2 – 0.6, up to >1 with trees	35 - 65
Mixed-use with large buildings in the open landscape.		Hospital, university, airport, etc.	5	0.1 – 0.5, depends on trees	< 40
Semi-rural development, scattered houses in a natural or agricultural area.		Farms, estates.	4	> 0.05, depends on trees	< 10

2.4.1. UCZ in UHI study in Bragança

The UHI effect was previously analyzed in Bragança, using data from a meteorological network with 23 sensors, without the use of RS data/techniques. In 2018, 958,985 surface air temperature records (41,689 from each point, approximately) collected by sensors from 2012 to 2016 were used. These data were statistically treated and analyzed (with a paired samples t-test) to verify the difference in mean air temperature for each UHI [17,18].

To assess the intensity of UHI, the seasonal differences in surface air temperature between urban and nearby rural UCZs, the monthly and hourly variation in intensity, average cooling and heating rates, and the influence of wind and precipitation were analyzed [18]. This study also included an analysis of the effect of Urban Cold Island on the city.

Focusing on the UHI results, the presence of this effect was most intense from mid-afternoon to sunrise, especially in densely urbanized areas, during the early morning (moments before sunrise), and on summer days. Vegetated areas played an important role in cooling the city during the day and in summer. The UCZs classes with lower urban densities showed lower UHI, a result corroborated, also, by the increased wind speed and periods of higher precipitation [18].

The lack of research using RS data may be an interesting contribution to the study area and to evaluate some standardized behaviors, which can be modeled for the region.

2.4.2. RS in UHI assessment in different UCZs

Studies on UHI can be conducted adopting various methodologies and study focus. This subitem will highlight some works that employ the UCZs as a methodology to evaluate the effect.

In Abu Dhabi, United Arab Emirates, the UHI effect was evaluated from the UCZs, calculated from Landsat images, and related to the physical properties of the surface. The city has heterogeneous surfaces, including building forms, and because it is in a coastal region in a desert environment, there are specificities in heat exchange. The study evaluated the UHI and seasonality in different seasons and times of the day and identified that the average temperature values, calculated throughout the day, pointed out the presence of UHI in different zones, especially in densely urbanized ones [86].

In Budapest, Hungary, UHI was analyzed from MODIS LST data in regions classified as UCZ. The paper cites the economic challenge in installing and operating a suitable meteorological network station, the possibility of using free RS data with extensive historical coverage. The results pointed out that the lower the density of construction, the lower the SUHI intensities. The largest variabilities were identified in summer, due to higher solar radiation input [87].

In West Bengal, India, the same methodology was applied, comparing data from an Urban Thermal Field Variance Index. The results showed an increase in surface temperature, especially in the summer, and suggest that the study should be considered by managers for restructuring urban planning [88].

In Wuhan, China, the UCZ parameters were used as predictors in the local LST and suggest that optimization of civil constructions, with the maintenance of water bodies and reconfiguration of skyscrapers, for example, be considered in urban design [89].

In Beijing, China, the UCZ technique adapted to the local reality was applied, considering 18 classes, based on Landsat data, morphological, and cover indicators. The results indicate that areas with vegetation and water bodies presented lower temperatures when compared to those with civil construction, even those of low density. During the day, areas with high density and skyscrapers present higher temperatures, unlike areas with water and trees (dense or scattered), which present the opposite behavior, *i.e.*, lower temperatures [90].

Other studies associate UCZs classifications as a tool to assess the influence of UHI on specific surfaces and that associate urban density to higher surface temperatures [91–95] which ratifies the methodology proposed in this thesis.

CHAPTER 3

3. Methodology

The methodology adopted in this work was subdivided into different steps, due to the nature of the data and the various sources of information used. Considering a generalized scheme, these steps can be summarized according to Figure 13.

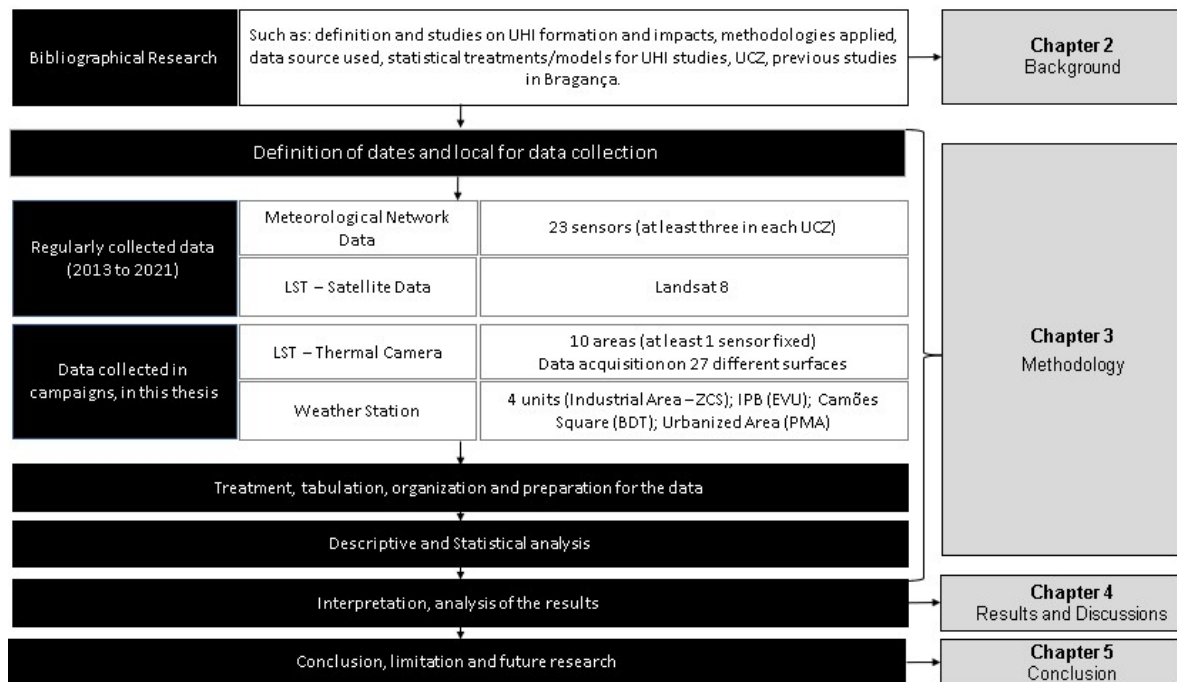


Figure 13. Summary of Methodological Procedures.

It is worth noting that all theoretical research, presented in chapter 2 - "Background", was supported by bibliographic surveys, prioritizing the use of scientific databases (e.g., SCOPUS and ISI Web of Science) and manuals that addressed relevant theoretical concepts for the understanding of the study, such as the characteristics of the study site, the use of satellite images to identify the UHI, standard methodologies for data processing and statistical models that could be applied, etc.

In addition, the analysis, interpretation of the results, and suggestions for improvement in future research will be presented in chapter 4 – "Results and Discussion". In this chapter, the following will be presented: i) the characteristics of the study area; ii) how the UHI analysis dates were set; iii) the selection criteria for the installation of the fixed sensors; iv) the definition of the locations for field data collection (both with the use of thermal camera and portable meteorological stations); v) how each data were treated; vi) obtaining and processing the LST data from Landsat 8 (ArcGIS and GEE); vii) how the temperature values were extracted from the LST; and

viii) statistical processing of the data and analysis of the results (qualitative and quantitative).

3.1. Study Area

Located in the extreme Northeast of Portugal mainland (41°48'20" N, 6°45'42" W) (Figure 14), Bragança Municipality has 24,078 inhabitants and an area of approximately 1,174 km². It is a mountainous region, with a relief considered complex due to the variability of its elevation [18].

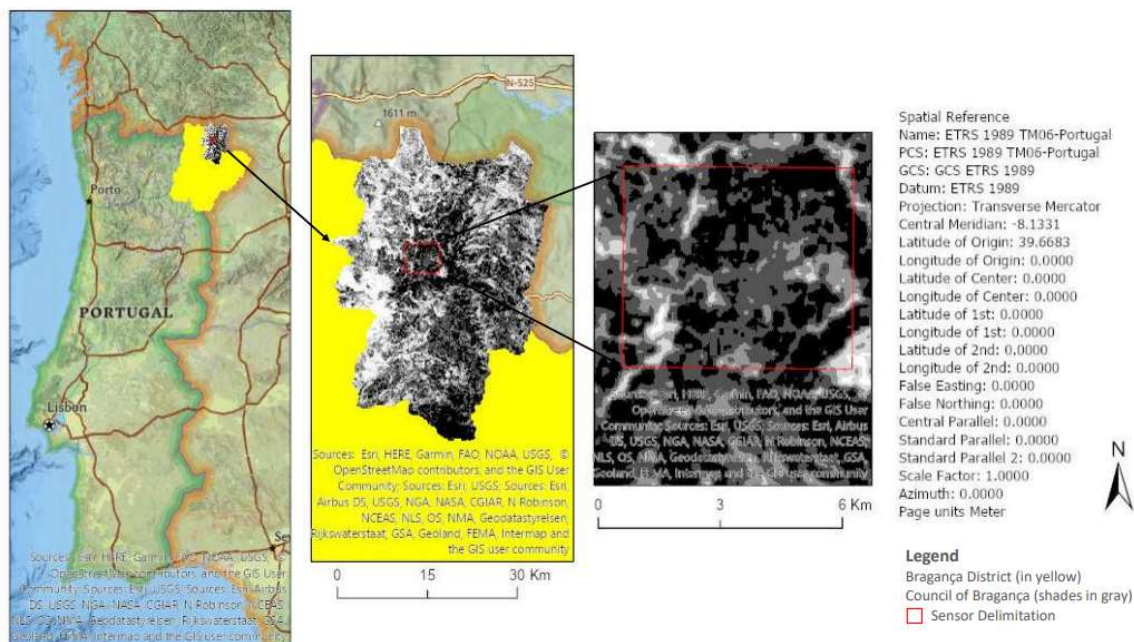


Figure 14. Identification of the study area, with the sensor delimitation in red (where the analyses took place).

The urban area of Bragança is composed of a diverse urban fabric, including different neighborhood densities and vegetation densities. The local economy is supported by service companies, most of them from the public sector. There are two main rivers in this city and its vicinity: the Fervença River, which runs throughout the city, and the Sabor River, which is in the peripheral region, with minor influence in the city. The climate is characterized by high annual and monthly thermal amplitude. Precipitation has characteristics of a Mediterranean climate, with frequent rainfall in the winter and relatively dry summers [18].

The city has extensive and uninterrupted thermal data collection using temperature and humidity sensors fixed at locations with distinct climatic characteristics and was chosen as a study area because previous research has already identified the presence of the UHI effect [17–19]. However, none of these studies uses local collection data in combination with RS techniques.

Climate change issues are relevant to Bragança, which is one of the municipalities that integrate the ClimAdapt.Local project, launched in 2015 and that supports projects that aim to develop adaptations to climate change in Portugal [96]. The "Municipal Strategy for Adaptation to Climate Change" document proposes climate change remediation actions to various areas, such as agriculture and livestock, water resources, forestry, in addition to proposals for awareness and environmental education of the population and policies that prioritize the green economy [96].

This document/proposal has already been studied in other countries [97], which reinforces the importance of research involving climate change (such as the proposal of this thesis), and that can offer new information to public managers, aiming to complement and enable customized and assertive mitigating actions that can be adapted to other realities, including international ones.

3.2. Dates for Data Collection

The initial intention was to conduct six field surveys for validation data collection, three in summer and three in winter, to identify the influence of seasonality on temperature, with dates coinciding with the satellite passage over the region, which occurs every 16 days.

Since weather conditions influence the results, the criterion of no precipitation and/or clouds on the day of data collection were used. Of the 16 possible dates, only four were performed, three in summer and one in spring.

Although no local data collection occurred in winter, to validate the influence of seasonality on thermal behavior, the LST data collected by Landsat 8 and the air temperature recorded by the local fixed sensors were kept. Table 3 presents a summary of the planned dates and their respective status. The local temperature data (minimum, maximum, and average) were obtained from the website of the Instituto Português do Mar e da Atmosfera [98].

It is worth mentioning that, as the field collections took place during a pandemic period (COVID-19), the flexibility of collection dates was compromised, especially during periods when traveling between different districts of Portugal was limited [99]. As the climatic conditions also influence the results [47], the criteria of no precipitation and no cloudy days were followed to realize the field campaigns.

Table 3. Planning of field visits in Bragança.

Date	Weekday	Season	Status	Local Temperature (° C)			Observation
				Min	Max.	Mean	
08/03/2020	Monday	Summer	R	12	26	19	
09/04/2020	Friday	Summer	R	12	34	23	
09/20/2020	Sunday	Summer	C	14	24	19	Canceled – Rain.
10/06/2020	Tuesday	Summer	C	14	20	17	Canceled - Cloudy.
01/10/2021	Sunday	Winter	C	1	6	3.5	Canceled - Cloudy.
01/26/2021	Tuesday	Winter	C	11	14	12.5	Canceled – Rain.
02/11/2021	Thursday	Winter	C	7	15	11	Canceled – Rain.
02/27/2021	Saturday	Winter	C	5	15	10	Canceled - Cloudy.
03/15/2021	Monday	Winter	C	0	16	8	Canceled - Cloudy.
03/31/2021	Wednesday	Spring	C	7	28	17.5	Canceled - Cloudy.
04/16/2021	Friday	Spring	R	2	16	9	
05/02/2021	Sunday	Spring	C	-1	15	7	Canceled - Cloudy and rainy.
05/18/2021	Tuesday	Spring	C	10	19	14.5	Canceled - Cloudy.
06/03/2021	Thursday	Spring	C	5	16	10.5	Canceled - Cloudy.
06/19/2021	Saturday	Spring	C	12	17	14.5	Canceled - Cloudy and rainy.
07/05/2021	Monday	Summer	R	14	25	19.5	Minimal cloud presence between 11h00 – 13h00 (UTC).

Status Legend: R = Realized; C = Cancelled

3.3. Research Data

The data used in this work can be divided into: i) data from 23 meteorological stations installed in Bragança, collected between 2013 and 2021; ii) data collected in the four field visits: photographs, LST obtained with the thermal camera at 10 points, prioritizing different surfaces, totaling 27 sampling points, and data measured by portable meteorological stations and; iii) Landsat 8 data, between 2013 and 2021.

The entire project and the methodological execution were accompanied by researchers from the Polytechnic Institute of Bragança (IPB), including the availability of equipment and a monitoring team. Each of the stages will be detailed in the following sections.

3.3.1. Meteorological Network Data

The UHI effect has already been studied in Bragança, through data obtained by 23 temperature and RH sensors (model TGP-4500, TinyTag, Gemini Data Loggers, Chichester, UK), installed in December 2011 and distributed according to UCZs classification, in the urban and peri-urban context (Figure 15) [18].

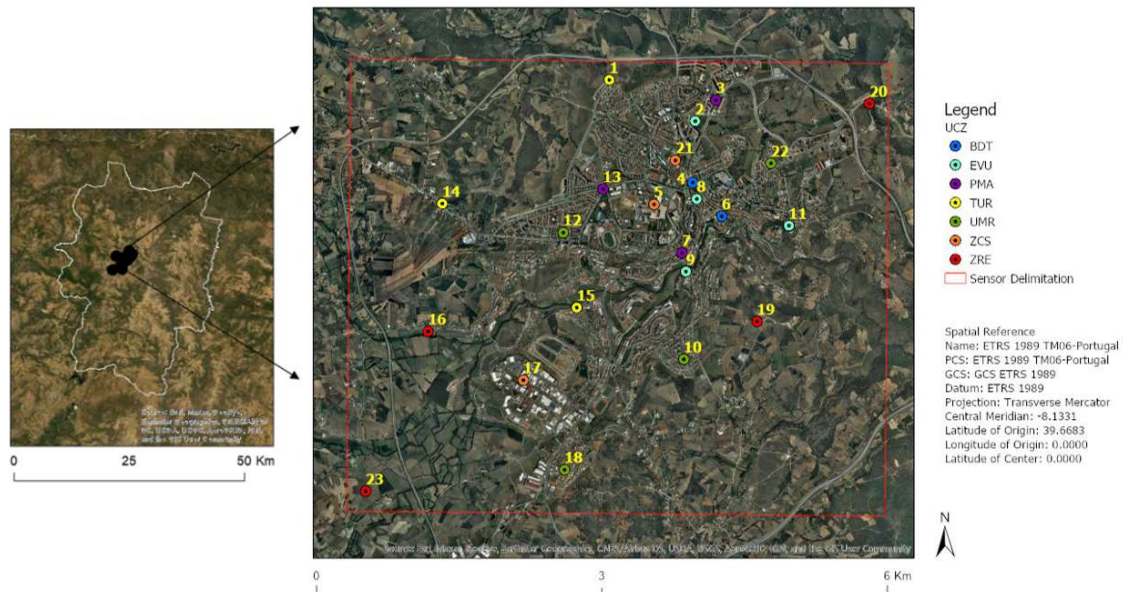


Figure 15. Meteorological network installation site (23 sensors).

The sensors were installed three meters above ground level, encapsulated by white boxes, facing south, and semi-leveled from street lights (Figure 16) [18].



Figure 16. Example of an installed sensor (adapted from [17]).

Table 4, displays the 2d coordinates and elevation data of the sensors. The classification of the UCZ followed the methodological procedures indicated by Oke [29], (presented in the “2. Background”, subchapter “2.4. UCZ in UHI studies”), and the definition of the installation point prioritized at least three sensors in each of the seven UCZs, in a dispersed way, considering the urban and rural gradient [4].

Table 4. Classification and Coordinates of the 23 sensors (adapted from [17]).

Point	UCZ	Elevation (m)	Longitude (°)	Latitude (°)
1	TUR	679,8	-6,770	41,818
2	EVU	644,9	-6,760	41,814
3	PMA	651,4	-6,757	41,815
4	BDT	670,8	-6,760	41,808
5	ZCS	712,9	-6,765	41,806
6	BDT	641,9	-6,757	41,805
7	PMA	677,9	-6,762	41,801
8	EVU	672,1	-6,760	41,806
9	EVU	659,7	-6,761	41,799
10	UMR	720,9	-6,761	41,791
11	EVU	664,9	-6,748	41,804
12	UMR	678,6	-6,777	41,803
13	PMA	710,2	-6,771	41,807
14	TUR	709,9	-6,792	41,806
15	TUR	660,7	-6,775	41,796
16	ZRE	673,6	-6,794	41,794
17	ZCS	714,2	-6,782	41,789
18	UMR	736,8	-6,777	41,781
19	ZRE	811,8	-6,753	41,795
20	ZRE	558,1	-6,738	41,815
21	ZCS	681,6	-6,763	41,810
22	BDT	629,8	-6,751	41,809
23	ZRE	709,6	-6,803	41,779

For each point, the following parameters were identified: i) the land use, occupation, and land cover; ii) the SVF (recorded through photographs - fisheye); iii) the roughness length (classified according to the method of Gal *et al.* [100]) and; iv) the fraction of impervious surface, within a radius of 25 m, estimated in ArcGIS software [18] (Table 5).

The data are collected from the sensors every two months and the equipment is calibrated every two years or whenever a punctual need is identified, corroborating for the security and reliability of the data [18].

For this thesis, the IPB made available data collected by this meteorological network, starting in 2013, with an average recording of temperature and RH every 10 minutes [18]. However, the analysis of the data focused on air temperature, and it is suggested that new approaches including RH be carried out in future studies.

No corrections were applied to the altitude variation, since the intention was to analyze the influence of temperature, in the different configurations/variations relative to soil/LULC.

Table 5. Climate zones and indicators of characterization of urban morphology in the city of Bragança (adapted from [17]).

Sigla	Description UCZ	SVF	Exemple SVF	Rugosity	Artificial Surface (%)
PMA	Existence of modern construction of medium-high height, high density, and paved surfaces.	0,43		1,54 – 2,5	94 - 99
BDT	The ancient center of the city, with medium-low height, high-density, built-in rock, and brick.	0,75		0,93 – 1,07	88 - 99
UMR	Medium density, streets of low height dwellings in bands or isolated.	0,72		0,74 – 0,76	90 - 99
ZCS	Commercial and industrial, low average density with low and high buildings with paved parking.	0,78		0,82 – 0,99	99
EVU	Urban green spaces, predominantly green cover with undergrowth and trees.	0,71 and 0,42 respectively		0,08 – 2,00	2 - 81
TUR	Transition space between urban and rural environments, scattered houses with agricultural and forestry surroundings.	0,92 and 0,90 respectively		0,00 – 0,15	23 – 57
ZRE	Isolated rural areas in the suburbs of the city are representative of the characteristics of the local landscape.	0,88 and 0,84 respectively		0	0 - 20

3.3.2. LST Estimation Using the Thermal Camera

The definition of the locations for the collection of LST with the thermal camera followed these criteria: i) 10 areas with diverse spatial distribution were chosen, to contemplate, at least, one sensor of each of the seven UCZs (Figure 17); ii) the data from the sensor present in the chosen area would serve as validation and; iii) for each of the 10 areas, different surfaces were sampled, considering, as much as possible, the local heterogeneity. As a result, 27 different surfaces were sampled, and the respective coordinates (for spatial reference) were registered.

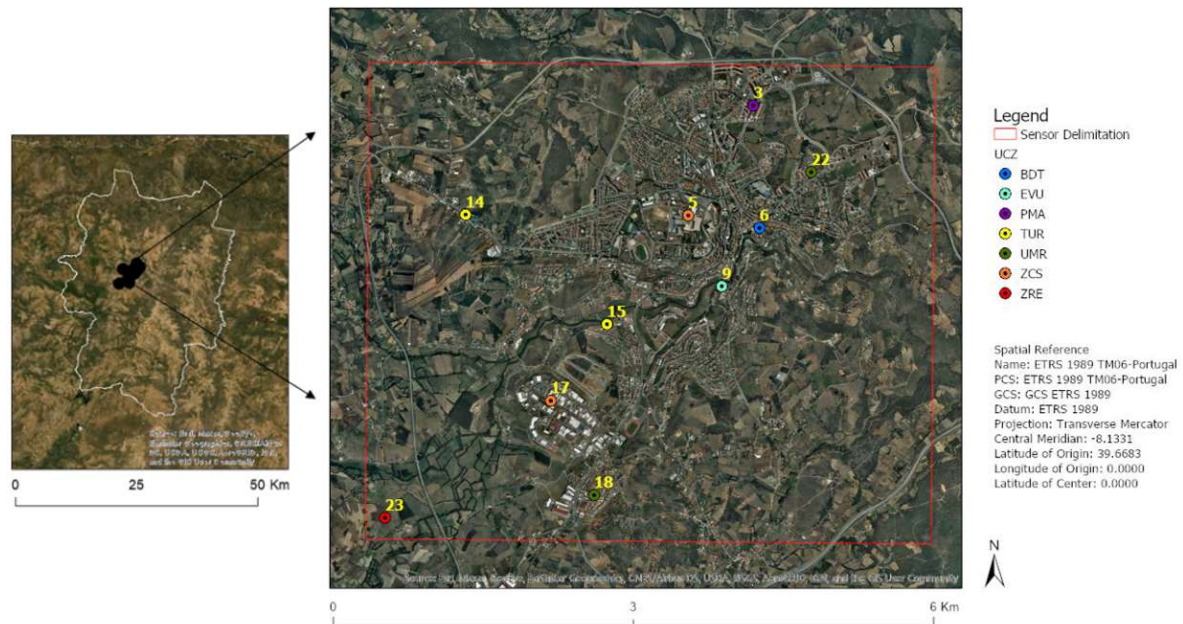


Figure 17. Identification of the 10 areas in which the thermal measurements of the different surfaces were carried out.

The thermal camera used was the HT Instruments THT33, with a resolution of 80x80 pixels, Field Of View (FOV) of 21°x 21°, the spectral field of 8 ÷ 14µm, and Instantaneous Field Of View (IFOV) (@1m) of 4.53 mrad. The collection followed a standard height of 1.5 meters between the camera and the target so that the error associated with the operator was the same for all sampled data. The HTMercury33 application [101] was used to record, visualize and export the results.

The samples were collected twice at each point: in the morning, between 10h00 and 12h00 (UTC) (considering the limit of 1 hour before and 1 hour after the satellite overpass); and in the afternoon, between 13h00 to 15h00 (UTC). Although the UHI effect is potentiated at night, it was not possible to use any equipment capable of measuring the LST with a night thermal sensor (such as an Unmanned Aerial Vehicles (UAV)) [102] in this research. In this case, the collections were made in the morning and afternoon to assess whether there was variability in the results collected at the time of solar peak compared to the afternoon period.

The relevance of obtaining LST *in situ* is emphasized because, when comparing the spatial resolution of the thermal camera with the satellite sensor, a considerable difference can be noted: the former will offer more precise details and with smaller mixing zones, especially in heterogeneous areas. This scenario occurs because the satellite registers the information contained in a pixel (100 m and is re-sampled at 30 m) [68] and the Digital Number (DN) registered will be equivalent to its average brightness contained therein. In transition zones (urban and vegetation, for example) or where the density of a surface cover type is less than one pixel, the satellite LST value will not show as much detail as the thermal camera.

In addition to the LST, photographs were recorded with the Canon EOS 800D camera to assist in the classification of the surfaces, according to their composition. Appendix III presents the recorded images of each of the 27 sampled surfaces recorded in the four collections, with the respective classifications.

3.3.3. Local Microclimate Measurements

Four portable monitoring equipment were positioned at different points on the days of field collection, considering the heterogeneity of the surfaces and the proximity to at least one of the 23 sensors: the first one located in the Industrial Zone (1 - ZCS); the second one inside the IPB (2 - EVU); the third one in “Praça Camões”, which belongs to the historical zone, where air temperature peaks are commonly identified (3 - BDT); and the fourth one in an Urbanized Zone with buildings in the surroundings (4 - PMA). Figure 18 shows the location of the portable monitoring equipment at the sampling points.



Figure 18. Identification of the four portable monitoring equipment measurement areas with different UCZ classification.

Portable monitoring equipment correspond to models HD32.1 and HD32.2. In all stations, there were the following sensors: AP3203 - Omnidirectional Hot Wire Probe; TP3275 - Globe Temperature Probe; HP3217R - Combined Temperature and RH Probe and HP3217DM - Double Thermal Comfort Probe (wet and dry bulb). The equipment positioned in the Industrial Zone (1 - ZCS) measured an extra parameter, called Wet Globe Temperature - WBGT ($^{\circ}\text{C}$), gauged by a wet bulb.

Each station was programmed to record several parameters every two minutes, between 10h00 and 15h00 (UTC), namely: Globe Temperature - T_g ($^{\circ}\text{C}$), Ambient Temperature - T_a ($^{\circ}\text{C}$), RH (%), Wind Speed - V_a (m/s), Average Radiation Temperature - T_r ($^{\circ}\text{C}$), Atmospheric Pressure - P_r (hPa). The software used for data

processing also calculated the Average Expected Classification - PMV; and Unsatisfied Percentage - PPD (%). For this study, the parameters T_a , V_a , and T_r were used, with T_a being the most relevant parameter for understanding the UHI effect.

To minimize the effects of shadow in the data collection process, we prioritized the installation in places with constant sunlight, even in the afternoon. Appendix IV presents the images of the weather stations, to contextualize the site chosen for data collection, as well as the surroundings involved.

3.3.4. Satellite Data

Data collection by the Landsat 8 satellite occurs in the Bragança area at 11h15 AM (UTC), with a time of 16 days to revisit the same location. The acquisition is performed by the TIRS and OLI sensors, with the acquisition angle almost perpendicular and close to the solar nadir, which minimizes shadow effects on the target. To compare the RS data with those obtained by the fixed weather stations, 87 winter and summer scenes were processed from 6/29/2013 to 7/5/2021.

3.4. Data Processing

Considering the diversity presented, each data were processed in a specific way. This subitem will detail each step applied.

3.4.1. Meteorological Network Data Processing

The data obtained by the 23 temperature and RH sensors between 2013 and 2021 were made available by the IPB. First, they were tabulated in Excel and processed in SPSS software to assess whether there were stations with unrecorded air temperature data in this period, using the "analyze missing data" tool.

Although the collection is uninterrupted and there is a database with many records, there may be some technical limitations in the sensors that make it impossible to store the data, such as the need for emergency maintenance, the day when the data is downloaded for analysis, battery replacement, etc., which justifies the absence of some values. Table 6 shows the summary of the results obtained, by the sensor, considering all the dates from 2013 to 2021 (including the days not coincident with the passage of Landsat 8).

Table 6. Missing values for Air Temperature (° C) after the SPSS processing, in all dates.

Sensor	UCZ	Air Temperature (° C)	
		N° of missing data	% of missing data
1	TUR	451	0.2
2	EVU	451	0.2
3	PMA	451	0.2
4	BDT	451	0.2
5	ZCS	451	0.2
6	BDT	451	0.2
7	PMA	8902	3.1
8	EVU	451	0.2
9	EVU	451	0.2
10	UMR	452	0.2
11	EVU	451	0.2
12	UMR	451	0.2
13	PMA	451	0.2
14	TUR	451	0.2
15	TUR	451	0.2
16	ZRE	451	0.2
17	ZCS	452	0.2
18	UMR	451	0.2
19	ZRE	451	0.2
20	ZRE	451	0.2
21	ZCS	452	0.2
22	BDT	451	0.2
23	ZRE	451	0.2

The data that was less than 5% missing were subjected to the "impute missing data values" tool in SPSS software, which relies on historical sensor data and values recorded by sensors with similar operating conditions (in this case, the UCZs) and applies a multiple regression to fill the gaps [103]. Then, a filter was performed, so that only the 87 dates that converged with the overpass of Landsat 8 were considered. Table 7 presents the fill values after SPSS software processing, for the dates analyzed in this thesis.

The measured values of air temperature and RH over the 87 days (relative to the Landsat 8 overpass) were averaged, considering one hour before and one hour after the satellite overpass, that is, between 10h00 and 12h00 (UTC). This choice was adopted to maintain equivalence between the collection times performed *in situ* and, considering the variation of one hour before and one hour after the passage of Landsat 8 (no large variations are expected within this interval). For the days on which field surveys occurred, an extra average was calculated, considering the values measured between 13h00 and 15h00 (UTC).

In addition to these dates, the following classes were assigned to the database: i) the season of the year relative to the collection date; and ii) the UCZ of each of the 23 sensors. These classes were used in the statistical treatment of the data.

Table 7. Missing values for Air Temperature (° C) after the SPSS processing (coincident with the passage of Landsat 8).

Sensor	UCZ	Air Temperature (° C)	
		Nº of missing data	% of missing data
1	TUR	0	0
2	EVU	0	0
3	PMA	0	0
4	BDT	0	0
5	ZCS	0	0
6	BDT	0	0
7	PMA	0	0
8	EVU	0	0
9	EVU	5	7.2
10	UMR	1	1.4
11	EVU	5	7.2
12	UMR	0	0
13	PMA	0	0
14	TUR	0	0
15	TUR	0	0
16	ZRE	0	0
17	ZCS	0	0
18	UMR	0	0
19	ZRE	0	0
20	ZRE	0	0
21	ZCS	1	1.4
22	BDT	0	0
23	ZRE	0	0

3.4.2. LST Processing Using the Thermal Camera

The data collected by the *in situ* thermal camera was tabulated in Excel, divided by each of the 27 sampled surfaces. Adapting methodologies that have analyzed the UHI on different surfaces, from photography images, thermal data, and/or Machine Learning (ML) algorithms [43,53,104]. In this thesis the sampled areas were separated into six classes, considering the LULC characteristics observed in the photographs taken *in situ*, namely: i) Asphalt (As); ii) Sidewalk (S); iii) Vegetation (V); iv) Vegetation with exposed Soil (Vs); v) Dry Vegetation (DV), and vi) Dry Vegetation and Rock (DVSt). It is worth noting that, since this is a work within *situ* collections, the proposed classification, although subjective, tried to cover the differences in LULC in a detailed way.

An identification code was created for each point and the temperature values (° C) generated by the HTMercury33 application [101] was transferred from pdf to Excel, namely: S (temperature associated with the fixed central cursor); H (temperature of the hottest point (Hot) of the image); C (temperature of the coldest point (Cold) of the image); Mean (average temperature). Figure 19 shows an example of how the result

for each surface was obtained (pdf generated by the application), as well as the respective photographic record. Figure 20 presents an example of the tabulation of the data and their classifications.

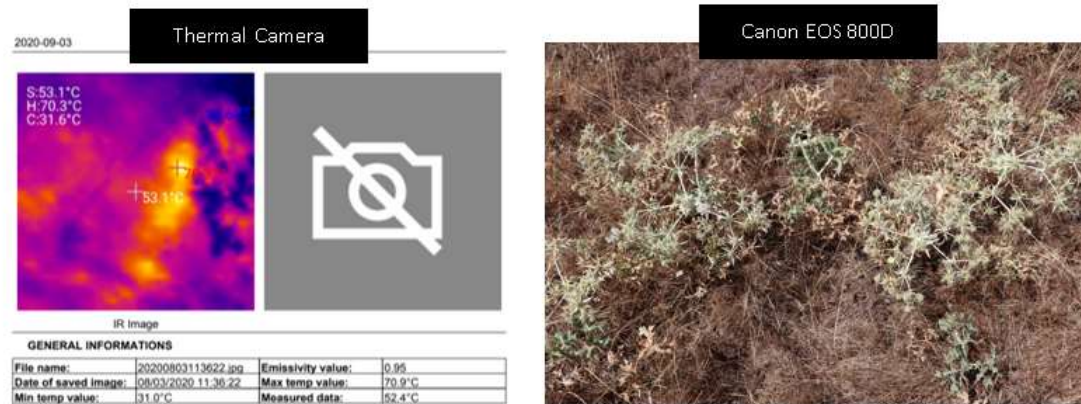


Figure 19. Example of LST Collection with the Thermal Camera and its sampled point image (point 1, surface B (Vs), collection on 08/03/2020, M).

Collection	Point	Indication	Period	ID_Point	Description			S	H	C	Average	Min temp value	Max temp value	Measured data	
CL	P1	P1A	M	P1AM_CL	CLP1M_DV	CLP1M	DV	Dry Vegetation	58.9	67.3	46.3	56.15	45	67.3	60.6
CL	P1	P1B	M	P1BM_CL	CLP1M_VS	CLP1M	VS	Vegetation with soil	53.1	70.3	31.6	50.95	31	70.9	52.4
CL	P2	P2A	M	P2AM_CL	CLP2M_As	CLP2M	As	Asphalt	51.5	52.6	48.2	50.25	47	53.5	51.6
CL	P2	P2B	M	P2BM_CL	CLP2M_S	CLP2M	S	Sidewalk	51.3	57.3	49.2	52.85	48	57.7	50.8
CL	P2	P2C	M	P2CM_CL	CLP2M_DV	CLP2M	DV	Dry Vegetation	51.1	60.1	33.9	46.75	33	60.5	49.4
CL	P3	P3A	M	P3AM_CL	CLP3M_As	CLP3M	As	Asphalt	48.4	50.4	46.4	47.75	44	51.5	47.9
CL	P3	P3B	M	P3BM_CL	CLP3M_VS	CLP3M	VS	Vegetation with soil	50.8	64.7	34.7	49.4	34	64.8	51.6
CL	P3	P3C	M	P3CM_CL	CLP3M_S	CLP3M	S	Sidewalk	44.9	49.1	42.2	45.65	42	49.3	45
CL	P3	P3D	M	P3DM_CL	CLP3M_V	CLP3M	V	Vegetation	36.4	41.9	31.5	36.55	31	42.1	37
CL	P4	P4A	M	P4AM_CL	CLP4M_As	CLP4M	As	Asphalt	52.5	53.5	50.7	51.95	49	54.9	52.7
CL	P4	P4B	M	P4BM_CL	CLP4M_S	CLP4M	S	Sidewalk	50.9	54.7	45.6	49.8	45	54.6	51.1
CL	P4	P4C	M	P4CM_CL	CLP4M_DVst	CLP4M	DVst	Dry Vegetation and stone	40.8	54.5	38.5	46.25	38	54.5	40.4
CL	P5	P5A	M	P5AM_CL	CLP5M_VS	CLP5M	VS	Vegetation with soil	32.3	41.2	27	33.6	26	41.2	35.3
CL	P5	P5B	M	P5BM_CL	CLP5M_V	CLP5M	V	Vegetation	36.8	43	27.8	35.25	27	43.5	36.8
CL	P6	P6A	M	P6AM_CL	CLP6M_V	CLP6M	V	Vegetation	33.4	40.3	30.2	35.4	30	40.8	34.9
CL	P6	P6B	M	P6BM_CL	CLP6M_As	CLP6M	As	Asphalt	55	55.9	52.9	53.95	51	56.9	54.8

Figure 20 Tabulated data of the surfaces sampled with the thermal camera.

3.4.3. Processing of Data from Portable Meteorological Stations and the Landsat 8

The data collected by the HD32.1 Microclimate Globe Thermometer and HD32.3 Microclimate Thermometer were tabulated in Excel, for later statistical treatment. Figure 21 presents an extraction of the data organization model.

Point	Reading log	Aquisition	Time	Tw (°C)	Tg (°C)	Ta (°C)	RH (%)	Va (m/s)	Tr (°C)	WBGT-i (°C)	WBGT-o (°C)	PMV	PPD (%)	Pr (hPa)
D_03_08_20	4	8/3/2020	10:06:00	17.5	39.9	26.4	26.9	0.7	60.1	24.2	22.9	3.64	99.99	934.9
D_03_08_20	5	8/3/2020	10:08:00	17.1	41.2	25.3	27.8	1.34	73.9	24.4	22.8	4.09	100	934.9
D_03_08_20	6	8/3/2020	10:10:00	17	41	24.6	30.5	1.99	82.3	24.2	22.6	4.22	100	934.9
D_03_08_20	7	8/3/2020	10:12:00	15.9	39.5	23.3	32.6	0.65	62.5	23	21.3	3.44	99.93	934.9
D_03_08_20	8	8/3/2020	10:14:00	16.3	38.4	23.5	32	1.79	75.1	22.9	21.4	3.55	99.97	934.8
D_03_08_20	9	8/3/2020	10:16:00	16.3	37.6	23.6	33	1.26	66.9	22.7	21.3	3.28	99.81	934.8
D_03_08_20	10	8/3/2020	10:18:00	16.3	38.1	24.2	30.6	1.34	67.8	22.8	21.4	3.4	99.91	934.8
D_03_08_20	11	8/3/2020	10:20:00	16.5	39.4	23.8	29.9	0.81	64.4	23.4	21.8	3.49	99.95	934.8
D_03_08_20	12	8/3/2020	10:22:00	18.2	40.3	26.9	28.8	0.06	48.4	24.8	23.5	3.5	99.96	934.8
D_03_08_20	13	8/3/2020	10:24:00	17	39.8	25.4	28.8	1.34	70.1	23.8	22.4	3.8	100	934.8
D_03_08_20	14	8/3/2020	10:26:00	16.7	39.9	24.9	28.7	0.29	53.5	23.7	22.2	3.38	99.9	934.8
D_03_08_20	15	8/3/2020	10:28:00	16.3	40.1	24.2	30.2	1.98	80.6	23.5	21.9	4.01	100	934.8

Figure 21. Data Organization Model - Portable Meteorological (with the parameters used highlighted).

The data recorded by satellite needs to be converted into LST. Although there is a standardized way to perform this calculation, there are several ways of processing, depending on the software and the parameters incorporated, as in the case of VIs used to correct the E of the soil and vegetation.

For this work, the GEE was used, which performs the data processing in a cloud, which favors fast processing and avoids the need for advanced hardware for this step. A first approach used the LANDSAT/LC08/C01/T1_SR collection, discontinued and replaced by LANDSAT/LC08/C02/T1_L2.

The new collection is already available with the calculated LST, including atmospheric and E correction and cloud mask application (when necessary). The processing details are in subitem "i) LST Calculation in GEE".

To evaluate if this collection presented reliable values, the calculation of the LST of 09/04/2020 was performed, using the raw Landsat 8 data, following the standardized procedures [70], and applying the equations that will be detailed in subitem "LST Calculation in ArcGIS".

The LST calculated in ArcGIS and GEE were compared, and for this date, the results showed a difference of 1.5 °C in the highest temperatures calculated in both tools. As GEE applies extra corrections, such as atmospheric and cloud masks, the differences can be associated with this [105]. However, since the results were equivalent, the GEE was adopted as the tool for this work.

i) LST Calculation in ArcGIS

The satellite images from 04/09/2020 (relative to the second date of the field visit) were acquired at levels 1 and 2 through the USGS website [106], with the absence and presence of pre-treatment, respectively. Figure 22 presents the necessary steps to generate the LST map, whose processing will be detailed below.

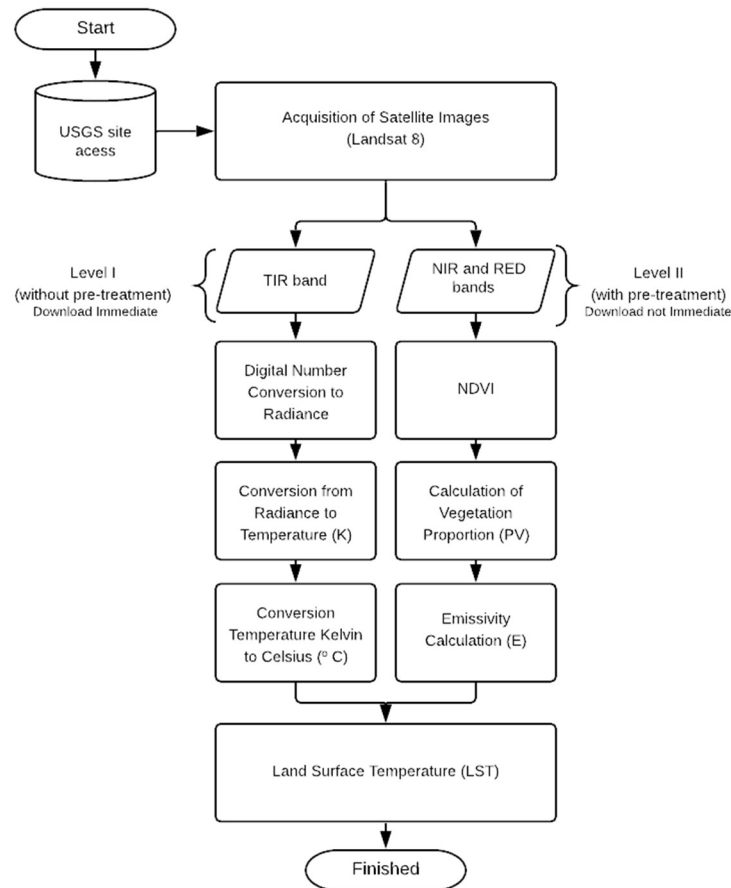


Figure 22. Steps for generating the LST map.

A shapefile (.shp) was created with the data of the LULC map of 2018, delimiting the study area for the district of Bragança and a clip was made in NIR, RED, and TIR bands, represented by bands 4, 5, and 10, respectively, already projected in the same coordinate system, ETRS89 Universal Transverse Mercator (UTM) Zone 29N. The processing of the bands was subdivided into two parts and the specific constants used in each one is shown in Table 8.

Table 8. Constants for LST generation.

Radiance_ mult_band_ 10	Radiance_add_ band_10	K1	K2	Spectral range	Emitted radiance wavelength
ML	AL			μm	Lλ
0.0003342	0.1	774.89	1321.0789	10.6 – 11.19	10.9

First, the DN recorded by the thermal sensor (Band 10) was converted to Top of Atmosphere (TOA) spectral radiance. TOA is a dimensionless measure and makes it possible to obtain the radiant flux from a normalized surface in each of the directions [61], according to Equation 6 [107,108].

$$L\lambda = MLQ_{cal} + AL \quad (6) [107,108]$$

Where, $L\lambda$ consists of the TOA spectral radiance ($\text{Watts}/(\text{m}^2 * \text{srad} * \mu\text{m})$); ML is the multiplicative scaling factor, which is band-specific and obtained in the metadata file ($\text{radiance_mult_band_x}$. The x represents the band number, in this case, 10); AL is also a scaling factor, in this case, additive, which can be obtained from the metadata ($\text{radiance_add_band_x}$. The x is 10, band number); the Q_{cal} represents the quantized and calibrated standard band 10, with values in DN.

Subsequently, $L\lambda$ is converted to Top of Atmosphere Brightness Temperature (Kelvin) applying Equation (7) [107,108].

$$TK = K_2 / (\ln(K_1 / L\lambda) + 1) \quad (7) [107,108]$$

The top of atmosphere brightness temperature (in K) is represented by TK ; TOA spectral radiance is $L\lambda$ ($\text{Watts}/(\text{m}^2 * \text{srad} * \mu\text{m})$); the band 10-specific thermal conversion constants obtained from the metadata are represented by K_1 and K_2 ($K_1_constant_band_10$ and $K_2_constant_band_10$).

The result was converted into Temperature in Celsius - TC by applying Equation (8) [107,109].

$$TC = TK - 273.15 \quad (8) [107,109]$$

The top of atmosphere brightness temperature (in °C) is TC .

Although valid for the entire spectrum, the LST includes the E of the soil and vegetation. Therefore, even though the radiance and temperature values are obtained, it is necessary to consider this parameter in the LST calculations. First, the NDVI was calculated, using the RED and NIR bands (4 and 5 of Landsat 8, respectively) (Equation 5). The result was then used to obtain the Vegetation Proportion (PV) [107,110]. To apply Equation 9, the minimum and maximum value of the NDVI previously obtained was identified to replace the constants that, in this case, were: - 0.860696 and 1, respectively.

$$PV = \sqrt{\frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}}} \quad (9) [107,110]$$

NDVI was the value calculated for each pixel with Equation (5), as well as $NDVI_{min}$ and $NDVI_{max}$ values.

After, the PV was applied to calculate the E to correct the data regarding the soil and vegetation E (Equation 10). In the case of this work, a reference value was adopted in the literature [83].

$$E = 0.004 \times PV + 0.986 \quad (10) \quad [83]$$

The soil E is 0.004 and the V E is 0.986, both literature constants.

The LST is then obtain according to Equation (11) [53,107,111].

$$LST = \frac{TB}{\left(1 + \left(L\lambda \times \frac{TB}{P}\right) \times \ln(E)\right)} \quad (11) \quad [53,107,111]$$

LST is the E-corrected temperature, converted to °C; TB is the brightness temperature at the sensor (in Celsius); the wavelength of the emitted radiance is $L\lambda$, and P is obtained by Equation (12) [53,107].

$$P = h \times c / \sigma \quad (1.438 \times 10^{-2} \text{ mk}) \quad (12) \quad [53,107]$$

σ is the Boltzmann constant (1.38×10^{-23} J/K); the Planck constant (6.626×10^{-34} Js) is h, and c is the speed of light ($2,998 \times 10^8$ m/s).

ii) LST Calculation in GEE

The same image used in ArcGIS was processed and, since the results obtained were similar, GEE was adopted to process all LST values. This software facilitates the visualization and analysis of a spatial dataset and allows the user to access and build codes (with Python language) for cloud processing, *i.e.*, without the need to upload or request the availability of the data by the USGS (as occurs in manual processing). This operation favors the time and storage capacity of the computer since it is already possible to download the processed LST [112].

The initial processing in GEE considered the USGS Landsat 8 Surface Reflectance Tier 1 collection, named LANDSAT/LC08/C01/T1_SR. However, in mid-June 2021, there was an update, and this collection was discontinued and replaced by

the USGS Landsat 8 Level 2, Collection 2, Tier 1, named LANDSAT/LC08/C02/T1_L2 [112,113]. All LST were recalculated, considering the products of the new collection.

The main increments compared to past collections, are: i) geometric accuracy: improvement in the interoperability of the global Landsat archive spatially and temporally, due to rebaselining of the Ground Control Points (GCPs) from OLI to the European Space Agency (ESA) Copernicus Sentinel-2 Global Reference Image (GRI); ii) Digital Elevation Models (DEM): 3 arcsecond, 90-meter sources of DEM, such as Global Land Survey Digital Elevation Model (GLS DEM); NASA Shuttle Radar Topography Mission (NASADEM) (reprocessed), among others; iii) radiometric calibration: improvement in the radiometric calibration for Landsat 5 TM and Landsat 8 OLI data, including the striping effect correction of the TIR; iv) Quality Assessment Bands (QA), which assists in the analysis of the validity of a pixel's information; and v) Cloud Optimized Georeferenced (COG): improves access to data in a cloud environment, making user access to one or several bands flexible [105].

Regarding the Landsat 8 products used in this thesis, the following data are available: Visible and Near-Infrared (VNIR) bands and two Short-Wave Infrared (SWIR) bands, processed to orthorectified Surface Reflectance (SR), and one TIR band processed to orthorectified brightness temperature. There are also intermediate bands used in the calculation of the ST products (defined in this thesis as LST) and the QA. The SR products are obtained through Land Surface Reflectance Code (LaSRC) [114], and the ST products are created with a single-channel algorithm, jointly devised by the Rochester Institute of Technology (RIT) and the National Aeronautics and Space Administration (NASA) Jet Propulsion Laboratory (JPL). This type of algorithm uses E data from external sources, according to the model that best fits the area of study [115].

For this LST calculation, it is necessary to use optical and thermal data in the ASTER NDVI application for temporal adjustment of the ASTER GED product to the Landsat scenario and, in places whose data acquisition is at night, it is not possible to perform the processing [105]. In the case of Bragança, with the satellite passage time being 11h15 (UTC), this limitation does not apply. It is worth noting that there are studies that point out that the recovery of the LST on days with clouds and their respective shadows can influence the observed values [45,116].

iii) Using ArcGIS to Extract Temperature data from the LST

To extract the LST data from Landsat 8, a 30m buffer was made around each of the 23 sensors. This criterion was defined to guarantee the representativeness of the temperature, considering the values measured in the radius corresponding to a pixel around the sensor.

To extract the average temperature of the pixels contained in the buffer, the "Zonal Statistics as Table" function was applied in ArcGIS. The calculation is performed considering the area of influence of the pixel in the buffer zone, *i.e.*, if there are four equally distributed pixels (Figure 23, A) the result will be the simple average temperature among them. If it is off-center, the pixels with greater representativeness will have a greater weighting in the calculation of the average of the values (Figure 23, B) [117].

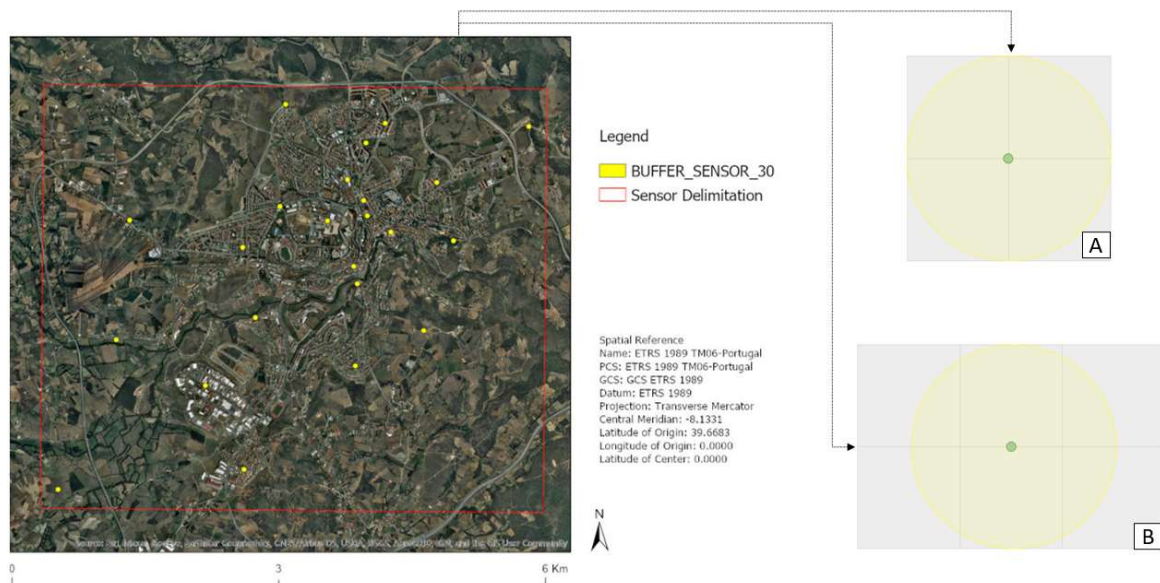


Figure 23. Exemplification of the calculation applied to the pixels (in gray) contained in the buffer (in yellow), generated from the sensor (in green).

3.5. Statistics Analysis

Different statistical approaches were applied, including descriptive and quantitative ones, which will be contextualized in this item.

3.5.1. Descriptive Data Analysis

LST Maps

From the plotting of the maps generated in the GEE, a general analysis of the influence of seasonality on surface temperatures and the discrepancies (if exists) was performed. The LST maps generated in this step were bounded to the sensor area and assigned a similar color scale to enable comparison and visual analysis of the products.

Boxplot

The boxplot, used in UHI studies [118,119], allows a summarized analysis of one or more numerical variables and is composed of [120]: i) a line representing the median of the data, *i.e.*, the central value of a sample with the ordered values; ii) the upper (Q3) and lower (Q1) quartiles, represented on the extremities of the plot (the quartiles represent the division of the ordered sample into four parts, *i.e.*, each quartile represents 1/4 of the data. Q1 represents 25% of the ordered sample, Q2 is the median and represents up to 50% of the sample and Q3 represents 75% of the sample and 25% of the values that are larger than the mean); iii) the interquartile range (IQR) (difference between Q1 and Q3; iv) the extreme lines present the highest and lowest value of the sample, without considering the outliers; and v) the potential outliers, represented by dots/markers, which symbolize the values that presented a behavior out of the commonly observed in the sample. The boxplot was generated in RStudio using the command `boxplot(database)` [121].

The boxplots generated in RStudio software, considering the parameters of air temperature (measured by the fixed meteorological network), and LST (Landsat 8), were analyzed, both by UCZ and seasonality (summer and winter data). The analysis of UHI Intensity (UHI_{Int}) also used boxplot as a tool and will be detailed in the sub-item " UHI_{Int} analysis"

Air Temperature variation versus Landsat 8 LST

The difference between the Landsat 8 LST and the air temperature measured by the fixed weather station was estimated, for each day and sensor, applying Equation 13. The differences were evaluated, by the sensor, to assess whether there was any behavior related to the UCZs.

$$\Delta t = LST_{RS} - T_{air} \quad (13) \quad [122]$$

Δt is the temperature difference between the Landsat 8 LST value (represented by LST_{RS}) and the air temperature, measured at the fixed weather station (represented by T_{air}).

For data analysis, the 23 sensors were assigned to different classes, according to the temperature variation. Considering the data of all days and summer, the scale considered an interval between classes of 1.5 °C (calculated from the subtraction between the highest and lowest temperature and dividing this amplitude by five). For the winter data, this interval was 1 °C, due to the smaller amplitude of the data. The results were grouped by UCZ, and the percentage of sensors was calculated for each temperature variation scale.

Although air temperature and LST are different parameters (as detailed in chapter 2 - “Background”), this comparison has already been applied in other scientific works [122]. Air temperature is measured at three meters above ground level by meteorological sensors fixed in Bragança and corresponds to the average radiant temperature of the horizontal surface [18]. While the LST is obtained from calculations that estimate the temperature of a surface, according to the spatial resolution of the sensor used. However, if the thermal behavior between the parameters is similar, it is possible to deduce one from the data of the other, with statistical models, such as regression (this method was applied and will be explained in the sub-item “3.5.2. Quantitative Data Analysis”).

UHI_{Int} analysis

To evaluate the UHI_{Int}, the average of the recorded values in air temperature and LST (Landsat 8), separately, in sensors 16, 19, 20, and 23, which integrate the UCZ ZRE (isolated rural areas). This average was used as a standard value to calculate the difference in temperatures measured at each point. Since these are

remote rural areas, it was considered that these sensors can register the expected temperature in vegetation and, from the analysis of the results, it will be possible to evaluate in which UCZs there will be more variability in the recorded data (Equation 14). This methodology has already been adopted in UHI studies [17,123].

$$UHI_{Int} = LST_{UCZ} - \overline{LST_{ZRE}} \quad (14)$$

Where, UHI_{Int} is the intensity value of the UHI at each point; LST_{UCZ} is the LST value extracted from the buffer at each sensor (data acquisition process detailed in "(iii) Using ArcGIS to Extract Temperature data from the LST"); and $\overline{LST_{ZRE}}$ refers to the average of the LST values extracted from the buffer for the ZRE sensors.

The same procedure was applied to the air temperature data separately (Equation 15).

$$UHI_{Int} = AirT_{UCZ} - \overline{AirT_{ZRE}} \quad (15)$$

Where, UHI_{Int} is the intensity value of the UHI at each point; $AirT_{UCZ}$ is the air temperature value registered in each sensor; and $\overline{AirT_{ZRE}}$ is the average air temperature registered in ZRE sensors.

The results were discussed considering boxplots and the UHI_{Int} minimum, maximum, standard deviation data were tabulated.

3.5.2. Quantitative Data Analysis

To define the most appropriate statistical method for the air temperature (fixed meteorological stations) and LST (Landsat 8) parameters, it was necessary to evaluate the data distribution model, as detailed below.

Shapiro Test

The Shapiro test was applied. It was first published in 1965 and calculates a W statistic (Equation (16)). The null hypothesis is that a sample $x_1, \dots, x_n$ comes from a normal population [124].

$$W = \frac{(\sum_{i=1}^n a_i x_{(i)})^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (16) \quad [124]$$

The number of observations of the sample is represented by n ; $x(i)$ is the ordered values of the sample, in increasing order; a_i are constants obtained in standard tables, calculated from the means, variances, and covariances of the statistics, considering a sample of n similar and with normal distribution.

In RStudio, the following function considering air temperature and LST (Landsat 8), per sensor, was used: `shapiro.test(nameofdatabase$AirTemperaturasensorX, LSTsensorX)` [121].

The p-value, the most important result, was obtained: if the p-value is greater than 0.05, the null hypothesis is accepted and the data have a normal distribution, with 95% confidence [124]. When the results point to a normal distribution, is indicated to apply the Pearson correlation method and, to non-normal distribution, the Spearman correlation.

Pearson's Correlation

The Person Coefficient is a descriptive statistic that measures the degree of correlation and its direction (positive or negative) between two variables. It is usually represented by ρ and the results vary between -1 and 1, where the closer to 1 (positive or negative), the greater the correlation between the variables analyzed, and at zero, there is no correlation [125] (Equation (17)).

$$\rho = \frac{\sum_{i=1}^n (x_i - \bar{x}) \times (y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \times \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} = \frac{cov(X,Y)}{\sqrt{var(X) \times var(Y)}} \quad (17) [125]$$

Where, $x_1, \dots, x_n$ and $y_1, \dots, y_n$ is the value measured in both variables; $\bar{x}$ is calculated with Equation (18) and $\bar{y}$ is calculated with Equation (19), and represents the arithmetic mean of both samples [125].

$$\bar{x} = \frac{1}{n} \times \sum_{i=1}^n x_i \quad (168) [125]$$

$$\bar{y} = \frac{1}{n} \times \sum_{i=1}^n y_i \quad (19) [125]$$

In RStudio, the code used to apply the statistical test is: `cor.test(nameofdatabase$parameterA; nameofdatabase$parameterB; method = "pearson")` [121]. The parameters that must be added in this case are the air temperature (fixed weather station) and the LST (Landsat 8), for each sensor.

Person Correlation tests are commonly used in UHI studies, especially when the data have a normal distribution, enabling the analysis of the relationship of temperature with several variables, such as air temperature (similar to the methodology adopted in this thesis), soil configuration, landscape metrics, and socioeconomic pattern, etc. [104,126–128].

Spearman's Correlation

Spearman's correlation was published by Spearman (1904) [129] and is recommended for quantitative variables, discrete or continuous, not symmetric or with discrepant values, and has been used in other UHI studies [130–132], including in Portugal [133]. Its coefficient can be defined as Pearson's but applied to variables ordered in ranks [134], that is, the smallest value of sample A is compared to the smallest value of sample B, by applying Equation (20).

$$r_s = \rho_{rgx,rgy} = \frac{\text{cov}(rg_x,rg_y)}{\sigma_{rg_x}\sigma_{rg_y}} \quad (20) \quad [129]$$

Where, r_s represents Spearman's correlation, ρ is equivalent to Pearson's correlation coefficient, only applied to the variables in ranks; $\text{cov}(rg_x,rg_y)$ is the covariance of these variables; σ_{rg_x} σ_{rg_y} represent the standard deviations of the variables [125,129].

If the numbers repeat when ordered, a simple arithmetic average between them is used, and when all ranks represent distinct whole numbers, Equation (21) [125,129], directly.

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2-1)} \quad (21) \quad [125,129]$$

Where, $d_i = rg(X_i) - rg(Y_i)$, which represents, in each observation, the difference between the two positions; and n is the number of observations.

The application of Spearman correlation allows us to understand if the correlation between the variables is positive (e.g. sample A grows while sample B also grows) or negative (e.g. sample A grows sample B decreases), being closer to 1 and -1, respectively.

In RStudio, the code used is similar to Pearson's correlation, with the change of method: `cor.test(nameofdatabase$parameterA; nameofdatabase$parameterB; method = "spearman")` [121].

The parameters are the same (air temperature and LST), and it is possible to obtain the results both by the sensor (considering all dates) and by season (seasonality).

The correlation method was not considered appropriate for the data obtained in the field collections (by the portable weather stations and the LST obtained by the thermal camera) due to the small amount of data available (four observations, in the 10 sampled points).

Correlations

The correlation between air temperature (fixed meteorological sensor) and LST data (Landsat 8) was calculated using the absolute values. This analysis intended to evaluate if there was a correlation between the parameters, how strong it was, and if, the comparisons between the magnitudes were pertinent.

Subsequently, the $\overline{LST_{ZRE}}$ were correlated with the respective LST (Landsat 8) absolute values in each sensor (LST_{UCZ}) to assess whether the data showed similar temperature behavior, even in other UCZs.

3.5.3. Validation

From the data collected in the field, an analysis was performed to verify the relationship between the parameters, in the different analytical scales. First, a classification of the surfaces where the LST was collected with the thermal camera was proposed. Subsequently, an analysis of the thermal behavior of each surface and period of collection (morning and afternoon) was performed, by UCZ, to identify if the LULC, especially with anthropic changes, presented higher temperatures compared to the rural ones.

Next, the behavior of air temperature at the fixed sensors equivalent to the ten points sampled in the field was evaluated, to assess whether the afternoon collection presented higher values than the morning, as indicated in the literature [135].

Wind speed was also analyzed in four different UCZs (ZCS, EVU, BDT, and PMA), to assess whether the urban context influenced the local circulation. At these same points, the analysis of Tr.

3.5.4. Linear Regression

Linear regression was applied to the data, to evaluate the possibility of modeling the air temperature data (response variable) from the LST (explanatory variable), considering all the sensors and the influence of seasonality. By applying a linear regression, it is possible to describe the relationship between two quantitative variables, one being independent (X) and the other, dependent (Y) [136] (Equation (22)).

$$y_i = \alpha + \beta X_i + \varepsilon_i \quad (172) \quad [136]$$

Where, Y_i is the dependent explanatory variable, which the model intends to predict (in this case, air temperature); α represents the intercept constant of the straight line with the vertical axis; β is the angular coefficient (slope) of Y_i , X_i is the independent explanatory variable (satellite LST derived) and ε_i are the residual factors and possible measurement errors. For the model to be applied, the assumptions about the errors are null values and constant variance; mutually independent and normally distributed [136].

In RStudio, the regression model was applied using the code `lmsensor_n <- lm (SnLST ~ SnT)`, whereby n represents each of the 23 sensors. The data from r^2 , r^2 adjusted and p-value was obtained by the command `summary (lmsensorx)` [121]. The same methodology was adopted in UHI's study [122].

CHAPTER 4

4. Results and Discussion

In this chapter, the results, and respective discussions, will be presented. The general objective of this work, which was to analyze the seasonal behavior of the UHI in Bragança (Portugal) and relate it to *in situ* data collection, to assess their possible correlations, was achieved through the results obtained in the specific objectives and will be detailed in this item.

To achieve the specific objective "i. Combine satellite data and *in situ* data to analyze the behavior of surface temperature in Bragança", data from several sources were used, such as RS, sensors installed in the city (with continuous data collection), and field surveys.

The integration of different sources and levels of information about a place allows for analysis at different scales. When using LST data, calculated from satellite data compared to those collected by the *in situ* thermal camera, these are different spatial scales. The RS offers a less detailed spatial scale, due to the pixel resolution, and in transition zones between two different LULC (such as vegetation and urbanization areas), the record considers the average of the spectral behavior contained in the pixel, which may influence the identification of site-specific and representative spectral contrasts [137].

On the other hand, *in situ* LST recording allows detailed thermal data from different surfaces (as was done at ten points in this research), which enables a more specific evaluation of the spectral responses of the surface materials. Although it offers more detail about the spatial scale of the satellite, the collection with this technique is of discrete/point data, *i.e.*, it does not enable mapping of a large continuously area, similar to Landsat 8 [138]

In addition, if the collection is performed point by point (as the methodology adopted), there is an hourly difference that can be influenced by the average air temperature and/or by weather changes, such as the presence/intensification of clouds or shadows at a given time/point, which can influence the net radiation reaching the analyzed surface [45,139,140].

The revisit time also presents specificity between the techniques: while Landsat 8 performs acquisitions every 16 days at the same local time (UTC) and with different environmental conditions, the field surveys are more flexible and can be performed with

shorter intervals (depending on the availability of financial, human and equipment resources). The satellite revisit time also ensures a data history that, in the case of this work, allowed analysis with data since 2013 [63,138].

The scheduling of the field surveys prioritized days with few clouds and no rain. About satellite data, there is registration at each revisit, even if some dates must be discarded due to the presence/influence of clouds. Furthermore, there are tools applied in the processing/treatment of the data to minimize these influences, such as the application of cloud masking and atmospheric models specific for the studied region [141,142].

Regarding the specific objective "ii. Use computational processing tools, to generate the LST from satellite data", GEE proved to be efficient in the generation of LST maps, especially for processing in the cloud, which corroborates in the optimization of the time dedicated to the data processing and in the need for more powerful hardware [141,143,144].

Since the processing occurs in the cloud, the user must have internet access. It is worth noting that GEE has a bank of free code for users, the result of documented methods (including academic research), which can be adjusted to the area of study that you wish to evaluate. If additions or custom code development is required, knowledge of JavaScript, GEE's recognized programming language, is required [141,145].

The data collection made available by the USGS, already with several corrections, including the application of cloud masking and atmospheric corrections (using models that best fit the specifics of the place of analysis), appear as an added value, given the appropriate/standardized application of correction factors, favoring the replication of the methodology in other areas and obtaining the same results in different research studies that analyze the same study area [141,142].

In this research, all the LST values were generated in GEE and exported for layout adjustment in ArcGIS software, such as the application of standardized color scale (to enable the global analysis of the maps) and the inclusion of the necessary elements for understanding a map (such as scale, north, and projection system). Although GEE offers the possibility of employing the color scale, some functions are less intuitive/under development, which does not offer as many options to the user, especially regarding the final layout. The code used/developed in GEE is available in Appendix V.

Finally, the specific objective "iii. Apply descriptive and quantitative statistical analyses (correlation and regression model), especially between air temperature and LST variables, to analyze the behavior of Bragança's UHI in each UCZ, in summer and

winter (seasonality)" corresponds to the descriptive and quantitative analyses performed, which will be presented in sub-items, below.

4.1. Descriptive Analysis

LST Maps

Analyzing the LST maps produced, it is observed that seasonality influences the behavior of the city's surface temperature, with the highest temperatures observed in summer, compared to winter, the same behavior was observed in other UHI studies [90,146,147].

Figure 24 shows an example of a map of each season - 7/31/2013 (summer) and 03/01/2016 (winter) and a map relative to the day 2/8/2014 (winter), whose result showed values below -5 °C in the analyzed area.

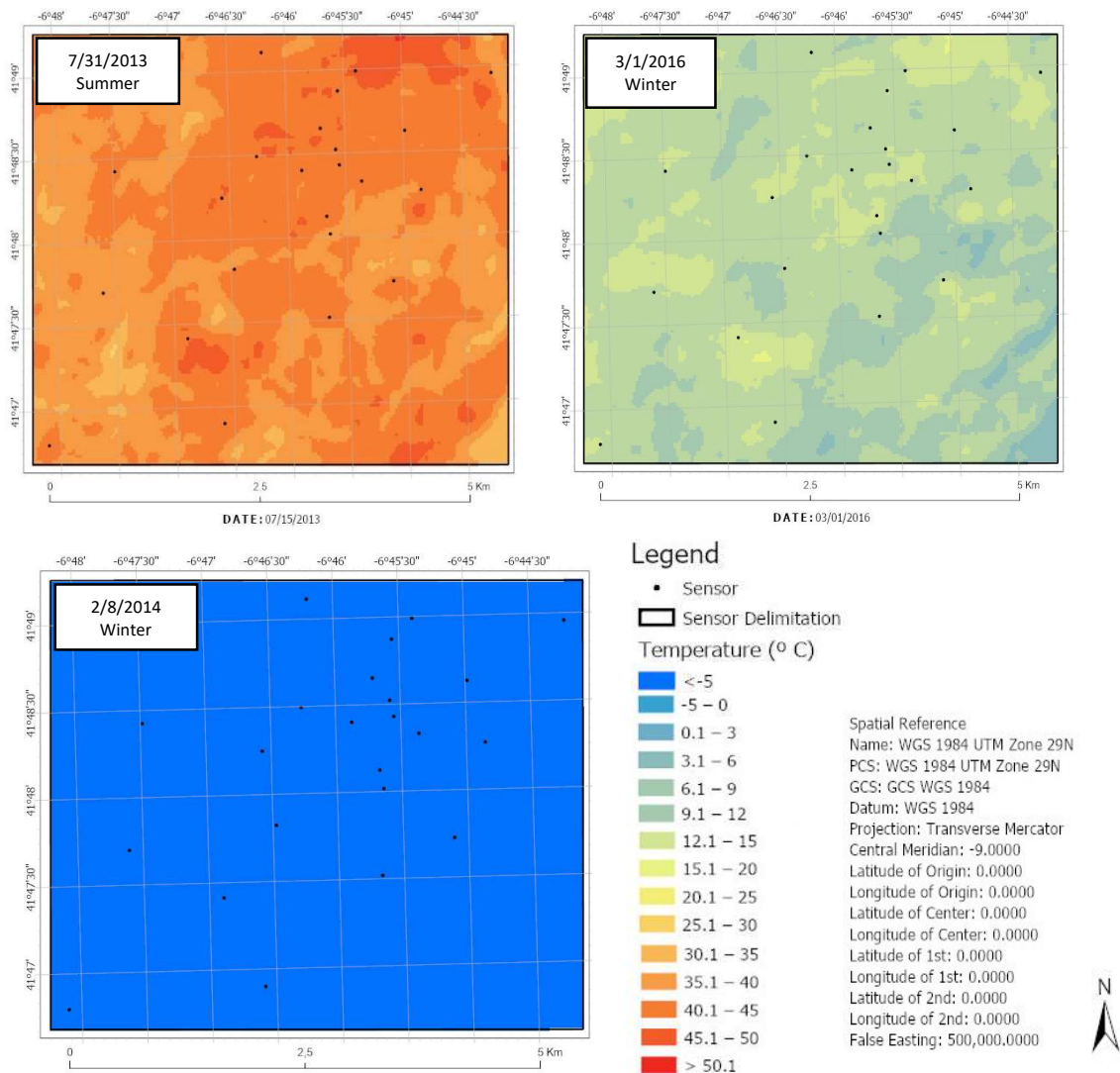


Figure 24. Example LST maps, calculated/generated in GEE, with the area delimitation of the 23 fixed sensors (black square) and the respective sensors plotted (black dots).

Considering that seasonality was observed in all dates/maps in most of the cases, the qualitative analysis by map was dismissed since it would not present distinct results and/or significant changes. However, these were the data used for quantitative analysis (correlation and regression model), from the extraction of temperature information, per sensor.

It is worth mentioning that, before starting the data statistical treatment, the raw results of the average temperature of the processed days were evaluated and the maps were visually analyzed. All generated LST maps are shown in Appendix VI.

When the calculated result was below -5°C in at least one of the 23 sensors, the data for that day were not considered in the processing. This negative value may be associated with the presence of dense clouds that influenced the data registration, even with the application of the mask and the standard methodologies adopted in the Landsat [148].

Thus, of the 87 dates/scenes processed, 17 were ignored in the qualitative and quantitative analyses, due to the negative temperature calculated in the LST. Of the remaining 70 dates, 4/16/2021 was considered the only one in the specific field collection analyses, as it refers to the day when the third field survey took place in Bragança. This date was not considered in the statistical analyses of the correlation and linear regression model because it refers to a spring day when field collection occurred (it was an exception). Due to movement restrictions between Counties due to COVID-19 [99] and cloudy days, no campaign could be conducted in the winter. Thus, the collection on 4/16/2021 was performed to analyze possible seasonality contrasts obtained in situ.

Appendix VII presents the 87 satellite review dates and their status, *i.e.* whether or not they have been considered in the data processing and analysis.

Boxplot

The interpretation of the boxplots provided a global overview of the results regarding air temperature (fixed weather station) and LST data (Landsat 8), for each sensor. In general, it was observed that the largest amplitudes observed between LST and air temperature were in the summer, followed by all dates (without separation by season). Winter was the period that showed the least variation. This behavior may be associated with the smaller solar angle in the winter and, conversely, the greater exposure to electromagnetic energy that the surfaces receive in the summer, corroborating the higher heat absorption by the surface [45,149].

It is worth noting that not all sensors measured air temperature and LST information for all 69 dates, even after filling in the missing data in SPSS. Considering a sensor with all the information filled in, for all dates the number of observations would be equal to 69, in summer it would be 43 and 26 in winter. 19 sensors presented this behavior (82.61%).

Figure 25 shows the list of sensors with different numbers of observations than those that presented all data. For example, sensor 9 had 62 data to elaborate the boxplot between air temperature (fixed weather station) and LST (Landsat 8), for all dates, 38 in summer and 24 in winter.

It is noteworthy that these same data were used in quantitative statistical treatments (correlation and regression).

Sensor	UCZ	Parameter	All Dates	Summer	Winter
			Air Temperature	Air Temperature	Air Temperature
9	EVU	LST	62	38	24
10	UMR	LST	68	42	26
11	EVU	LST	64	38	26
21	ZCS	LST	68	42	26

Figure 25. Number of observations between air temperature (fixed weather station) and LST (Landsat 8), used in the boxplot for the sensors that did not present the complete data, on all analyzed dates.

As no discrepant behaviors were identified when comparing sensor data from different UCZs, as in other UHI studies [150], more thorough analysis of the Sensor 4 and 19 boxplots were performed. Appendix VIII contains all the boxplots generated.

Sensor 4 (UCZ BDT)

The air temperature values obtained at the fixed weather station on all dates are more heterogeneous when compared to those of summer and winter (where the extent of the box, is smaller). The same behavior can be observed in the LST data, obtained from the Landsat 8 (Figure 26).

In summer, both parameters presented outliers, the former above 30 °C and the latter for values below 20 °C. The air temperature values in all dates have a median near 20 °C, with maximum values below 40 °C, while LST had its median near 30 °C and values near 50 °C. The minimum values were measured and both parameters were corresponding.

This same behavior was observed at the stations, especially in the summer, in which LST showed higher temperature when compared to air temperature: while the median of the former recorded values close to 40 °C, that of the latter was around 27 °C. In winter, the data did not show high variability between the maximum and minimum values measured, and the statistical modeling of the data were similar in

these two parameters, in terms of the median (about 8 °C). The maximum values were highest in LST (near 30 °C), while those in air temperature were around 22 °C (Figure 26).

Sensor 19 (UCZ ZRE)

Regarding air temperature (fixed weather station) compared to LST (Landsat 8), a similar behavior to that of sensor 4 is observed: considering all the data, the median of LST refers to Q3 of the air temperature boxplot (that is, it corresponds to 75% of the air temperature samples) (Figure 27).

In summer, it is observed that air temperature presents more homogeneous and concentrated results than LST, and the median of the latter exceeds the highest value of air temperature. In winter, similar behavior is observed between air temperature and LST, with a median close to 10 °C in both, and higher temperature values (close to 30 °C compared to around 20 °C, measured at the weather station) (Figure 27).

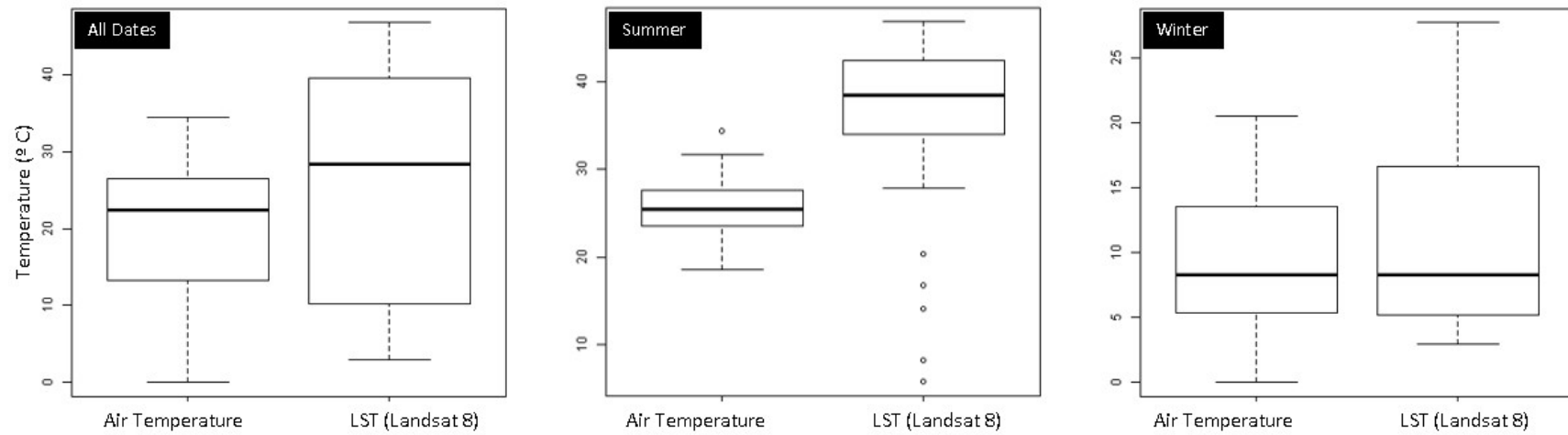


Figure 26. Boxplot of sensor 4, representing the distribution of air temperature data (fixed weather station) and the LST (Landsat 8), split across all analyzed dates, the summer and winter dates, respectively.

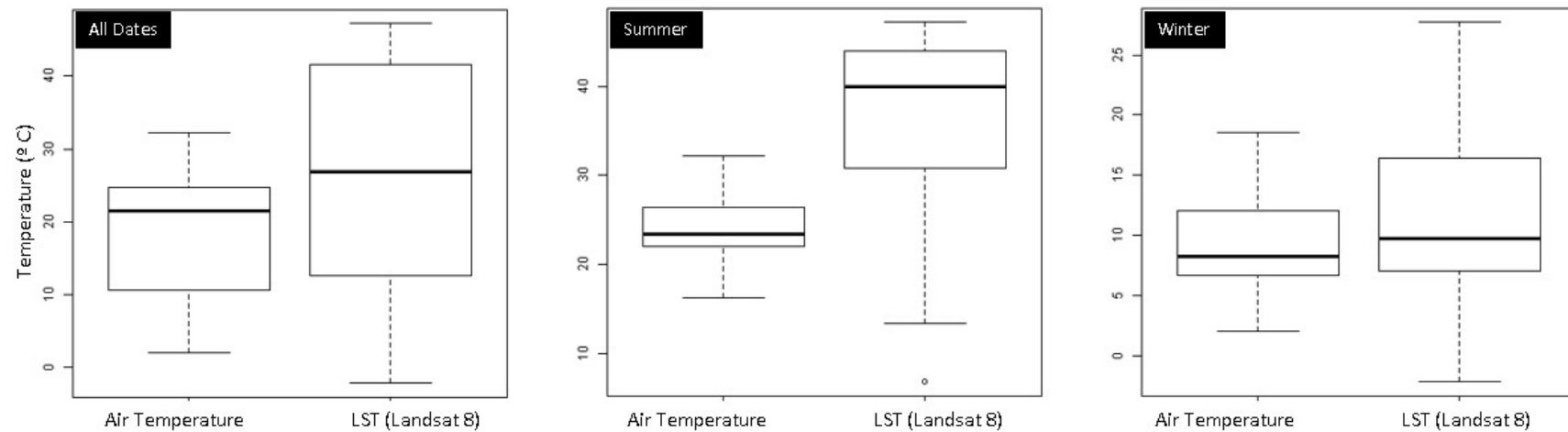


Figure 27. Boxplot of sensor 19, representing the distribution of air temperature data (fixed weather station) and the LST (Landsat 8), split across all analyzed dates, the summer and winter dates, respectively.

Temperature difference between air temperature (fixed weather station) and LST (Landsat 8)

The evaluation of the direct temperature differences between air temperature and the LST (Landsat 8) was performed by UCZ. As there is not the same number of sensors in each classification, Table 9 presents this distribution, in absolute value and percentage.

Table 9. List of the sensors, per UCZs, and the respective percentages of representativeness about the 23 sensors.

UCZ	Nº of Sensors	Sensor Nº	% total
ZRE	4	16, 19, 20 and 23	17.39
BDT	2	4 and 6	8.70
TUR	3	1, 14 and 15	13.04
UMR	4	10, 12, 18 and 22	17.39
EVU	4	2, 8, 9 and 11	17.39
PMA	3	3, 7 and 13	13.04
ZCS	3	5, 17 and 21	13.04
Total	23		100

The graphs were generated considering the absolute temperature differences on the "x" axis and the number of sensors on the "y" axis, whose coloring corresponds to the UCZs.

Figure 28 presents the value obtained considering the data from all dates, in each UCZ.

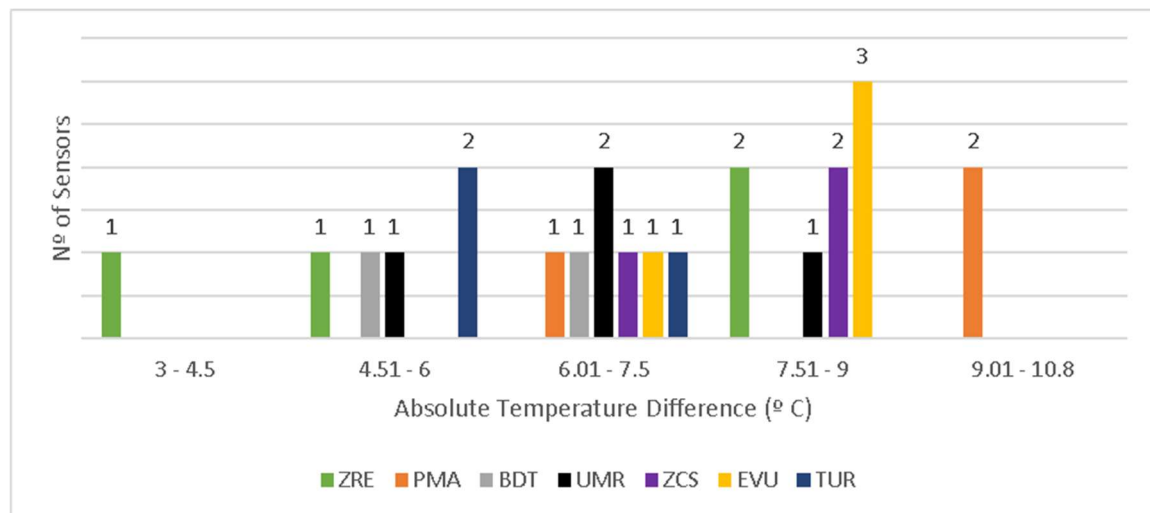


Figure 28. Absolute temperature difference between air temperature and Landsat 8 LST in all dates.

Figure 29 presents the same information for the summer and Figure 30 for the winter.

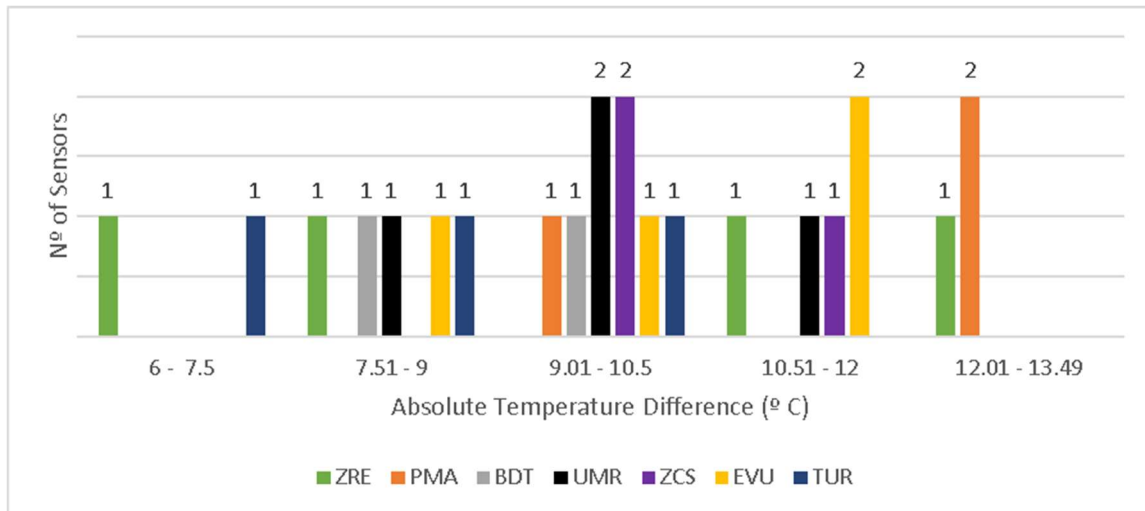


Figure 29. Absolute temperature difference between air temperature and Landsat 8 LST in summer.

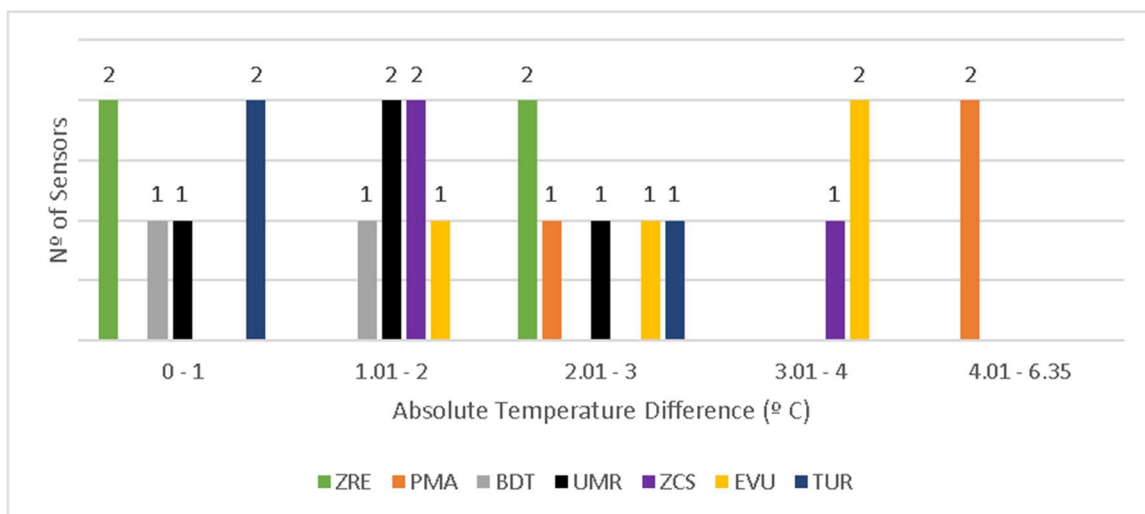


Figure 30. Absolute temperature difference between air temperature and Landsat 8 LST in winter.

Considering the general data, it is observed that the range of temperature difference between air temperature (fixed meteorological station) and LST (Landsat 8) was higher in summer compared to winter, which can be justified by the greater exposure of electromagnetic energy, which results in greater heating of the surfaces compared to that of the air, at the time of the satellite passage. In winter, the availability of electromagnetic energy is lower, the surfaces heat less and the difference obtained between the parameters (air temperature and LST) is also lower [45,149].

Analyzing the data in general, the results were positive and greater at sensor 13, UCZ PMA, both when considering all data (maximum mean difference of 10.80 °C) and in summer (maximum mean variation of 13.49 °C). Winter showed smaller amplitudes in the results, with maximum value observed at the same sensor 13, with 6.35 °C, that converges with those identified in the boxplots, in which winter presented fewer outliers and more homogeneity [151].

As for the BDT sensors, considering all data, there was a difference from 4.51 to 6.00 °C at sensor 6 and from 6.01 to 7.50 °C at sensor 4. In summer, the difference was from 7.51 to 9.00 °C at sensor 6 and from 9.01 to 10.50 °C at sensor 4. As it is, a class that has the presence of civil construction at medium height, the difference was not as intense as in PMA. In winter, the difference was smaller, presenting data ranging from 0.00 to 1.00 °C at sensor 6 and 1.01 to 2.00 °C at sensor 4, which may be associated with the projected shadow of the buildings [44,45].

The TUR sensors showed a difference from 4.51 to 6.00 °C at sensors 14 and 15 and from 6.01 to 7.50 °C at sensor 1, when considering all dates. In summer, the difference was more homogeneous, and sensors presented difference from 6.00 to 7.50 °C at sensor 15, from 7.51 to 9.00 °C at sensor 14, and from 9.01 to 10.50 °C at sensor 1. In winter, sensors 14 and 15 presented a difference from 0.00 to 1.00 °C, and sensor 1, from 2.01 to 3.00 °C. It is possible to verify that, as what occurred with the BDT sensors, there was a minimization of the amplitude of the difference, especially in winter. It is worth mentioning that the presence of vegetation in this class may have helped in regulating the temperature, which was not observed in the PMA sensor [152,153].

As for the UMR sensors, it was observed that sensor 2 showed a difference of 4.51 to 6.00 °C, sensors 12 and 22 varied between 6.01 to 7.50 °C, and sensor 18, from 7.51 to 9.00 °C on all dates. In summer, the difference was 7.51 to 9.00 °C at sensor 10, 9.01 to 10.50 °C at sensors 12 and 22, and 10.51 to 12.00 °C at sensor 18. In winter, there was a difference of 0 to 1 °C at sensor 10, 1.01 to 2.00 °C at sensors 12 and 22, and 2.01 to 3.00 °C at sensor 18. The fact that the sensors did not present the maximum difference may be associated with the with the absence of a high-density construct [154].

The EVU sensors presented difference between 6.01 and 7.50 °C at sensor 11 and from 7.51 to 9.00 °C at sensors 2, 8, and 9, considering all dates. In summer, the difference was 7.51 to 9.00 °C at sensor 11, 9.01 to 10.50 °C at sensor 2, and 10.51 to 12.00 °C at sensors 2 and 9. In winter, the difference was 1.01 to 2.00 °C at sensor 8, 2.01 to 3.00 °C at sensor 9, and 3.01 to 4.00 °C at sensors 2 and 11.

Although the EVU has vegetation cover, including trees, there is variability between air temperature and LST, similar to the more urbanized sites. It is natural that there is still surface heating in the vegetation, as occurs in all surfaces, due to the incoming electromagnetic energy and that the cooling in places with the presence of vegetation is not exactly linear [155,156]

Some studies have identified that despite the thermal comfort and shade projection promoted by large trees, the spatial configuration and leaf density can result

in negative effects during (nighttime) cooling [157], as it can retain heat arising from the smaller SVF [158].

For more assertive conclusions related to the reality of Bragança, it is recommended to collect and analyze complementary data, to understand the effects of vegetation on surface temperature, such as the spatial pattern, canopy cover, and shape [159], leaf density, shade effects, area of influence of local trees [160–162], as well as to verify if vegetation acts as natural obstacles to wind direction and circulation, interfering in the dissipation of electromagnetic energy [15].

As for the ZCS sensors, when considering all dates, we observe that the difference was between 6.01 and 7.50 °C at sensor 5 and 7.51 to 9.00 °C at sensors 17 and 21. In summer, the difference was between 9.01 to 10.50 °C at sensors 5 and 21 and 10.51 to 12.00 °C at sensor 17. In winter, the difference was 1.01 to 2.00 °C at sensors 5 and 17 and 3.01 to 4.00 °C at sensor 21. The higher surface temperature in this UCZ may be associated with the surface composition characteristics, which show anthropogenic changes [163,164].

It is worth noting that the LST values (Landsat 8) were higher than those of air temperature (fixed weather station), especially in summer. Although they are both temperature-related parameters, in LST there are additional influencing factors, especially those related to the albedo of the surface constituent materials. In addition, the LST is affected by shadow projection, both from buildings and dense trees, which can affect the results [165].

UHI_{Int}

From the boxplots analysis, both the UHI_{Int}, relative to air temperature (fixed weather station) (Figure 31) and LST (Landsat 8) (Figure 32) showed similar behavior in the UCZs. The data from the UHI_{Int} of air temperature in summer showed fewer outliers than those of the LST, and in winter, the UHI_{Int} of air temperature showed more amplitude in the data, especially for the EVU sensors, compared to the UHI_{Int} of LST.

The PMA sensors (3, 7, and 13, in red), characterized by the existence of high volume constructions, showed medians near zero or negative UHI_{Int} at both stations in air temperature and LST.

The BDT sensors (4 and 6, in gray), representing the city center, presented median values of UHI_{Int} close to zero, in air temperature in winter and summer. In the UHI_{Int} of the LST, the behavior was similar, despite presenting median values slightly below 0 °C (near - 2.00 °C in sensors 4 and 6 in summer and sensor 6 in winter).

Sensors 10, 12, 18, and 22, which represent UMR (in blue), with medium density buildings and isolated streets, presented median values in the UHI_{Int} of air temperature also close to 0.00 °C, except sensor 22 in summer, with a median close to 2.00 °C and sensor 18 that, in winter, presented a median close to -3.00 °C. As for the LST UHI_{Int} , was observed that the median in summer was around 0.00 °C in all sensors, except for sensor 10, which was around -2.00 °C. The median in winter was close to -2.00 °C, except for sensor 12, whose value was close to 0.00 °C.

As for sensors 5, 17, and 21, of the ZCS (in orange), which represent industrial and commercial areas, the median UHI_{Int} of air temperature was close to -2.00 °C in the summer. In the winter, the behaviors were distinct: near -1.00 °C at sensor 5, 1.00 °C at sensor 17, and -3.00 °C at sensor 21. As for the UHI_{Int} of the LST, in the summer sensors 5 and 21 showed median values near -3.00 °C and for sensor 17 around 1.00 °C. In winter, sensor 17 maintained its behavior, and sensors 5 and 21 showed similar results -1.00 °C.

The EVU sensors (2, 8, 9, and 11, in green), which were mostly vegetated (including trees), showed negative UHI_{Int} values in both winter and summer in both parameters, with the highest air temperature amplitudes recorded in winter and the lowest median in sensor 9. This result may be associated with the lack of filling of all data in this sensor (Figure 25).

In the TUR UCZ (sensors 1, 14, and 15, in purple), which represents the transition between rural and urban space, the UHI_{Int} of air temperature was varied in winter and summer, but recorded results were close to 0.00 °C (exceptions in sensor 1, which presented - 3.00 °C in winter and summer and in sensor 15, which presented 2.00 °C in summer). As for the UHI_{Int} of the LST, the data presented more outliers, especially in the summer. The median results in both stations ranged between 0.00 and -2.00 °C, except for sensor 15, which showed a median of -3.00 °C in the summer.

As for the maximum UHI_{Int} value of air temperature in the summer, it was recorded by the BDT sensor (6) followed by PMA (3). In the winter, the highest UHI_{Int} were recorded at the ZCS (17) and BDT (6) sensors. In the UHI_{Int} of the LST, the highest values in the summer were recorded by the UMR sensors (12 and 22). In the winter were recorded by sensors UMR (12) and ZCS (17).

The lowest UHI_{Int} values of air temperature in the summer were recorded by the PMA (13) and EVU (9) sensors. In the winter, the lowest UHI_{Int} were recorded by sensors EVU (9 and 11) and BDT (6). In the UHI_{Int} of the LST, the lowest values in the summer were recorded by sensors EVU (9), TUR (15), and ZCS (5). In the winter, by sensors EVU (9 and 11) and UMR (10).

In a general analysis of the results, lower UHI_{int} values are observed in anthropically altered areas for both air temperature and LST. This behavior can be justified, especially, by the time considered for the analysis of this effect, due to the Landsat 8 overpass in Bragança.

During the morning, the penetration of electromagnetic energy tends to be different in anthropically altered areas compared to rural areas. In flat/horizontal areas (such as vegetated ones), there are no barriers for the penetration of electromagnetic energy, which corroborates to the higher heat storage in the early hours of the day in these areas compared to anthropically altered ones [5,34,104,166].

This dynamic results in a behavior opposite to what is expected in studies of UHI, *i.e.*, the vegetated areas tend to have higher values of air and surface temperatures than the anthropically altered areas, resulting in a phenomenon called Cold Islands, which has already been identified in previous studies conducted in Bragança, in the morning period [18].

As the Landsat 8 overpass occurs near the solar nadir (11h15 UTC), which minimizes the projection of shadows, it was expected that the Cold Island effect would have been less evident. However, considering that the vegetated areas had more exposure time to electromagnetic energy at the early morning hours compared to urban areas and the temperature values (both air and surface temperature), this conditions have determined the presence of higher LST and air temperature in these areas [18], thus determining a negative UHI_{int} .

It is noteworthy that, although the warming effect of the UHI has not been evident due to the issues mentioned above, the behavior of UHI_{int} data, both in air temperature and in LST were consistent, which reinforces potential of using RS data for analysis of this climatic phenomenon, from the records of the thermal band. It is noteworthy that complementary analyses are needed to ratify the coherence of these results, which are presented in the item “4.2. Analytical Statistics”.

For further studies, we recommend the use of RS data obtained at night (from satellite or UAV), a period in which the UHI effect is enhanced and there is no influence of shadows projected in urban areas. Moreover, considering the morphological characteristics of Bragança, it is suggested that a potential altitude bias should be corrected for temperature data, as performed in previous studies, and the morphological details of the surroundings of each sensor should be considered [17,102].

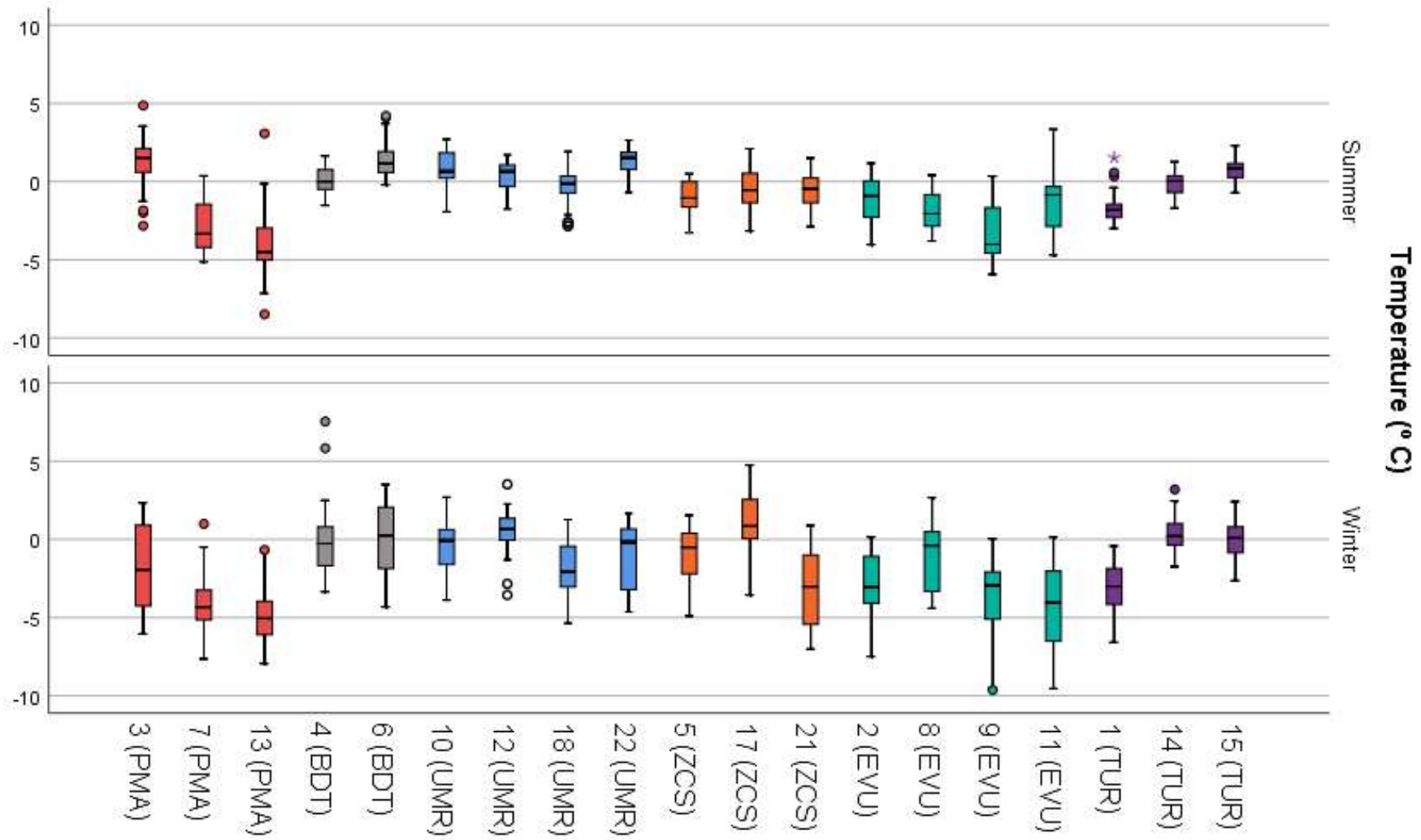


Figure 31. Boxplot with the Air temperature UHI_{int}, calculated for summer and winter, at each sensor and its respective UCZ.

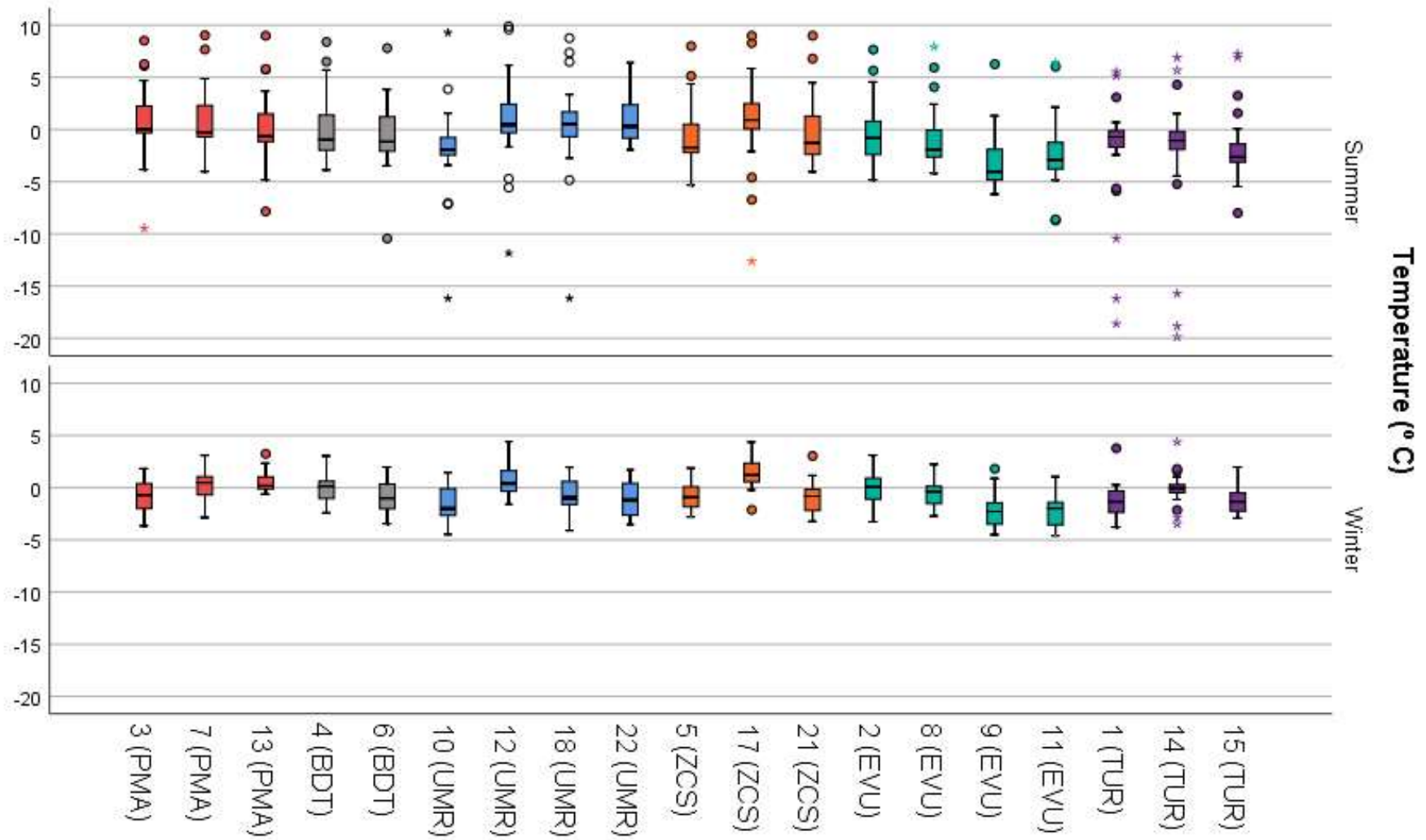


Figure 32. Boxplot with the LST UHI_{int} calculated for summer and winter, at each sensor and its respective UCZ.

4.2. Analytical Statistics

Shapiro's Test

The results obtained in the Shapiro test applied to air temperature (fixed weather station) and LST (Landsat 8), considering all data, *i.e.*, without separation by season, indicated a non-normalized behavior in all sensors (p-value less than 0.05), which justifies the application of the Spearman correlation method (as illustrated in Table 10).

Table 10. Results obtained in the Shapiro test using all dates, with 95% confidence level (p-value data greater than 0.05 are highlighted in red).

All data					
Sensor	UCZ	Air Temperature		LST (Landsat 8)	
		W	p-value	W	p-value
1	TUR	0.900	0.000	0.881	0.000
2	EVU	0.904	0.000	0.888	0.000
3	PMA	0.912	0.000	0.884	0.000
4	BDT	0.923	0.000	0.883	0.000
5	ZCS	0.932	0.001	0.882	0.000
6	BDT	0.912	0.000	0.884	0.000
7	PMA	0.881	0.000	0.886	0.000
8	EVU	0.903	0.000	0.881	0.000
9	EVU	0.896	0.000	0.892	0.000
10	UMR	0.911	0.000	0.893	0.000
11	EVU	0.910	0.000	0.893	0.000
12	UMR	0.922	0.000	0.880	0.000
13	PMA	0.885	0.000	0.878	0.000
14	TUR	0.926	0.000	0.895	0.000
15	TUR	0.914	0.000	0.872	0.000
16	ZRE	0.941	0.002	0.900	0.000
17	ZCS	0.927	0.001	0.895	0.000
18	UMR	0.910	0.000	0.901	0.000
19	ZRE	0.934	0.001	0.899	0.000
20	ZRE	0.923	0.000	0.877	0.000
21	ZCS	0.897	0.000	0.880	0.000
22	BDT	0.905	0.000	0.892	0.000
23	ZRE	0.927	0.000	0.889	0.000

Considering all dates (without separation by season), the sensors present data with a non-normal distribution, therefore Spearman's statistical method was adopted.

The same test was applied, separating the dates into seasons (winter and summer). In the summer, the same non-normalized behavior was observed for LST data (Landsat 8). The behavior of the air temperature data followed a normal distribution (Table 11). As the assumption of the Pearson method is that all data that will be used in the processing present normality, the Spearman method was also applied in the summer.

Table 11. Results obtained in the Shapiro test, using the summer dates, with 95% confidence level (p-value data greater than 0.05 are highlighted in red).

Summer data					
Sensor	UCZ	Air Temperature		LST (Landsat 8)	
		W	p-value	W	p-value
1	TUR	0.981	0.684	0.781	0.000
2	EVU	0.977	0.543	0.779	0.000
3	PMA	0.982	0.714	0.799	0.000
4	BDT	0.990	0.961	0.808	0.000
5	ZCS	0.983	0.783	0.801	0.000
6	BDT	0.985	0.830	0.815	0.000
7	PMA	0.992	0.992	0.788	0.000
8	EVU	0.985	0.851	0.804	0.000
9	EVU	0.988	0.946	0.809	0.000
10	UMR	0.963	0.196	0.842	0.000
11	EVU	0.989	0.960	0.843	0.000
12	UMR	0.994	0.998	0.769	0.000
13	PMA	0.981	0.688	0.768	0.000
14	TUR	0.986	0.878	0.768	0.000
15	TUR	0.982	0.713	0.781	0.000
16	ZRE	0.981	0.699	0.795	0.000
17	ZCS	0.978	0.587	0.796	0.000
18	UMR	0.983	0.764	0.825	0.000
19	ZRE	0.979	0.608	0.821	0.000
20	ZRE	0.988	0.924	0.761	0.000
21	ZCS	0.977	0.543	0.801	0.000
22	BDT	0.982	0.728	0.826	0.000
23	ZRE	0.990	0.967	0.817	0.000

In the winter, the data mostly presented p-values greater than 0.05, except for satellite LST for three sensors (Table 12). To make the analysis coherent and apply the appropriate method in data analysis, Pearson's correlation was adopted (even for the data that did not present a p-value greater than 0.05 - LST dates in sensors 9, 16, and 9), to minimize possible discrepancies that could be associated with the difference of the analytical method in the same sample group). The normalized behavior of the winter data may be associated with a smaller temperature range, due to the specific environmental conditions of winter, which affect the net solar radiation available [149], and the smaller number of observations, compared to the summer data.

In summary, Spearman was the method applied for all data and summer data and Pearson was applied to winter data.

Table 12. Results obtained in the Shapiro-Wilk test, using the winter dates, with 95% confidence level (p-value data greater than 0.05 are highlighted in red).

Winter data					
Sensor	UCZ	Air Temperature		LST (Landsat 8)	
		W	p-value	W	p-value
1	TUR	0.954	0.310	0.962	0.464
2	EVU	0.969	0.614	0.968	0.602
3	PMA	0.974	0.740	0.968	0.594
4	BDT	0.967	0.573	0.932	0.097
5	ZCS	0.962	0.458	0.934	0.106
6	BDT	0.973	0.710	0.928	0.080
7	PMA	0.966	0.541	0.921	0.054
8	EVU	0.957	0.350	0.927	0.075
9	EVU	0.982	0.925	0.901	0.019
10	UMR	0.955	0.327	0.924	0.063
11	EVU	0.963	0.488	0.922	0.056
12	UMR	0.946	0.201	0.964	0.498
13	PMA	0.965	0.531	0.954	0.307
14	TUR	0.951	0.261	0.965	0.517
15	TUR	0.938	0.133	0.931	0.093
16	ZRE	0.937	0.128	0.912	0.034
17	ZCS	0.925	0.066	0.922	0.056
18	UMR	0.938	0.134	0.953	0.293
19	ZRE	0.940	0.148	0.919	0.048
20	ZRE	0.976	0.806	0.945	0.190
21	ZCS	0.971	0.666	0.946	0.198
22	BDT	0.966	0.545	0.957	0.354
23	ZRE	0.943	0.178	0.928	0.078

Correlation Between Air Temperature (Fixed Weather Station) and LST (Landsat 8)

A first approach was performed considering the air temperature data (measured by the meteorological sensors fixed in the city) and the LST data, calculated from the data recorded by Landsat 8. It should be noted that because they are different parameters (air temperature and LST), the correlations may not be very strong as they are influenced by different external factors [122].

In this first approach, all sensors/dates analyzed presented a p-value greater than 0.05, *i.e.*, it is possible to consider the statistical result obtained, with 95% confidence. To classify the level of correlation in a standardized way in all parameters that will be addressed, a scale was created, which will be applied in all statistical results, when the p-value is greater than 0.05 (Table 13). All parameters of this correlation, including the respective p-values, are available in Appendix IX.

Table 13. Scale for data correlation analysis (adapted from [167,168]).

Statistical Value (+ or -)	Correlation
0.00 – 0.19	Null
0.20 – 0.29	Weak
0.30 – 0.39	Moderate
0.40 – 0.69	Strong
≥ 70	Very Strong

All correlations were positive, and, considering all days, all results were rated “Very Strong”. In the summer, 17 sensors (73.91%) showed a "Strong" correlation and six sensors (26.09%) had a "Very Strong" correlation. In winter, all correlation was “Very Strong” (Figure 33).

Regarding seasonality, in the summer, the results showed slightly weaker correlations than in winter, which converges with the behavior observed in the boxplots, in which there is greater heterogeneity and thermal amplitude of LST, compared to air temperature. It is worth noting that the number of scenes processed in the summer differs from winter, which may also influence the results (Figure 33).

Also regarding seasonality, in the summer there is a higher incidence of solar energy and, consequently, the influence of shadows on the targets may be more intense when compared to winter. These shadows may be associated with: i) the configuration of buildings, which in periods of greater availability of electromagnetic energy can influence the result obtained by comparing a shaded area concerning another exposed, unobstructed area; and ii) the vegetation, specially bu trees as a consequence of the canopy cover, who will provide shadow. Unlike most urban structures, some trees (deciduous) will present changes in their capacity to intercept solar radiation, due to the changes in foliage around the year, with notable influence on the microclimate in its surroundings [45,149].

Although the satellite passes occur near the solar nadir, which minimizes these shadow effects, this condition can still exert some influence on the results. On the other hand, because of the disregard of winter scenes due to LST temperatures below -5 °C, the number of scenes is smaller compared to summer scenes, which may also interfere with the correlations obtained (Figure 33).

Analyzing the correlations in each UCZ, when considering all dates, it is possible to identify that the LST converged positively with the behavior of air temperature and can be considered as a representative parameter of the local reality and in the UHI study. Sensor 10 was the one that presented the highest correlation (0.903), represented by the UMR UCZ, which demonstrates the ability to obtain data from locations with medium density, housing, and low height or isolated streets [169].

Considering the summer data, the highest correlations encompassed sensors from different UCZs. Of the 3 sensors classified as TUR, two showed a "very strong" correlation (sensor 1 and 14, with a correlation of 0.708 and 0.743, respectively). This result presents the ability of the RS to obtain data on local air temperature behavior in rural transition zones [170].

Sensor 10 (UMR), already mentioned above, also showed "very strong" correlation results in the summer (0.740). Sensor 4 - BDT, which represents the downtown area, with medium and small buildings, also showed a "very strong" correlation with air temperature (0.737). Similar behavior in sensors 16 and 17, corresponding to the UCZs ZRE (isolated rural area) and ZCS (commercial and industrial area), respectively, both with 0.708 (Figure 33). Considering that the summer data were diverse concerning the UCZs, it is possible to identify the ability to map thermal behavior from RS in heterogeneous zones in Bragança, in this season.

As for the winter data, two of the sensors that showed higher correlations refer to the UMR UCZ, sensor 22 (0.940) and sensor 10 (0.913). Sensor 20 (ZRE), showed a correlation of 0.937. Sensors 21 (ZCS), 3 (PMA) and 8 (EVU), showed correlations of 0.915, 0.915 and 0.906, respectively.

In a general analysis, for winter data it was possible to identify that the RS was able to identify patterns in the thermal behavior of the different UCZs in Bragança, which are correlated to the air temperatures, recorded by the fixed air temperature sensors. In the summer, although only six sensors showed "very strong" correlation, no correlations lower than "strong" were identified, which reiterates the possibility of using RS methodologies in studies of UHI, ensuring the representativeness of the behavior of the locally acquired data.

It is worth mentioning that, since these data are obtained at different scales, the results of the correlations may have been influenced by it, since the local sensors record data in a microscale context, while the LST is obtained covering a more extended scale, closer to the level of generalization used for the definition of the UCZs [171]. For future studies, these behaviors may be better modeled by increasing the number of RS days/scenes analyzed, especially in winter.

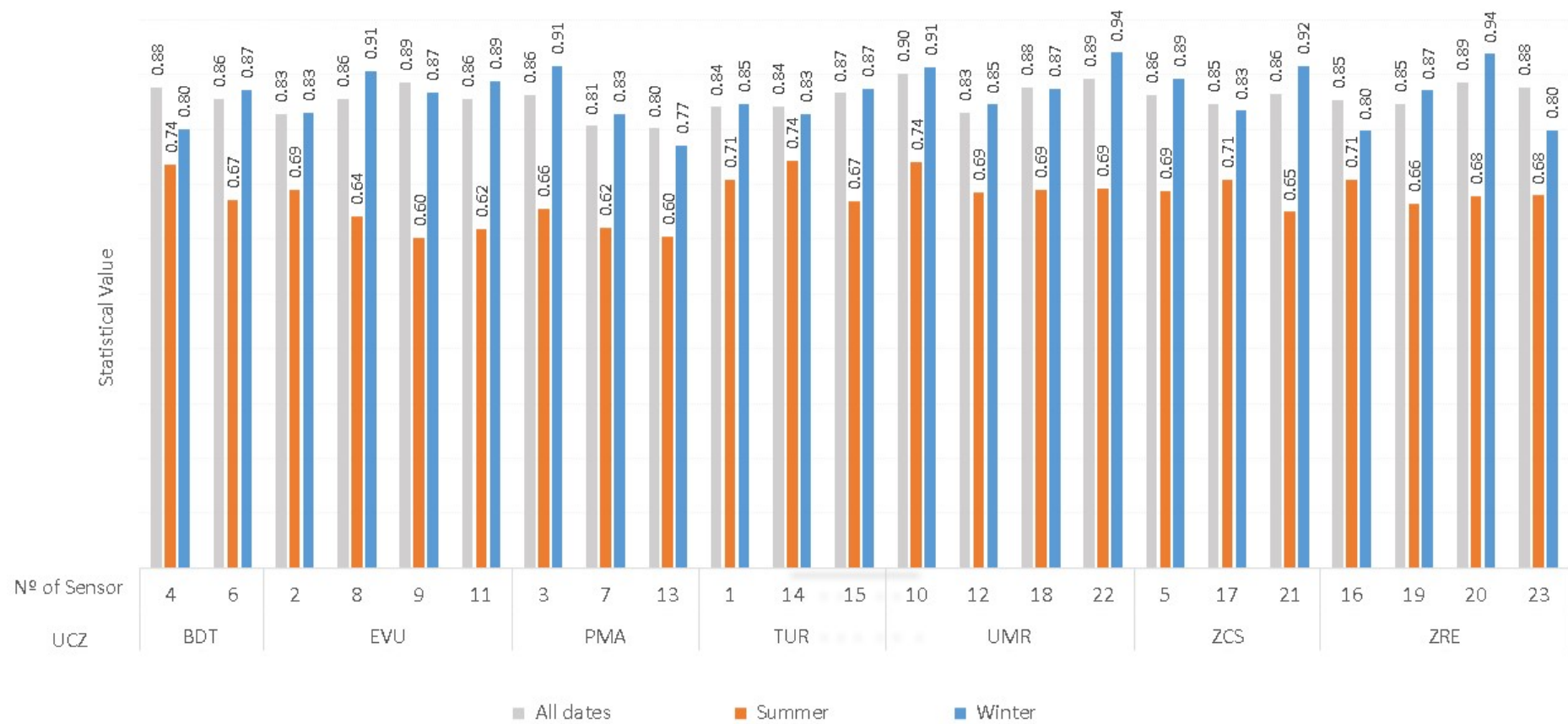


Figure 33. Statistical values were obtained from the correlation between air temperature, measured by the fixed weather station and the LST, estimated from Landsat 8 data (absolute values).

Correlation between $\overline{LST_{ZRE}}$ and LST_{UCZ}

The correlation test was applied between the average of the values obtained in the ZRE UCZ ($\overline{LST_{ZRE}}$) and the LST measured in each sensor of the other UCZs LST_{UCZ} , to evaluate if there was any convergence between the behavior of the UCZs with the presence of vegetation and the others. The results showed a "very strong" correlation in all, even when considering all dates and seasonality (winter and summer). The lowest values were recorded for sensors 9 (EVU), 6 (BDT) and 15 (TUR) in winter, corresponding to 0.87, 0.89, 0.92 respectively (Figure 34).

These results allow us to understand that the behavior in the UCZs is similar, due to the high positive correlation between the results. *i.e.*, it is possible to verify that the LST (Landsat 8) thermal variations found and discussed throughout this thesis are associated with LULC factors, such as roughness, porosity, albedo, W/H/L, urban canyons, SVF, anthropogenic heat, etc. (Figure 34).

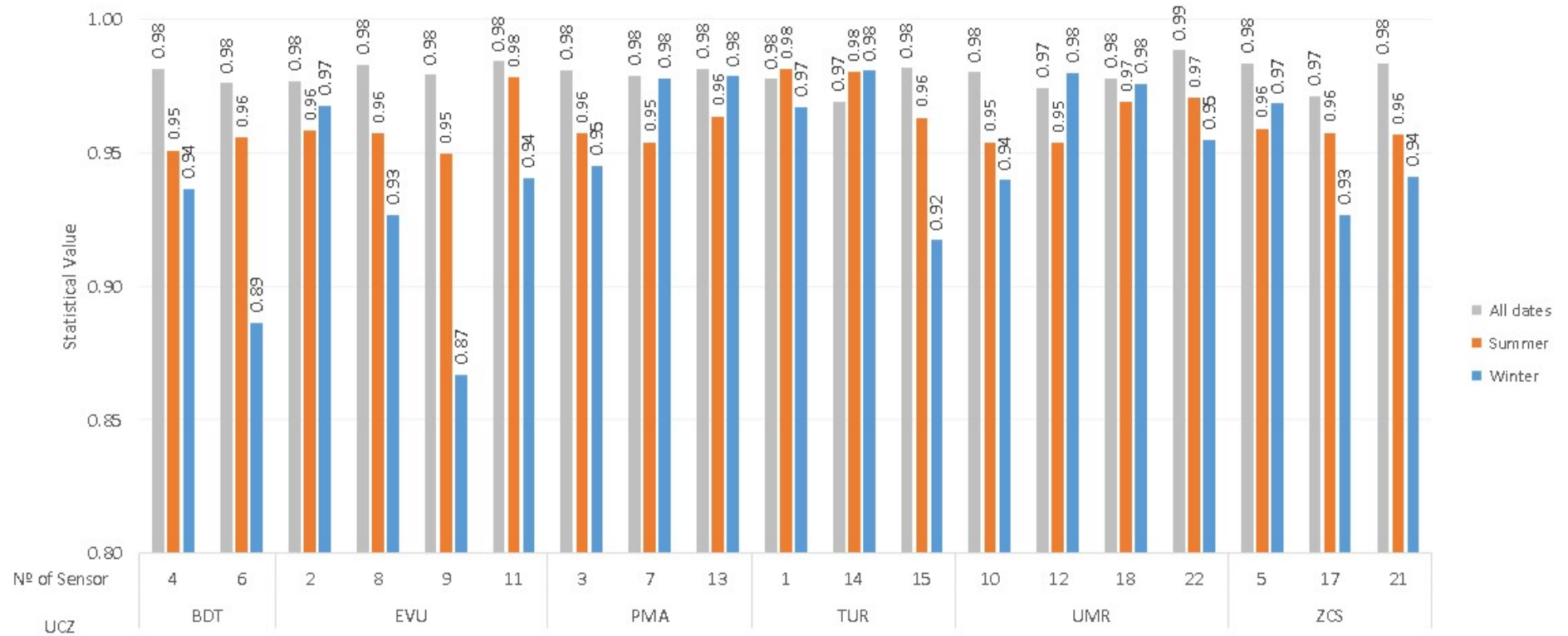


Figure 34. Statistical values were obtained from the correlation between LST UHI_{int} LST *versus* LST of other UCZs (Landsat 8).

4.3. Field Data for Validation

Classification of the Surfaces Sampled by the Thermal Camera Portable

The classification of the surfaces measured with the manual thermal camera was performed and, in Table 14 there is the identification of the area, the equivalent fixed sensor, the classification of UCZs, the number of surfaces collected in each point, and the respective description, based on the data obtained by the photo camera.

Table 14. Classification of the points sampled with the thermal camera. Where: i) Asphalt (As); ii) Sidewalk (S); iii) Vegetation (V); iv) Vegetation with exposed Soil (Vs); v) Dry Vegetation (DV), and vi) Dry Vegetation and Rock (DVSt).

Point	Equivalent fixed Sensor	UCZs	Nº of surfaces sampled	Description/Surface Classification
1	23	ZRE	2	P1A – DV (collection 1, 2, and 4) P1A – V (collection 3) P1B – Vs (collection 1, 2 and 4) P1B – V (collection 3)
2	18	UMR	3	P2A – As (all collections) P2B – S (all collections) P2C – Vs (collection 1, 2 and 4) P2C – V (collection 3)
3	17	ZCS	4	P3A – As (all collections) P3B – Vs (collection 1 and 2) P3B – V (collection 3 e 4) P3C – S (all collections) P3D – V (collection 1, 2 and 4) P3D – Vs (collection 3)
4	15	TUR	3	P4A – AS (all collections) P4B – S (all collections) P4C – DVSt (collection 1, 2, and 4) P4C – VSt (collection 3)
5	9	EVU	2	P5A – Vs (collection 1, 2 and 4) P5A – V (collection 3) P5B – V (collection 1, 2 and 3) P5B – DV (collection 4)
6	5	ZCS	5	P6A – V (collection 1, 2 and 4) P6A – DV (collection 3) P6B – As (all collections) P6C – S (all collections) ¹⁰ P6D – S (all collections) P6E – S (all collections)
7	6	BDT	2	P7A – S (all collections) P7B – S (all collections)
8	3	PMA	2	P8A – S (all collections) P8B – As (all collections)
9	14	TUR	2	P9A – V (collection 1, 2 and 4) P9A – Vs (collection 3) P9B – As (all collections)
10	22	UMR	2	P10A – As (all collections) P10B – S (all collections)

¹⁰ Point disregarded in the analyses because it has undergone surface material changes unrelated to seasonality.

Due to seasonality, some points with the presence of vegetation had their surface classification changed throughout the measurements taken, going from vegetation areas to vegetation areas with exposed soil, for example. In addition, point 6C showed variations in surface material and, because it was not associated with seasonality, it was disregarded in the analysis.

The number of points sampled in each collection area was variable since it was prioritized the collection of data on heterogeneous surfaces (such as an area with vegetation and another with asphalt surface, for example). Therefore, areas with lower LULC variability were sampled with a smaller number of points compared to more heterogeneous areas.

Analysis of the LST on the various sampled surfaces (LST obtained by Landsat 8 and the manual thermal camera)

The LST data from the handheld thermal camera sampled on each surface in the morning compared to the satellite LST showed higher temperatures in most of the cases. The justification for this behavior may be associated with the scale of the collection, since the LST averages the thermal values existing in a pixel, while the thermal camera presents a smaller FOV, with the ability to present more details of the sampled surface [15].

As the collections made in the field are punctual and considering a specific class, no averages are made per pixel, as in the case of the satellite, which can influence the results, especially in heterogeneous areas. Details about the acronyms/classifications were presented in Table 14.

Furthermore, there are different influencing factors between both techniques, such as the atmosphere that affects satellite data. The presence of clouds, while casting possible shadows, is less impactful in local collections.

The results will be presented by UCZ and the corresponding sensors. Considering that this analysis intends to evaluate the thermal behavior of the different sampled surfaces and to facilitate visualization, the coloring of the classes was standardized, *i.e.*, green coloring was prioritized for vegetation (identified as V) and shades of gray for sidewalks and asphalt (S and A, respectively). In points where two different surfaces were measured, but with similar classification, as occurred in point 6, where two sidewalks with different compositions were measured, the color assigned to both was the same (P6D and P6E).

As for vegetation, there are cases in which two classes were assigned to the same sampled point, due to seasonality, as in point 1: sample A was classified as DV in collections 1, 2, and 4, and V in collection 3. In the legend of the graph, it will be represented as DV/V. Table 14 presents these specificities.

At point 1 (ZRE), it can be observed that the temperature values obtained in the vegetation classes were similar, even in dry vegetation. Collection 3, which refers to spring, presented temperature data lower than the obtained in the summer collections, which demonstrates the influence of seasonality. In this data collection, the LST calculated *in situ* and that of Landsat 8 presented closer values than in the others, which may be associated with the availability of electromagnetic energy [149]. It is noteworthy that, because it is an area of isolated vegetation, no shadow effects were observed (Figure 35).

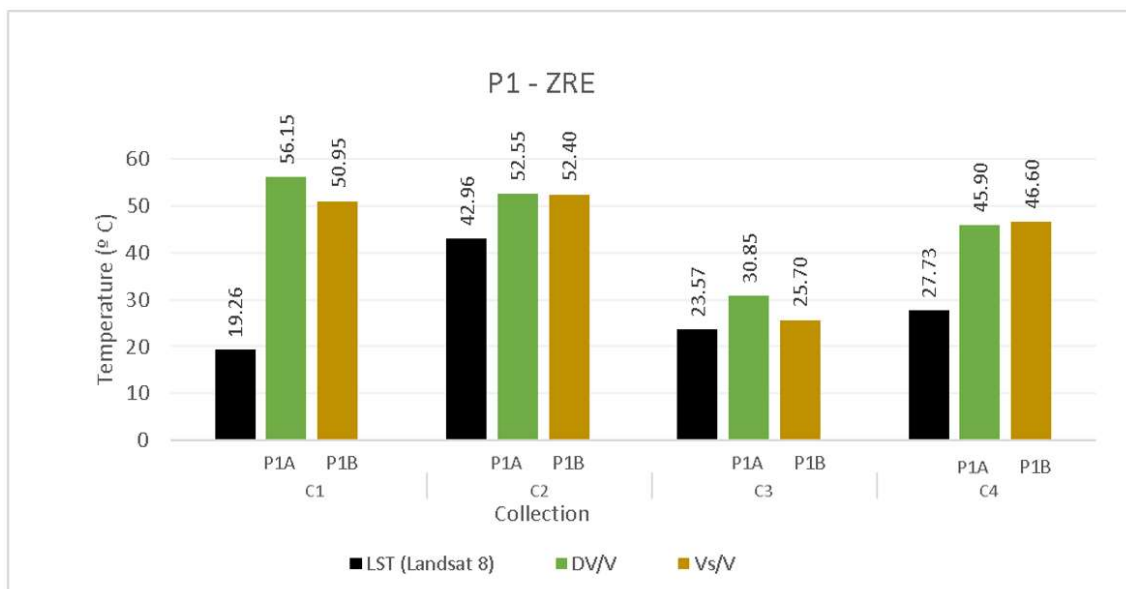


Figure 35. Analysis of the temperatures on the various sampled surfaces at point 1 (ZRE).

Regarding the ZCS, point 3 showed similar LST values collected by satellite and *in situ* with the exception of the first collection. The temperatures of points AS and S (anthropically altered) presented, mostly, the highest temperature values, except collection 1, where the dry vegetation (Vs) presented 49.40 °C.

In collection 1, the vegetation of point D (which did not present dryness characteristics like in point B), presented lower temperatures, which may be associated with the ability to soften the temperature, due to its use in metabolic processes of healthy vegetation [156] (Figure 36).

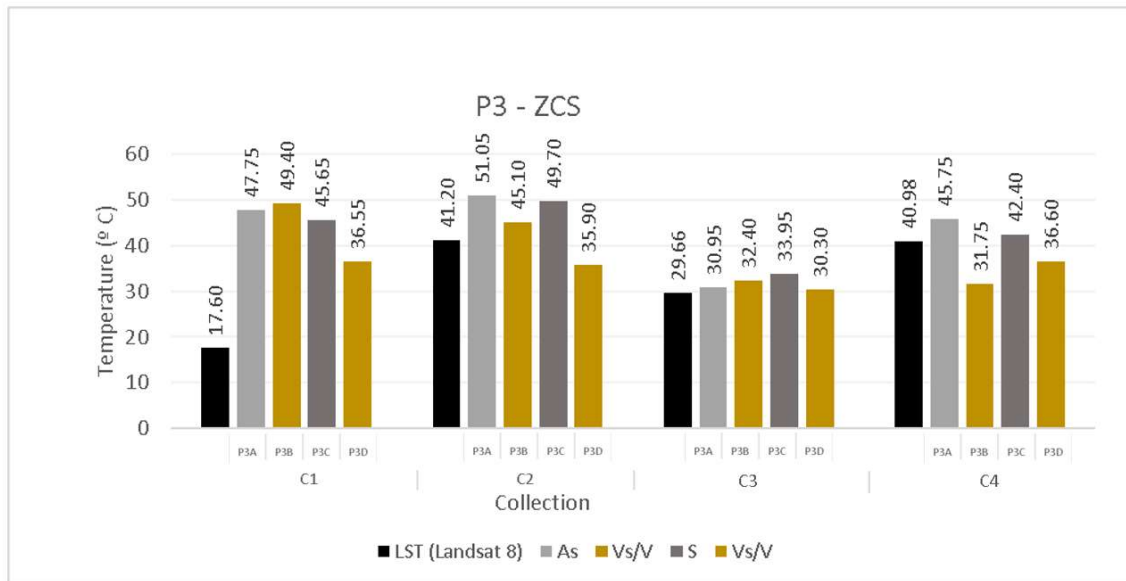


Figure 36. Analysis of the temperatures on the various sampled surfaces at point 3 (ZCS).

As for point 6, it is observed that the values recorded on the vegetation surfaces were the lowest in all collections, compared to the anthropic surface materials (As, S and S), except collection 3, in which the area sampled D showed slightly lower values. The highest temperatures were measured on asphalt [21,43]. The maximum temperatures observed in the UCZ are similar to those in the ZRE (Figure 37).

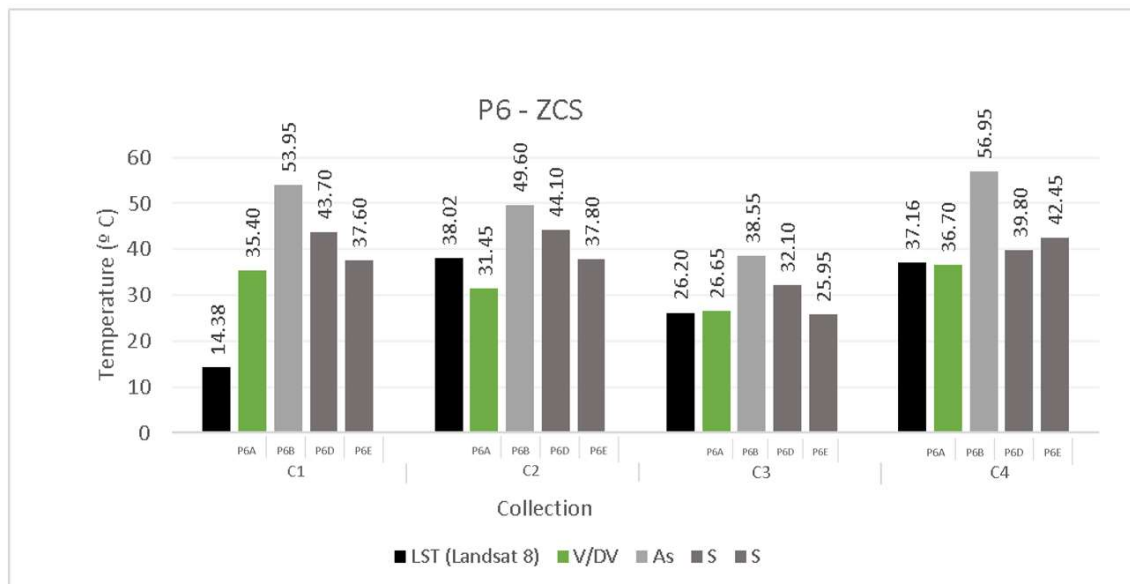


Figure 37. Analysis of the temperatures on the various sampled surfaces at point 6 (ZCS).

In the TUR class, the maximum temperatures are similar to those observed in the ZRE, being lower in spring, which may be associated with seasonality. Point 4 presented the same behavior regarding maximum temperatures associated with anthropically altered areas [29,172]. The dry vegetation surface and the presence of

rock (DVSt/VSt) showed milder temperature values, which corroborates the possible thermal regulation at the site (Figure 38).

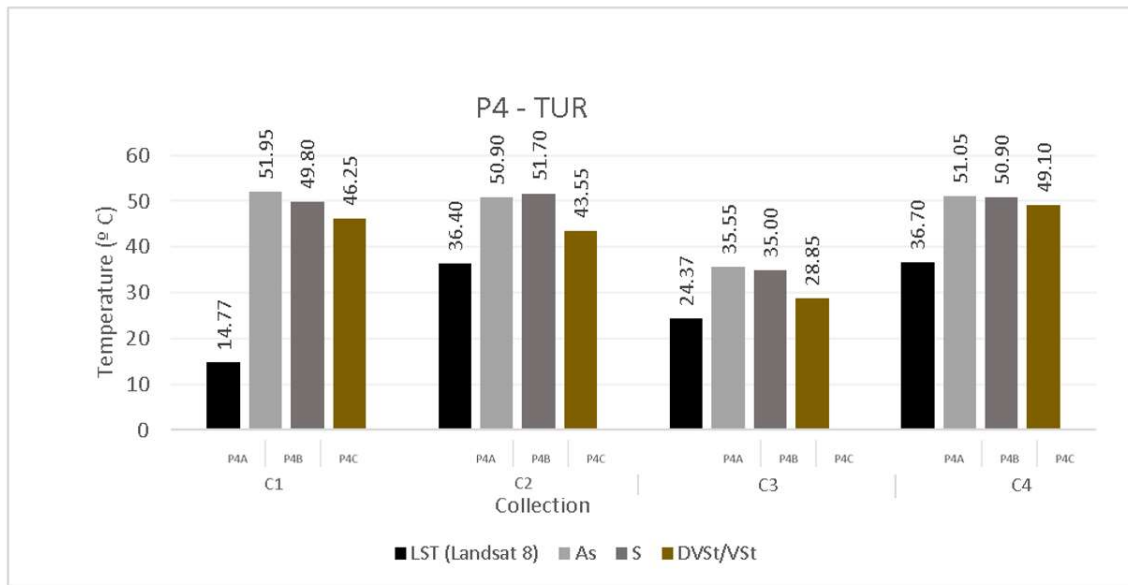


Figure 38. Analysis of the temperatures on the various sampled surfaces at point 4 (TUR).

Point 9 (TUR), showed the same behavior, with the data recorded in the LST (Landsat 8) being lower in all cases, followed by the V/Vs data. It is important to emphasize that, as the satellite performs the averaging of values within a pixel, point behaviors in transition zones, as this case, may have less detail [61]; if averages are performed between points, the specifics of the albedos are lost and, consequently, the LST value recorded by the satellite, will be lower (Figure 39).

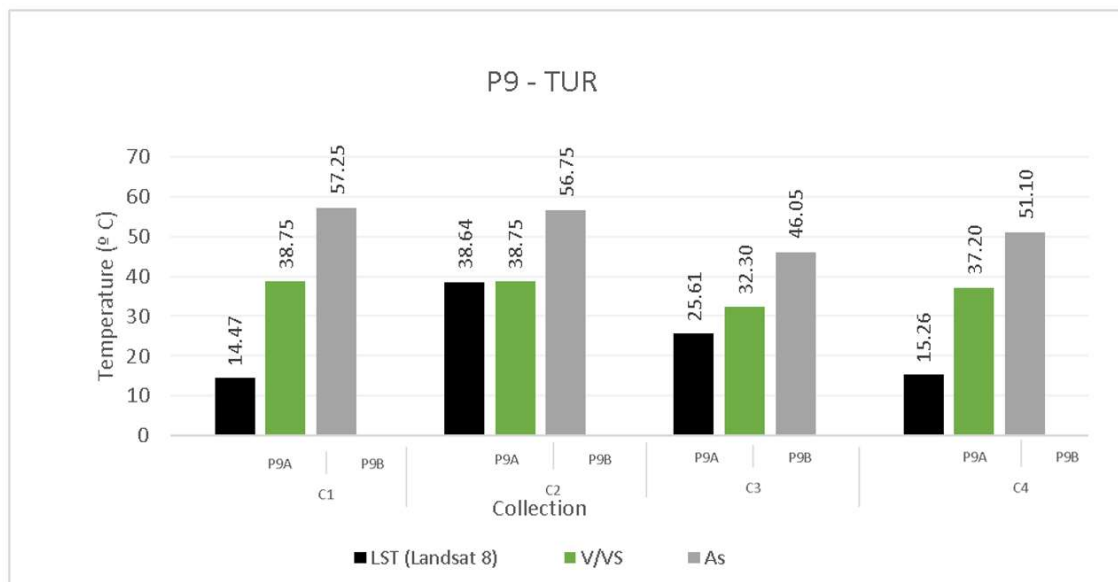


Figure 39. Analysis of the temperatures on the various sampled surfaces at point 9 (TUR).

Point 5 (EVU), characterized by the presence of vegetation and trees, showed lower maximum temperature data compared to P4 (TUR), and P3 (ZCS). The dry

vegetation (Vs) in collections 2 and 4, showed slightly higher temperatures than in vegetation (V), corroborating the hypothesis that vegetation health influences local thermal regulation. In this UCZ, the LST (Landsat) data were also similar, except for collection 1 (Figure 40).

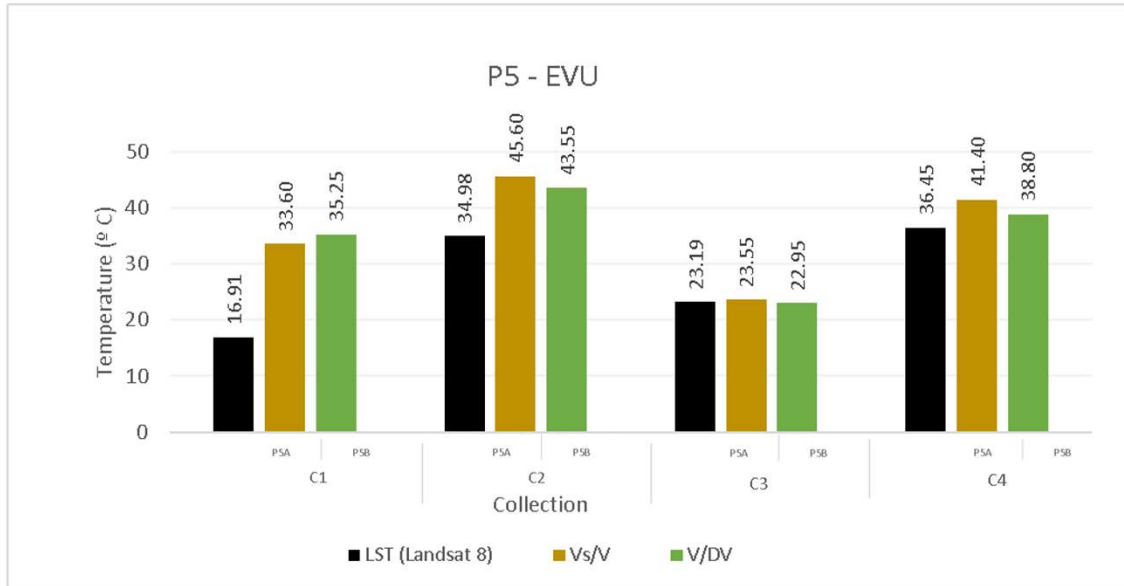


Figure 40. Analysis of the temperatures on the various sampled surfaces at point 5 (EVU).

As for the BDT UCZ, which represents the old city center, point 7 presents higher temperatures simulating the UCZs that have anthropic elements in their composition. Both sampled areas, classified as S, presented high-temperature values, being sample A the one with the highest LST in all collections (Figure 41).

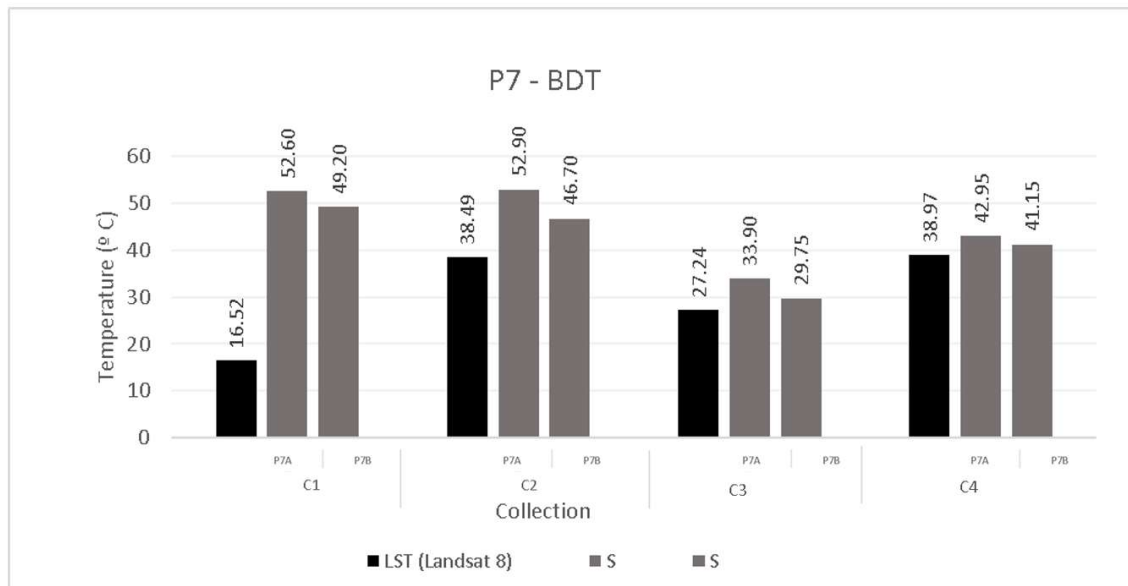


Figure 41. Analysis of the temperatures on the various sampled surfaces at point 7 (BDT).

The PMA UCZ, which corresponds to dense buildings, represented by point 8, showed the highest temperature measured at all points in collection 2, surface S. In the

other collections, As showed a higher value. The LST (Landsat 8) was lower on the first day of collection and higher on the last day but showed relatively close results. It is worth mentioning that, on the last collection day, there were moments with the presence of clouds, which may justify the lower results *in situ* than those measured by the satellite. Moreover, because it is an area with many buildings, the projection of shadows may have affected this result (Figure 42).

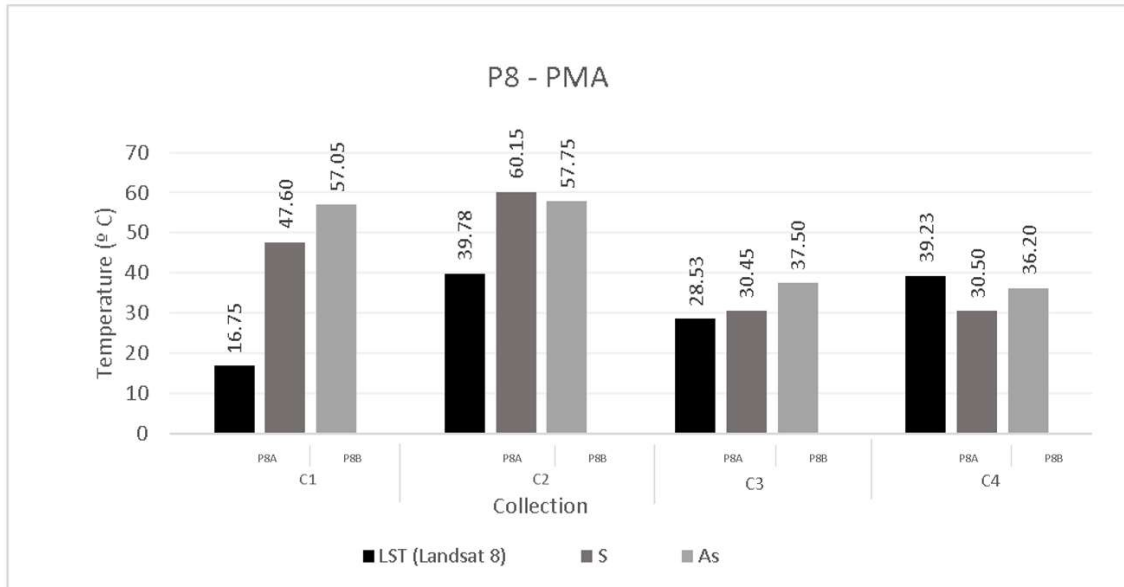


Figure 42. Analysis of the temperatures on the various sampled surfaces at point 8 (PMA).

In the UCZ UMR, area of isolated streets and medium-density buildings, point 2 presented similarity between the behavior of temperatures measured by Landsat 8 and thermal camera in all collections, except collection 1, in which the values recorded in the field were higher. It is worth noting that, in comparison with point 1, with vegetation, the temperatures in the morning presented lower maximum data, which may be associated with the UHI characteristic being more evident after sunset and because the anthropically altered areas take longer to heat up than the vegetated ones (Figure 43).

The maximum temperatures observed in the LULCs did not present great differences and, in collections 1 and 3, the anthropically altered surfaces presented higher temperatures [173–175]. The thermal behavior of the vegetation in spring resulted in a lower temperature than in other surfaces and, because it was spring, it was a period when the vegetation was not dry, which can corroborate the influence of green bodies in regulating the local temperature (Figure 43).

Point 10, showed equivalent temperature values between the anthropically altered surfaces (As and S). The Landsat 8 LST data were lower than the field collections, especially in collection 1, whose amplitude was higher (Figure 44).

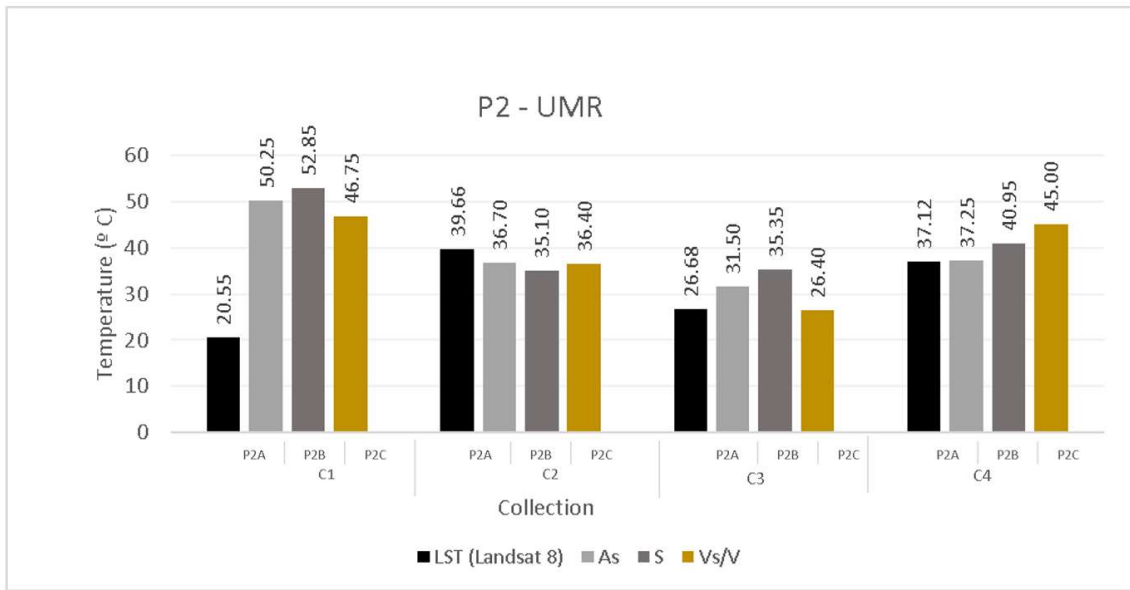


Figure 43. Analysis of the temperatures on the various sampled surfaces at point 2 (UMR).

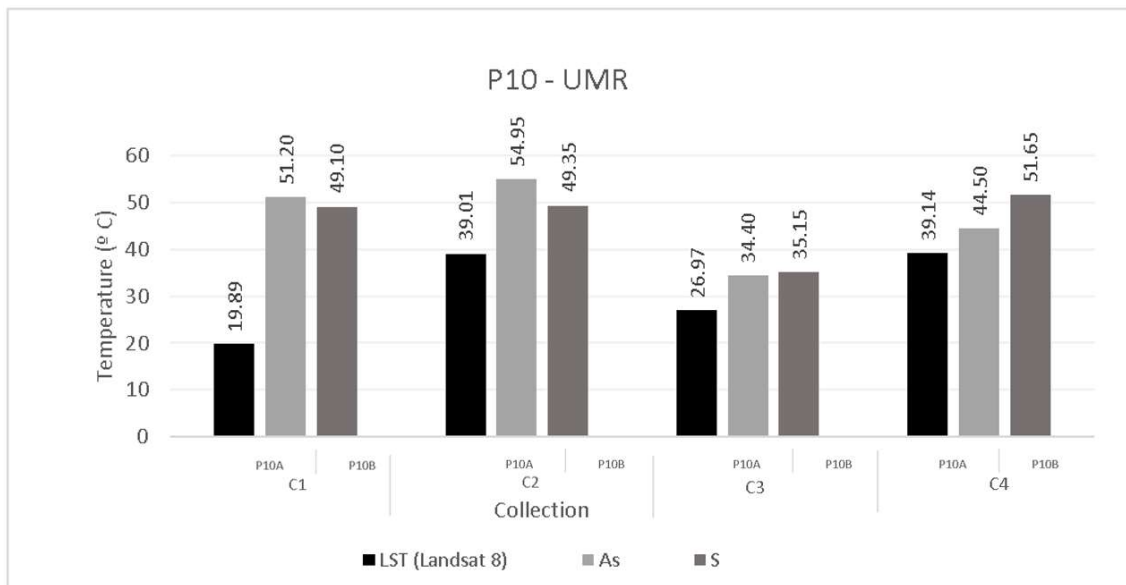


Figure 44. Analysis of the temperatures on the various sampled surfaces at point 10 (UMR).

Overall, it is observed that vegetated surfaces showed lower temperatures than anthropic ones, and, in addition to LULC, the configuration of the surroundings exerts influences on the results, since densely urbanized areas can corroborate to air circulation obstacles [155,160,173–176].

The results obtained from the in situ LST measurements showed higher temperatures compared to Landsat 8, which can be justified by the data collection methodology. The measurement of LST in situ (with the portable thermal camera) was performed on surfaces exposed to solar radiation and without shadow effects. On the other hand, data collection by the satellite thermal sensor occurs without considering this criterion, and the greatest differences recorded in an urban context may be

associated with buildings and other elements that cast their shadow over their surroundings.

The collection 4 took place with the presence of clouds in some points, but the weather forecast did not indicate a cloudy day and, for this reason, this date was considered in the analyses. Furthermore, the LST is a sensitive parameter and can interact with several factors besides soil composition and surface albedo, *i.e.*, any change regarding electromagnetic energy availability or minimization of wind speed and circulation at the site, can affect the LST values [116] which may justify its lower values, especially in collection 1 in heterogeneous zones, which reinforces the importance of including extra indicators to complement the information.

Analysis of LST (handheld thermal camera) differences between morning and afternoon collections

Regarding the LST measured with the thermal camera, at P1 (ZRE), the temperatures measured in the morning and afternoon did not show significant variations, per collection (Figure 45).

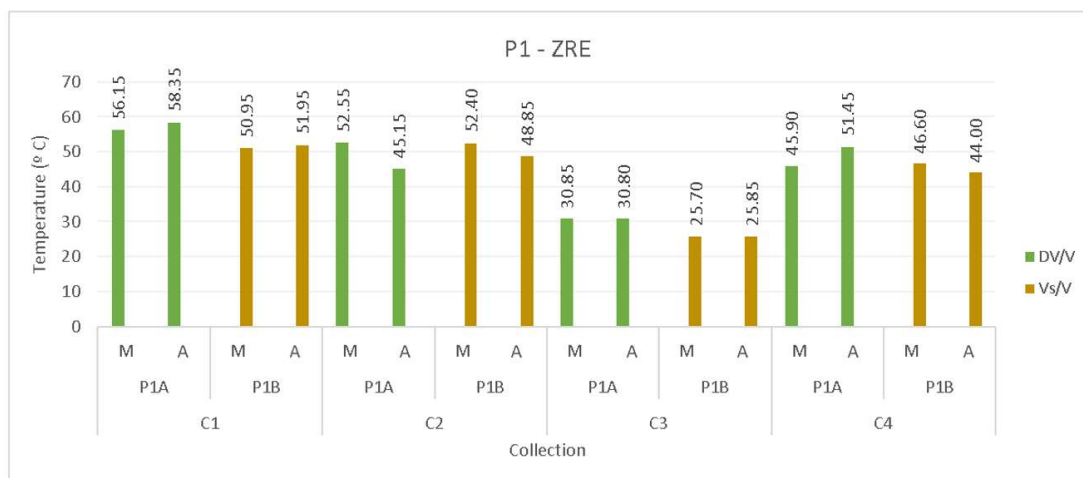


Figure 45. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P1 (ZRE).

As for the ZCS (commercial and industrial area), P3 showed higher temperature values in the afternoon collection, especially in the As and S areas (anthropic changes), except for collections 2 and 4, due to the presence of clouds on the day. In addition, it is observed that Vs/V, despite being the same type of surface as P1 - ZRE, the surface temperature was higher (Figure 46).

P6 showed higher temperature data in the afternoon collections for the AS and S surfaces, apart from surface P6B (As) at collection 4. This influence can be attributed

to the presence of clouds that may have also affected the temperature of P6A (V/DV) in the same collection. It is noteworthy that, in general, the temperatures on the V/DV surfaces were always lower than those observed in the anthropic areas, except for collection 3, which occurred in spring and the temperatures recorded in P6E (S) were the lowest (Figure 47).

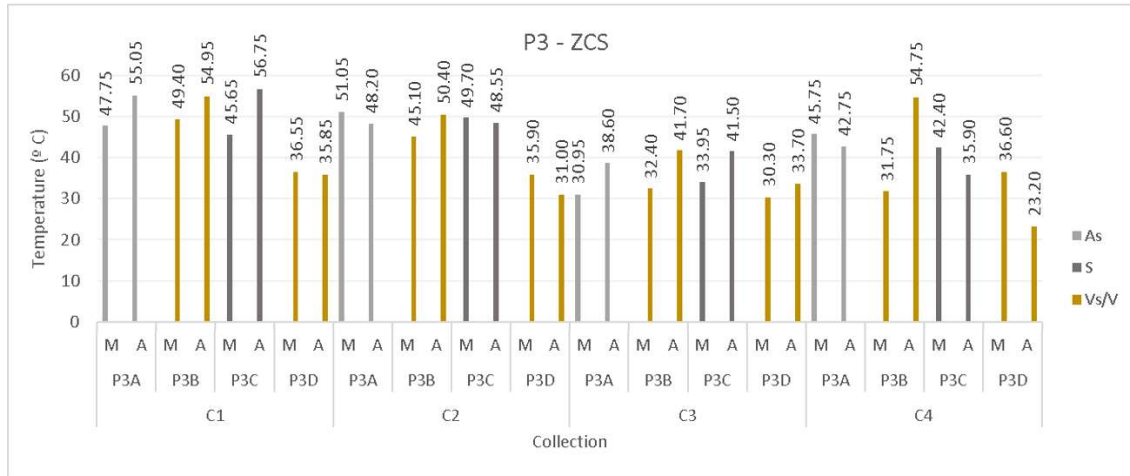


Figure 46. Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P3 (ZCS).

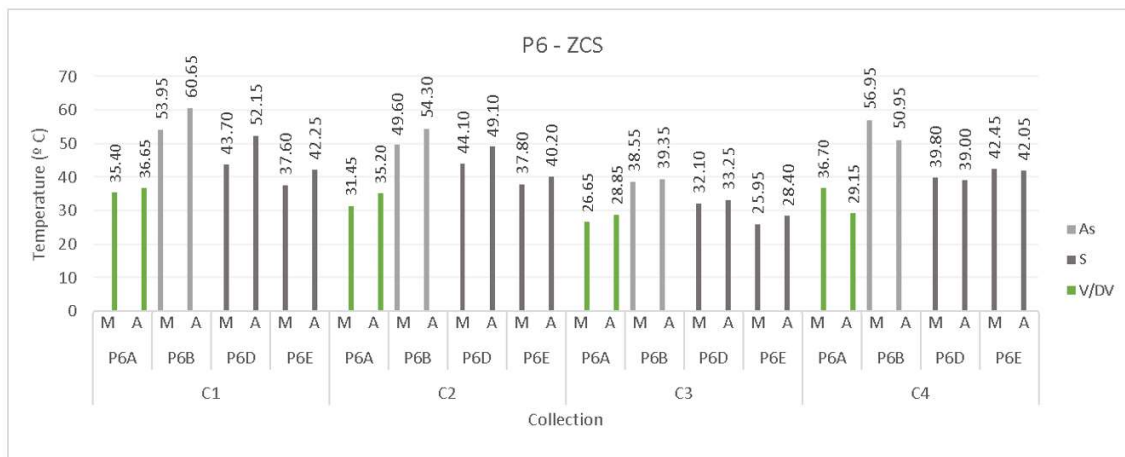


Figure 47. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P6 (ZCS).

In the TUR UCZ (transition between rural and urban areas), a higher temperature record is observed in all points, except for the last collection, where the temperatures were lower in the S and DVSt/VSt profiles. It is noteworthy that, in spring, the temperature ranges recorded on the surfaces were lower compared to the summer collections (Figure 48).

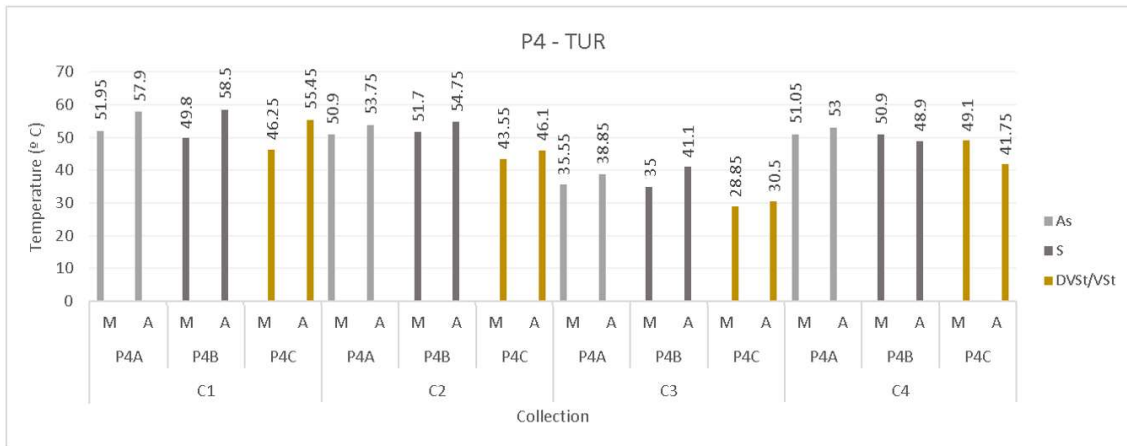


Figure 48. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P4 (TUR).

In P9, the temperatures in the V/Vs present slight variations between the morning and afternoon collection on the same day. Collection 3, where there was more variation, may be associated with the presence of clouds at the site. The values recorded at As were slightly altered between measurements, as occurred at P4. Since this is a transition area, the vegetation may act in regulating the local temperature (Figure 49).

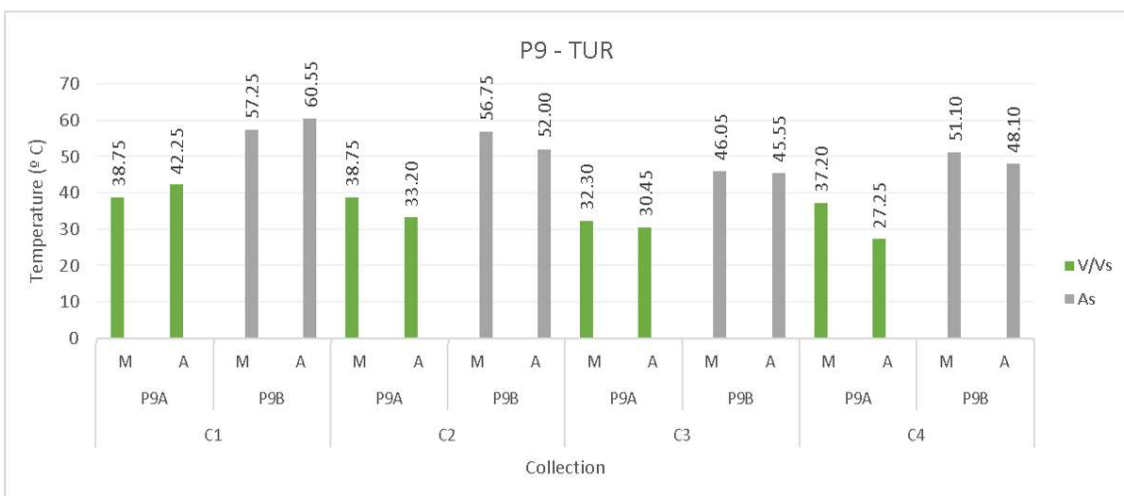


Figure 49. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P9 (TUR).

At P5, it is observed that the Vs/V surfaces showed higher LST values in the afternoon collections compared to the morning ones, apart from collection 2, which may be influenced by the clouds at the site. The V/DV surface was possibly affected, as in collection 2, where the temperature was lower than the first one in the morning. In general, the V/DV showed similar thermal behavior between the morning and afternoon collections (Figure 50).

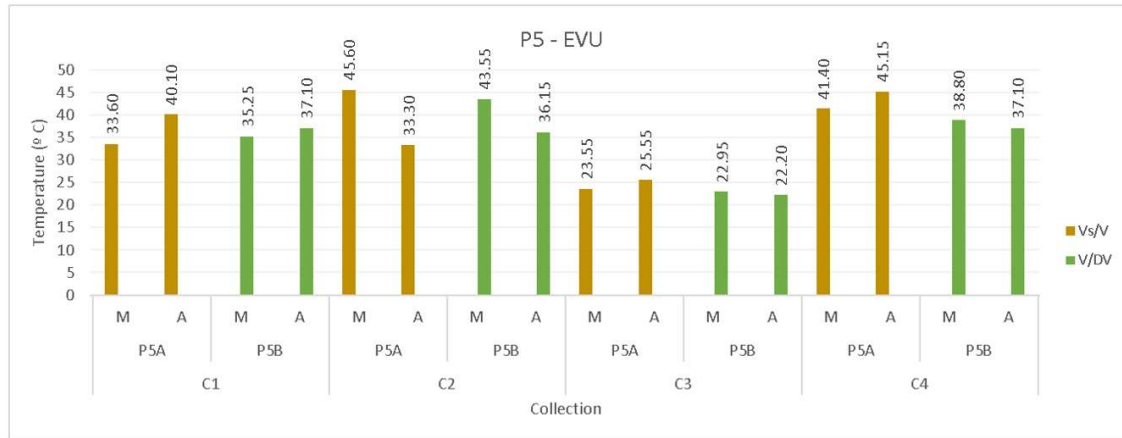


Figure 50. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P5 (EVU).

In the BDT (P7), both sidewalk profiles showed higher values in the afternoon collection, apart from P7A, in collection 2 (influence of clouds at the site). The temperature data were lower in the spring collection, corroborating the influence of seasonality on the data (Figure 51).

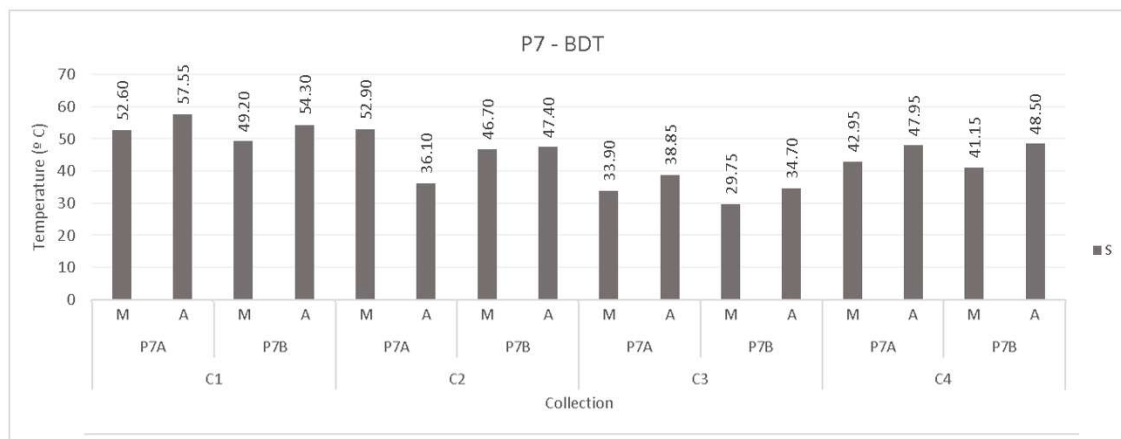


Figure 51. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P7 (BDT).

In PMA (P8), characterized by the presence of densely concentrated buildings, it was observed that the temperatures of the second measurement were lower, apart from collection 2 (clouds) and collection 3 (P8A - S), due to seasonality (Figure 52).

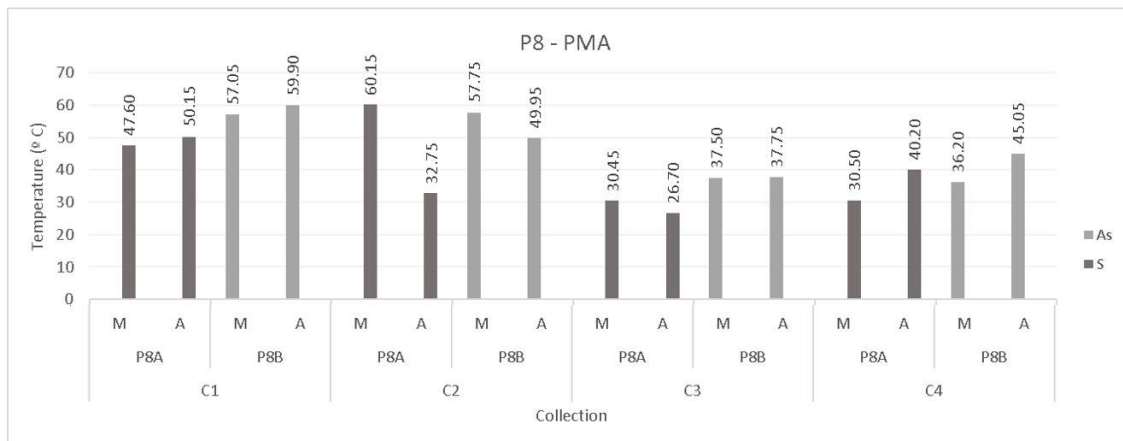


Figure 52. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P8 (PMA).

In the UMR (P2), where there is low-density construction, similar behavior of higher temperature register is observed in the afternoon, about the morning, except for P2C (Vs/V), in collections 3 and 4, which practically presented a similar behavior (Figure 53).

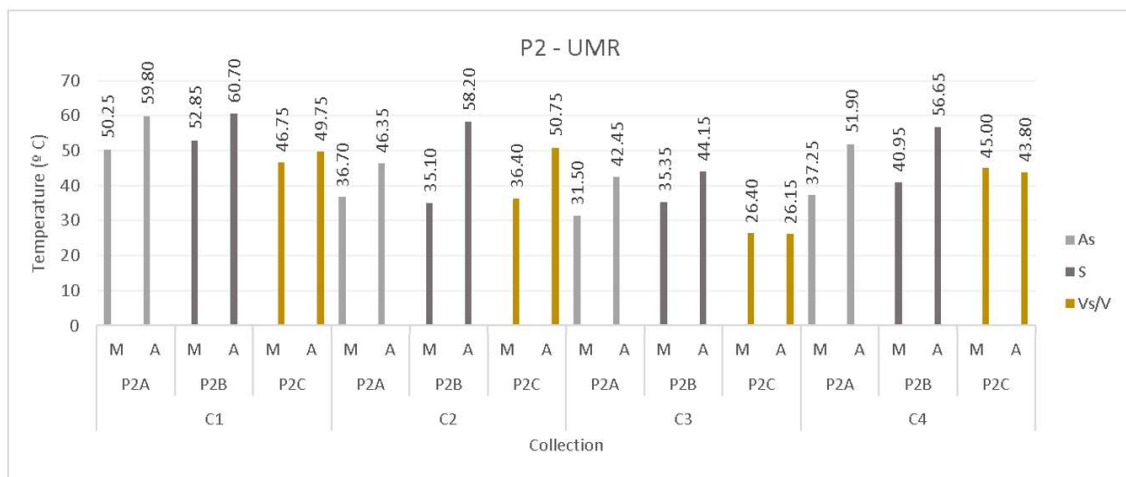


Figure 53. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P2 (UMR).

In P10, higher temperatures are observed in the afternoon collection, in comparison with the morning collection, except for collections 2 and 4 (presence of clouds) (Figure 54).

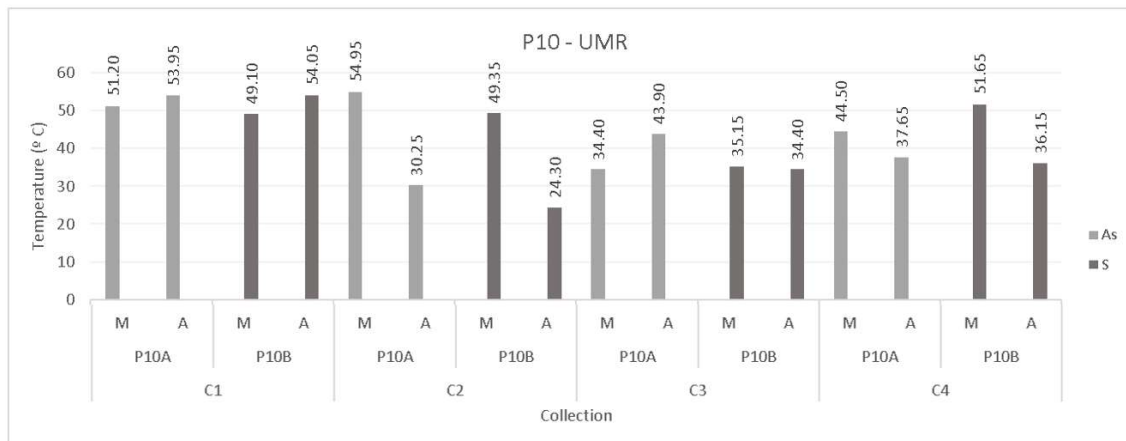


Figure 54. Surface Temperature data recorded at Morning (M) and Afternoon (A) collection, at each surface of P10 (UMR).

In general, the thermal behavior, especially of the anthropically altered surfaces, indicated higher temperatures compared to those with vegetation. Moreover, on days with the presence of clouds (collections 2 and 4), these same areas were more affected than the vegetated ones, which corroborates that clouds/shadow effects have a direct influence on thermal behavior.

Analysis of air temperature differences (fixed meteorological station) between morning and afternoon collections

The air temperatures showed variability between the field collections in most of the points, being more intense in the afternoon period, ratifying the importance of using RS data that can be collected at night to analyze the phenomenon. This behavior can be justified by the accumulation of electromagnetic energy that occurs throughout the day and that enhances the UHI effect in places with a considerable density of urban construction, especially after sunset [135].

Considering that there is a similarity in the behavior of the air temperature in most of the sensors, that is, higher values in the afternoon compared to the morning collection, the results that diverge from this observed pattern will be highlighted and discussed. In Figure 55 there is an equivalence between the behavior of air temperature at all points, being the temperatures measured in the afternoon higher than in the morning. Point 8 (PMA), showed the maximum value of air temperature of 31.15°C, in the afternoon. This UCZ consist of modern, high-density construction, which may have contributed to the increase in air temperature due to surfaces

materials (mostly low albedo), and obstacles regarding wind circulation and heat dissipation [177].

As for point 5 (EVU), the greatest amplitude of air temperature is observed, which may be associated with the existence of trees that can act as a natural obstacle to air circulation and, consequently, to the dissipation of absorbed heat (Figure 55) [172,178].

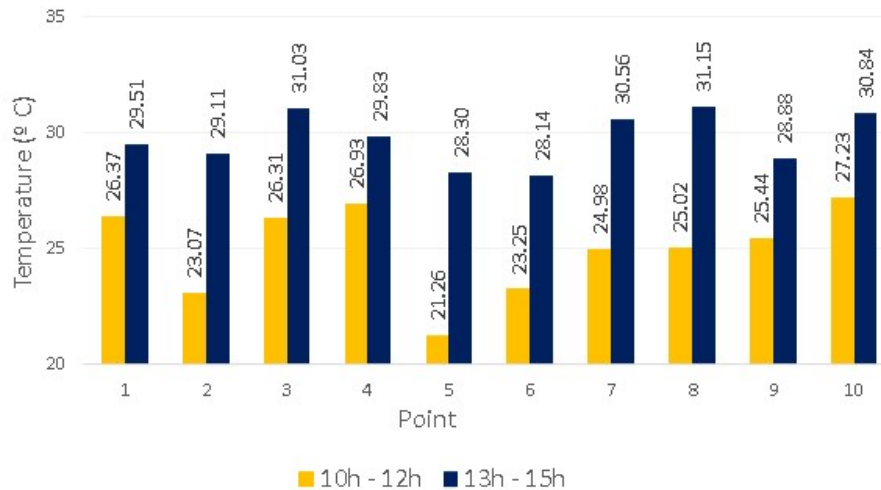


Figure 55. Analysis of the air temperature data collected in the morning and afternoon of collection 1 (08/03/2020 - Summer).

In Figure 56, a similar behavior was observed at point 5 with collection 1. Point 8 (PMA) also presented temperature data with considerable amplitude and, because it is an area with the presence of modern construction of medium-high height, high density, and paved surfaces, may be associated with difficulties imposed on air circulation [104,179,180].

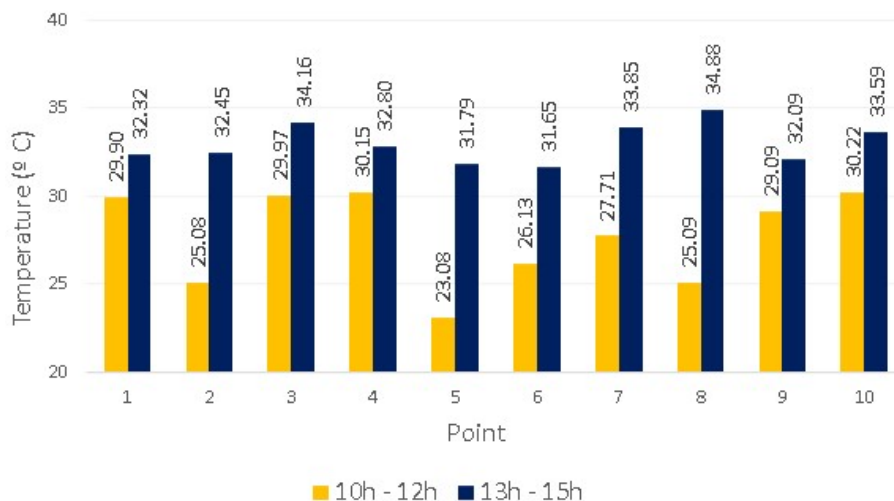


Figure 56. Analysis of the air temperature data collected in the morning and afternoon of collection 2 (04/09/2020 - Summer).

Figure 57 showed the air temperature with smaller amplitudes, comparing the morning and afternoon collections. This behavior may be associated with seasonality, since this collection occurred in spring and because it is a period with lower maximum air temperature, compared to the summer [176,181].

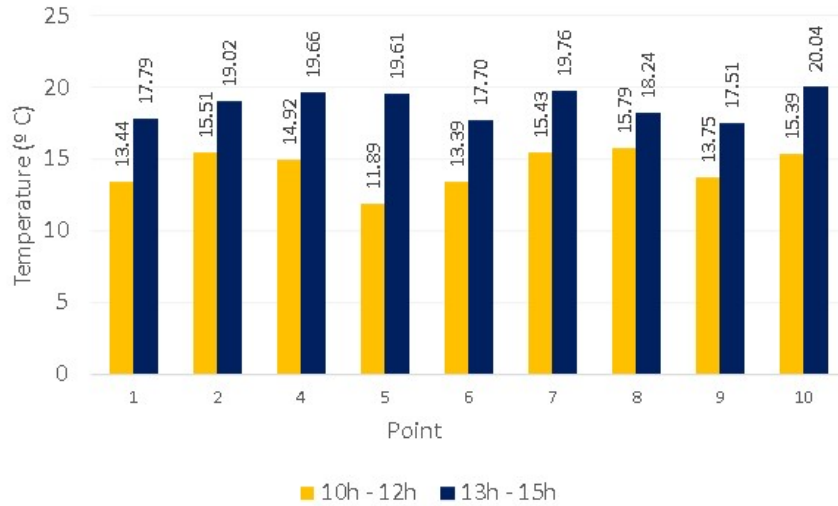


Figure 57. Analysis of the air temperature data collected in the morning and afternoon of collection 3 (04/16/2021 - Spring).

In Figure 58, it is observed a similar behavior to samples 1 and 2, with air temperature data higher in the afternoon compared to daytime samples. Point 5 showed similar behavior to the summer collections.

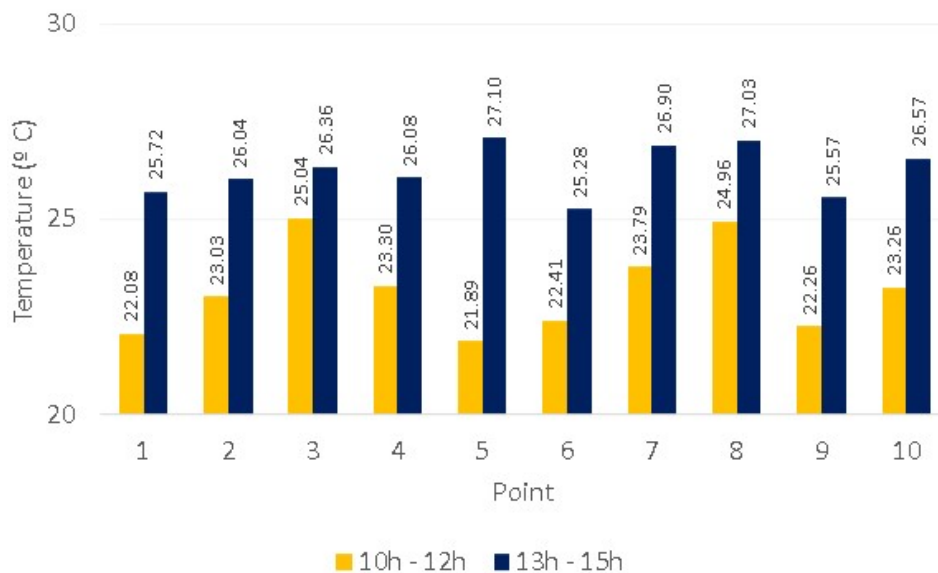


Figure 58. Analysis of the air temperature data collected in the morning and afternoon of collection 4 (07/05/2021 - Summer).

In the afternoon measurement, the data followed a typical urban gradient, corresponding to the formation of the UHI effect. About the morning period, this relationship assumes the inverse perspective (Urban Cold Island), similar to what was

discussed in the item “Analysis of LST (handheld thermal camera) differences between morning and afternoon collections”. Both effects are already identified in Bragança in previous studies and that corroborate the results identified in this thesis [18].

Wind Speed analysis (Portable Monitoring Equipment)

Regarding wind speed, it is observed that the last day of collection (07/05/2021) showed the highest values in all portable meteorological stations, with the highest results observed at station 4 (PMA). This behavior may be associated with the Venturi effect, recorded in street canyon contexts [182] (Figure 59).

The radiation balance of a site is associated with the constituent surfaces, which will be variable depending on shadows, street canyon floor, etc. The radiation emitted by walls is long-wave while the incoming (solar) radiation is short energy and depends on the orientation and reflective power of the surfaces. Therefore, the SVF influences the energy exchange at a site and is associated with the W and H of the canyon [183].

When considering a street, the temperature may be somewhat higher than that from above, due to the trapping of solar radiation. If the ambient flow is approximately perpendicular to the axis of a street canyon, a vortex can form, which will carry the ambient air down and the canyon air up the canyon. This mechanism causes the wind speed to be enhanced and, in the case of places with air contamination, can serve to transport the polluting elements to other places [183,184]. For this characteristic to be confirmed at this point, it is recommended that complementary field collections be carried out.

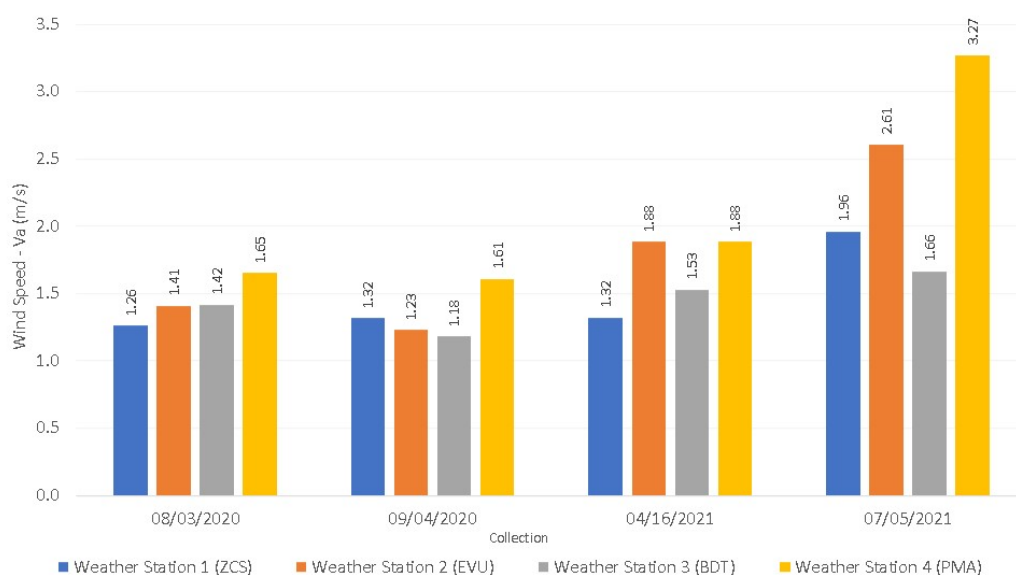


Figure 59. Comparison of wind speed at each portable monitoring equipment, per collection day.

However, it would be interesting to continue with the collection of more local data, to refine the mapping of the behavior of this parameter with greater accuracy, since it is expected that the highest speeds occur in flatter areas, as in EVU, which was also the portable monitoring equipment that showed higher wind speed results both in collection 3 and 4.

Tr analysis (Portable Monitoring Equipment)

Regarding the average Tr values calculated at the time of the satellite overpass, it is observed that there is an equivalence between the values measured in each of the collections, with the highest temperatures relating to the collections that occurred in the summer, confirming the influence of seasonality on a local scale.

Tr considers the heat that the surrounding elements emit from the radiation they release [185]. In a general analysis, it is observed that the data collected in the summer presented slightly higher temperatures than the spring collection, which shows that seasonality influences the results. In the last collection, the presence of clouds possibly affected the results, especially PMA (station 4), which showed the highest data in collections 1, 2, and 3. Being an area with medium and high-density construction, this behavior may be associated with the retention of solar energy in this UCZ (Figure 60).

The portable monitoring equipment 1 installed in the ZCS, which refers to the area of commerce and industry, showed similar results in all collections, except for 3, which may be associated with seasonality. As for the EVU, it is observed that the recorded data were similar to the data from ZCS (station 1) and BDT (station 3), except in collection 4, which presents the highest temperature of this collection (69.38 °C). In collection 4, lower results than those observed in the other summer collections were observed, which may be associated with the presence of clouds on that day. The station installed in the BDT showed temperature regularity in the collections performed (Figure 60).

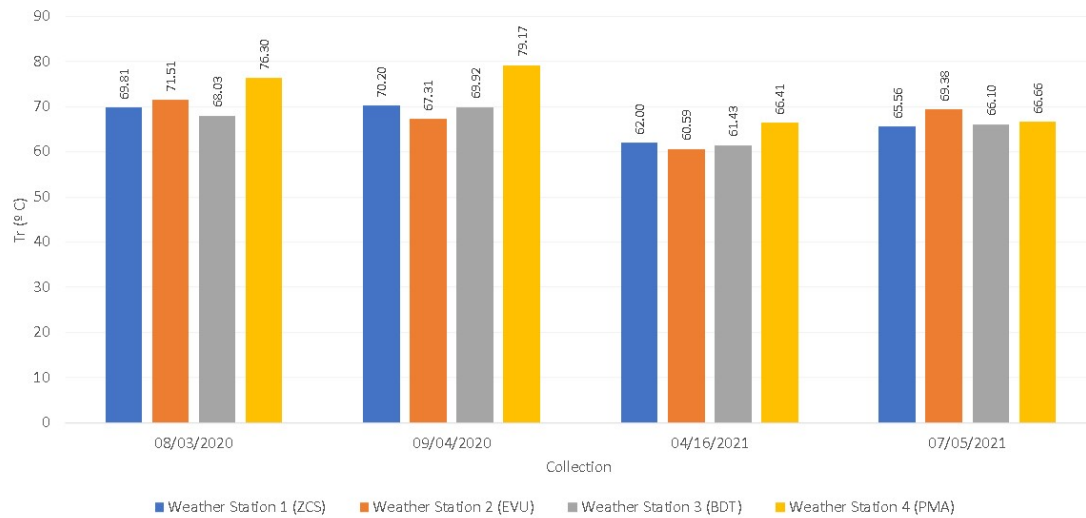


Figure 60. Comparison of Tr at each portable monitoring equipment, per collection day.

4.4. Linear Regression between Air Temperature (Fixed Weather Station) and LST (Landsat 8)

The p-value obtained in the regressions was analyzed to assess whether air temperature is a significant parameter for the model. Since all results were lower than 0.05 (which counters the null hypothesis that the parameter is neutral in the model), it was possible to proceed with the analyses of the results, by UCZ (Table 15).

Table 15. P-values obtained in the linear regression model.

Sensor	UCZ	All dates	Summer	Winter
1	TUR	2E-18	0.000	5E-08
2	EVU	1E-19	0.001	2E-07
3	PMA	2E-22	0.000	6E-11
4	BDT	1E-21	0.000	9E-07
5	ZCS	5E-21	0.001	9E-10
6	BDT	4E-20	0.001	6E-09
7	PMA	1E-18	0.008	2E-07
8	EVU	5E-21	0.001	2E-10
9	EVU	3E-23	0.002	4E-08
10	UMR	1E-24	0.000	8E-11
11	EVU	9E-20	0.008	2E-09
12	UMR	3E-18	0.002	6E-08
13	PMA	4E-17	0.015	4E-06
14	TUR	1E-17	0.000	2E-07
15	TUR	2E-21	0.001	6E-09
16	ZRE	2E-20	0.000	1E-06
17	ZCS	1E-19	0.001	1E-07
18	UMR	8E-24	0.000	6E-09
19	ZRE	1E-20	0.001	7E-09
20	ZRE	1E-22	0.003	2E-12
21	ZCS	2E-21	0.002	6E-11
22	BDT	4E-25	0.000	1E-12
23	ZRE	5E-23	0.000	1E-06

4.5. Coefficient of Determination (r^2)

The results of r^2 demonstrate that, when using all data for winter and summer, it is possible to predict air temperature (weather fixed station) from the LST data (Landsat 8) in all sensors, with explainability starting at 65% (lowest value observed in sensor 13 - PMA) (Figure 61).

Considering the UCZs, sensors 1, 14, and 15 (TUR), presented similar explainability results, with 68, 67, and 74%, respectively. Sensors 4 and 6 (BDT) presented higher explainability results, with 75 and 72%, respectively. This behavior may be associated with the variety in the surface composition in each of the classes, since TUR refers to a transition space between urban and rural areas and BDT to the old traditional city center, with the presence of anthropogenic elements, mostly, *i.e.*, more heterogeneous surfaces (Figure 61). To ratify this association, it is recommended that further studies be conducted, including the incorporation of urban variables of each sensor in regression models, to assess whether there is influence and at what level it occurs, as performed in other studies of UHI.

About sensors 2, 8, 9, and 11 (EVU), they had the result of 71, 74, 81, and 74% of explainability. Sensors 3, 7, and 13 (PMA), on the other hand, presented results of 76, 69, and 65%, respectively. Despite being UCZs with opposite characteristics of surface composition, since the first is an urban space and the second a modern medium-sized construction, it is possible to verify that the explainability of the EVU is higher than the PMA. To explain this result it is suggested that further analyses be performed in future studies. (Figure 61).

Sensors 10, 12, 18, and 22 (UMR), showed explainability of 80, 68, 78, and 80%, respectively. Sensors 15, 17 and 21 (UCZ), resulted in 74, 74 and 75% explainability and sensors 16, 19, 20 and 23 (ZRE), accounted for 72, 73, 76 and 77%, respectively. These three UCZs showed similar behavior in the results, with the highest representatives observed in the UMR sensors (except for 12), which have isolated building surfaces of medium density (Figure 61).

Regarding the adjusted r^2 , it is observed that the software maintained the percentages of model explainability, except for sensors 2, 4, 5, 8, 12, 14, and 21, which decreased by 1% after the parameter adjustments by RStudio (Figure 62).

Considering seasonality, it is observed that in summer the explainability of air temperature is lower than in winter. In addition, a large part of the sensors in the same UCZ presented variable data. This behavior may be associated with the smaller number of observations and the greater homogeneity of the data in winter, compared to those of summer (Figure 63).

Sensor 13 (PMA) was the one that presented the lowest explainability, both in summer and winter (14 and 59%, respectively). Sensors 1, 14, and 15 (TUR) showed similar data in winter (70, 67, and 75%) and in summer (28, 27, and 24%).

In the BDT sensors (4 and 6), in summer the air temperature could be explained from the LST with 29 and 23%, respectively. In winter, the results were 64 and 76%, respectively. Regarding sensors 2, 8, 9, and 11 (EVU), the first three presented 24% explainability, while for the last one, was 18%. In winter, the results were 69, 82, 75, and 79%. It can be seen that the winter results, despite being higher, were less homogeneous than in the summer. Sensors 3, 7, and 13 (PMA), showed results of 30, 16, and 14% in summer, and 84, 69, and 59% in winter. Sensors 10, 12, 18, and 22 (UMR), showed explainability of 33, 20, 32, and 28% in summer and 79, 71, 76, and 88% in winter. Sensors 15, 17 and 21 (ZCS) resulted in 26, 25 and 21% in summer and 76, 70 and 84% in winter (Figure 63). Regarding the adjusted r^2 , no drastic changes in explainability are observed, as occurred with the overall data. Sensors 1, 10, 16, 19 varied, negatively, by 1% and sensors 2, 3, 4, 5, 6, 7, 8, 9, 11, 12, 13, 14, 15, 17, 18, 20, 21, 22, 23, by 2% (Figure 64). The values generated in each linear regression can be found in Appendix XI of this work.

Despite the low explainability indicated by the model, especially in the summer, it should be reinforced that there is consistency between the values measured in both air temperature and LST, as proven by the statistical tests applied previously, in which none of the results showed a negative correlation. Although the average values of both parameters are greater in the summer (as observed in the item “Temperature difference between air temperature (fixed weather station) and LST (Landsat 8)” the factors that influence heat storage are different and the LST suffers more influences from the constitution of the surface material, which may have influenced the low applicability of the model, despite the existence of consistency between the parameters [165].

Moreover, when comparing air temperature (fixed weather station) with LST (Landsat 8), which are different thermal evaluation variables, scale is also a factor that must be considered, especially because air temperature is influenced by the urban context (as it is in LST), but also by the characteristics of the microclimate of the site, which can assume variations in a short distance, as observed in the results obtained with the thermal camera (item “Analysis of the LST on the various sampled surfaces (LST obtained by Landsat 8 and the manual thermal camera)” [122].

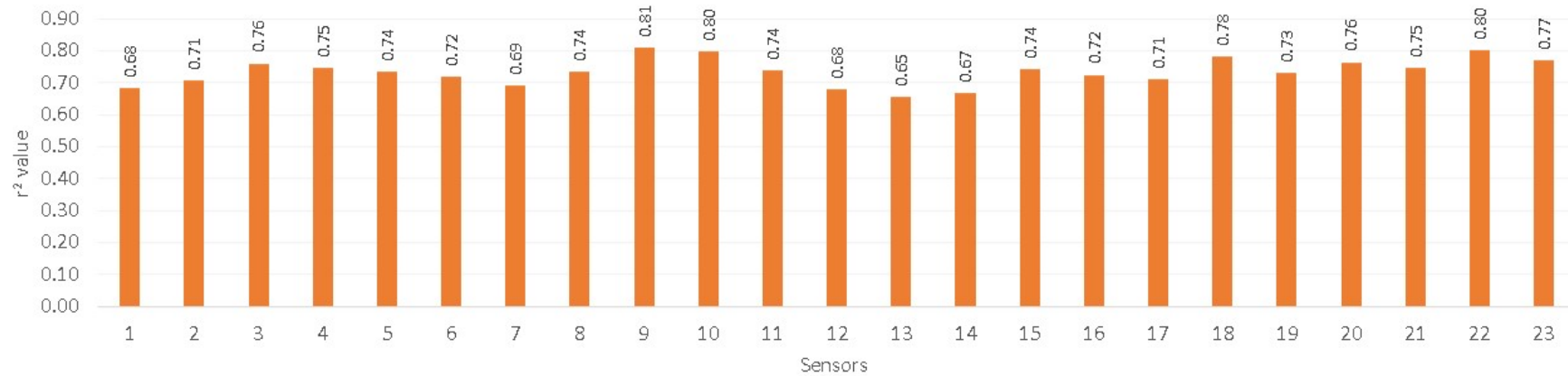


Figure 61. R^2 refers to the linear regression model between air temperature (measured at the fixed meteorological network) and the LST (Landsat 8).

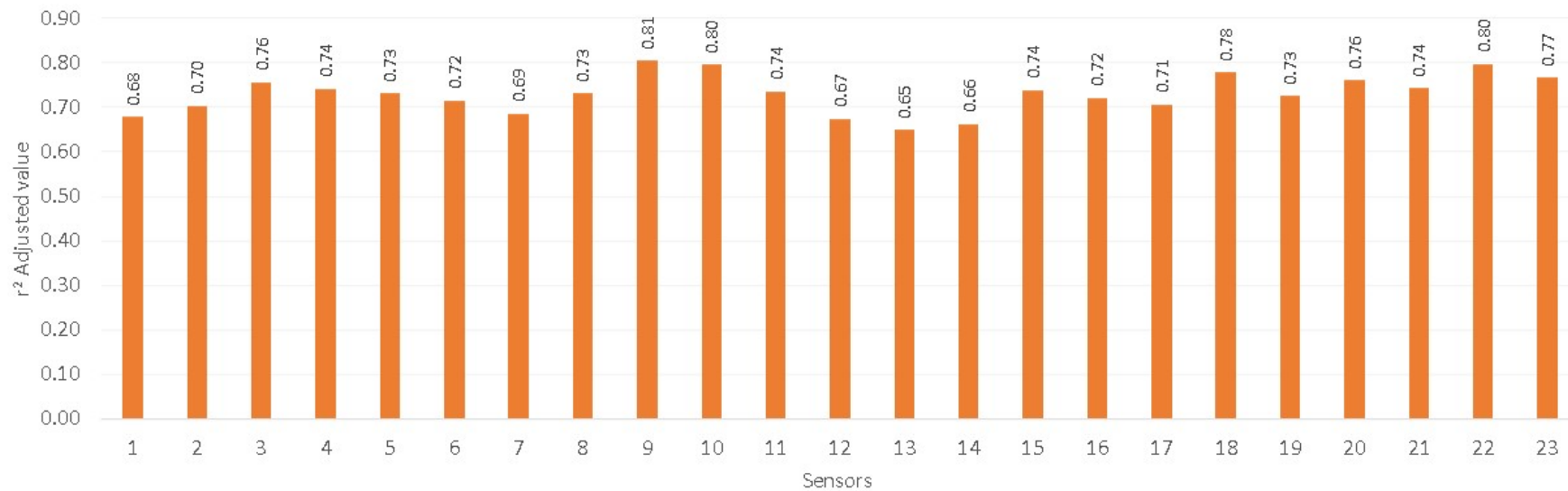


Figure 62. R^2 adjusted referring to the linear regression model between air temperature (measured at the fixed meteorological network) and the LST (Landsat 8).

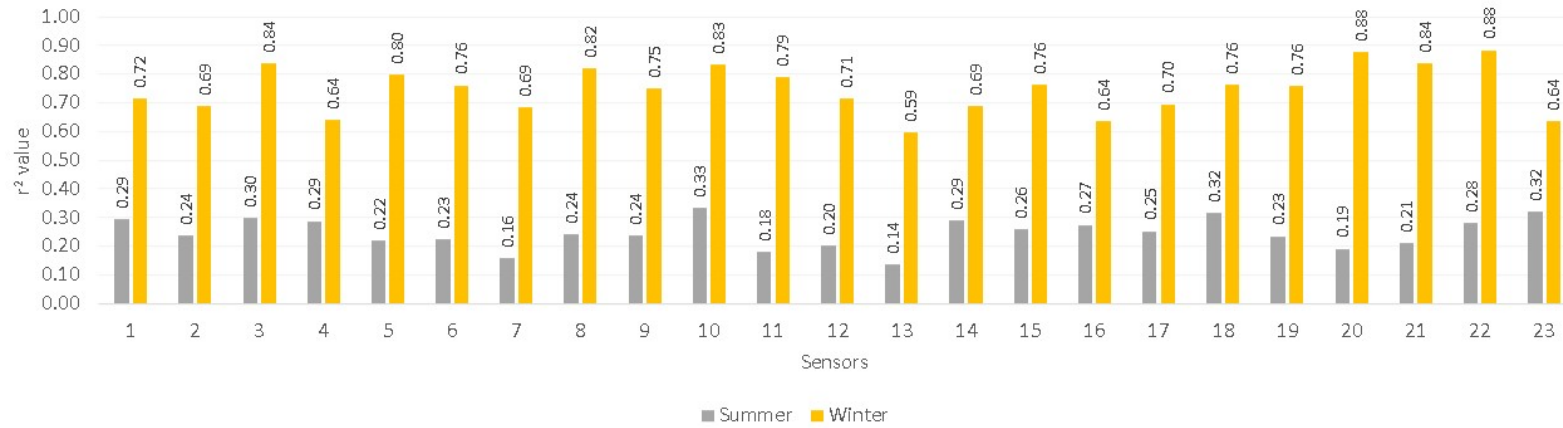


Figure 63. R^2 refers to the linear regression model between air temperature (measured at the fixed meteorological network) and the LST (Landsat 8) – Seasonality.

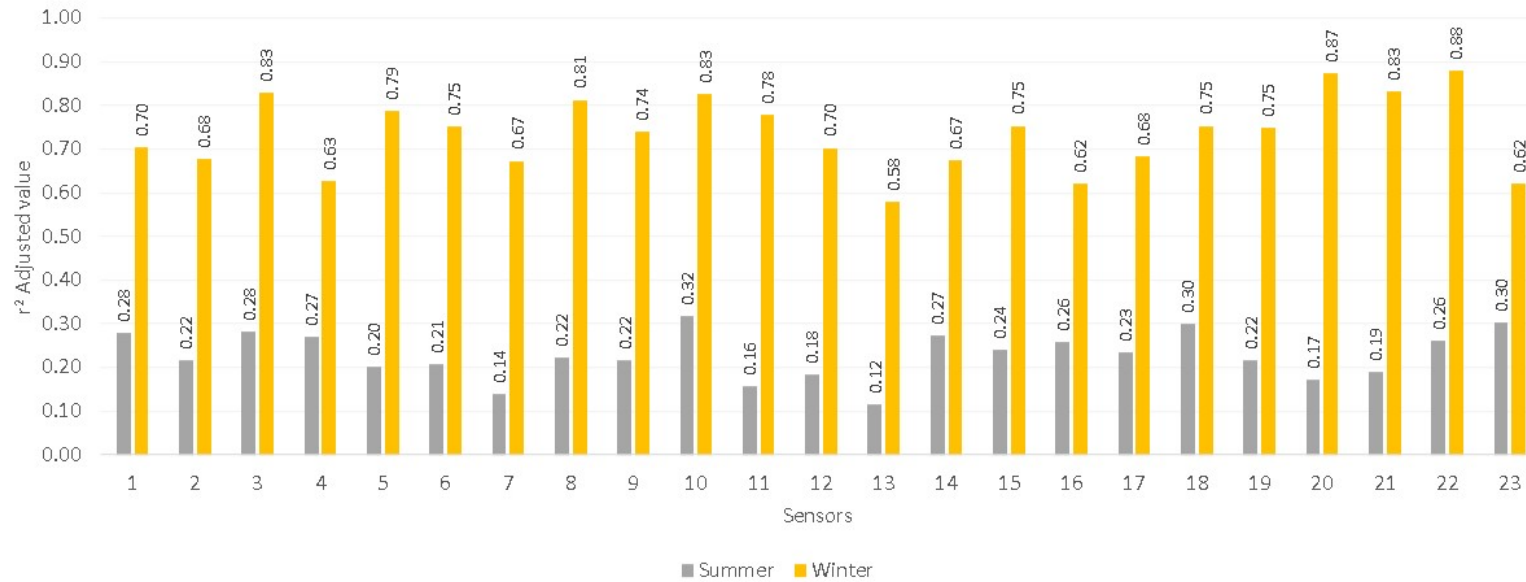


Figure 64. R^2 adjusted referring to the linear regression model between air temperature (measured at the fixed meteorological network) and the LST (Landsat 8) – Seasonality.

CHAPTER 5

5. Conclusion

Studies based on climate change and the analysis of its impacts on microclimates are a growing trend. The UHI, an effect that increases temperatures in places with a higher density of urban construction compared to the surroundings and that can promote impacts on the health and welfare of a population, has been increasingly studied and associated with public policy measures focused on its mitigation.

Because it is an effect with transversal influence, its identification, and analysis, especially in mountainous regions, as in the case of Bragança, becomes a methodological challenge since its formation is associated with several direct and/or indirect factors. For instance, the mountainous configuration of Bragança, added to the urban density, especially in the city center, corroborates the intensification of the effect, which has been previously identified through scientific research developed in the region, using data from fixed meteorological stations installed in the city.

Aiming to complement the studies carried out in Bragança, this work used a multivariate methodology, including the use of GEE software, RS and fixed meteorological network data from 2013 to 2021, with additional field data (meteorological network and portable thermal camera), in addition to qualitative and quantitative analysis of the UHI, at different spatial scales. For the collection *in situ*, the selection of sites prioritized the diversity of UCZs (established in previous studies).

Considering the specificities and different origins of the data used, the processing was challenging, since it was intended to maintain the integrity of the analysis and adopt the most pertinent and scientifically adequate methodology for each case.

Starting with the GEE software, it was possible to compute the LST from Landsat 8, optimizing the computer's processing time and capacity. The collection used with the application of atmospheric and cloud corrections was an added value, since it allowed the use of standardized raw data, with minimization of climatic influences and subjective effects that could be associated with the calculation of each scene, individually.

The integration of several data made it possible to obtain more detailed information of the study site and to overcome some limitations inherent to using one technique, with the addition of complementary results.

By incorporating LST data obtained by the handheld thermal camera, with lower IFOV and, consequently, with a higher of spatial detail, some of the surfaces could be mapped, considering the transition zones and the different LULC.

Regarding the analysis of the results, it is observed that seasonality (winter and summer) was identified in all data. This behavior can be justified as a function of the amount of electromagnetic energy available for exchange with the environment, which reaches greater amplitudes during the summer. The thermal behavior of the surfaces in winter showed less heterogeneity concerning the summer data, both in the boxplot and the linear correlations. It is reinforced that the sample n for this season was smaller, due to the need to disregard 12 scenes in winter versus 5 in summer, due to LST results lower than $-5.00\text{ }^{\circ}\text{C}$. Despite ensuring the representativeness of at least one scene in summer and one in winter in each of the years, the difference in the n may have influenced the results, which recommends a standardization in future studies.

Regarding the air temperature variation for the LST (from Landsat 8), a larger amplitude is observed in the summer. Although they are different parameters and do not necessarily present a strong correlation between them, since the result of the LST (satellite) depends on the characteristics of the surface, how heterogeneous is the site of analysis, and their respective albedos, the results obtained in this work showed “strong” and “very strong” correlation in all sensors.

In the summer, approximately 74% of the results showed a “strong correlation” and 26 % showed a “very strong” correlation between the air temperature and LST (Landsat 8). In the winter, all data showed a “strong correlation”. The observed differences point to the influence of seasonality, where the air temperature data and the LST are more convergent when considering winter measurements. Considering that the UHI is a phenomenon affected by several parameters, the availability of electromagnetic energy in the summer for longer periods and at a solar angulation that corroborates for energy storage, can be a justification for this behavior. In addition, as the number of observations considered in winter was lower than in summer, this may have influenced the results. It is worth mentioning that, because they are considerable correlations (strong and very strong), RS data/techniques proved to be an effective complementary methodology for UHI studies in Bragança.

As for the UHI, it was not possible to identify the effect due to the time of Landsat 8 overpass in Bragança, which occurs near the solar nadir (11h15 UTC). Due to the obstacles inherent to anthropic areas (urban canyon, the albedo of surface materials, roughness, shadows projected by buildings, etc.), the availability of electromagnetic energy is higher in horizontal areas (such as rural areas) and

temperatures (both air and surface temperatures) are higher in more vegetated areas when compared to anthropically altered areas.

This effect, called the Cooling Island Effect, is the complementary opposite to the UHI_{int} , *i.e.*, the construction areas present air temperatures and LST lower/approximate to those recorded in the vegetated areas, in the early morning hours, which coincides with the time of Landsat 8 passage. This behavior was identified in the UHI_{int} results for both LST (Landsat 8) and air temperature (fixed weather station), *i.e.*, the effect is observed at different analytical scales, since the fixed sensors collect air temperature information at the micro-scale and Landsat 8 records information at a level closer to the UCZ scale. This equivalence ratifies the possibility of integrating RS data in UHI studies, which presented itself as a possible technique for validation, with field data.

For the UHI effect to be evident in the results, it is recommended that thermal data obtained from sunset, from satellite missions (thermal sensor or microwave) or by conducting local data collection campaigns, with UAVs, be considered.

The correlation of the UHI_{int} data from LST (Landsat 8) with the LST data (Landsat 8) recorded from the other sensors was "very strong" and positive, which may indicate that the differences in thermal behavior are associated with surface albedo, LULC, roughness, permeability, and other urban parameters.

As for the local measurements, although none of them were performed in winter, due to the limitations imposed by both the pandemic and the weather conditions, seasonality can be assessed, on a local scale, by considering the three summer collections and one in spring.

The LST analysis obtained by the thermal camera showed higher temperatures in anthropically altered surfaces when compared to vegetated areas (even dry vegetation). The afternoon collections showed mostly higher temperatures when compared to the morning ones, especially on the anthropically altered surfaces. Seasonality influences the LULC characteristics (like in the vegetation), as well as the thermal behavior of the surfaces since the lowest maximum temperatures were recorded at spring.

As for the wind speed parameter, not very discrepant results were observed, except for the last collection, that the highest speed was associated with the PMA (3.27 m/s), which may be associated with the Venturi phenomenon, is recommended to be studied in future studies. It is worth noting that wind speed is a relevant parameter from the point of view of heat propagation. Tr also followed the same behavior and did not present significant differences in the results, although station 4 (PMA) presented the highest temperatures relative to the samples 1 to 3.

Regarding the linear regression and the determination coefficient, it is observed that the air temperature is a relevant parameter in the equation (considering the calculated p-value) and that it is possible to obtain its estimated values from the LST data, especially when using all the data and the winter data. Again, the summer data present lower predictive/explainability values compared to winter.

Considering the results in general, the adopted methodology enabled the analysis of air temperature and LST, from RS data and collected in situ, with similar behavior, at different scales. The complementation of the UHI study with freely available data/tools (such as data from Landsat missions and software like GEE, RStudio), can be an added value and corroborate for studies in other areas and contexts.

It is worth noting that the study of urban climate transcends urban geometry and surface materials and includes the dynamics of housing, commerce, industry, vehicle circulation, which corroborates the complexity and the need to develop public policies aimed at minimizing the impacts that can be caused to the local population and the environment.

5.1. Limitations and Future Research

The study of UHI in its essence is challenging since it involves several external factors that can influence the local thermal behavior. As the methodology adopted in this work can be considered innovative, since it used data from different sources and scales, besides testing the efficiency of the GEE software in estimating the LST from Landsat 8, some limitations were identified and will be presented in this item.

Initially, the available literature integrating data from RS, meteorological stations (fixed and portable), and portable thermal camera for studies of UHI is restricted, which culminated in the need to adapt studies with other focuses to complement the bibliographic references (such as papers focused on ML, from the study of other climatic phenomena).

As for external influences, the atmosphere was a limiting factor for the selection of RS thermal data to be treated, especially in winter and with the intense presence of clouds. Although the collection available from GEE includes atmospheric correction models, of the 87 Landsat 8 scenes, 17 were disregarded due to LST results of less than -5.00°C . Of these, 12 (70.60%) were winter scenes (which can be justified due to the higher occurrence of rainfall and cloudiness at the site).

The addition of complementary techniques could be a way to minimize this limitation, such as the local thermal mapping using data from UAVs, which, due to the

altitude of the flight, does not suffer the same atmospheric influences as satellites. However, the presence of clouds would also affect the data collection due to possible shadows on the surface targets. Furthermore, as there is no scheduled revisit time like Landsat 8, it would not be possible to work with historical data, nor to perform a municipal level mapping, due to the extension of Bragança.

An alternative regarding the shadow effect is to conduct night flights, for instance, considering UAVs. In this period, the UHI tends to be more intense, and the results could complement the literature and methodologies for studying the effect. In addition, at night there is no shadow effect associated with the positioning of the Sun and the objects/buildings analyzed, which makes the SVF more stable and the analysis of the UHI, more coherent.

Still, regarding climatic influences, some local collection campaigns were not performed due to days with a dense cloud presence. Additionally, due to COVID-19, circulation between Counties was limited, which made it impossible to acquire data in winter. As the goal is to proceed with the research, it is expected that this limitation will be overcome, and that winter data will be acquired to enable an analysis of local seasonality from field validation data.

As for the statistical treatment, considering that this study was preliminary in the use of RS data for UHI analysis, the maximum number of observations in each season was considered. As the number sample was higher in summer compared to winter, in the next analyses it would be interesting to evaluate if the observed thermal behavior is recurrent or if it is necessary to perform methodological adaptations, considering the same n in all seasons.

In addition, correlation methods were applied to the data processed in SPSS, a technique commonly used in long time series with 5% of the total data missing. However, to enable further discussions, it is recommended that the correlations are also applied to the database without filling in the omissions, considering at least one sensor of each UCZ, and evaluate if there is variation in the results obtained.

As for data collection in the field, since the objective was to map different surfaces, the number sampled at each point is different (more heterogeneous areas had more sampled surfaces). In the continuity of the work, it is recommended to standardize them, especially when the data of the average thermal behavior of an area is used in the analyses, even if surface points of similar structures are collected.

As for the classification of the UCZs, in some proposed analyses, similar thermal behaviors were noticed, even with different classifications. The classification methodology followed the one recommended by Oke and Stewart (2012), but needs periodic updates, since the urban context is dynamic and it is necessary to minimize

subjectivity in the observation of parameters, such as building height, wind speed, and direction, etc.

Updating the parameters used in the classification of the UCZs (urban variables) can provide complementary analyses for the regression models. With this level of local detail, it is possible to assess if/how the behavior of air temperature and LST at each point is influenced by local urban variables.

One way to update the UCZs optimally and minimize subjectivity is to include, in addition to qualitative/observational parameters, techniques based on Artificial Intelligence (AI), such as ML for LULC classification (supervised and unsupervised classification), to map the main soil changes. Complementary parameters such as VIs, aspect, and hillshade maps can also be considered in the processing to present more detail on LULC.

The use of RS data as complementary tools for detailing the LULCs also allows one to obtain continuous data, which can be analyzed with the LSTs (also continuous) and allow the application of spatial statistical analyses, such as the GWR, which assigns weights and calculates the influence of parameters concerning an observed spatial behavior.

It is worth noting that the spatial scale will depend on the resolution of the sensor acquiring the data and that it is possible to integrate satellite missions to complement the data (such as Sentinel-2 and Landsat). It also allows historical analyses to be carried out/extended, depending on the period of their revisit of each. Sentinel mission does not collect thermal data and that inclusion in the analyses would be to complement optical information.

Regarding the modeling of local thermal behavior, it is recommended that in future studies the parameters of morphology, wind speed, and direction, LULC, etc., applied in the classification of UCZs, should be considered in regression models, aiming at explain/predict the UHI as a function of specific local characteristics.

Furthermore, it is suggested that a more detailed analysis regarding the Bragança monitoring network sites should be performed, to complement the understanding of some of the presented results and to glimpse methodologies that can be adopted to complement the analyses at the local micro-scale level. In addition to applying altitude corrections to the air temperature data, to evaluate the influence of this parameter on the results.

Reference

1. Nations, U. The 17 Goals Available online: <https://sdgs.un.org/goals> (accessed on Aug 31, 2021).
2. Duarte, D. Padrões de ocupação do solo e microclimas urbanos na região de clima tropical continental. *Pós. Rev. do Programa Pós-Graduação em Arquitetura e Urban. da FAUUSP* **2000**, 88, doi:10.11606/issn.2317-2762.v0i9p88-107.
3. Oke, T.R. The energetic basis of the urban heat island (Symons Memorial Lecture, 20 May 1980). *Q. Journal, R. Meteorol. Soc.* **1982**, 108, 1–24.
4. Stewart, I.D.; Oke, T.R. Local climate zones for urban temperature studies. *Bull. Am. Meteorol. Soc.* **2012**, 93, 1879–1900, doi:10.1175/BAMS-D-11-00019.1.
5. Imhoff, M.L.; Zhang, P.; Wolfe, R.E.; Bounoua, L. Remote sensing of the urban heat island effect across biomes in the continental USA. *Remote Sens. Environ.* **2010**, 114, 504–513, doi:10.1016/j.rse.2009.10.008.
6. Arnfield, A.J. Two decades of urban climate research: a review of turbulence, exchanges of energy and water, and the urban heat island. *Int. J. Climatol.* **2003**, 23, 1–26, doi:10.1002/joc.859.
7. Grimmond, C.S.B. Progress in measuring and observing the urban atmosphere. *Theor. Appl. Climatol.* **2006**, 84, 3–22, doi:10.1007/s00704-005-0140-5.
8. Gawu, L. Relationship between Surface Urban Heat Island intensity and sensible heat flux retrieved from meteorological parameters observed by road weather stations in urban area. **2017**, 19, 16820.
9. Hanifah, M.; Mohmadisa, H.; Nasir, N.; Yazid, S.; Saiyidatina Balkhis, N. Mapping of Student Sustainable Development Education Knowledge in Malaysia using Geographical Information System (GIS). *World J. Educ.* **2018**, 8, 27, doi:10.5430/wje.v8n1p27.
10. Voogt, J.A.; Oke, T.R. Thermal remote sensing of urban climates. *Remote Sens. Environ.* **2003**, 86, 370–384, doi:10.1016/S0034-4257(03)00079-8.
11. Weng, Q.; Fu, P. Modeling annual parameters of clear-sky land surface temperature variations and evaluating the impact of cloud cover using time series of Landsat TIR data. *Remote Sens. Environ.* **2014**, 140, 267–278, doi:10.1016/j.rse.2013.09.002.
12. Almeida, C.M. de Aplicação dos sistemas de sensoriamento remoto por imagens e o planejamento urbano regional. *Rev. Eletrônica Arquitetura e Urban.* **2010**, 98–123.
13. Pachêco, A.P. Sensoriamento Remoto na Faixa espectral do Infravermelho

- termal (8 - 12 μm) Available online: <https://agencia.ufpe.br/documents/39451/1778670/GEODE'SIA+online+++++2%252F2001.pdf/1a8b61d5-da8c-487e-9103-485313f03aa7> (accessed on Jan 4, 2021).
14. Oke, T.R. *Boundary Layer Climates*; Routledge, Ed.; 2nd ed.; London, 1987; ISBN 0203407210.
 15. Almeida, C.R. de; Teodoro, A.C.; Gonçalves, A. Study of the Urban Heat Island (UHI) Using Remote Sensing Data/Techniques: A Systematic Review. *Environments* **2021**, *8*, 105, doi:10.3390/environments8100105.
 16. Rodrigues, C.; Teodoro, A.C.M. Relationship between the land surface temperature and the vegetation proportion to identify Heat Islands. Case study of Brasília (Brazil). In *Proceedings of the Earth Resources and Environmental Remote Sensing/GIS Applications XI*; Schulz, K., Nikolakopoulos, K.G., Michel, U., Eds.; SPIE, 2020; p. 34.
 17. Menezes, G. de O. *Análise do Clima Urbano da Cidade de Bragança (2012-2016): Estudo da Ilha de Calor*, Instituto Politécnico de Bragança, 2017.
 18. Gonçalves, A.; Ornellas, G.; Ribeiro, A.C.; Maia, F.; Rocha, A.; Feliciano, M. Urban cold and Heat Island in the City of Bragança (Portugal). *Climate* **2018**, *6*, 1–14, doi:10.3390/cli6030070.
 19. Maia, F.; Rocha, A.; Ribeiro, A.C. *Avaliação da Ilha de Calor de Bragança*; Borrego, C., Miranda, A.I., Arroja, L., Fidélis, T., Castro, E.A., Gomes, A.P., Eds.; Departamen.; Aveiro - Portugal, 2013; ISBN 978-989-92673-0-7.
 20. Rasheed, A.; Robinson, D. Multiscale modelling of urban climate. *IBPSA 2009 - Int. Build. Perform. Simul. Assoc. 2009* **2009**, *4531*, 505–512.
 21. Pires, R.A.G.; Calado, J. da C.; Silva Neto, W.L.B. da; Carrilho, B.B.; Galvão, R.G. Asfalto Convencional Ou Permeável? Viabilidade Técnica Na Prevenção De Enchentes. *Investig. Científica nas Ciências Sociais Apl.* **2019**, *254–265*, doi:10.22533/at.ed.88119071019.
 22. US Geological Survey Urban Heat Islands Available online: <https://www.usgs.gov/media/images/urban-heat-islands> (accessed on Mar 1, 2020).
 23. Corradini, S. Aerosol extinction coefficient profile retrieval procedure for satellite measurements in multiple scattering atmosphere, Università degli Studi di Genova, 2004.
 24. He, J.F.; Liu, J.Y.; Zhuang, D.F.; Zhang, W.; Liu, M.L. Assessing the effect of land use/land cover change on the change of urban heat island intensity. *Theor. Appl. Climatol.* **2007**, *90*, 217–226, doi:10.1007/s00704-006-0273-1.

25. Aguiar, C.; Rodrigues, O.; Azevedo, J.; Domingos, T. *Montanha*; Pereira, H.M., Domingos, T., Vicente, L., Proença, V., Eds.; Bragança - Portugal, 2009; ISBN 9789725922743.
26. Barry, R.G. *Mountain Weather and Climate*; Press, C.U., Ed.; Cambridge, 2008; ISBN 978-0-521-86295-0. XXIV + 506 PP.
27. Azevedo, J.C.; Cadavez, V.; Arrobas, M.; Pires, J.M. Sustentabilidade da montanha portuguesa: realidades. *Sustentabilidade da Mont. Port. Real. e Desafios. Bragança, IPB* **2016**, 9–38.
28. Andrade, H. O Clima Urbano - Natureza, escalas de análise e aplicabilidade. *Finisterra* **2012**, *40*, doi:10.18055/Finis1479.
29. Oke, T.R. Initial guidance to obtain representative meteorological observations at urban sites. *World Meteorol. Organ.* **2006**, 51.
30. Oke, T.R. Methods in urban climatology. *Appl. Climatol.* **1984**, *14*, 19–29.
31. Marques, D.M.G. Contributo da climatologia para a sustentabilidade urbana: o caso da Figueira da Foz. **2012**, 191.
32. Stull, R.B. An introduction to boundary layer meteorology. *An Introd. to Bound. layer Meteorol.* **1988**, doi:10.1007/978-94-009-3027-8.
33. EPA - United States Environmental Protection Agency Ilhas de calor Available online: <http://www.epa.gov/heat-islands> (accessed on Jan 29, 2020).
34. Santamouris, M.; Cartalis, C.; Synnefa, A. Local urban warming, possible impacts and a resilience plan to climate change for the historical center of Athens, Greece. *Sustain. Cities Soc.* **2015**, *19*, 281–291, doi:10.1016/j.scs.2015.02.001.
35. Santamouris, M. On the energy impact of urban heat island and global warming on buildings. *Energy Build.* **2014**, *82*, 100–113, doi:10.1016/j.enbuild.2014.07.022.
36. Tan, J.; Zheng, Y.; Tang, X.; Guo, C.; Li, L.; Song, G.; Zhen, X.; Yuan, D.; Kalkstein, A.J.; Li, F.; Chen, H. The urban heat island and its impact on heat waves and human health in Shanghai. *Int. J. Biometeorol.* **2010**, *54*, 75–84, doi:10.1007/s00484-009-0256-x.
37. Keikhosravi, Q. The effect of heat waves on the intensification of the heat island of Iran's metropolises (Tehran, Mashhad, Tabriz, Ahvaz). *Urban Clim.* **2019**, *28*, 100453, doi:10.1016/j.uclim.2019.100453.
38. Romero, M.A.B. *Arquitetura do lugar. Uma visão bioclimática da sustentabilidade em Brasília*; Editorial, N.T., Ed.; São Paulo, 2011; ISBN 9788562889035.
39. Santamouris, M. *Environmental Design of Urban Buildings – An Integrated*

- Approach*; Routledge, 2006; ISBN 9780367390518.
40. Gartland, L.; Gonçalves, H. *Ilhas de Calor*; Oficina de Textos: São Paulo - Brasil, 2010; ISBN 9788586238994.
 41. Oke, T.R.; Mills, G.; Christen, A.; Voogt, J.A. *Energy Balance*; Cambridge University Press, 2017; ISBN 9781139016476.
 42. See, L.; Ching, J.; Masson, V.; Feddema, J.; Mills, G.; Neophytou, M.; Foley, M.; O'Connor, M.; Milčinski, G.; Repse, M.; Perger, C.; Duerauer, M.; Fritz, S.; Bechtel, B. *Generating WUDAPT's Specific Scale -dependent Urban Modeling and Activity Parameters: Collection of Level 1 and Level 2 Data*; ICUC9 - 9th International Conference on Urban Climate jointly with 12th Symposium on the Urban Environment: Toulouse - France, 2015.
 43. Vianna, E.O. O Campo Térmico Urbano - Ilhas de Calor em Brasília DF, Universidade de Brasília - UnB, 2018.
 44. Oke, T.R. Street design and urban canopy layer climate. *Energy Build.* **1988**, *11*, 103–113, doi:10.1016/0378-7788(88)90026-6.
 45. Yu, K.; Chen, Y.; Wang, D.; Chen, Z.; Gong, A.; Li, J. Study of the Seasonal Effect of Building Shadows on Urban Land Surface Temperatures Based on Remote Sensing Data. *Remote Sens.* **2019**, *11*, 497, doi:10.3390/rs11050497.
 46. Becker, F.; Zhao-Liang Li Surface temperature and emissivity at various scales: definition, measurement and related problems. *Remote Sens. Rev.* **1995**, *12*, 225–253, doi:10.1080/02757259509532286.
 47. Kuenzer, C.; Dech, S.; Arvidson, T.; Barsi, J.; Jhabvala, M.; Reuter, D. *Thermal Infrared Remote Sensing*; 2013; Vol. 17; ISBN 978-94-007-6638-9.
 48. Chapman, L.; Thornes, J.E.; Bradley, A. V. Rapid determination of canyon geometry parameters for use in surface radiation budgets. *Theor. Appl. Climatol.* **2001**, *69*, 81–89, doi:10.1007/s007040170036.
 49. Souza, L.C.L.; Pedrotti, F.S.; Leme, F.T. Consumo de energia urbano: influência do perfil do usuário, da geometria urbana e da temperatura. *Encontro Nac. Conforto no Ambient. Construído*, VIII 2005, 1960–1969.
 50. Vilela, J.A.; Assis, E.S.; Paiva, J.E.M. de Variáveis do clima urbano: análise da situação atual e prognósticos para a região do bairro Belvedere III, Belo Horizonte, MG. In Proceedings of the X Encontro Nacional e VI Encontro Latino Americano de Conforto no Ambiente Construído; 2009; pp. 295–304.
 51. Lima, I.; Scalco, V.; Lamberts, R. Estimating the impact of urban densification on high-rise office building cooling loads in a hot and humid climate. *Energy Build.* **2019**, *182*, 30–44, doi:10.1016/j.enbuild.2018.10.019.
 52. Teobaldo Neto, A.; Amorim, M.C. de C.T. Ilha de Calor Urbana e desconforto

- térmico: uma análise episódica em Cuiabá/MT. *Os Desafios da Geogr. Física na Front. do Conhecimento* **2017**, 1492–1506, doi:10.20396/sbgfa.v1i2017.2059.
53. Weng, Q.; Lu, D.; Schubring, J. Estimation of land surface temperature-vegetation abundance relationship for urban heat island studies. *Remote Sens. Environ.* **2004**, *89*, 467–483, doi:10.1016/j.rse.2003.11.005.
 54. Lombardo, M.A. *A ilha de calor nas metrópoles: O exemplo de São Paulo*; Hucitec: São Paulo - Brasil, 1985;
 55. Li, D.; Bou-Zeid, E. Synergistic interactions between urban heat islands and heat waves: The impact in cities is larger than the sum of its parts. *J. Appl. Meteorol. Climatol.* **2013**, *52*, 2051–2064, doi:10.1175/JAMC-D-13-02.1.
 56. Leal Filho, W.; Echevarria Icaza, L.; Neht, A.; Klavins, M.; Morgan, E.A. Coping with the impacts of urban heat islands. A literature based study on understanding urban heat vulnerability and the need for resilience in cities in a global climate change context. *J. Clean. Prod.* **2018**, *171*, 1140–1149, doi:10.1016/j.jclepro.2017.10.086.
 57. Kershaw, T.; Sanderson, M.; Coley, D.; Eames, M. Estimation of the urban heat island for UK climate change projections. *Build. Serv. Eng. Res. Technol.* **2010**, *31*, 251–263, doi:10.1177/0143624410365033.
 58. Chapman, S.; Thatcher, M.; Salazar, A.; Watson, J.E.M.; McAlpine, C.A. The impact of climate change and urban growth on urban climate and heat stress in a subtropical city. *Int. J. Climatol.* **2019**, *39*, 3013–3030, doi:10.1002/joc.5998.
 59. Sachindra, D.A.; Ng, A.W.M.; Muthukumaran, S.; Perera, B.J.C. Impact of climate change on urban heat island effect and extreme temperatures: A case-study. *Q. J. R. Meteorol. Soc.* **2016**, *142*, 172–186, doi:10.1002/qj.2642.
 60. Ordóñez, J.L. Espectro electromagnético y espectro radioeléctrico. *Acta* 2012, *1*, 17–31.
 61. Sousa, A.; José, S. Fundamentos Teóricos de Deteção Remota. *Univ. Évora - Dep. Eng. Rural* **2011**, 1–57.
 62. Soni, D.K. Estimation of Rainfall - Runoff in a Watershed Using Remote Sensing and GIS, National Institute of Technology Kurukshetra, 2013.
 63. Wulder, M.A.; White, J.C.; Loveland, T.R.; Woodcock, C.E.; Belward, A.S.; Cohen, W.B.; Fosnight, E.A.; Shaw, J.; Masek, J.G.; Roy, D.P. The global Landsat archive: Status, consolidation, and direction. *Remote Sens. Environ.* **2016**, *185*, 271–283, doi:10.1016/j.rse.2015.11.032.
 64. US Geological Survey Landsat Missions Available online: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-4?qt-science_support_page_related_con=0#qt-science_support_page_related_con

- (accessed on Sep 12, 2020).
65. US Geological Survey Landsat Missions Available online: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-5?qt-science_support_page_related_con=0#qt-science_support_page_related_con.
 66. NASA A Landsat Timeline Available online: <https://landsat.gsfc.nasa.gov/about/landsat-timeline> (accessed on Sep 4, 2021).
 67. US Geological Survey Landsat Missions Available online: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-7?qt-science_support_page_related_con=0#qt-science_support_page_related_con (accessed on Sep 12, 2020).
 68. US Geological Survey Landsat Missions Available online: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-8?qt-science_support_page_related_con=0#qt-science_support_page_related_con (accessed on Sep 12, 2020).
 69. Hulley, G.C.; Ghent, D.; Göttsche, F.M.; Guillevic, P.C.; Mildrexler, D.J.; Coll, C. *Land Surface Temperature*; 2019; ISBN 9780128144589.
 70. Guillevic, P.; Göttsche, F.; Nickeson, J.; Hulley, G.; Ghent, D.; Yu, Y.; Trigo, I.; Hook, S.; Sobrino, J.A.; Remedios, J.; Román, M.; Camacho, F. Land surface temperature product validation best practice protocol version 1.1. *Best Pract. Satell. L. Prod. Valid. (p. 60) L. Prod. Valid. Subgr.* **2018**, doi, 58, doi:10.5067/doc/ceoswgcv/lpv/lst.001.
 71. Kustas, W.; Anderson, M. Advances in thermal infrared remote sensing for land surface modeling. *Agric. For. Meteorol.* **2009**, *149*, 2071–2081, doi:10.1016/j.agrformet.2009.05.016.
 72. Agam, N.; Kustas, W.P.; Anderson, M.C.; Li, F.; Colaizzi, P.D. Utility of thermal image sharpening for monitoring field-scale evapotranspiration over rainfed and irrigated agricultural regions. *Geophys. Res. Lett.* **2008**, *35*, 1–7, doi:10.1029/2007GL032195.
 73. Hall, D.K.; Comiso, J.C.; Digirolamo, N.E.; Shuman, C.A.; Key, J.R.; Koenig, L.S. A satellite-derived climate-quality data record of the clear-sky surface temperature of the greenland ice sheet. *J. Clim.* **2012**, *25*, 4785–4798, doi:10.1175/JCLI-D-11-00365.1.
 74. Schneider, P.; Hook, S.J. Space observations of inland water bodies show rapid surface warming since 1985. *Geophys. Res. Lett.* **2010**, *37*, 1–5, doi:10.1029/2010GL045059.
 75. Pasotti L, Maroli M, Giannetto S, Brianti E. Agrometeorology and models for the parasite cycle forecast. *Parassitologia*. 2006 Jun;48(1-2):81-3. PMID: 16881403.

76. Neteler, M.; Roiz, D.; Rocchini, D.; Castellani, C.; Rizzoli, A. Terra and Aqua satellites track tiger mosquito invasion: Modelling the potential distribution of *Aedes albopictus* in north-eastern Italy. *Int. J. Health Geogr.* **2011**, *10*, doi:10.1186/1476-072X-10-49.
77. Dousset, B.; Gourmelon, F. Satellite multi-sensor data analysis of urban surface temperatures and landcover. *ISPRS J. Photogramm. Remote Sens.* **2003**, *58*, 43–54, doi:10.1016/S0924-2716(03)00016-9.
78. Luvall, J.C.; Quattrochi, D.A.; Rickman, D.L.; Estes, M.G. *Boundary Layer (Atmospheric) and Air Pollution: Urban Heat Islands*; Second Edi.; Elsevier, 2015; Vol. 1; ISBN 9780123822260.
79. Zhao, K.; Valle, D.; Popescu, S.; Zhang, X.; Mallick, B. Hyperspectral remote sensing of plant biochemistry using Bayesian model averaging with variable and band selection. *Remote Sens. Environ.* **2013**, *132*, 102–119, doi:10.1016/j.rse.2012.12.026.
80. Zarate-Valdez, J.L.; Metcalf, S.; Stewart, W.; Ustin, S.L.; Lampinen, B. Potentials and limits of vegetation indices for LAI and APAR assessment. *Precis. Agric.* **2015**, *16*, 161–173, doi:10.2136/sssaj1977.03615995004100040037x.
81. Ponzoni, F.J. Sensoriamento Remoto No Estudo Da Vegetação: Diagnosticando a Mata Atlântica. *Curso Uso Sensoriamento Remoto No Estud. Do Meio Ambient.* **2002**, *27*.
82. Miura, T.; Huete, A.R.; Yoshioka, H.; Holben, B.N. An error and sensitivity analysis of atmospheric resistant vegetation indices derived from dark target-based atmospheric correction. *Remote Sens. Environ.* **2001**, *78*, 284–298, doi:10.1016/S0034-4257(01)00223-1.
83. Carlson, T.N.; Ripley, D.A. On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sens. Environ.* **1997**, *62*, 241–252, doi:10.1016/S0034-4257(97)00104-1.
84. Duarte, L.; Teodoro, A.C.; Gonçalves, H. Deriving phenological metrics from NDVI through an open source tool developed in QGIS. *Earth Resour. Environ. Remote Sensing/GIS Appl. V* **2014**, 9245, 924511, doi:10.1117/12.2066136.
85. Hmimina, G.; Dufrêne, E.; Pontailier, J.Y.; Delpierre, N.; Aubinet, M.; Caquet, B.; de Grandcourt, A.; Burban, B.; Flechard, C.; Granier, A.; Gross, P.; Heinesch, B.; Longdoz, B.; Moureaux, C.; Ourcival, J. M.; Rambal, S.; Saint André, L.; Soudani, K. Evaluation of the potential of MODIS satellite data to predict vegetation phenology in different biomes: An investigation using ground-based NDVI measurements. *Remote Sens. Environ.* **2013**, *132*, 145–158, doi:10.1016/j.rse.2013.01.010.

86. Manandhar, P.; Bande, L.; Tsoupos, A.; Marpu, P.R.; Armstrong, P. A Study of Local Climate Zones in Abu Dhabi with Urban Weather Stations and Numerical Simulations. *Sustainability* **2019**, *12*, 156, doi:10.3390/su12010156.
87. Dian, C.; Pongrácz, R.; Dezső, Z.; Bartholy, J. Annual and monthly analysis of surface urban heat island intensity with respect to the local climate zones in Budapest. *Urban Clim.* **2020**, *31*, 100573, doi:10.1016/j.uclim.2019.100573.
88. Das, M.; Das, A. Assessing the relationship between local climatic zones (LCZs) and land surface temperature (LST) – A case study of Sriniketan-Santiniketan Planning Area (SSPA), West Bengal, India. *Urban Clim.* **2020**, *32*, 100591, doi:10.1016/j.uclim.2020.100591.
89. Wang, Y.; Zhan, Q.; Ouyang, W. Impact of Urban Climate Landscape Patterns on Land Surface Temperature in Wuhan, China. *Sustainability* **2017**, *9*, 1700, doi:10.3390/su9101700.
90. Quan, J. Multi-Temporal Effects of Urban Forms and Functions on Urban Heat Islands Based on Local Climate Zone Classification. *Int. J. Environ. Res. Public Health* **2019**, *16*, 2140, doi:10.3390/ijerph16122140.
91. Mushore, T.D.; Dube, T.; Manjowe, M.; Gumindoga, W.; Chemura, A.; Rousta, I.; Odindi, J.; Mutanga, O. Remotely sensed retrieval of Local Climate Zones and their linkages to land surface temperature in Harare metropolitan city, Zimbabwe. *Urban Clim.* **2019**, *27*, 259–271, doi:10.1016/j.uclim.2018.12.006.
92. Mutani, G.; Todeschi, V. The Effects of Green Roofs on Outdoor Thermal Comfort, Urban Heat Island Mitigation and Energy Savings. *Atmosphere (Basel)* **2020**, *11*, 123, doi:10.3390/atmos11020123.
93. Budhiraja, B.; Agrawal, G.; Pathak, P. Urban heat island effect of a polynuclear megacity Delhi – Compactness and thermal evaluation of four sub-cities. *Urban Clim.* **2020**, *32*, 100634, doi:10.1016/j.uclim.2020.100634.
94. Zhao, C.; Jensen, J.L.R.; Weng, Q.; Currit, N.; Weaver, R. Use of Local Climate Zones to investigate surface urban heat islands in Texas. *GIScience Remote Sens.* **2020**, *57*, 1083–1101, doi:10.1080/15481603.2020.1843869.
95. Fricke, C.; Pongrácz, R.; Gál, T.; Savić, S.; Unger, J. Using local climate zones to compare remotely sensed surface temperatures in temperate cities and hot desert cities. *Morav. Geogr. Reports* **2020**, *28*, 48–60, doi:10.2478/mgr-2020-0004.
96. Bragança, M. de Estratégia Municipal de Adaptação às Alterações Climáticas Available online: https://www.cm-braganca.pt/cmbraganca2020/uploads/writer_file/document/6050/B__8-_Publica__o_do_Plano_Municipal_de_Ambiente.pdf (accessed on Dec 1, 2020).

97. Guerra, J.; Schmidt, L.; Penha-Lopes, G. O caso ClimAdaPT.Local. *Ambient. Educ.* **2021**, *25*, 9–30, doi:10.14295/ambeduc.v25i3.12478.
98. Instituto Português do Mar e da Atmosfera (IPMA) Available online: <https://www.ipma.pt> (accessed on Mar 1, 2021).
99. Portuguesa, R. Covid 19 estamos ON Available online: <https://covid19estamoson.gov.pt/> (accessed on Dec 20, 2020).
100. Gál, T.; Unger, J. Detection of ventilation paths using high-resolution roughness parameter mapping in a large urban area. *Build. Environ.* **2009**, *44*, 198–206, doi:10.1016/j.buildenv.2008.02.008.
101. User manual - HTMercury33 Available online: <https://www.ht-instruments.com/en/products/mercury/download/manual/> (accessed on Jul 1, 2020).
102. Soto-Estrada, Engelberth Correa-Echeverri, Sebastián Posada-Posada, M.I. Thermal analysis of urban environments in Medellin, Colombia, using an unmanned aerial vehicle (UAV). *J. Urban Environ. Eng.* **2017**, *11*, 142–149, doi:10.4090/juee.2017.v11n2.142149 Journal.
103. IBM IBM SPSS Missing Values Available online: <https://www.ibm.com/br-pt/products/spss-missing-values> (accessed on Oct 9, 2021).
104. Connors, J.P.; Galletti, C.S.; Chow, W.T.L. Landscape configuration and urban heat island effects: Assessing the relationship between landscape characteristics and land surface temperature in Phoenix, Arizona. *Landsc. Ecol.* **2013**, *28*, 271–283, doi:10.1007/s10980-012-9833-1.
105. USGS Landsat Collection 2 Available online: <https://pubs.usgs.gov/fs/2021/3002/fs20213002.pdf> (accessed on Aug 1, 2021).
106. US Geological Survey Available online: <https://earthexplorer.usgs.gov/> (accessed on Jul 1, 2020).
107. Avdan, U.; Jovanovska, G. Algorithm for automated mapping of land surface temperature using LANDSAT 8 satellite data. *J. Sensors* **2016**, *2016*, doi:10.1155/2016/1480307.
108. US Geological Survey Using the USGS Landsat Level-1 Data Product Available online: <https://www.usgs.gov/core-science-systems/nli/landsat/using-usgs-landsat-level-1-data-product> (accessed on Jul 25, 2021).
109. Xu, H.Q.; Chen, B.Q. Remote sensing of the urban heat island and its changes in Xiamen City of SE China. *J. Environ. Sci.* **2004**, *16*, 276–281.
110. Sobrino, J.A.; Jiménez-Muñoz, J.C.; Paolini, L. Land surface temperature retrieval from LANDSAT TM 5. *Remote Sens. Environ.* **2004**, *90*, 434–440, doi:10.1016/j.rse.2004.02.003.

111. Stathopoulou, M.; Cartalis, C. Daytime urban heat islands from Landsat ETM+ and Corine land cover data: An application to major cities in Greece. *Sol. Energy* **2007**, *81*, 358–368, doi:10.1016/j.solener.2006.06.014.
112. Developers, G. Earth Engine Data Catalog Available online: https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C01_T1_SR#description (accessed on Aug 1, 2021).
113. USGS USGS Landsat 8 Surface Reflectance Tier 1 [deprecated] Available online: <https://gee.stac.cloud/BJmBzK1uPSS1qPWphBuPHgfbcqSkzxvCWZ94q> (accessed on Aug 1, 2021).
114. Vermote, E.; Justice, C.; Claverie, M.; Franch, B. Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. *Remote Sens. Environ.* **2016**, *185*, 46–56, doi:10.1016/j.rse.2016.04.008.
115. Ermida, S.L.; Soares, P.; Mantas, V.; Götsche, F.M.; Trigo, I.F. Google earth engine open-source code for land surface temperature estimation from the landsat series. *Remote Sens.* **2020**, *12*, 1–21, doi:10.3390/RS12091471.
116. Cook, M.; Schott, J.R.; Mandel, J.; Raqueno, N. Development of an Operational Calibration Methodology for the Landsat Thermal Data Archive and Initial Testing of the Atmospheric Compensation Component of a Land Surface Temperature (LST) Product from the Archive. *Remote Sens.* **2014**, *6*, 11244–11266, doi:10.3390/rs6111244.
117. Esri Buffer (Analysis) Available online: <https://pro.arcgis.com/en/pro-app/latest/tool-reference/analysis/buffer.htm> (accessed on Sep 22, 2021).
118. Saher, R.; Stephen, H.; Ahmad, S. Understanding the summertime warming in canyon and non-canyon surfaces. *Urban Clim.* **2021**, *38*, 100916, doi:10.1016/j.uclim.2021.100916.
119. Schwarz, N.; Lautenbach, S.; Seppelt, R. Exploring indicators for quantifying surface urban heat islands of European cities with MODIS land surface temperatures. *Remote Sens. Environ.* **2011**, *115*, 3175–3186, doi:10.1016/j.rse.2011.07.003.
120. Eugénia Graça Martins, M. Quantis. *Rev. Ciência Elem.* **2014**, *2*, doi:10.24927/rce2014.267.
121. Kronthaler, F.; Zöllner, S. *Data Analysis with RStudio*; 2021; ISBN 9783662625170.
122. Azevedo, J.; Chapman, L.; Muller, C. Quantifying the Daytime and Night-Time Urban Heat Island in Birmingham, UK: A Comparison of Satellite Derived Land Surface Temperature and High Resolution Air Temperature Observations.

- Remote Sens.* **2016**, *8*, 153, doi:10.3390/rs8020153.
123. Zhou, B.; Rybski, D.; Kropp, J.P. On the statistics of urban heat island intensity. *Geophys. Res. Lett.* **2013**, *40*, 5486–5491, doi:10.1002/2013GL057320.
 124. Shapiro, S.S.; WILK, M.B. An analysis of variance test for normality (complete samples). *Biometrika* **1965**, *52*, 591–611, doi:10.1093/biomet/52.3-4.591.
 125. Fieller, E.C.; Hartley, H.O.; Pearson, E.S. Tests for Rank Correlation Coefficients. I. *Biometrika* **1957**, *44*, 470–481, doi:10.1093/biomet/44.3-4.470.
 126. Li, C.; Zhao, J.; Thinh, N.X.; Yang, W.; Li, Z. Analysis of the spatiotemporally varying effects of urban spatial patterns on land surface temperatures. *J. Environ. Eng. Landsc. Manag.* **2018**, *26*, 216–231, doi:10.3846/jeelm.2018.5378.
 127. Kumari, M.; Singh, C.K.; Bakimchandra, O.; Basistha, A. Geographically weighted regression based quantification of rainfall–topography relationship and rainfall gradient in Central Himalayas. *Int. J. Climatol.* **2017**, *37*, 1299–1309, doi:10.1002/joc.4777.
 128. Tang, J.; Di, L.; Xiao, J.; Lu, D.; Zhou, Y. Impacts of land use and socioeconomic patterns on urban heat island. *Int. J. Remote Sens.* **2017**, *38*, 3445–3465, doi:10.1080/01431161.2017.1295485.
 129. Spearman, C. “General Intelligence,” Objectively Determined and Measured. *Am. J. Psychol.* **1904**, *15*, 201, doi:10.2307/1412107.
 130. Sun, R.; Chen, A.; Chen, L.; Lü, Y. Cooling effects of wetlands in an urban region: The case of Beijing. *Ecol. Indic.* **2012**, *20*, 57–64, doi:10.1016/j.ecolind.2012.02.006.
 131. Padmanaban, R.; Bhowmik, A.K.; Cabral, P. Satellite image fusion to detect changing surface permeability and emerging urban heat islands in a fast-growing city. *PLoS One* **2019**, *14*, 1–20, doi:10.1371/journal.pone.0208949.
 132. Li, Y.; Wang, L.; Liu, M.; Zhao, G.; He, T.; Mao, Q. Associated Determinants of Surface Urban Heat Islands across 1449 Cities in China. *Adv. Meteorol.* **2019**, *2019*, 1–14, doi:10.1155/2019/4892714.
 133. Pinho, O.S.; Manso Orgaz, M.D. The urban heat island in a small city in coastal Portugal. *Int. J. Biometeorol.* **2000**, *44*, 198–203, doi:10.1007/s004840000063.
 134. Myers, J.L.; Well, A.D. *Research Design and Statistical Analysis*; Erlbaum, L., Ed.; 2nd ed.; 2003; ISBN 978-0-8058-4037-7.
 135. Anniballe, R.; Bonafoni, S.; Pichierri, M. Spatial and temporal trends of the surface and air heat island over Milan using MODIS data. *Remote Sens. Environ.* **2014**, *150*, 163–171, doi:10.1016/j.rse.2014.05.005.
 136. Rodrigues, S.C.A. Modelo de Regressão Linear e suas Aplicações,

Universidade da Beira Interior, 2012.

137. Hartz, D.A.; Prashad, L.; Hedquist, B.C.; Golden, J.; Brazel, A.J. Linking satellite images and hand-held infrared thermography to observed neighborhood climate conditions. *Remote Sens. Environ.* **2006**, *104*, 190–200, doi:10.1016/j.rse.2005.12.019.
138. Landsat Missions Available online: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-8?qt-science_support_page_related_con=0#qt-science_support_page_related_con (accessed on Sep 12, 2020).
139. Martinuzzi, S.; Gould, W.A.; Ramos Gonzalez, O.M. *Creating cloud-free Landsat ETM+ data sets in tropical landscapes: cloud and cloud-shadow removal*; 2007;
140. Kour, R.; Patel, N.; Krishna, A.P. Influence of shadow on the thermal and optical snow indices and their interrelationship. *Remote Sens. Environ.* **2016**, *187*, 119–129, doi:10.1016/j.rse.2016.10.017.
141. Ermida, S.L.; Soares, P.; Mantas, V.; Götsche, F.-M.; Trigo, I.F. Google Earth Engine Open-Source Code for Land Surface Temperature Estimation from the Landsat Series. *Remote Sens.* **2020**, *12*, 1471, doi:10.3390/rs12091471.
142. Wang, M.; Zhang, Z.; Hu, T.; Wang, G.; He, G.; Zhang, Z.; Li, H.; Wu, Z.; Liu, X. An Efficient Framework for Producing Landsat-Based Land Surface Temperature Data Using Google Earth Engine. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 4689–4701, doi:10.1109/JSTARS.2020.3014586.
143. Parastatidis, D.; Mitraka, Z.; Chrysoulakis, N.; Abrams, M. Online Global Land Surface Temperature Estimation from Landsat. *Remote Sens.* **2017**, *9*, 1208, doi:10.3390/rs9121208.
144. Fashae, O.A.; Adagbasa, E.G.; Olusola, A.O.; Obateru, R.O. Land use/land cover change and land surface temperature of Ibadan and environs, Nigeria. *Environ. Monit. Assess.* **2020**, *192*, 109, doi:10.1007/s10661-019-8054-3.
145. Jamei, Y.; Rajagopalan, P.; Sun, Q.C. Time-series dataset on land surface temperature, vegetation, built up areas and other climatic factors in top 20 global cities (2000–2018). *Data Br.* **2019**, *23*, 103803, doi:10.1016/j.dib.2019.103803.
146. Li, Y.; Wang, L.; Zhang, L.; Liu, M.; Zhao, G. Monitoring Intra-annual Spatiotemporal Changes in Urban Heat Islands in 1449 Cities in China Based on Remote Sensing. *Chinese Geogr. Sci.* **2019**, *29*, 905–916, doi:10.1007/s11769-019-1080-9.
147. Gao, M.; Shen, H.; Han, X.; Li, H.; Zhang, L. Multiple timescale analysis of the urban heat island effect based on the Community Land Model: a case study of the city of Xi'an, China. *Environ. Monit. Assess.* **2018**, *190*, 8, doi:10.1007/s10661-017-6320-9.

148. Cook, M.; Schott, J.; Mandel, J.; Raqueno, N. Development of an Operational Calibration Methodology for the Landsat Thermal Data Archive and Initial Testing of the Atmospheric Compensation Component of a Land Surface Temperature (LST) Product from the Archive. *Remote Sens.* **2014**, *6*, 11244–11266, doi:10.3390/rs6111244.
149. Hu, D. Analysis of surface radiation budget during the summer and winter in the metropolitan area of Beijing, China. *J. Appl. Remote Sens.* **2010**, *4*, 043513, doi:10.1117/1.3374329.
150. Unal Cilek, M.; Cilek, A. Analyses of land surface temperature (LST) variability among local climate zones (LCZs) comparing Landsat-8 and ENVI-met model data. *Sustain. Cities Soc.* **2021**, *69*, 102877, doi:10.1016/j.scs.2021.102877.
151. Geletič, J.; Lehnert, M.; Savić, S.; Milošević, D. Inter-/intra-zonal seasonal variability of the surface urban heat island based on local climate zones in three central European cities. *Build. Environ.* **2019**, *156*, 21–32, doi:10.1016/j.buildenv.2019.04.011.
152. Kumar, S.; Ghosh, S.; Hooda, R.S.; Singh, S. Monitoring and prediction of land use land cover changes and its impact on land surface temperature in the central part of hisar district, Haryana under semi-arid zone of India. *J. Landsc. Ecol. Republic)* **2019**, *12*, 117–140, doi:10.2478/jlecol-2019-0020.
153. Dai, Z.; Guldmann, J.M.; Hu, Y. Thermal impacts of greenery, water, and impervious structures in Beijing's Olympic area: A spatial regression approach. *Ecol. Indic.* **2019**, *97*, 77–88, doi:10.1016/j.ecolind.2018.09.041.
154. Guo, J.; Han, G.; Xie, Y.; Cai, Z.; Zhao, Y. Exploring the relationships between urban spatial form factors and land surface temperature in mountainous area: A case study in Chongqing city, China. *Sustain. Cities Soc.* **2020**, *61*, 102286, doi:10.1016/j.scs.2020.102286.
155. Alavipanah, S.; Wegmann, M.; Qureshi, S.; Weng, Q.; Koellner, T. The role of vegetation in mitigating urban land surface temperatures: A case study of Munich, Germany during the warm season. *Sustain.* **2015**, *7*, 4689–4706, doi:10.3390/su7044689.
156. Jones, H.G.; Rotenberg, E. Energy, Radiation and Temperature Regulation in Plants. In *eLS*; Wiley, 2011.
157. Sodoudi, S.; Shahmohamadi, P.; Vollack, K.; Cubasch, U.; Che-Ani, A.I. Mitigating the Urban Heat Island Effect in Megacity Tehran. *Adv. Meteorol.* **2014**, *2014*, doi:10.1155/2014/547974.
158. Yuan, C.; Chen, L. Mitigating urban heat island effects in high-density cities based on sky view factor and urban morphological understanding: a study of

- Hong Kong. *Archit. Sci. Rev.* **2011**, *54*, 305–315, doi:10.1080/00038628.2011.613644.
159. Greene, C.S.; Millward, A.A. Getting closure: The role of urban forest canopy density in moderating summer surface temperatures in a large city. *Urban Ecosyst.* **2017**, *20*, 141–156, doi:10.1007/s11252-016-0586-5.
 160. Grover, A.; Singh, R.B. Monitoring Spatial patterns of land surface temperature and urban heat island for sustainable megacity: A case study of Mumbai, India, using landsat TM data. *Environ. Urban. ASIA* **2016**, *7*, 38–54, doi:10.1177/0975425315619722.
 161. Masoudi, M.; Tan, P.Y.; Liew, S.C. Multi-city comparison of the relationships between spatial pattern and cooling effect of urban green spaces in four major Asian cities. *Ecol. Indic.* **2019**, *98*, 200–213, doi:10.1016/j.ecolind.2018.09.058.
 162. Bao, T.; Li, X.; Zhang, J.; Zhang, Y.; Tian, S. Assessing the Distribution of Urban Green Spaces and its Anisotropic Cooling Distance on Urban Heat Island Pattern in Baotou, China. *ISPRS Int. J. Geo-Information* **2016**, *5*, 1–13, doi:10.3390/ijgi5020012.
 163. Zheng, H.; Chen, Y.; Pan, W.; Cai, Y.; Chen, Z. Impact of Land Use/Land Cover Changes on the Thermal Environment in Urbanization: A Case Study of the Natural Wetlands Distribution Area in Minjiang River Estuary, China. *Polish J. Environ. Stud.* **2019**, *28*, 3025–3041, doi:10.15244/pjoes/93743.
 164. Chandra, S.; Sharma, D.; Dubey, S.K. Linkage of urban expansion and land surface temperature using geospatial techniques for Jaipur City, India. *Arab. J. Geosci.* **2018**, *11*, 31, doi:10.1007/s12517-017-3357-6.
 165. Gallo, K.; Hale, R.; Tarpley, D.; Yu, Y. Evaluation of the Relationship between Air and Land Surface Temperature under Clear- and Cloudy-Sky Conditions. *J. Appl. Meteorol. Climatol.* **2011**, *50*, 767–775, doi:10.1175/2010JAMC2460.1.
 166. Mitchell, B.C.; Chakraborty, J. Exploring the relationship between residential segregation and thermal inequity in 20 U.S. cities. *Local Environ.* **2018**, *23*, 796–813, doi:10.1080/13549839.2018.1474861.
 167. Dancey, C.; Reidy, J. *Statistics Without Maths for Psychology*; 7th ed.; Pearson Education: Harlow, United Kingdom, 2017; ISBN 978-1292128856.
 168. Leclezio, L.; Jansen, A.; Whittemore, V.H.; de Vries, P.J. Pilot Validation of the Tuberous Sclerosis-Associated Neuropsychiatric Disorders (TAND) Checklist. *Pediatr. Neurol.* **2015**, *52*, 16–24, doi:10.1016/j.pediatrneurol.2014.10.006.
 169. Martin, P.; Baudouin, Y.; Gachon, P. An alternative method to characterize the surface urban heat island. *Int. J. Biometeorol.* **2015**, *59*, 849–861, doi:10.1007/s00484-014-0902-9.

170. Zhang, P.; Bounoua, L.; Imhoff, M.L.; Wolfe, R.E.; Thome, K. Comparison of MODIS Land Surface Temperature and Air Temperature over the Continental USA Meteorological Stations. *Can. J. Remote Sens.* **2014**, *40*, 110–122, doi:10.1080/07038992.2014.935934.
171. Azevedo, J.; Chapman, L.; Muller, C. *Quantifying the Daytime and Night-Time Urban Heat Island in Birmingham, UK: A Comparison of Satellite Derived Land Surface Temperature and High Resolution Air Temperature Observations*; Vol. 8, p. 153;.
172. Karakuş, C.B. The Impact of Land Use/Land Cover (LULC) Changes on Land Surface Temperature in Sivas City Center and Its Surroundings and Assessment of Urban Heat Island. *Asia-Pacific J. Atmos. Sci.* **2019**, *55*, 669–684, doi:10.1007/s13143-019-00109-w.
173. Mullerova, D.; Williams, M. Satellite Monitoring of Thermal Performance in Smart Urban Designs. *Remote Sens.* **2019**, *11*, 2244, doi:10.3390/rs11192244.
174. Li, L.; Zha, Y. Satellite-based spatiotemporal trends of canopy urban heat islands and associated drivers in China's 32 major cities. *Remote Sens.* **2019**, *11*, 1–17, doi:10.3390/rs11010102.
175. Feng, Y.; Du, S.; Myint, S.W.; Shu, M. Do urban functional zones affect land surface temperature differently? A case study of Beijing, China. *Remote Sens.* **2019**, *11*, doi:10.3390/rs11151802.
176. Zhao, Q.; Myint, S.W.; Wentz, E.A.; Fan, C. Rooftop surface temperature analysis in an Urban residential environment. *Remote Sens.* **2015**, *7*, 12135–12159, doi:10.3390/rs70912135.
177. Le Roy, B.; Lemonsu, A.; Kounkou-Arnaud, R.; Brion, D.; Masson, V. Long time series spatialized data for urban climatological studies: A case study of Paris, France. *Int. J. Climatol.* **2020**, *40*, 3567–3584, doi:10.1002/joc.6414.
178. Peres, L. de F.; Lucena, A.J. de; Rotunno Filho, O.C.; França, J.R. de A. The urban heat island in Rio de Janeiro, Brazil, in the last 30 years using remote sensing data. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *64*, 104–116, doi:10.1016/j.jag.2017.08.012.
179. Cai, M.; Ren, C.; Xu, Y.; Lau, K.K.L.; Wang, R. Investigating the relationship between local climate zone and land surface temperature using an improved WUDAPT methodology – A case study of Yangtze River Delta, China. *Urban Clim.* **2018**, *24*, 485–502, doi:10.1016/j.uclim.2017.05.010.
180. Van Nguyen, O.; Kawamura, K.; Trong, D.P.; Gong, Z.; Suwandana, E. Temporal change and its spatial variety on land surface temperature and land use changes in the Red River Delta, Vietnam, using MODIS time-series imagery.

- Environ. Monit. Assess.* **2015**, *187*, doi:10.1007/s10661-015-4691-3.
181. Gao, M.; Chen, F.; Shen, H.; Barlage, M.; Li, H.; Tan, Z.; Zhang, L. Efficacy of possible strategies to mitigate the urban heat island based on urbanized high-resolution land data assimilation system (U-HRLDAS). *J. Meteorol. Soc. Japan* **2019**, *97*, 1075–1097, doi:10.2151/jmsj.2019-060.
 182. Li, B.; Luo, Z.; Sandberg, M.; Liu, J. Revisiting the ‘Venturi effect’ in passage ventilation between two non-parallel buildings. *Build. Environ.* **2015**, *94*, 714–722, doi:10.1016/j.buildenv.2015.10.023.
 183. Rotach, M.W.; Calanca, P. Microclimate. In *Encyclopedia of Atmospheric Sciences*; Elsevier, 2003; pp. 1301–1307.
 184. Fariña Tojo, J.; Huerta, M.; Hernández, A. *Manual de Diseño Bioclimático Urbano Manual de Desenho Bioclimático Urbano*; 2013; ISBN 9789727451579.
 185. Fernandes, L.C.; Krüger, E.L. Temperatura Radiante média obtida via termômetro de globo: análise crítica de dados de um estudo de campo. *Rev. Arquitetura IMED* **2019**, *8*, 147, doi:10.18256/2318-1109.2019.v8i1.3456.

Review

Study of the Urban Heat Island (UHI) Using Remote Sensing Data/Techniques: A Systematic Review

Cátia Rodrigues de Almeida ^{1,*}, Ana Cláudia Teodoro ^{1,2}  and Artur Gonçalves ³ 

¹ Department of Geosciences, Environment and Land Planning, Faculty of Sciences, University of Porto, Rua Campo Alegre, 687, 4169-007 Porto, Portugal; amteodor@fc.up.pt

² Earth Sciences Institute (ICT), Pole of the FCUP, University of Porto, 4169-007 Porto, Portugal

³ Centro de Investigação de Montanha (CIMO), Campus de Santa Apolónia, Instituto Politécnico de Bragança, 5300-253 Bragança, Portugal; ajg@ipb.pt

* Correspondence: up201600831@fc.up.pt

Abstract: Urban Heat Islands (UHI) consist of the occurrence of higher temperatures in urbanized areas when compared to rural areas. During the warmer seasons, this effect can lead to thermal discomfort, higher energy consumption, and aggravated pollution effects. The application of Remote Sensing (RS) data/techniques using thermal sensors onboard satellites, drones, or aircraft, allow for the estimation of Land Surface Temperature (LST). This article presents a systematic review of publications in Scopus and Web of Science (WOS) on UHI analysis using RS data/techniques and LST, from 2000 to 2020. The selection of articles considered keywords, title, abstract, and when deemed necessary, the full text. The process was conducted by two independent researchers and 579 articles, published in English, were selected. Qualitative and quantitative analyses were performed. Cfa climate areas are the most represented, as the Northern Hemisphere concentrates the most studied areas, especially in Asia (69.94%); Landsat products were the most applied to estimates LST (68.39%) and LULC (55.96%); ArcGIS (30.74%) was most used software for data treatment, and correlation (38.69%) was the most applied statistic technique. There is an increasing number of publications, especially from 2016, and the transversality of UHI studies corroborates the relevance of this topic.

Keywords: review; LST; Landsat; MODIS; correlation; regression



Citation: Almeida, C.R.d.; Teodoro, A.C.; Gonçalves, A. Study of the Urban Heat Island (UHI) Using Remote Sensing Data/Techniques: A Systematic Review. *Environments* **2021**, *8*, 105. <https://doi.org/10.3390/environments8100105>

Academic Editor: Paul C. Sutton

Received: 22 August 2021

Accepted: 5 October 2021

Published: 9 October 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Urbanization is an anthropic alteration that generates modifications in surface materials due to vegetation suppression, albedo variation, and soil sealing, influencing the local energy balance, contributing to the formation of the Urban Heat Island (UHI) [1]. This effect is a consequence of the greater absorption of electromagnetic energy and the slow cooling of urbanized surfaces compared to surrounding areas with the presence of vegetation [2,3].

This local dynamic contributes to an increase in surface temperature, with a subsequent reduction in relative humidity and latent heat, and an intensification of sensible heat. The main causes of UHI formation are: (i) the ability of building materials to store heat; (ii) anthropogenic heat production; (iii) alteration and minimization of wind speed as a function of surface roughness; and (iv) increased absorption of solar radiation from lower albedo surfaces, among others [4–7].

Due to the relevance of the topic, studies focusing on understanding the causes and effects of UHI are increasing, including the analysis of the variability in air temperature in urbanized areas and its underlying mechanisms [8–11]. Voogt and Oke (2003) [12] suggested a sub-classification analogous to UHI, called Surface Urban Heat Island (SUHI) which, in addition to studying surface temperature differences between urban and rural areas, also addresses temporal variability [13]. In this review, considering that not all the papers reviewed made the distinction between UHI and SUHI, the term UHI will be

mentioned in the broad sense, and in the case of studies dealing with surface temperature, it assumes that the study focuses on SUHI.

The most recurrent impacts associated with this effect are: (i) influence on the local microclimate; (ii) thermal discomfort; (iii) impacts on public health; and (iv) changes in hydrological behavior, with a displacement of water masses, for example [4–7]. UHI and SUHI combined with natural phenomena, such as Heat Waves (HWs), can potentiate the impacts on human health, culminating in increased mortality [14]. Climate change will most likely generate an increase in air temperatures, raising the negative effects of UHI and SUHI, and thus demanding climate-resilient cities that can accurately analyze and promote urban planning solutions to mitigate this effect [15–18].

During the morning period, the SUHI presents great amplitude and variable behavior, especially in urbanized areas. In these same areas, the UHI presents lower temperatures when compared to those with the presence of vegetation, due to the amount of mass per unit area for heating, i.e., places with fewer horizontal and vertical constructions will need less time to heat (Figure 1) [19–22].

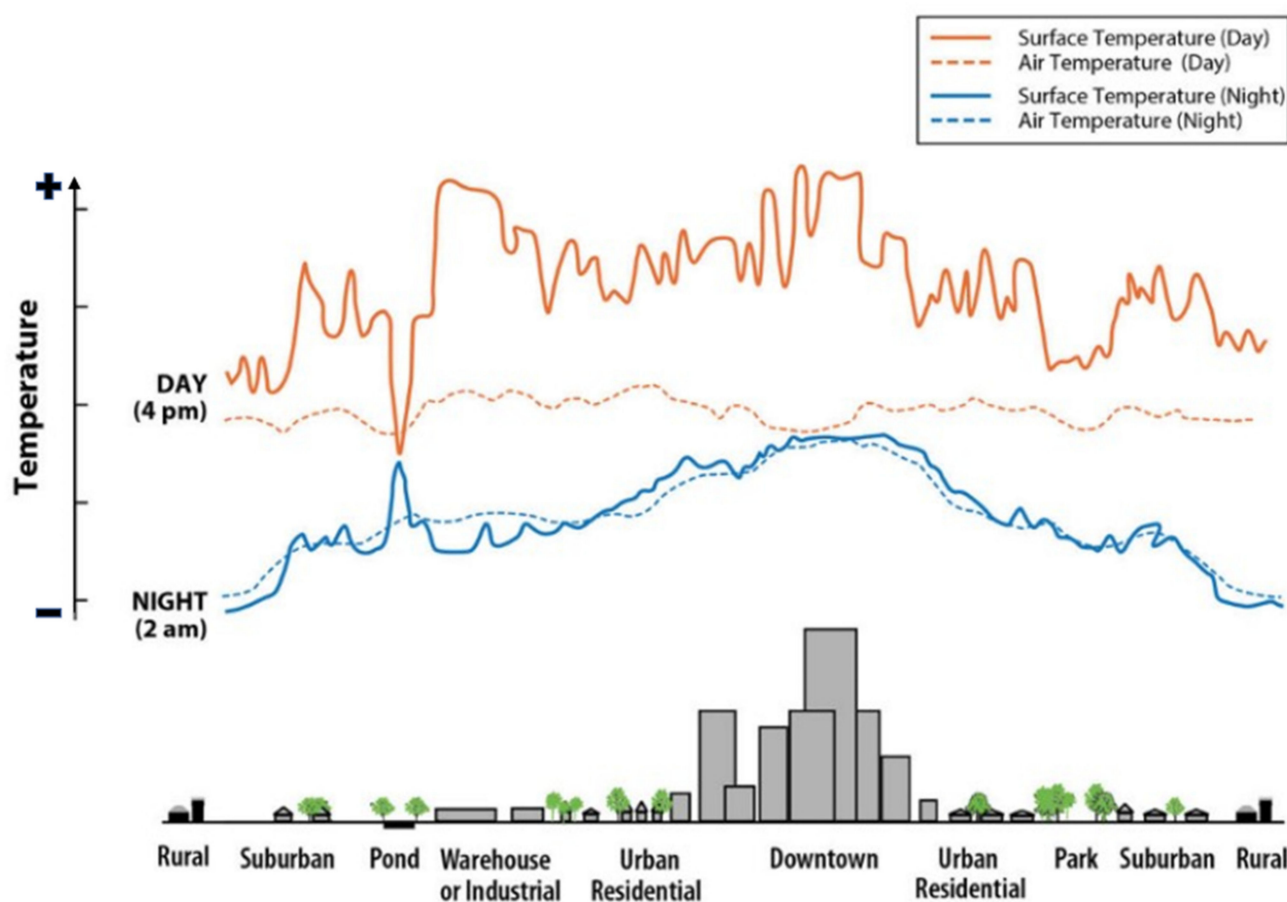


Figure 1. The temperature profile in different areas, with the formation of the UHI (adapted from [3]).

In addition, there is an influence regarding the thermal properties of the constituent materials and their arrangement, which can generate shading effects and corroborate to the local heat exchange characteristics: the more heterogeneous their composition, the more complex the local heating and cooling relationship (as in the case of civil constructions). In urban areas, SUHI gains intensity around noon, and during the night, urban areas retain more heat due to the thermal behavior of buildings, surface materials, and areas that have reduced view of the skydome/hemisphere, as a function of lower Sky View Factor (SVF) (Figure 1) [19–22].

There are several techniques to study the thermal behavior of a site, such as Remote Sensing (RS) [23], data from fixed meteorological stations, data from qualified entities, in situ campaigns with portable thermal cameras, etc. Some studies adopt more than one of the aforementioned data sources to complement the information, both at the atmospheric and surface-level (UHI and SUHI, respectively). This variety of sources allows the access to diurnal and/or nocturnal data and in different seasons of the year, although the effect is more intense in summer and winter [19–22].

From the RS data, it is possible to compute the Land Surface Temperature (LST), a relevant variable that can be used to determine the radiative load of the earth's surface. It conducts longwave radiation and turbulent heat fluxes between the earth and the atmosphere, i.e., it is a variable in the physics of local and global surface processes, linked to radiative, latent, and sensible heat fluxes at the interface with the surface, allowing analyses of warming trends at the earth's surface [24–27].

The LST, also known as radiometric or “skin” temperature, refers to the direct measurement of the earth's surface temperature. Unlike the measurements taken by meteorological stations that record the temperature near the surface, the LST allows for a more detailed scale of analysis: in areas of dense vegetation it will represent the temperature of the leaves of the canopy; in areas of sparse vegetation the temperature will correspond to the whole canopy, subsurface (limbs, branches, etc.), and the ground surface; and on the bare ground it will correspond to the temperature of the top (few micrometers) from the ground surface [25].

In RS, the aggregated radiometric temperature is represented per pixel, according to the sensor display field. The LST is recovered by estimating the emitted surface radiance, obtained by the atmospheric correction in the radiance sensor, and inventing the Planck function, considering the effects of emissivity variation [25].

LST can be used to retrieve relevant climate variables, as evapotranspiration, water-stress vegetation, soil moisture, and thermal inertia [28,29]. Its application is vast, being effective in UHI research [30,31], global warming, cryosphere melting [32,33], insect infestation [34], vector-borne diseases [35], etc.

1.1. Satellites More Used to Estimate Land Surface Temperature

Considering the use of RS data for studying UHI and SUHI, the most commonly used sensors in RS concerning the works evaluated in this review were thermal sensors, which detect emitted and/or reflected terrestrial radiation [2,24]. Thermal sensors present challenges in recording the collection, especially when clouds are present, which can affect the reliability of the results and the temporal analysis of a site [36,37].

Another technique is the adoption of passive microwave sensors [36,38] which, although they do not present as detailed spatial scale as thermal sensors, overcome the challenge of atmospheric influence and allow for a thermal analysis of the atmospheric boundary layer, as in the case of Moscow, where profiles up to 600 m high were created for the study of UHI [38].

It is emphasized that there are studies that use data from both collection methodologies, to complement the information in the study area [36]. Details regarding the operation of each methodology will be presented in sequence (Sections 1.1.1 and 1.1.2).

1.1.1. Thermal Sensors

Thermal sensors operate in the 8–14 μm range, known as one atmospheric window. This range includes the emission part of the earth's spectrum, making heat detection by RS sensors possible. The emitted radiation is recorded as Digital Number (DN) and subsequently converted into temperature data [2,26].

Each sensor has its spectral resolution that defines its ability and sensitivity to generate data within the electromagnetic spectrum, which includes both visible and non-visible zones. In practice, the sensors are cooled to temperatures close to absolute zero so that their eventual emissions do not influence the measurements and the temperature data records

of the targets. A comparison is made between the measured radiation temperature (target) and the internal reference temperatures of the sensors (related to the absolute radiation temperature) [2]. The main advantage of RS sensors is their continuous spatial coverage and temporal repeatability of the study area [39].

The most applied satellite/sensors to study LST are Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS), and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). Some studies used data obtained by polar and/or geostationary satellites, which prioritize the temporal mapping of the study area [40].

Table 1 presents a summary of the thermal sensors most applied in UHI studies. It is emphasized that this list is not intended to end or encourage that only these satellites be used to obtain information about the LST (the OSCAR—Observing Systems Capability Analysis and Review Tool, offers a query base for users, who can filter the choices of satellites, sensors, or products) [41].

Table 1. Summary of the thermal sensors most commonly applied in UHI studies (adapted from [37,41]).

Sensor	Satellite Platform	Orbital Frequency	Spatial Resolution	Spectral Bands (μm)	Number Band	Data Available Since
AATSR	Envisat	35 days	1 km (approx.)	11 and 12	TIR	2002–2012
ASTER	Terra	Twice daily	90 m	8.125–8.475	10	1999
				8.475–8.825	11	
				8.925–9.275	12	
				10.25–10.95	13	
				10.95–11.65	14	
AVHRR (Advanced Very High Resolution Radiometer)	NOAA 6, 8 10, TIROS-N	Twice daily	1.1 km (approx.)	10.3–11.3 11.5–12.5	4 5	1978–2001
AVHRR/2 (Advanced Very High Resolution Radiometer/2)	NOAA 7, 9, 11, 12, 13, 14	Twice daily	1.1 km (approx.)	10.3–11.3 11.5–12.5	4 5	1981–2007
AVHRR/3 (Advanced Very High Resolution Radiometer)	METOP-A, B, C	29 days	1.1 km (approx.)	10.3–11.3 11.5–12.5	4 5	2006
AVHRR/3 (Advanced Very High Resolution Radiometer/3)	NOAA 15, 16, 17, 18, 19	Twice daily	1.1 km (approx.)	10.3–11.3 11.5–12.5	4 5	1998
ETM+	Landsat 7	16 days	Collected at 60 m and resampled to 30 m	10.4–12.5	6	1999
GOES Imager	GOES	Geostationary	4 km (approx.)	10.2–11.2 11.5–12.5	TIR	1974
IRMSS (Infrared Multispectral Scanner)	HJ-1B	31 days	300 m	10.5–12.5	TIR	2008–2018

Table 1. Cont.

Sensor	Satellite Platform	Orbital Frequency	Spatial Resolution	Spectral Bands (μm)	Number Band	Data Available Since
IRMSS (Infrared Multispectral Scanner)	CBERS 1	26 days	160 m	10.4–12.5	4	1999–2003
IRMSS (Infrared Multispectral Scanner)	CBERS 2	26 days	160 m	10.4–12.5	4	2003–2009
IRMSS (Infrared Multispectral Scanner)	CBERS 2B	26 days	160 m	10.4–12.5	4	2007–2010
IRMSS-2 (HJ) (Infrared Multispectral Scanner-2)	HJ-2A and HJ-2B	4 days	300 m	10.5–12.5	TIR	2020
IRS (Infrared Medium Resolution Scanner)	CBERS 4	26 days	80 m	10.4–12.5	12	2014
IRS (Infrared Medium Resolution Scanner)	CBERS 4A	31 days	80 m	10.4–12.5	12	2019
MODIS	Terra	Twice daily	1 km (approx.)	10.78–11.28 11.77–12.27	31 32	1999
MODIS	Aqua	Twice daily	1 km (approx.)	10.78–11.28 11.77–12.27	31 32	2002
SEVIRI	Meteosat-8	Geostationary	3 km (approx.)	10.812	TIR	2005
TIRS	Landsat 8	16 days	Collected at 100 m and resampled to 30 m	10.6–11.2 11.5–12.5	10 11	2013
TIRS 2	Landsat 9	16 days	Collected at 100 m and resampled to 30 m	Similar TIRS	Similar TIRS	Launch planned for 09/23/2021
TM	Landsat 4	16 days	Collected at 120 m and resampled to 30 m	10.4–12.5	6	1982–1993
TM	Landsat 5	16 days	Collected at 120 m and resampled to 30 m	10.4–12.5	6	1984–2011

In the next subsections, a brief description will be given considering these sensors.

- **Landsat mission**

The Landsat mission began in 1972, but only in the following decade, with Landsat 4, thermal data began to be collected, due to the recording capabilities of the following sensors: in Landsat 4 and 5, the Thematic Mapper (TM) [42,43]; in Landsat 7, the Enhanced

Thematic Mapper Plus (ETM+) [44]; and in Landsat 8, the Thermal Infrared Sensor (TIRS) and Operational Land Imager (OLI) [45]. The Landsat family operates in heliosynchronous and near-polar orbit with a nominal altitude of 705 km, an orbital inclination of 98.2°, and a revision time of 16 days [42–45].

The Thematic Mapper (TM), present on Landsat 4 (operation from July 1982 to June 2001) and Landsat 5 (operation from March 1984 to January 2013), is a multispectral sensor, with seven spectral bands that detect information, simultaneously. Thermal infrared radiation is detected by band 6, whose records occur only at night. The Instantaneous Field of View (IFOV) of this sensor is 30 × 30 m in bands 1–5 and 7, and 120 × 120 m in band 6 [42,43].

ETM+ of Landsat 7 began operation on 15 April 1999, and since June 2003 has acquired and provided data with gaps caused by the Scan Line Corrector (SLC) failure [44]. It consists of a fixed scanning, multispectral radiometer with eight spectral bands, including a panchromatic and a thermal band. The spectral resolution of the bands is in the range of 0.45 to 12.5 µm and it has a spatial resolution of 30 m (except for band 6, which is 60 m, resampled to 30 m, and the panchromatic band, which is 15 m). The radiometric resolution, which is the sensor's ability to discriminate small variations in energy, which in images refers to the number of distinguishable shades of gray between black and white, is related to the sensor's bits, and is 8 bits and records Digital Number (DN) values between 0 and 255 gray levels [44].

Concerning Landsat 8, the OLI consists of one panchromatic band and eight multispectral bands, with a resolution of 15 and 30 m, respectively. In the TIRS sensor, there are two thermal bands with a resolution of 100 m, whose data are resampled to 30 m [45]. Landsat 9 is planned to be launched at the end of 2021. There is a similarity regarding the operation and characteristics of the Landsat 8 thermal sensors, renamed to TIRS 2 and OLI 2 [46].

Landsat has a long and uninterrupted observation program [47] and its heliosynchronous orbit favors temporal studies of the same place, since its revisit occurs at the same point and UTM time, with an interval of 16 days. Its data are released free of charge by the United States Geological Survey (USGS), in levels 1 and 2 (with absence and presence of pretreatment, respectively).

To compute the LST, it is necessary to process the two levels of data: NIR and RED bands from level 1 and thermal band from level 2 [48]. The standard processing will be presented below [27].

The conversion from Digital Number (DN) to Top Of Atmosphere (TOA) spectral radiance ($L\lambda$)—physical quantity defined as the radiant flux in each direction, considering a surface normalized concerning surface area and unit solid angle [26]. It is calculated according to Equation (1) [49,50], using the thermal band.

$$L\lambda = MLQ_{cal} + AL \quad (1)$$

where $L\lambda$ is the TOA spectral radiance (Watts/(m² * srad * µm)); band-specific multiplicative rescaling factor from the metadata (radiance_mult_band_x, where x is the band number) is the ML; the band-specific additive rescaling factor from the metadata (radiance_add_band_x, where x is the band number) is represented by AL; and the quantized and calibrated standard product pixel values (DN) is Q_{cal} , i.e., the thermal band.

TOA spectral radiance ($L\lambda$) is converted to Top Of Atmosphere brightness temperature (Kelvin) by Equation (2) [49,50].

$$TK = K_2 / (\ln(K_1 / L\lambda) + 1) \quad (2)$$

where TK is the Top Of Atmosphere brightness temperature (K);

$L\lambda$ is TOA spectral radiance (Watts/(m² * srad * µm)); K_1 and K_2 are band-specific thermal conversion constants from the metadata (K_1 or $K_2_constant_band_x$, where x is the thermal band number).

Subsequently, the result is converted into Temperature in Celsius— TC , according to Equation (3) [49,51].

$$TC = TK - 273.15 \quad (3)$$

where TC is Top Of Atmosphere brightness temperature ($^{\circ}\text{C}$).

The thermal band includes the Emissivity (E) of the soil and vegetation. Although it is possible to deduce radiance and temperature values, it is necessary to include emissivity in the computation for the generation of the LST, using the NIR and RED bands. For that purpose, first, the Normalized Difference Vegetation Index ($NDVI$) is calculated (according to Equation (4)). $NDVI$ was first proposed by Rouse et al. (1974) [52].

$$NDVI = (NIR - RED) / (NIR + RED) \quad (4)$$

where NIR is the near-infrared satellite band and RED is the red satellite band.

This result is used to obtain the Vegetation Proportion (PV) (Equation (5) [49,53].

$$PV = ((NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}))^{\frac{1}{2}} \quad (5)$$

where $NDVI_{min}$ and $NDVI_{max}$ are the minimum and maximum values obtained in the $NDVI$ calculation, respectively.

In Equation (6), the emissivity (E) is estimated [54].

$$E = 0.004 * Pv + 0.986 \quad (6)$$

Finally, the LST was computed according to Equation (7) [39,49].

$$LST = (TC / (1 + (\lambda * TC / \rho) * \ln(E))) \quad (7)$$

where LST is the temperature, with correction by emissivity ($^{\circ}\text{C}$); TC is the temperature of the brightness at the sensor ($^{\circ}\text{C}$); λ is the wavelength of the emitted radiance; E is the emissivity; P is which is deduced from Equation (8) [23,49].

$$\rho = h \frac{c}{\sigma} = (1.438 \times 10^{-2} \text{ mk}) \quad (8)$$

where σ is the Boltzmann constant ($1.38 \times 10^{-23} \text{ J/K}$), h is Planck's constant ($6.626 \times 10^{-34} \text{ Js}$), and c is the speed of light ($2998 \times 10^8 \text{ m/s}$).

The standard process is presented in Figure 2.

• MODIS

MODIS is an instrument onboard Terra (1999) and Aqua (2002) satellites, both launched by NASA. It has a spectral resolution of 36 bands, divided into the visible, NIR, and infrared wavelengths (comprising the bands 20, 22, 23, 29, 31, and 32, centered at 3.79, 3.97, 4.06, 8.55, 11.03, and 12.02 μm , respectively) [55]. With a revisit time of every one or two days, its spatial resolution is low: bands 1 and 2 are recorded with 250 m, bands 3 to 7 with 500 m, and bands 8 to 36, with 1 km. MODIS sensors can measure the physical and biological properties of the oceans and land and the physical properties of the atmosphere [55].

Thermal data has a resolution of 1 km, which makes its products applicable to larger regions. There are several pre-processed products for users, such as ocean surface temperature, ice, snow, evaporation, precipitation [56], LST with daytime and nighttime data, and emissivity, from MOD11C3, MOD11A1, and MOD11A2 products, respectively.

In MODIS products, the LST value is retrieved by applying the generalized split-window algorithm [57]. In MODIS LST Collection-6 products, the MODIS Land Surface Temperature and Emissivity (LST&E) product (MOD21), the LST is calculated by the ASTER Temperature Emissivity Separation (TES) algorithm and are more sensitive to land cover changes when compared to other emissivity products [55,58].

TES applies physics concepts to dynamically and simultaneously retrieve both LST and spectral emissivity for the MODIS thermal infrared bands (29, 31, and 32) through simulations of radiative transfers for atmospheric correction, called Water Vapor Scaling (WVS), and a model of the variation of surface radiation data, resulting in accuracies at the 1 K level for various surfaces (deserts, water, and vegetation) [59].

Studies using products from sensors onboard satellites may be useful to show differentiation in the daytime and nighttime LST levels when there is not much cloud concentration. For this purpose, a study used a sensor onboard the Aqua satellite to analyze heat wave episodes in Cyprus [60]. The combined use of Terra and Aqua MODIS data can also provide valuable results, especially when complemented with daytime data, as it increases the spatial, temporal, and angular coverage of clear-sky data [61].

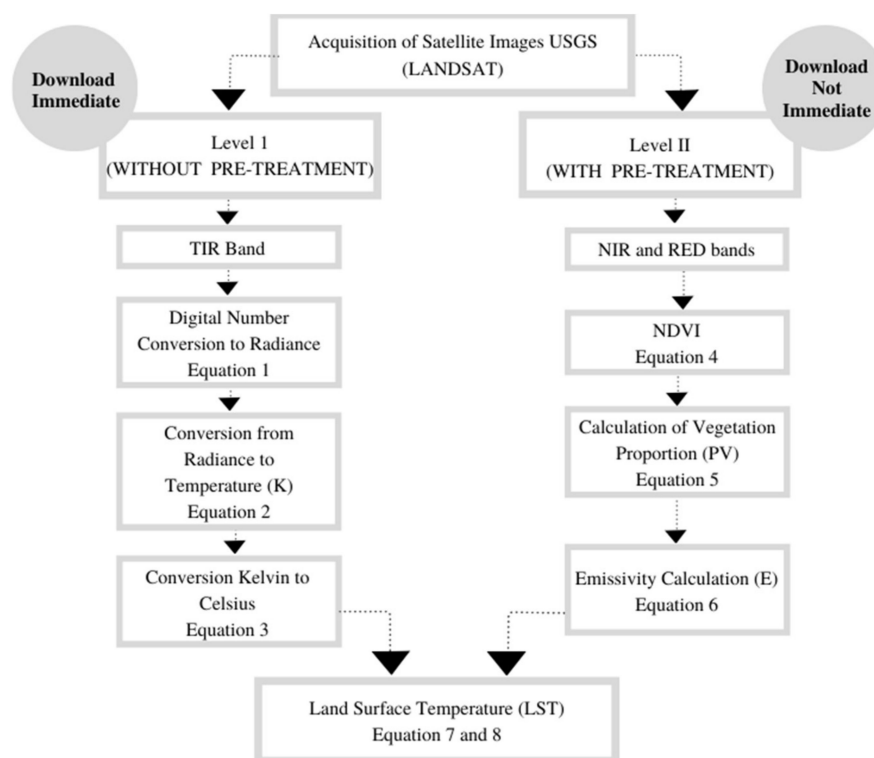


Figure 2. Steps for generating the LST map.

- **ASTER**

Advanced Spaceborne Thermal Emission Reflection Radiometer (ASTER) is a sensor onboard NASA's Terra satellite, launched in December 1999. It operates with three independent imaging subsystems and collects data in different regions of the electromagnetic spectrum: in the Visible Spectrum (VIS) and NIR region there are three spectral bands with 15 m spatial resolution (bands 1 to 3); in the shortwave infrared there are six bands with 30 m resolution (bands 4 to 9), and in the thermal infrared region there are five bands with 90 m resolution (bands 10 to 14) [62–65].

Additionally, there is the VIS-NIR system, consisting of two telescopes. One of them operates with rear-view, with a difference of seconds relative to the nadir view, making it possible to generate stereoscopic pairs in band 3. The revisit time is 16 days or less since the subsystems have a side view of ± 24 degrees beyond nadir. Each image covers a 60×60 km area [62–65].

The data are available in different treatment levels. Level 1A, unsuitable for most users, refers to raw data, without calibration or noise correction pretreatment, and with non-co-recorded bands. Level 1B, a product suitable for many applications, has geometric and radiometric calibration and co-registered bands. Level 2 includes more specific products,

identified by acronyms, the most used of which are AST04—surface temperature; AST05—surface emissivity; AST06—decorrelation-enhanced color compositions; AST07—surface reflectance; AST08—kinetic temperature (in which it is possible to obtain the LST, with an accuracy of 1.5 K and there may be nighttime records of the study area, which is interesting for UHI studies); and AST09—surface radiance. Level 3 products are more sophisticated and include, for instance, digital elevation models (AST14). Level 2 and 3 products are freely available on the Internet, although they were charged from 1999 to April 2016 (resulting in fewer search results in this period) [58,62–66].

- **Polar and geostationary satellites**

Polar and geostationary satellites can also be used for LST estimation. Their fixed positioning at a point on earth provides wide temporal coverage of local data, even allowing for a more adequate characterization of the diurnal cycle compared to other orbits [40]. However, the spatial resolution and coverage area do not present much detail, which can compromise the identification of land surfaces in a more refined way [37,67], and are not suitable for analyses of UHI patterns and dynamics about heat-associated health risk at urban scales [67].

The best-known satellites for LST estimation are Suomi National Polar-orbiting Partnership (NPP), Spinning Enhanced Visible InfraRed Imager (SEVIRI) [68], aboard Meteosat Second Generation (MGS) [69]; and Geostationary Operational Environmental System (GOES) [67].

NPP consists of a mission to monitor biological productivity and long-term climate trends. It acts between the measurements gauged by EOS Terra and Aqua, complementing the data between NASA's EOS missions and the Joint Polar Satellite System (JPSS) [70].

MGS operates in geostationary orbit, 36,000 km above the equator and can be directed for data collection at different locations, and is currently operated over Europe, Africa, and the Indian Ocean. Its sensor, SEVIRI, has 12 spectral channels and provides data on the atmosphere, assisting in the generation of predictive weather models. It has eight channels in the thermal infrared region, including High-Resolution Visible (HRV), which performs sampling with a nadir distance of 1 km, with daytime cycle coverage every five minutes, due to its fast scanning [68,71].

The GOES mission is controlled by the National Aeronautics and Space Administration (NASA) and operated by the National Oceanic and Atmospheric Administration (NOAA). Its orbit is geosynchronous equatorial, 35,800 km above the earth, and scans the continental United States and its surroundings (Atlantic and Pacific oceans), Central and South America, and southern Canada [67]. The GOES LST product is based on the split-window technique, which corrects atmospheric absorption and surface emissivity. It has a spatial resolution between 4 and 8 km [72].

Considering that most of the materials analyzed in this review do not use data from polar and geostationary sensors, the treatment processes for estimating the LST will not be detailed.

1.1.2. Passive Microwave Sensors

LST can also be computed from processing data from passive microwave radiometers. Passive sensors are microwave instruments that receive and measure natural emissions, which are produced by the earth's atmospheric and surface constituents. The power associated with the measurement is related to the composition and roughness of the surface being measured, and the physical temperature. The frequency bands are determined by fixed physical properties of what is being measured and cannot be duplicated in other bands [73]. They generate products capable of measuring biogeophysical variables, such as air temperature [36,74], even at night [36]. Compared to thermal sensors, passive microwave sensors have a greater ability to penetrate clouds, snow, rain, arid surfaces, and vegetation, complementing the data for UHI studies [75].

The limitations of these data relate mainly to the coarseness of spatial resolution (low) and the inability to recover temperatures on frozen surfaces [36].

The first attempts to obtain data from passive sensors were performed in the 1990s, i.e., compared to thermal sensors, there are limitations of historical and coverage areas [76–78].

The Advanced Microwave Scanning Radiometer-Earth observing system (AMSR-E) on the Aqua satellite was responsible for collecting data at high temporal resolution and contributed to the mapping of global near-surface air temperatures on a near-daily basis and for over a decade, until there was a failure of its antenna in October 2011 [36]. A combination of data from AMSR-E and AMSR2 (onboard the Japan Aerospace eXploration Agency's Global Change Observation Mission-Water1 (JAXA's GCOM-W1)) was released in May 2012 [36,79]. The data gap was filled with data obtained by the Microwave Radiation Imager (MWRI), onboard on the Chinese satellite FengYun-3B (FY3B) [36]. An example application is the use of data from these sensors to obtain information about the three-dimensional structure of urban temperature. The Atmospheric Boundary Layer (ABL) acts as a buffer zone and accumulates heat, pollutants, and moisture. The ABL influences the intensity of vertical exchange, and the more unstable it is, the more favorable the removal of pollutants in the lower layer [38].

Moreover, the information from passive sensors can be combined with thermal ones for the complementarity information in locations with a higher presence of clouds or obstacles that influence the collected results. It is noteworthy that the methodology employing the use of passive sensors was not recurrent in the analyzed papers.

1.2. SUHI and LST Studies Applying Different Techniques

Information on the surface temperature of a location can be useful in different fields of investigation, either to assess climate change of natural and/or anthropogenic origin or to predict climatic behavior based on statistical models and time series. LST prediction can be an important tool for mitigating possible social impacts and promoting improvements in the quality of life of the populations.

Although LST is widely applied for studies that aim to analyze SUHI, this parameter is cross-cutting and can corroborate for the analysis of other topics, for example: environmental analyses with research on aquifers/water bodies [80], biomes [2], forest dynamics [81], and natural hazards such as volcanic activity studies [82]; air pollution [83] and determination of particulate concentration in urbanized areas [84]; architectural assessment to identify the building area and building layout with the least impact to the local microclimate [85] and identification of Local Climate Zones (LCZ) [86], from the identification of regions with uniform characteristics, from hundreds of meters to several kilometers, with respect to land cover, surface structure, building materials and human activities [10], use of hybrid data, including physical and mobile equipment for climate characterization of a site [87], socioeconomic and cultural analysis, including studies on biophysical and socioeconomic impacts [88–90], and social events [91]; and public health and mortality associated with HWs [92].

1.3. Study Objectives

Given the relevance of the studies in this area, this work aimed to identify the publications from 2000 to 2020 that address the UHI effect using RS data, namely the LST, and to perform a qualitative and quantitative analysis considering the following parameters: (i) number of publications in the considered period; (ii) geographic location and climate zone of the study areas; (iii) keywords; (iv) general objectives and application areas; (v) equipment/sensor used to obtain information about the thermal data; (vi) information sources used to obtain Land Use Land Cover (LULC) and additional data; (vii) software employed to process the data; (viii) Vegetation Index (VI) and additional data used for the comparative analyses; (ix) statistical methods employed to evaluate the relationship between indices and LST; (x) authors' main conclusions (quantitative and qualitative analysis); (xi) bibliographical references; (xii) authors; and (xiii) citations.

2. Materials and Methods

2.1. Bibliographic Database

The databases selected for this study were Scopus and Web of Science (WOS). Scopus has been available since 2004. Its publications are peer-reviewed, and it is one of the largest databases of literature abstracts and citations worldwide, with more than 25,100 active titles from over 5000 international publishers, divided into the fields of science, technology, medicine, social sciences, arts, and humanities. In 2020, it included 23,452 peer-reviewed journals. Its tools for information retrieval and aggregation are efficient, allowing data extraction in several formats, which facilitates the analytical process [93]. WOS is a global database of various publishers. It has consistent indexing in its main base, which is approximately 50 years old. In the WOS platform version, there are more than 34,586 publications, including journals, books, proceedings, patents, and datasets. Like Scopus, peer review occurs independently, and it is possible to filter by area or publication type and to issue customized reports in different extensions, which allows the analysis of the publications available in the database [94].

2.2. Search Strategy and Validity

Considering the relevance of reviews to provide a broad picture on a given subject from the contextualization of a topic, its methodological approaches, the direction of research, and the challenges and points for improvement discussed [95], the selection process of the evaluated papers is important.

The following steps were performed: firstly, the papers were screened to select those applying RS in UHI studies; secondly, the data from the selected papers were systematized, identified, and filtered, considering the titles, abstracts, methodologies, and other parts that could correspond to the 13 criteria analyzed (described in Section 1.3); subsequently, the resulting data were identified and filtered, descriptive statistics were applied, and analytical graphs were plotted; finally, the results were discussed, by class.

Not all steps contained in a meta-analysis were adopted in this review, since it was not intended to assign weight or relevance to any of the criteria evaluated in the papers, such as the number of citations or year of publication [96]. The intention was to select and evaluate all papers quantitatively and qualitatively, from a manual review, using synthesis study techniques similar to those adopted in other reviews in the area of RS [97].

The details of each step are presented below.

The search in both databases considered publications that occurred from 2000 to 2020. The keywords ((UHI*) OR (satellite image*)) existing in the article title, abstract, or keywords fields were searched. Search results were saved in a list so that the base was static and Excel software was used for data tabulation and manipulation.

The process of selection of the publications approved for analysis in this paper was carried out by two independent researchers. A total of 1239 documents were considered, 872 (70.4%) published in Scopus, 199 (16%) in WOS, and 168 (13.6%) in both bases, divided into Papers (978—78.9%), Conference Paper/Works (222—17.9%), and Reviews (39—3.2%).

In the first stage, only the publications classified as “papers” were considered, to maintain in the database as many unpublished documents as possible, since some research may be first presented at conferences and later submitted as journal papers. Thus, 222 (17.9%) publications classified as “Conference/Proceedings Paper” and 39 (3.2%) as “Reviews” were discarded. The second step to refine the database consisted of the identification of duplicated documents based on the criteria of similarity of the Digital Object Identifier (DOI), title, and abstract, resulting in the elimination of 136 papers (13.91%). For each repeated title, one was kept, and the other was deleted.

Next, the title, abstract, and keywords were evaluated to check if the UHI studies used RS data (satellite, drone, or aerial imagery), to estimate LST. In cases where the fields did not spell out which data sources were used, the researchers performed a full reading of the paper methodology. At this stage, 43 papers (5.10%) were excluded, resulting in 799 publications (64.49% of the initial selection).

To refine the database and allow a more effective qualitative analysis of the remaining papers, a third analysis was performed, considering the papers published in English and without the “in press” status. Thus, of the 799 approved publications, 756 (94.62%) were in English; 36 in Chinese (4.5%); 3 in Spanish (0.38%), and the others correspond to 1 publication in other languages: German, French, Croatian, and Portuguese (totaling 0.50%). Thus, 43 papers (5.38%) were discarded. Additionally, 14 papers with “in press” status were also discarded for the next selection step.

Thus, 742 papers were selected for the next stage of analysis, which consisted of a thorough reading regarding the adherence of their objectives and methods regarding this review. In this step, 163 papers were discarded because they did not use RS data as the main sources of information or because they did not present in a clean form the main objective (UHI effect).

As each researcher performed this process separately, the titles approved by both were included in the final database. Finally, 579 papers (46.73% of the initial total), were selected. All these papers applied remote sensing techniques for UHI and SUHI analysis. Figure 3 presents a summary of the steps and the respective pass/fail criteria at different stages.

For the presentation of the results, in addition to graphs generated in Excel, the VOSviewer tool [98] and ArcGIS version 10.7 software [99] were used to present the data in grouping and map format, respectively.

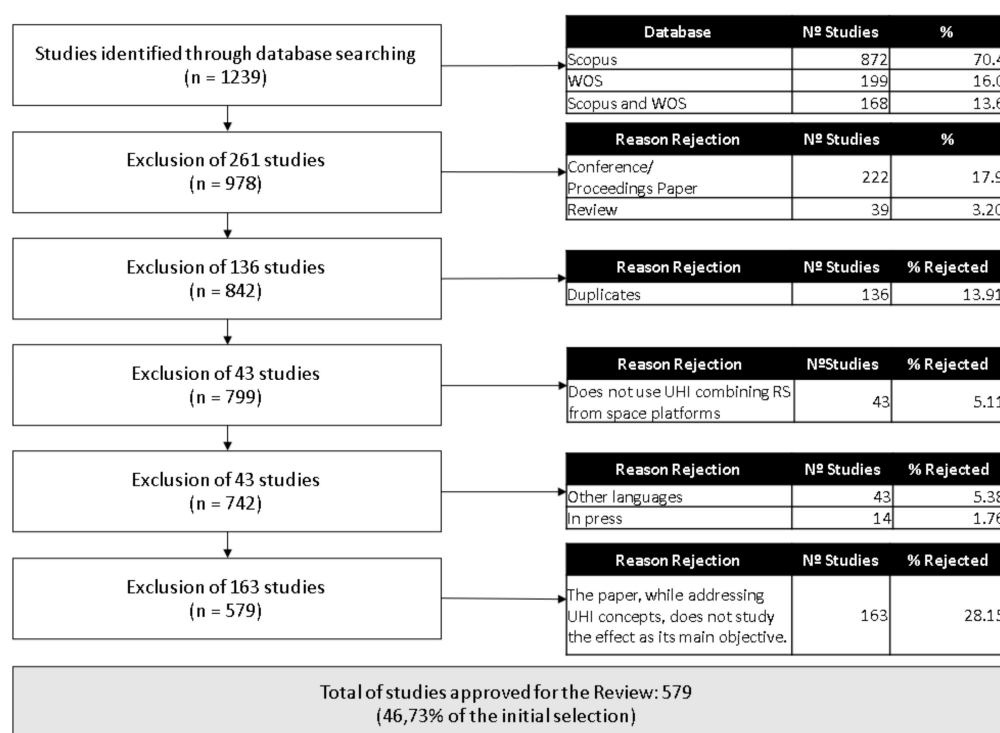


Figure 3. Article selection criteria and approval process.

3. Results

In this item, the most relevant results identified during the development of this work will be presented.

3.1. Publication Period

The evolution in the number of publications concerning the study of UHI with RS data/techniques in the last 20 years can be observed in Figure 4. From 2000 to 2008, this methodological combination resulted in fewer publications when compared to the following years. In 2001 and 2002, the database search did not show any publications. In this case, a second search was performed, using only the term “UHI” as a criterion, to

assess whether there had been any inconsistency. As a result, 26 papers published in this period were identified (adding the two databases), but none met the selection criteria of this paper (either using data only from meteorological stations or applying the acronym UHI to other phenomena, such as in health areas).

It is possible to verify a significant increase of publications in the last 20 years, especially in the last five years, the period which concentrated 399 (68.91%) of the analyzed papers. This increase reinforces the relevance of the topic in the scientific community, as well as the applicability of RS to analyze the UHI effect.

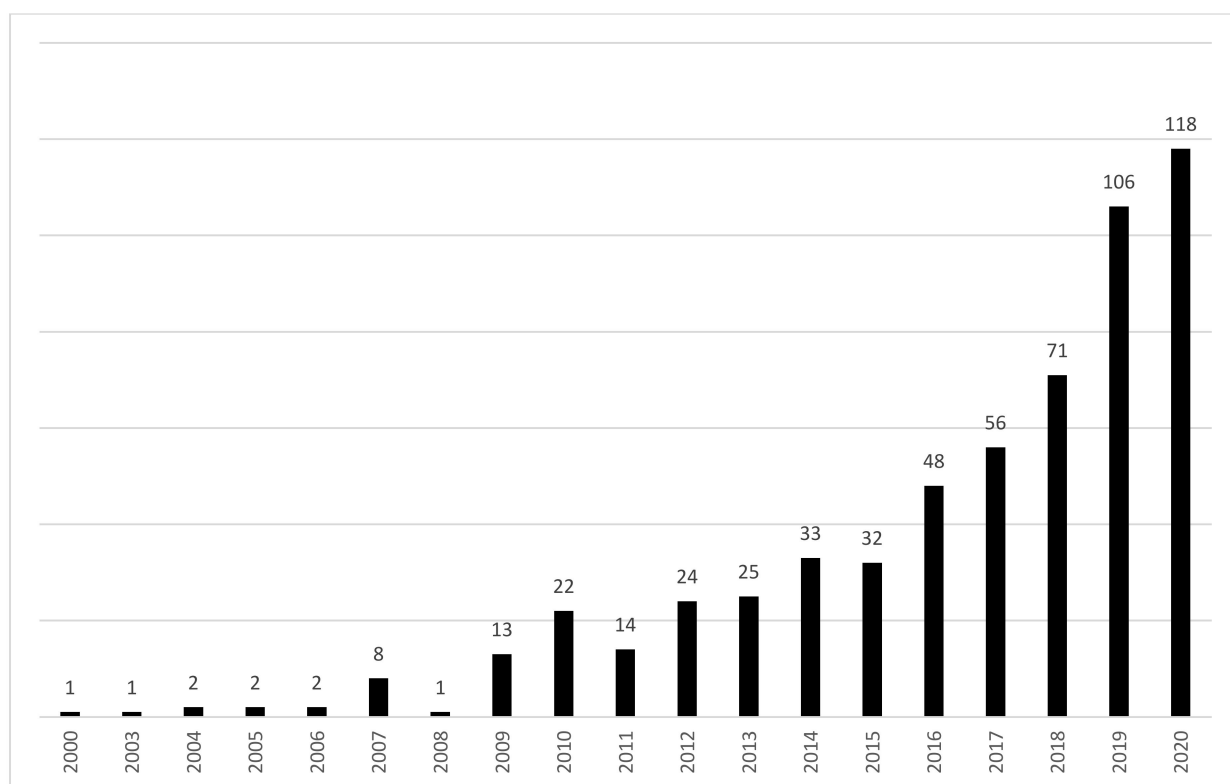


Figure 4. Publications per year between 2000 and 2020.

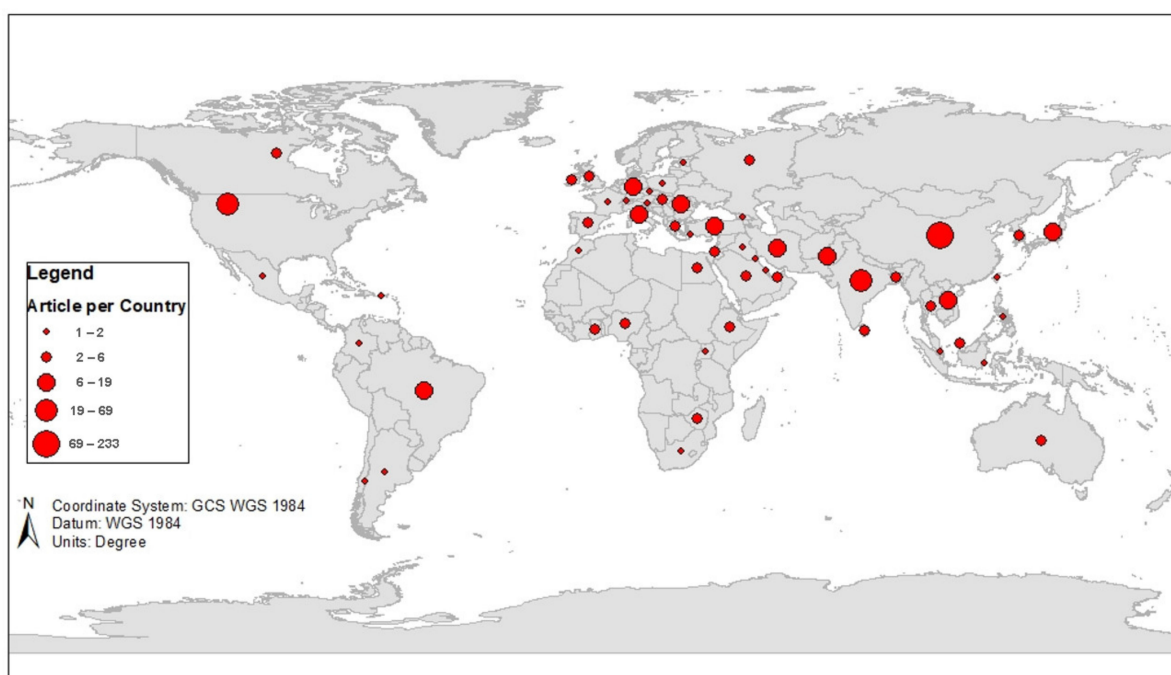
3.2. Geographic Location and Climate Zone of the Study Areas

Regarding the study areas, the most studied continents or subcontinents were Asia (405–69.94%), Europe (65–11.23%), and North America (59–10.19%), totaling 529 (91.36%) papers. Besides the papers with continental delimitation, 14 papers were produced with data from at least two continents, representing 2.42% of the analyzed papers. Table 2 shows the number of publications and their respective percentages.

Considering the countries, China was the most studied, with 233 (40.24%) papers, followed by India with 69 (11.92%), the United States (50–8.64%), and Iran (19–3.28%). These four countries are accountable for 64.08% (371) of the material analyzed. Figure 5 shows the spatial distribution of the papers by country. Studies that were conducted on more than one continent (3–0.52%) were not considered in this map in order not to generate duplication of information.

Table 2. Published papers by continent/sub-continent.

Continent	No. of Publications	% of Publications
Asia	405	69.94
Europe	65	11.23
North America	59	10.19
Africa	18	3.11
South America	12	2.07
Australian Area	4	0.69
Antarctic Area	2	0.35
Studies Involving More than One Continent/Sub-Continent		
Africa and Europe	1	0.17
Asia and Europe	7	1.21
Asia and North America	3	0.52
More than two continents	3	0.52
Total	579	100

**Figure 5.** Published papers by country.

Regarding climatic zones, in this work, we adopted the Köppen–Geiger global classification, proposed in 1900 by climatologist Wladimir Köppen and improved in 1918, 1927, and 1936 with the help of Rudolf Geiger to separate the papers analyzed. According to the concepts of phytosociology and ecology, the regional natural vegetation correlates with the predominant climate of the area. In this classification, these climate types are designated considering seasonality, and annual and monthly mean values of precipitation and air temperature [100,101].

In the nominal representation of the climate type, there are uppercase and lowercase letters that symbolize the types and subtypes considered, respectively. Table 3 shows the division of the study sites by climate zones.

Regions with a Cfa climate were the most studied, followed by Dwa and Cwa. It is noteworthy that, of the 579 papers evaluated, 41 (7.08%) addressed more than one climate zone in the same study. In addition, 31 papers analyzed different climates in the same study. As expected, there is a correspondence between the continents with most case studies and the climate of such studies.

All keywords are associated with topics and methodologies that can be employed for the study of UHI, except for the word “China”, which stands out among the 15 most cited because of the high number of publications in the area.

Table 4. Top 15 most frequently cited keywords.

Keyword	No. of Citation
land surface temperature	285
urban heat island	285
heat island	282
atmospheric temperature	279
remote sensing	211
surface temperature	196
landforms	188
land surface	171
surface properties	164
surface measurement	149
China	141
satellite imagery	140
urbanization	134
land use	111
urban planning	110

3.4. General Objectives and Application Areas

The qualitative analysis of the objectives of the papers resulted in the identification of seven main areas addressed, presented in Table 5.

Table 5. Study of the UHI effect.

Study Approach	Main Data Used	No. of Papers	%
Rural versus urban areas and Seasonality	Including papers that used extra data (weather network, LULC, building construction, LCZs, on-site measurement)	416	71.85
Environmental	Environmental Data Vegetation, biophysical, biochemical, water body, and wetland data	61	10.53
Models (IVs, mathematical, computational)	Satellite data; extra data (weather network, LULC, building construction, LCZs, on-site measurement, historical data)	31	5.35
Health and Social	Census, health data, questionnaire application	28	4.84
Specific areas of study	Complementary data to identify local specificities (as petrochemical, arid zones, and mountainous areas)	21	3.63
Air pollution, energy consumption, and economic factors	Consumption and pollutant data	15	2.60
Focus on Predictability	Historical data	7	1.20
	Total	579	100

The most recurrent objectives/areas in the papers focused on studying the UHI effect, using a comparison between the temperature amplitude of anthropically altered areas versus vegetated ones (416 papers—71.85%). Secondly, studies focused on analyzing the environmental characteristics, conditions, and impacts of UHI, considering biophysical, biochemical parameters, and data on water bodies and wetlands, totaling 61 (10.53%) papers.

It is important to emphasize the subjectivity of this classification, especially in the case of papers that worked with interdisciplinary topics, which were framed in the subclass that presented more affinity.

3.5. Equipment/Sensor Used to Obtain Information about the Thermal Data

Regarding the satellite/sensor selection to obtain the thermal data, 446 papers (77%) used RS data from a single source, 114 (19.69%) combined at least two sources of information, 16 (2.76%) used three data sources, 2 (0.35%) used data from four sources, and 1 (0.17%) combined data from five sources.

The most used satellites/sensors were Landsat, with 396 papers (68.39%), considering those that used complementary sources of data and 317 (54.75%) that used only Landsat products; MODIS, with application in 185 (31.95%) papers, being the exclusive source of data in 103 (17.79%) of the papers; and ASTER, which figures as the third most used, with 36 papers (6.22%), being the exclusive source in 15 (2.59). Considering the sum of the papers that cited the three satellites as exclusive sources, there are 435 (75.13%) of all the papers studied. It is emphasized that since most of the papers aimed a more detailed spatial monitoring of the study area, the authors adopted to use data from heliosynchronous orbits, rather than increasing the temporal resolution.

Table 6 presents the list of five satellites most used and the number of papers that cited them.

Table 6. Most used satellites/sensors to obtain LST data.

Satellite	Exclusive Use		Combination	
	No. of Papers	%	No. of Papers	%
Landsat	317	54.75	396	68.39
MODIS	103	17.79	185	31.95
ASTER	15	2.59	36	6.22
NOAA/AVHRR	1	0.17	7	1.21
METEOSAT	-	-	3	0.52

Considering data from complementary sources, the use of meteorological networks was cited in 41 (7.08%) of the papers, followed by in situ measurements in 14 (2.42%) publications. The data collection by drones, helicopters, and airborne were cited in 13 publications (2.25%).

The combination RS data with complementary information, such different resolution [102], in situ measurement data, especially in daylight [69] and model information, can be a good strategy to obtain data with better temporal resolution (due to the possibility of collection in the interval between satellite passes), as well as to improve spatial and spectral scales.

3.6. Information Sources Used to Obtain LULC and Extra Data

For the LULC computation, 446 (77.03%) papers used data from a single source, 144 (19.69%) considered two sources, 16 (2.76%) of the papers considered three sources, 2 (0.35%) four sources, and 1 (0.17%) five sources.

Considering RS sources, 324 papers (55.96%) used Landsat data, with 211 papers (36.44%) using this data exclusively. MODIS was the second most used, with 95 (16.41%) citations, where 51 (8.81%) were exclusive sources. Next, ASTER was cited in 32 (5.53%) papers, of which 11 (1.90%) were exclusive. Table 7 shows the five main satellites/sensors used in LULC computation.

Table 7. Most used satellites sensors in the LULC estimation.

Satellite	Exclusive Use		Combination	
	No. of Papers	%	No. of Papers	%
Landsat	211	36.44	324	55.96
MODIS	51	8.81	95	16.41
ASTER	11	1.90	32	5.53
IKONOS	5	0.86	21	3.63
SPOT	9	1.55	14	2.42

In addition to the derivation of LULC through satellite data, eight papers (1.38%) used information recorded by drones and sensors onboard helicopters and airborne, and two (0.35%) used exclusively these sources. One of the advantages of using data from these sources is the improvement in spatial and temporal resolution when compared to satellites, making it possible to record information at more detailed levels and, in areas of considerable heterogeneity, the distinction between land-use types can be useful for the researchers. However, the cost associated with this technology can be a limiting factor, given the small number of publications found.

3.7. Software Employed

Regarding RS data processing, 208 (35.92%) papers did not specify the name of the software used for processing the data. Considering those that did, 193 (33.33%) processed the data in a single software program, 111 (19.17%) used two software packages, and the other 67 papers (11.58%) used three to six different packages. Depending on the complexity of the study, a single software program may not answer all the processing needs, which justifies the combination and complementary use of different software. Figure 7 presents the number of papers concerning the number of software programs used.

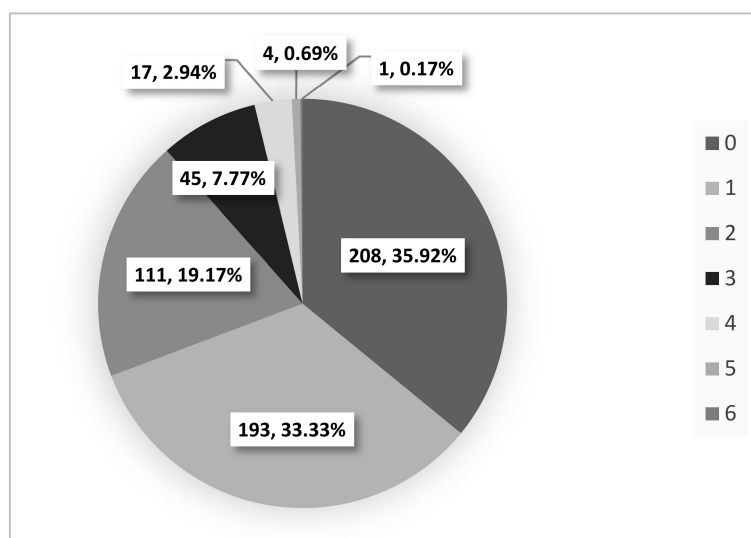
**Figure 7.** The number of papers by the software used.

Table 8 highlights the six most used software programs.

ArcGIS and ENVI were the most used software programs in the papers analyzed. ArcGIS was used as the exclusive tool in 60 articles (10.36%) and 178 (30.74%) combined with other software. For ENVI, 28 articles (4.84%) used it exclusively and 93 (16.06%) combined with other software.

In addition to spatial image processing and analysis software, other software/systems were used to supplement information. For instance, FRAGSTATS, used for calculating landscape metrics, was used as complementary software in 39 papers (6.74%) and SPSS, applied for statistical processing, was used in 33 papers (5.70%).

Table 8. Six most used software programs.

Keyword	Key Applications in Papers	Exclusive Use		Combination	
		No. of Papers	%	No. of Papers	%
ArcGIS	Spatial image analysis and processing	60	10.36	178	30.74
ENVI		28	4.84	93	16.06
Google Earth	3D representation of the earth based mainly on satellite imagery used to identify LULC classes	30	5.18	71	12.26
ERDAS Image	Spatial image analysis and processing	11	1.90	43	7.43
FRAGSTATS	Calculating landscape metrics	-	-	39	6.74
SPSS	Statistical calculations	-	-	33	5.70

3.8. Vegetation Index and Extra Data

Several complementary/auxiliary indices and indicators have been used in addition to the LST analysis. The ten indices/extra data most used are shown in Table 9.

Table 9. Ten indices/indicators most used.

Index	No. of Citation
NDVI	190
Enhanced Vegetation Index (EVI); Fraction Vegetation Cover (FVC);	105
Photosynthesis	
Built-up	78
LULC and Bareness	73
NDBI	71
Percent of Impermeable Surface (%ISA)/Impervious Surface Areas (ISA)	68
Dimension, Altitude, Latitude, Digital Elevation Model (DEM)	42
Demographic/Social Data	33
Water Bodies	31
Albedo	26

Most indicators are associated with different topics, such as urban morphology and construction data, and indices obtained through RS data processing, such as NDVI, Normalized Difference Built-Up Index (NDBI)—an index that allows the identification mapping of built-up areas [103], census (demographic), environmental, social, and financial data. NDVI figures as the most cited indicator (190), followed by indices that use vegetation data such as EVI, FVC, and photosynthesis (105). It should be noted that the classification of the indicators considered the adoption of identical names by the authors.

3.9. Applied Statistical Methods

As for the statistical methods, 36 papers (6.22%) did not explicitly mention how the results were evaluated, 232 (40.07%) relied on one type of analysis, and 195 (33.68%) used two methods for data analysis. Table 10 presents the proportion of papers concerning the methods employed.

Table 10. Papers by the number of statistical techniques applied.

No. of Statistical Techniques Applied	No. of Papers	%
0	36	6.22
1	232	40.07
2	195	33.68
3	62	10.71
4	30	5.18
5	14	2.42
6	8	1.38
Total	579	100

The combination of methods can be a strategy when it comes to evaluating the best-fitting model for the data set, as well as complementing analytical information.

Table 11 shows the list of the most applied statistics. It is noteworthy that, since there are papers that applied different statistical techniques, the sum of the percentages exceeds 100%.

Table 11. Papers by statistical technique.

No. of Statistical Techniques Applied	No. of Papers	%
Correlation	224	38.69
Regression	210	36.27
Descriptive Statistics	128	22.11
Others	60	10.36
Machine Learning	27	4.66
Model/Method	27	4.66
Dispersion	25	4.32
Tests	20	3.45
Variance	12	2.07
Spatial Statistics	3	0.52

The correlation technique was the most applied in the studies selected, corresponding to 224 papers (38.69%), followed by the regression technique (210 papers, 36.27%), and descriptive statistics (128 papers, 22.11%). The data most applied in the correlations were the NDVI with the LST values.

3.10. Authors' Main Conclusions

This section highlights the main conclusions of the analyzed in this work, considering quantitative data, and highlighting some works for qualitative analysis, that were chosen to exemplify the study of UHI and SUHI in different contexts/areas, aiming for a systemic understanding of the causes identified for the interpretation of this effect. For that, included was the discussion regarding the methodologies employed and statistical analysis, suggestions, and mitigation strategies.

3.10.1. Quantitative Analysis

Considering the main authors' findings, in all studies selected, the UHI effect was evidenced. In addition to this finding, some papers discussed additional measures, highlighted in Table 12.

Table 12. Main findings of the studies.

Main Conclusions	No. of Papers	%
UHI identified at a study site	579	100
Recommendations for mitigating measures considering civil construction, vegetation, and maintenance of water bodies	229	39.55
Seasonality influences the results (different times of the day and/or seasons)	71	12.26
The methods and models tested for the study of UHI were efficient	49	8.46
The morphology, density, and choice of vegetation was appropriate to the specificity of the site and enhances the mitigation effects	38	6.56
Recommendations on socioenvironmental, economic, and health measures to mitigate the effects of UHI	15	2.59
Association of the UHI with atmospheric contamination and wind circulation, with recommendations for mitigating measures	11	1.90
Association of the UHI with flooding and rainfall	8	1.39

Most of the papers identified the presence of the UHI in the studied areas and recognized the importance of local studies to identify the most appropriate mitigation measures. Two hundred and twenty-nine papers (39.55%) recommended mitigation measures, including such actions as interventions on the built-up structures, and maintenance/increase of water bodies and vegetation areas.

3.10.2. Qualitative Analysis

In this item, some UHI and SUHI studies will be presented to explore possible causes, consequences, methodologies, and mitigations. The selection of the papers was made considering the abstract and the diversity prioritized in the approach, without intending to emphasize any research or recommend standardized methodologies.

Each site presents its specificities, both in relation to LULC and Urban Functional Zones (UFZs), which refers to divisions of the urban surface, considering socioeconomic and landscape data [104].

To propose appropriate mitigation measures, it is necessary to understand these structures, as well as the climatic characteristics and local soil type/LULC [105], which vegetation would best fit the study area, the socioeconomic data, technical resources, and other additional indicators, relevant to public management.

The UHI and SUHI were associated with the formation factors shown in Table 13.

Table 13. Highlight of some reasons for UHI and SUSHI's formation.

Factors	
Civil Constructions	Topographical features, building standards, building cooling, landscape configuration, urban morphology, spatial patterns of land use and occupancy [106–108], texture and spatial distribution [109], rural/urban areas with low vegetation density, in bare soil [110–113].
	Three-dimensional urban design (such as height, volume, and surface area of the buildings, and the footprint and shadow volume) showed greater influence relative to two-dimensional ones (such as building rooftop area, street, and vegetation) [114].
	Heterogeneity in the composition of built surfaces and areas [115].
	Hydrological and soil permeability interference [116].
Urban Size	Influence on surface heat flux, soil/air temperature, humidity, and wind circulation, resulting in differences in urban–rural energy balance [117].
Heat Emission	Night lights [118,119], heat emission from industrial and transportation sources [120–122].
Environment	Wind [123], wind speed, and land surface conditions, especially in the morning, corroborate the advance of warm air [124], aerosols can influence/limit diurnal surface heating in dry seasons [125].

Table 14 presents some of the elements that can help in understanding the dynamics of UHI and SUHI.

Table 14. Indicators for understanding UHI and SUHI.

Indicator	
IV	NDVI, NDBI [126], PV (that can show better results in the regressions applied when compared to NDVI) [127], landscape effects (that may have more impact than socioenvironmental data) [89].
Construction and soil	Characteristics and types of soils, LULC [128,129], imperviousness [130], albedo-exposed land areas [131], presence of surface contaminants, as hydrocarbons used in bioremediation processes, whose soils can present higher thermal signatures when revegetated [132].
Social, economic, and health	Population size [1], especially in cities with continental climate [133], economics, social, environmental, population health, anthropogenic heat flux [134–144], and in specific events/actions [91,145].

As for data analysis, several comparative and correlative statistical tools were applied. Among the papers analyzed, some compared two of these tools and presented critical conclusions regarding the applicability and reliability of the results, namely: the Ordinary Least Squares (OLS) and the Geographically Weighted Regression (GWR).

The OLS is based on the assumption of data independence, ignoring the spatial effect between spatial items [146,147], whereas the GWR assumes that relationships between variables are influenced and change according to geographic distribution, allowing estimation of regression coefficients for each site [148–151].

GWR was found to be effective [151], more than OLS [152–155], and provides an analysis of the multiple spatial data layers with autocorrelated structures [156], predicts the behavior of variables with better accuracy, and can describe spatial non-stationarity [157].

It is recommended to apply GWR at finer scales than 480 m and in flat cities, since at larger spatial scales (720–1200 m), the model does not show significant differences from OLS [158].

As for the satellites used in the studies, most use Landsat [159,160], and there are considerations pointed out in some of the analyzed papers. MODIS is pointed out as interesting for research, but some studies concluded that temperature data are overestimated, especially during the daytime, and underestimated at the nighttime when compared to in situ data [161,162], or showed higher LST results in winter when compared to in situ data [163] and variability in measured temperature [164], especially in very dry or very wet weather conditions [165]. Landsat was found to be more efficient than ASTER in differentiating targets and temperature records. In areas with clear seasonality and thermal anisotropy, LST acquisition is challenging [166].

Regarding the consequences, Table 15 shows some examples.

Table 15. Main consequences of the UHI and SUHI effect.

	Main Consequences
Environment	Atmospheric instability [167] that can influence the dispersion of pollutants [83], thermal circulations [168], convective precipitation [135,169], urban flooding [136].
Social and health	Biological risks [170], as the increase in mortality and health [134,144], heat stress-related diseases (especially at night) [143], such as cardiovascular, respiratory, circulatory, emotional disorders [171], anxiety, sleep problems, and depression [142].
Economic	Regulation of the values practiced in the real estate market, whose properties most affected by the effect are cheaper [138], and preference in housing green areas and open spaces by high-income and educated families [88], which suggests understanding and studies regarding social vulnerability associated with residential segregation [172]. Increased electricity consumption in summer (due to the need for cooling/use of air conditioning), and minimized in winter (where the need for heating was not so necessary) [173], especially in areas inhabited by the high-income population, which have the means to regulate temperature, promoting thermal comfort [140]. It is noteworthy that the use of air conditioning can corroborate the increase of primary pollutant emissions and ozone generation [174], and increases the financial costs [175].

As mitigation measures, the analyzed papers suggest a series of actions that range from behavioral changes to structural changes in the analyzed areas, as presented in Table 16.

Table 16. Mitigation of the UHI and SUHI effect.

	Mitigation
Construction and LULC	Conversion of vacant land into green areas to minimize the effects of thermal discomfort [139], knowledge of local parameters, urban plantation, decentralization of urban areas [176–179], minimizing impervious areas and bare soils (such as abandoned land) [176], and diversification and balance of LULC elements, combining urban and vegetated areas, optimizing spatial configuration [178]; industrial relocation, buildings demolition, and brownfield redevelopment [180]; optimization of green land cover configuration [181] (in relatively small cities) or controlling sprawl (in larger cities) reducing the ratio of compaction in urban sprawl [182]; keeping the balance between urban and non-urban uses [183]; light-colored skyscrapers with glass curtain walls systems (which showed relatively low LST) [184].
Environmental	Preservation of water bodies [80,174,185,186] with simple geometry. The area of the waterbody is also a factor that influences temperature variation and, with high surface moisture, are less efficient than a water body (such as a river) [187] but can attenuate surface temperature better than vegetation cover, especially in dry seasons [188]. Increased proportion of vegetation at the expense of impermeable areas [189,190], distribution of trees and taking advantage of their shade effects [191], green surfaces/roofs [192–200]. The relationship between the presence of vegetation and cooling is not linear [201], and additional studies are needed to evaluate local specificities and needs. There are cases, for example, that associate the use of large trees with negative effects on nighttime cooling [202], due to higher heat retention as a consequence of a lower SVF [203]. Therefore, their characteristics must be evaluated to identify the most suitable and favorable vegetal species, arrangements, and strategies for heat exchange in a region. In addition to increasing the volume of vegetation areas at a site [204], evaluating the spatial pattern, shape, canopy cover [205], leaf density, and area of influence of heat regulation/shade effects [206–208]. Large parks did not present advantages over small ones [209].
Social, economic, and health	Encouraging the use of public transportation to reduce the circulation of cars and the emission of atmospheric pollutants [137]. Development of social measures, such as subsidies for electricity [173], and creation of heat warning and health surveillance systems, which alert users to the occurrence of heat waves [141].

As for punctual events, a study conducted in Dehradun, India, identified the increase in the number of hot spots and the minimization of the thermal comfort level associated with the post-lockdown period (COVID-19) considered in the paper on 14 April 2020, compared to data from 28 April 2019, 25 April 2018, and 8 May 2017 [145]. About the adaptations made for the 2008 Beijing Olympic Games, mitigations were carried out, such as increasing water-permeable areas, with the inclusion of green parks distributed among the central cities, minimizing the effects of the UHI [91].

3.11. Bibliographical References

The VOSviewer software was used to verify the similarities regarding the materials used for the theoretical basis of the papers. Table 17 shows the eight most cited references.

Table 17. Eight most recurrent bibliographic references in the studies.

Reference	No. of Papers	%
J. A. Voogt and T. R. Oke, "Thermal remote sensing of urban climates," <i>Remote Sens. Environ.</i> , vol. 86, no. 3, pp. 370–384, 2003, doi: 10.1016/S0034-4257(03)00079-8 [12].	105	18.13
F. Yuan and M. E. Bauer, "Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery," <i>Remote Sens. Environ.</i> , vol. 106, no. 3, pp. 375–386, Feb. 2007, doi: 10.1016/j.rse.2006.09.003 [210].	42	7.25
M. L. Imhoff, P. Zhang, R. E. Wolfe, and L. Bounoua, "Remote sensing of the urban heat island effect across biomes in the continental USA," <i>Remote Sens. Environ.</i> , vol. 114, no. 3, pp. 504–513, 2010, doi: 10.1016/j.rse.2009.10.008.n [2].	30	5.18
Q. Weng, D. Lu, and J. Schubring, "Estimation of land surface temperature-vegetation abundance relationship for urban heat island studies," <i>Remote Sens. Environ.</i> , vol. 89, no. 4, pp. 467–483, 2004, doi: 10.1016/j.rse.2003.11.005 [23].	30	5.18
A. J. Arnfield, "Two decades of urban climate research: a review of turbulence, exchanges of energy and water, and the urban heat island," <i>Int. J. Climatol.</i> , vol. 23, no. 1, pp. 1–26, Jan. 2003, doi: 10.1002/joc.859 [8].	28	4.84
T. R. Oke, "The energetic basis of the urban heat island (Symons Memorial Lecture, 20 May 1980).," <i>Q. Journal, R. Meteorol. Soc.</i> , vol. 108, no. 455, pp. 1–24, 1982, doi:10.1002/qj.49710845502 [1].	28	4.84
J. A. Sobrino, J. C. Jiménez-Muñoz, and L. Paolini, "Land surface temperature retrieval from LANDSAT TM 5," <i>Remote Sens. Environ.</i> , vol. 90, no. 4, pp. 434–440, Apr. 2004, doi: 10.1016/j.rse.2004.02.003 [53].	26	4.49
X.-L. Chen, H.-M. Zhao, P.-X. Li, and Z.-Y. Yin, "Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes," <i>Remote Sens. Environ.</i> , vol. 104, no. 2, pp. 133–146, Sep. 2006, doi: 10.1016/j.rse.2005.11.016 [211].	25	4.32

It is important to note that the software performs combinations considering the similarity of the work cited; that is, the identical texts.

3.12. Authors

With the support of the VOSviewer software, 1475 authors were identified, with the number of publications ranging from 1 to 18. Table 18 shows the relationship between the number of publications, the number of authors, and the respective percentage.

Table 18. Number of publications by author.

No. of Publications Associated with the Author's Name	No. of Authors	% of Authors
1	1136	77.02
2	181	12.27
3	78	5.29
4	27	1.83
5	17	1.15
6	12	0.81
7	4	0.27
8	5	0.34
9	3	0.20
10	2	0.14
>10	10	0.68
Total	1475	100

It was found that 1136 (77.02%) of the identified authors are involved in the publication of one article. The sum between the authors who published from one to three articles corresponds to 1.395 (94.58%), which concentrates most of the authors.

Of the 1475 authors, 719 (48.75%) showed interrelationship in publications. Using the software's association strength tool, the authors' interrelationships were identified and separated into 37 classes, distinguished by colors in Figure 8.

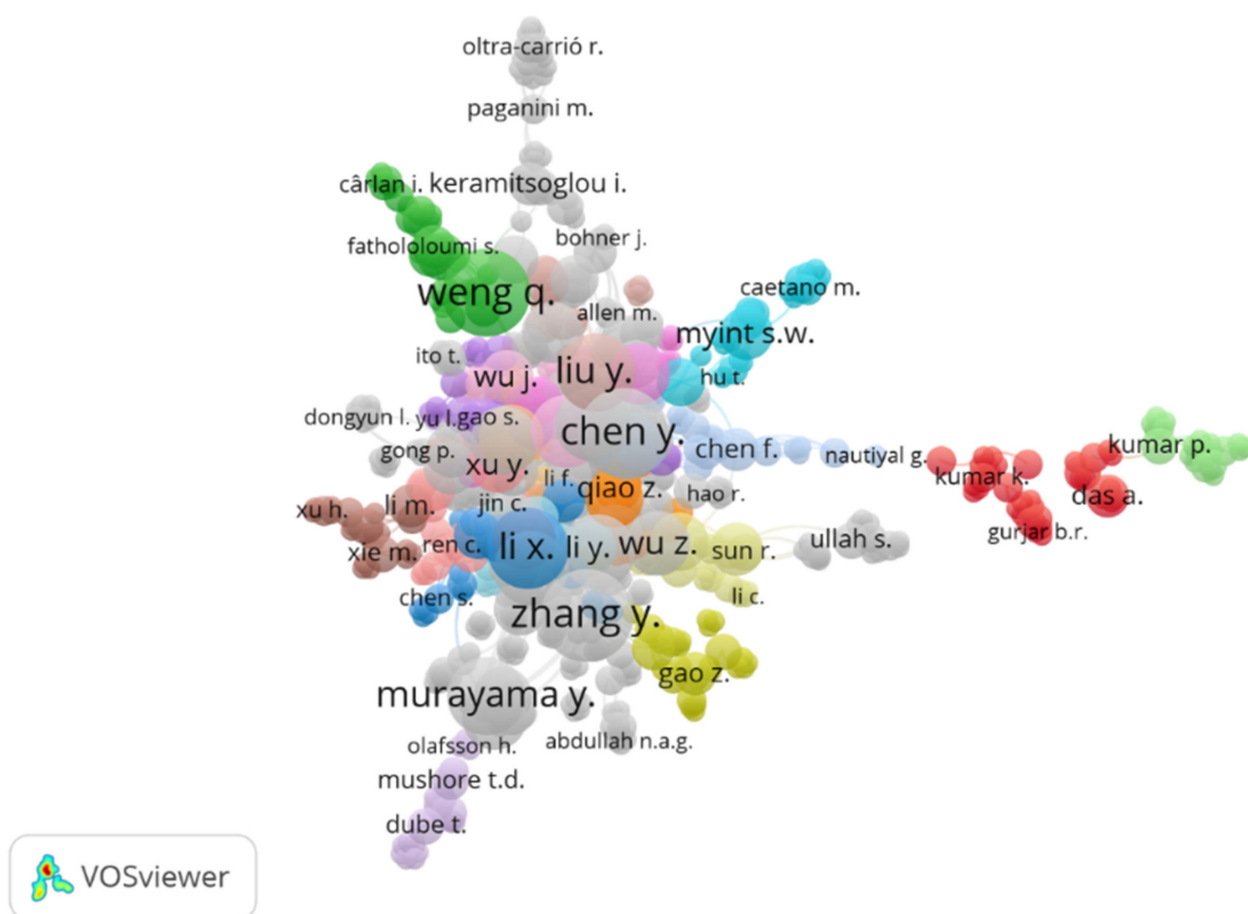


Figure 8. Interrelationships of authors in publications. The diameter of the circle corresponds to the number of published articles, with the authors Zhang Y., Chen Y., and Weng Q. standing out, with 18, 17, and 16 articles, respectively.

3.13. Citations

Table 19 presents the ten most cited papers in the analyzed papers.

Table 19. Ten most cited papers.

Paper	No. of Citations
X.-L. Chen, H.-M. Zhao, P.-X. Li, and Z.-Y. Yin, "Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes," <i>Remote Sens. Environ.</i> , vol. 104, no. 2, pp. 133–146, Sep. 2006, doi: 10.1016/j.rse.2005.11.016. [211]	849
M. L. Imhoff, P. Zhang, R. E. Wolfe, and L. Bounoua, "Remote sensing of the urban heat island effect across biomes in the continental USA," <i>Remote Sens. Environ.</i> , vol. 114, no. 3, pp. 504–513, 2010, doi: 10.1016/j.rse.2009.10.008. [2]	648
J. Li, C. Song, L. Cao, F. Zhu, X. Meng, and J. Wu, "Impacts of landscape structure on surface urban heat islands: A case study of Shanghai, China," <i>Remote Sens. Environ.</i> , vol. 115, no. 12, pp. 3249–3263, Dec. 2011, doi: 10.1016/j.rse.2011.07.008. [212]	499
W. Zhou, G. Huang, and M. L. Cadenasso, "Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes," <i>Landsc. Urban Plan.</i> , vol. 102, no. 1, pp. 54–63, 2011, doi: 10.1016/j.landurbplan.2011.03.009. [213]	418
A. Buyantuyev and J. Wu, "Urban heat islands and landscape heterogeneity: Linking spatiotemporal variations in surface temperatures to land-cover and socioeconomic patterns," <i>Landsc. Ecol.</i> , vol. 25, no. 1, pp. 17–33, 2010, doi: 10.1007/s10980-009-9402-4. [156]	416
X. Cao, A. Onishi, J. Chen, and H. Imura, "Quantifying the cool island intensity of urban parks using ASTER and IKONOS data," <i>Landsc. Urban Plan.</i> , vol. 96, no. 4, pp. 224–231, Jun. 2010, doi: 10.1016/j.landurbplan.2010.03.008. [214]	266
J. P. Connors, C. S. Galletti, and W. T. L. Chow, "Landscape configuration and urban heat island effects: Assessing the relationship between landscape characteristics and land surface temperature in Phoenix, Arizona," <i>Landsc. Ecol.</i> , vol. 28, no. 2, pp. 271–283, 2013, doi: 10.1007/s10980-012-9833-1. [107]	257
R. Amiri, Q. Weng, A. Alimohammadi, and S. K. Alavipanah, "Spatial-temporal dynamics of land surface temperature in relation to fractional vegetation cover and land use/cover in the Tabriz urban area, Iran," <i>Remote Sens. Environ.</i> , vol. 113, no. 12, pp. 2606–2617, Dec. 2009, doi: 10.1016/j.rse.2009.07.021. [215]	235
Q. Weng, "Fractal analysis of satellite-detected urban heat island effect," <i>Photogramm. Eng. Remote Sensing</i> , vol. 69, no. 5, pp. 555–566, 2003, doi: 10.14358/PERS.69.5.555. [109]	204
N. Schwarz, S. Lautenbach, and R. Seppelt, "Exploring indicators for quantifying surface urban heat islands of European cities with MODIS land surface temperatures," <i>Remote Sens. Environ.</i> , vol. 115, no. 12, pp. 3175–3186, Dec. 2011, doi: 10.1016/j.rse.2011.07.003. [216]	199

Table 20 shows a scale of citations and the respective papers, in absolute numbers and percentages.

Table 20. Number of citations per paper (data analyzed by consulting the database on 15 March 2021).

Citation	No. of Papers	%
0	48	8.29
1–3	97	16.75
4–6	63	10.88
7–10	55	9.50
11–18	85	14.68
19–25	45	7.77
26–40	66	11.40
41–60	38	6.56
61–80	33	5.70
81–100	10	1.73
101–125	9	1.55
126–160	13	2.25
161–250	10	1.73
251–500	5	0.86
501–849]	2	0.35
Total	579	100

A relatively small number of the analyzed articles were not cited (8.29%). Most articles had between 1 and 25 citations, with 345 papers (59.59%) in total, corresponding to more than half of the articles.

4. Discussion and Conclusions

The growing number of papers published on the UHI effect, especially since 2016, from 48 to 118 publications at the time, emphasizes the interest by the scientific community in the dissemination of this issue, considering its causes and consequences in several dimensions, such as environmental, social, and economic. This scientific relevance should add to the need for the promotion of an integrated urban climate planning [217], using valuable data as a primary input [218], as a way to tackle the challenges posed by this complex effect.

In the evaluated papers, it was observed that the methodological approaches and the impacts analyzed concerning the UHI were diverse and transversal, which adds to the complexity of this issue and corroborates with the need for researchers to know, as much as possible, the specificities inherent to the areas of study.

Most of the studies were concentrated in Asia (405—69.94%) which can be explained by interest from the scientific community in understanding the impacts of rapid urban growth in some parts of this continent that is often associated with the generation of intense UHI [219]. China was the most studied country.

As for climate regions, Cfa was the most recurrent. In this climatic region, the minimum temperatures range from 0 to -3°C , there are at least four months with an average temperature of 10°C , and at least one month with an average temperature above 22°C . Precipitation does not vary significantly between seasons, i.e., there is no extremely dry month [220]. Considering that there are several areas in Asia and North America with this classification, it is natural that the number of publications regarding this particular climate region is higher (Figure 9, with Cfa in focus).

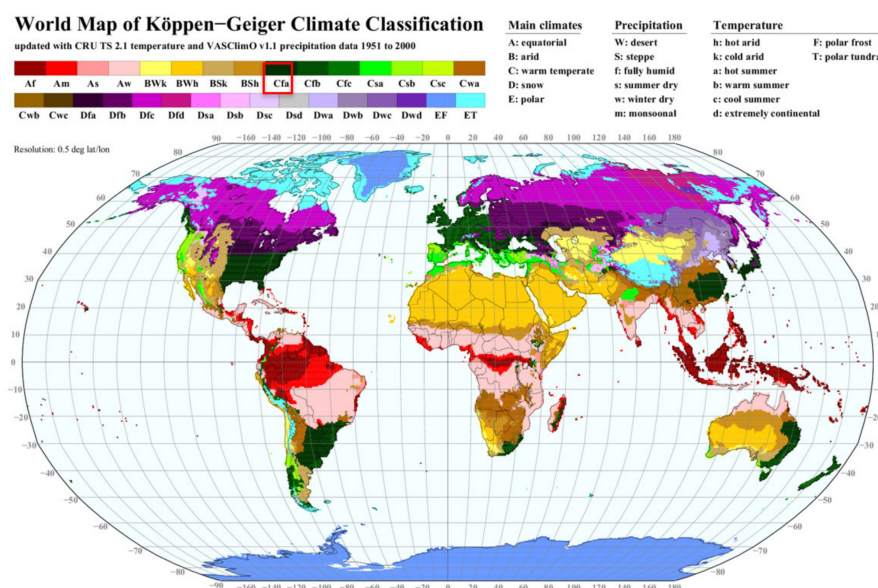


Figure 9. Köppen–Geiger world climate classification map for the period 1951 to 2000 on a 0.5-degree regular grid (in both latitude and longitude). Updated mean monthly temperature and precipitation data (CRU TS 2.1 and VASCLIM v1.1, respectively) (adapted from [221]).

The most recurrent keywords were “land surface temperature”, “urban heat island”, and “heat island”. Considering the words used for the initial selection of papers for analysis, it was expected that “urban heat island” and “heat island” are recurrent, because they are associated with the acronym (UHI*) and “land surface temperature” is a product that can be derived even from RS, associating the keyword (satellite image*).

There are several techniques to obtain LST data, from thermal sensors present in heliosynchronous, geostationary, polar satellites, passive microwave radiometers, and data processed with statistical modeling. The choice of the most suitable methodology should consider the available resources (whether financial, data processing capacity, hardware, software, human resources, etc.).

The most used RS data came from Landsat missions, both for LULC identification and LST calculation. This preference can be explained by the free availability of historical data, the easy and intuitive access to the platform (USGS) [48], and the greater detail of the thermal band, especially of the transition and heterogeneous areas, compared to MODIS.

LULC data were mainly obtained by satellites, followed by models available from competent agencies such as the European Environment Agency (EEA) [222]. Techniques combining in situ data collection and/or UAV use were also applied and present advantages in data validation, providing greater spatial detail, especially in small and heterogeneous areas, and a cost–benefit analysis is indicated to assess the feasibility of their implementation.

NDVI was the most used index, especially for its effectiveness in distinguishing areas with the presence of vegetation, water bodies, and anthropic zones. Considering that the computation of the indices is performed from sensor data collected at the same instant when the thermals are obtained, as in the case of Landsat, MODIS, and ASTER, there is temporal concomitance of collection in the same study area.

Regarding the software used for data processing, among the papers that explained, ArcGIS stood out as the most recurrent. Although it is not free software, its interface is intuitive, and its data processing is effective. Moreover, some universities have licenses for research purposes, which can corroborate the adoption of this software in the methodology.

Correlation and regression models were the most employed to evaluate the quantitative relationship between indicators, such as LST, LULC, and additional data (socioeconomic, climatic, and from weather stations). The choice of these models is due to the methodological need to assess whether an action causes some reaction in another indicator,

such as whether the increase in urban density causes changes in the local microclimate. In this sense, researchers must evaluate and compare relevant subjects, in a sample number adequate for the research objective, to avoid possible biases in the results obtained.

Studies that related the UHI effect to surrounding areas, especially vegetated surfaces, were the most recurrent, which converges with the publication by Voogt and Oke (2003), which mentions that this comparison between anthropic structures with the anisotropic thermal behavior of vegetated surfaces is more modeled and documented [12]. It is worth mentioning that there are publications focused on improving UHI methodologies and analyses, such as applications of mathematical and computational modeling to understand the behavior of the effect and the consequences for the microclimate, in addition to identifying gaps in mitigating measures, such as evaluating suitable vegetation to mitigate UHI influences at the site, pointing out the basic requirements regarding canopy, leaf density, and physical distribution at a site, etc.

The most cited bibliographies in the papers reviewed were from Voogt and Oke (2003) [12] and Yuan and Bauer (2007) [210]. The abstract of both publications is adherent to the UHI study and both methodologies employ RS data. Voogt and Oke (2003) [12] cite that despite the progressive scenario, research must transcend the application of simple correlations in data processing, as well as a qualitative description of urban surface land use and include indicators such as emissivity and RS techniques, both to analyze surface radiative parameters and to better describe the urban surface and ensure the effectiveness of the atmospheric models used in the studies, respectively. The authors also recommend advances in the spectral and spatial resolution of current sensors and the next-generation satellites to optimize the details of urban surfaces, as well as the availability of affordable high-resolution portable thermal scanners.

As for the consequences, the analyzed papers highlighted several areas that can be influenced and affected by UHI, and that are intrinsically associated with local specificities and anthropic activities developed in the region. In the atmosphere, for example, UHI can influence the displacement of air masses and the transport of particles harmful to health. From an economic perspective, some studies have addressed the influence of UHI on real estate market values, since, in regions where the phenomenon is more evident, costs can be reduced. As for the population's health, thermal comfort was pointed out as a concern, especially when considering low-income families, who may have restrictions on the acquisition and maintenance of equipment such as air conditioners. The risks of death associated with cardiovascular diseases, development of depression, and sleep complaints [142] were also addressed.

Concerning UHI and SUHI mitigation measures, existent papers can be used as a source of information for local managers and representatives to identify the effect, understand its dynamics, and minimize its impacts. Understanding the local microclimate, urban growth, LULC, and complementary data (economic, socioenvironmental, and public health), can be key elements to structure a strategy.

Regarding the possible applications and perspectives of UHI studies, it was possible to identify multiple approaches, areas, and objects of study, which reinforces that the applicability transcends the identification of areas affected by the microclimate, in terms of temperature, but that encompasses social, economic, and health factors and well-being of the population.

Moreover, most of the papers analyzed presented solutions for minimizing and mitigating the UHI effect, which can compose advisory material for managers. At this point, the need to understand the local specificities is reinforced, so that more assertive decisions can be made for each case. Publications aimed at improving the methodology of UHI studies, data processing, which can occur in software that operates in clouds, as in the case of Google Earth Engine [102], and the inclusion of artificial intelligence. Machine learning algorithms, such as artificial neural networks [223], are of great value to the research and can assist in the creation of new techniques. In addition, the combination of data from different sources can contribute to minimizing the technical limitations of collection equip-

ment or techniques. A more systemic look at the UHI effect will favor the advancement in studies in the area, already identified as growing from the results presented in this review.

The design of a local bioclimatic model can be an interesting tool, as it is based on the strategic use of urban elements to minimize heat storage [224,225]. Some strategies that can be incorporated include: (i) analyze and adjust the distribution of built-up areas, reducing continuous high rise and dense urban development; (ii) add humid or vegetated areas to urban areas, corroborating for heat exchange; (iii) preserve and revitalize parks, water bodies, and vegetation surfaces, considering the extension, density, and size of the canopy aiming to maximize heat exchange capacity concerning the surroundings; and (iv) evaluate civil construction materials, prioritizing those with lower heat retention.

It should be noted that UHI and SUHI are a consequence of specific factors on the study sites, such as climatic, anthropogenic, and environmental characteristics, corroborating so that the choice of methodology, scale, data sources, study objectives, diagnosis, and possible mitigation proposals consider these particularities, transcending a standard methodology.

Despite this, there is recurring information and methodological approaches in the studies reviewed. Figure 10 presents a suggestion of the steps necessary for the study of IHU and SUHI, which does not disregard the need to assess local characteristics and identify approaches specific to the study area.

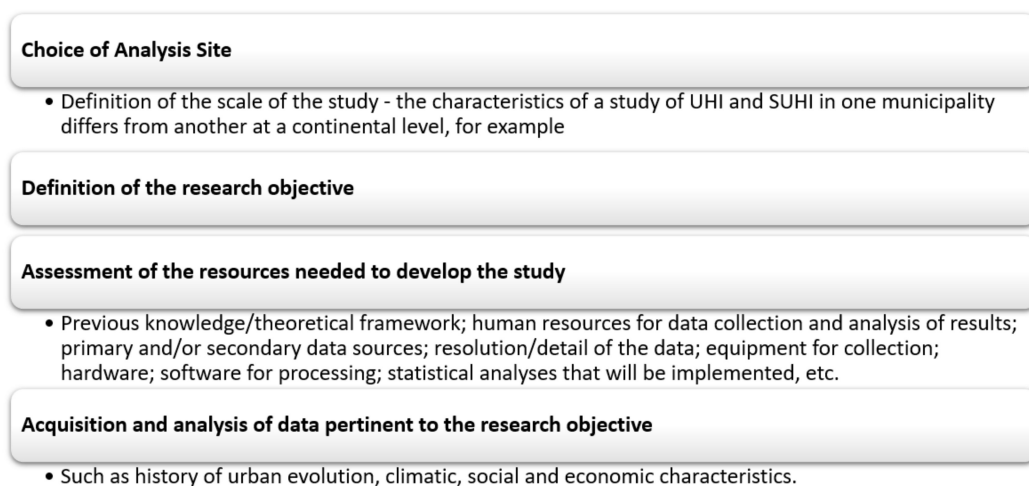


Figure 10. Suggested steps for UHI and SUHI studies.

We believe that this work can contribute to a comprehensive overview of the current state of the art regarding the UHI effect using RS data, considering the last 20 years.

Author Contributions: C.R.d.A. participated in the manuscript design, study selection, analysis and selection of study data, data processing in software, and systematic review. A.C.T. participated in the manuscript design, study selection, analysis and selection of study data, and systematic review. A.G. participated in the manuscript design and systematic review. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by National Funds through the FCT-Foundation for Science and Technology and FEDER, under the projects UIDB/04683/2020 and PT2020 Program for financial support to CIMO UIDB/00690/2020.

Acknowledgments: This work was funded by National Funds through the FCT-Foundation for Science and Technology and FEDER, under the projects UIDB/04683/2020 and PT2020 Program for financial support to CIMO UIDB/00690/2020.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Oke, T.R. The energetic basis of the urban heat island (Symons Memorial Lecture, 20 May 1980). *Q. J. R. Meteorol. Soc.* **1982**, *108*, 1–24. [\[CrossRef\]](#)
- Imhoff, M.L.; Zhang, P.; Wolfe, R.E.; Bounoua, L. Remote sensing of the urban heat island effect across biomes in the continental USA. *Remote Sens. Environ.* **2010**, *114*, 504–513. [\[CrossRef\]](#)
- US Geological Survey Urban Heat Islands. Available online: <https://www.usgs.gov/media/images/urban-heat-islands> (accessed on 1 March 2020).
- Oke, T.R.; Mills, G.; Christen, A.; Voogt, J.A. *Urban Climate*; Cambridge University Press: Cambridge, MA, USA, 2017; ISBN 978-113-901-64-76. [\[CrossRef\]](#)
- Romero, M.A.B. *Arquitetura do Lugar. Uma Visão Bioclimática da Sustentabilidade em Brasília*; Técnica: São Paulo, Brazil, 2011; ISBN 9788562889035.
- Gartland, L.; Gonçalves, S.H. (translation); *Ilhas de Calor: Como mitigar zonas de calor em áreas urbanas*; Oficina de Textos: São Paulo, Brazil, 2010.
- Santamouris, M. *Environmental Design of Urban Buildings—An Integrated Approach*; Routledge: London, UK, 2006.
- Arnfield, A.J. Two decades of urban climate research: A review of turbulence, exchanges of energy and water, and the urban heat island. *Int. J. Climatol.* **2003**, *23*, 1–26. [\[CrossRef\]](#)
- Grimmond, C.S.B. Progress in measuring and observing the urban atmosphere. *Theor. Appl. Climatol.* **2006**, *84*, 3–22. [\[CrossRef\]](#)
- Stewart, I.D.; Oke, T.R. Local climate zones for urban temperature studies. *Bull. Am. Meteorol. Soc.* **2012**, *93*, 1879–1900. [\[CrossRef\]](#)
- Gawu, L. Relationship between Surface Urban Heat Island intensity and sensible heat flux retrieved from meteorological parameters observed by road weather stations in urban area. *EGU Gen. Assem. Conf. Abstr.* **2017**, *19*, 16820.
- Voogt, J.A.; Oke, T.R. Thermal remote sensing of urban climates. *Remote Sens. Environ.* **2003**, *86*, 370–384. [\[CrossRef\]](#)
- Weng, Q.; Fu, P. Modeling annual parameters of clear-sky land surface temperature variations and evaluating the impact of cloud cover using time series of Landsat TIR data. *Remote Sens. Environ.* **2014**, *140*, 267–278. [\[CrossRef\]](#)
- Li, D.; Bou-Zeid, E. Synergistic interactions between urban heat islands and heat waves: The impact in cities is larger than the sum of its parts. *J. Appl. Meteorol. Climatol.* **2013**, *52*, 2051–2064. [\[CrossRef\]](#)
- Leal Filho, W.; Echevarria Icaza, L.; Neht, A.; Klavins, M.; Morgan, E.A. Coping with the impacts of urban heat islands. A literature based study on understanding urban heat vulnerability and the need for resilience in cities in a global climate change context. *J. Clean. Prod.* **2018**, *171*, 1140–1149. [\[CrossRef\]](#)
- Kershaw, T.; Sanderson, M.; Coley, D.; Eames, M. Estimation of the urban heat island for UK climate change projections. *Build. Serv. Eng. Res. Technol.* **2010**, *31*, 251–263. [\[CrossRef\]](#)
- Chapman, S.; Thatcher, M.; Salazar, A.; Watson, J.E.M.; McAlpine, C.A. The impact of climate change and urban growth on urban climate and heat stress in a subtropical city. *Int. J. Climatol.* **2019**, *39*, 3013–3030. [\[CrossRef\]](#)
- Sachindra, D.A.; Ng, A.W.M.; Muthukumaran, S.; Perera, B.J.C. Impact of climate change on urban heat island effect and extreme temperatures: A case-study. *Q. J. R. Meteorol. Soc.* **2015**, *142*, 172–186. [\[CrossRef\]](#)
- Santamouris, M.; Cartalis, C.; Synnefa, A. Local urban warming, possible impacts and a resilience plan to climate change for the historical center of Athens, Greece. *Sustain. Cities Soc.* **2015**, *19*, 281–291. [\[CrossRef\]](#)
- Santamouris, M. On the energy impact of urban heat island and global warming on buildings. *Energy Build.* **2014**, *82*, 100–113. [\[CrossRef\]](#)
- Tan, J.; Zheng, Y.; Tang, X.; Guo, C.; Li, L.; Song, G.; Zhen, X.; Yuan, D.; Kalkstein, A.J.; Li, F.; et al. The urban heat island and its impact on heat waves and human health in Shanghai. *Int. J. Biometeorol.* **2010**, *54*, 75–84. [\[CrossRef\]](#) [\[PubMed\]](#)
- Keikhosravi, Q. The effect of heat waves on the intensification of the heat island of Iran's metropolises (Tehran, Mashhad, Tabriz, Ahvaz). *Urban Clim.* **2019**, *28*, 100453. [\[CrossRef\]](#)
- Weng, Q.; Lu, D.; Schubring, J. Estimation of land surface temperature-vegetation abundance relationship for urban heat island studies. *Remote Sens. Environ.* **2004**, *89*, 467–483. [\[CrossRef\]](#)
- De Almeida, C.M. Aplicação dos sistemas de sensoriamento remoto por imagens e o planejamento urbano regional. *Rev. Eletrôn. Arquit. Urban.* **2010**, *3*, 98–123.
- Hulley, G.C.; Ghent, D.; Götsche, F.M.; Guillevic, P.C.; Mildrexler, D.J.; Coll, C. Land Surface Temperature. In *Taking the Temperature of the Earth*, 1st ed.; Elsevier: Amsterdam, The Netherlands, 2019. [\[CrossRef\]](#)
- Sousa, A.; Silva, J. Fundamentos Teóricos de Detecção Remota. *Univ. Évora—Dep. Eng. Rural* **2011**, 1–57. Available online: http://www.rdp.uevora.pt/bitstream/10174/4822/1/Sebenta_DR_fundamentosTericos_2011.pdf (accessed on 12 September 2020).
- Guillevic, P.; Götsche, F.; Nickeson, J.; Hulley, G.; Ghent, D.; Yu, Y.; Trigo, I.; Hook, S.; Sobrino, J.A.; Remedios, J.; et al. Land Surface Temperature Product Validation Best Practice Protocol Version 1.1. 2018. Available online: https://lpvs.gsfc.nasa.gov/PDF/CEOS_LST_PROTOCOL_Feb2018_v1.1.0_light.pdf (accessed on 20 August 2021). [\[CrossRef\]](#)
- Kustas, W.; Anderson, M. Advances in thermal infrared remote sensing for land surface modeling. *Agric. For. Meteorol.* **2009**, *149*, 2071–2081. [\[CrossRef\]](#)
- Agam, N.; Kustas, W.P.; Anderson, M.C.; Li, F.; Colaizzi, P.D. Utility of thermal image sharpening for monitoring field-scale evapotranspiration over rainfed and irrigated agricultural regions. *Geophys. Res. Lett.* **2008**, *35*, 1–7. [\[CrossRef\]](#)
- Dousset, B.; Gourmelon, F. Satellite multi-sensor data analysis of urban surface temperatures and landcover. *ISPRS J. Photogramm. Remote Sens.* **2003**, *58*, 43–54. [\[CrossRef\]](#)

31. Luvall, J.C.; Quattrochi, D.A.; Rickman, D.L.; Estes, M.G. *Boundary Layer (Atmospheric) and Air Pollution: Urban Heat Islands*, 2nd ed.; Elsevier: Amsterdam, The Netherlands, 2015; pp. 310–318. [\[CrossRef\]](#)
32. Hall, D.K.; Comiso, J.C.; Digirolamo, N.E.; Shuman, C.A.; Key, J.R.; Koenig, L.S. A satellite-derived climate-quality data record of the clear-sky surface temperature of the greenland ice sheet. *J. Clim.* **2012**, *25*, 4785–4798. [\[CrossRef\]](#)
33. Schneider, P.; Hook, S.J. Space observations of inland water bodies show rapid surface warming since 1985. *Geophys. Res. Lett.* **2010**, *37*, 1–5. [\[CrossRef\]](#)
34. Pasotti, L.; Maroli, M.; Giannetto, S.; Brianti, E. Agrometeorology and models for the parasite cycle forecast. *Parassitologia* **2006**, *48*, 81–83. [\[PubMed\]](#)
35. Neteler, M.; Roiz, D.; Rocchini, D.; Castellani, C.; Rizzoli, A. Terra and Aqua satellites track tiger mosquito invasion: Modelling the potential distribution of *Aedes albopictus* in north-eastern Italy. *Int. J. Health Geogr.* **2011**, *10*. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Nguyen, L.H.; Henebry, G.M. Urban heat islands as viewed by microwave radiometers and thermal time indices. *Remote Sens.* **2016**, *8*, 831. [\[CrossRef\]](#)
37. Tomlinson, C.J.; Chapman, L.; Thornes, J.E.; Baker, C. Remote sensing land surface temperature for meteorology and climatology: A review. *Meteorol. Appl.* **2011**, *18*, 296–306. [\[CrossRef\]](#)
38. Khaikine, M.N.; Kuznetsova, I.N.; Kadygrov, E.N.; Miller, E.A. Investigation of temporal-spatial parameters of an urban heat island on the basis of passive microwave remote sensing. *Theor. Appl. Climatol.* **2006**, *84*, 161–169. [\[CrossRef\]](#)
39. Stathopoulou, M.; Cartalis, C. Daytime urban heat islands from Landsat ETM+ and Corine land cover data: An application to major cities in Greece. *Sol. Energy* **2007**, *81*, 358–368. [\[CrossRef\]](#)
40. Freitas, S.C.; Trigo, I.F.; Macedo, J.; Barroso, C.; Silva, R.; Perdigão, R. Land surface temperature from multiple geostationary satellites. *Int. J. Remote Sens.* **2013**, *34*, 3051–3068. [\[CrossRef\]](#)
41. WMO. OSCAR. Available online: <https://space.oscar.wmo.int/gapanalyses> (accessed on 13 September 2021).
42. US Geological Survey Landsat Missions. Available online: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-4?qt-science_support_page_related_con=0#qt-science_support_page_related_con (accessed on 12 September 2020).
43. US Geological Survey Landsat Missions. Available online: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-5?qt-science_support_page_related_con=0#qt-science_support_page_related_con (accessed on 12 September 2021).
44. US Geological Survey Landsat Missions. Available online: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-7?qt-science_support_page_related_con=0#qt-science_support_page_related_con (accessed on 12 September 2020).
45. US Geological Survey Landsat Missions. Available online: https://www.usgs.gov/core-science-systems/nli/landsat/landsat-8?qt-science_support_page_related_con=0#qt-science_support_page_related_con (accessed on 12 September 2020).
46. Masek, J.G.; Wulder, M.A.; Markham, B.; McCorkel, J.; Crawford, C.J.; Storey, J.; Jenstrom, D.T. Landsat 9: Empowering open science and applications through continuity. *Remote Sens. Environ.* **2020**, *248*, 111968. [\[CrossRef\]](#)
47. Wulder, M.A.; White, J.C.; Loveland, T.R.; Woodcock, C.E.; Belward, A.S.; Cohen, W.B.; Fosnight, E.A.; Shaw, J.; Masek, J.G.; Roy, D.P. The global Landsat archive: Status, consolidation, and direction. *Remote Sens. Environ.* **2016**, *185*, 271–283. [\[CrossRef\]](#)
48. US Geological Survey. Available online: <https://earthexplorer.usgs.gov/> (accessed on 1 July 2020).
49. Avdan, U.; Jovanovska, G. Algorithm for automated mapping of land surface temperature using LANDSAT 8 satellite data. *J. Sensors* **2016**, *2016*, 1480307. [\[CrossRef\]](#)
50. US Geological Survey Using the USGS Landsat Level-1 Data Product. Available online: <https://www.usgs.gov/core-science-systems/nli/landsat/using-usgs-landsat-level-1-data-product> (accessed on 25 July 2021).
51. Xu, H.Q.; Chen, B.Q. Remote sensing of the urban heat island and its changes in Xiamen City of SE China. *J. Environ. Sci.* **2004**, *16*, 276–281. [\[PubMed\]](#)
52. Rouse, J.W.; Haas, R.H.; Schell, J.A.; Deering, D.W. *Monitoring Vegetation Systems in the Great Plains with ERTS*; NASA: Washington, DC, USA, 1974; pp. 309–317.
53. Sobrino, J.A.; Jiménez-Muñoz, J.C.; Paolini, L. Land surface temperature retrieval from LANDSAT TM 5. *Remote Sens. Environ.* **2004**, *90*, 434–440. [\[CrossRef\]](#)
54. Carlson, T.N.; Ripley, D.A. On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sens. Environ.* **1997**, *62*, 241–252. [\[CrossRef\]](#)
55. Hulley, G.; Veraverbeke, S.; Hook, S. Thermal-based techniques for land cover change detection using a new dynamic MODIS multispectral emissivity product (MOD21). *Remote Sens. Environ.* **2014**, *140*, 755–765. [\[CrossRef\]](#)
56. NASA Aqua Earth-Observing Satellite Mission. Available online: <https://aqua.nasa.gov/> (accessed on 6 September 2021).
57. Zhang, Y.Z.; Jiang, X.G.; Wu, H. A generalized split-window algorithm for retrieving land surface temperature from GF-5 thermal infrared data. *Prog. Electromagn. Res. Symp.* **2017**, 2766–2771. [\[CrossRef\]](#)
58. Zhou, D.; Xiao, J.; Bonafoni, S.; Berger, C.; Deilami, K.; Zhou, Y.; Frolking, S.; Yao, R.; Qiao, Z.; Sobrino, J.A. Satellite remote sensing of surface urban heat islands: Progress, challenges, and perspectives. *Remote Sens.* **2019**, *11*, 48. [\[CrossRef\]](#)
59. Hulley, G.; Freepartner, R.; Malakar, N.; Sarkar, S. *Moderate Resolution Imaging Spectroradiometer (MODIS) MOD21 Land Surface Temperature and Emissivity Product (MOD21) Users' Guide—Collection 6*; NASA: Washington, DC, USA, 2016; pp. 1–29.
60. Retalis, A.; Paronis, D.; Michaelides, S.; Tymvios, F.; Charalambous, D.; Hadjimitsis, D.; Agapiou, A. Urban Heat Island and Heat Events in Cyprus. In Proceedings of the 10th International Conference on Meteorology, Climatology and Atmospheric Physics, Patras, Greece, 25–28 March 2010.

61. Wan, Z.; Zhang, Y.; Zhang, Q.; Li, Z.-L. Quality assessment and validation of the MODIS global land surface temperature. *Int. J. Remote Sens.* **2004**, *25*, 261–274. [CrossRef]
62. US Geological Survey ASTER. Available online: https://asterweb.jpl.nasa.gov/content/06_links/default.htm (accessed on 20 January 2021).
63. US Geological Survey ASTER and MODIS Data Now Available through The LP DAAC On-Line Data Pool. Available online: <https://lpdaac.usgs.gov/news/aster-and-modis-data-now-available-through-the-lp-daac-on-line-data-pool/> (accessed on 20 January 2021).
64. US Geological Survey Earth Resources Observation and Science (EROS) Center. Available online: <https://www.usgs.gov/centers/eros> (accessed on 20 January 2021).
65. US Geological Survey GloVis. Available online: <https://glovis.usgs.gov/> (accessed on 20 January 2021).
66. Abrams, M.; Hook, S. ASTER User Handbook. Version 2. Jet Propulsion Laboratory. Available online: https://lpdaac.usgs.gov/documents/262/ASTER_User_Handbook_v2.pdf (accessed on 12 September 2020).
67. Weng, Q.; Fu, P. Modeling diurnal land temperature cycles over Los Angeles using downscaled GOES imagery. *ISPRS J. Photogramm. Remote Sens.* **2014**, *97*, 78–88. [CrossRef]
68. Zakšek, K.; Oštir, K. Downscaling land surface temperature for urban heat island diurnal cycle analysis. *Remote Sens. Environ.* **2012**, *117*, 114–124. [CrossRef]
69. Bechtel, B.; Bohner, J.; Zakšek, K.; Wiesner, S. Downscaling of diurnal land surface temperature cycles for urban heat island monitoring. *Jt. Urban Remote Sens. Event* **2013**, 91–94. [CrossRef]
70. NASA Suomi National Polar-Orbiting Partnership (Suomi NPP). Available online: <https://eosps.nasa.gov/missions/suomi-national-polar-orbiting-partnership> (accessed on 9 September 2021).
71. SEVIRI. Available online: <https://www.eumetsat.int/seviri> (accessed on 9 September 2021).
72. NOAA GOES Land Surface Temperature. Available online: <https://www.ospo.noaa.gov/Products/land/glst/> (accessed on 18 September 2021).
73. NASA What Are Passive and Active Sensors? Available online: https://www.nasa.gov/directorates/heo/scan/communications/outreach/funfacts/txt_passive_active.html (accessed on 9 September 2021).
74. NASA Daily Global Land Surface Parameters Derived from AMSR-E, Version 1. Available online: <https://nsidc.org/data/NSIDC-0451> (accessed on 9 September 2021).
75. Duan, S.B.; Han, X.J.; Huang, C.; Li, Z.L.; Wu, H.; Qian, Y.; Gao, M.; Leng, P. Land surface temperature retrieval from passive microwave satellite observations: State-of-the-art and future directions. *Remote Sens.* **2020**, *12*, 2573. [CrossRef]
76. McFarland, M.J.; Miller, R.L.; Neale, C.M.U. Land surface temperature derived from the SSM/I passive microwave brightness temperatures. *IEEE Trans. Geosci. Remote Sens.* **1990**, *28*, 839–845. [CrossRef]
77. Mohamadi, B.; Chen, S.; Balz, T.; Gulshad, K.; McClure, S.C. Normalized Method for Land Surface Temperature Monitoring on Coastal Reclaimed Areas. *Sensors* **2019**, *19*, 4836. [CrossRef] [PubMed]
78. Fily, M.; Royer, A.; Goita, K.; Prigent, C. A simple retrieval method for land surface temperature and fraction of water surface determination from satellite microwave brightness temperatures in sub-arctic areas. *Remote Sens. Environ.* **2003**, *85*, 328–338. [CrossRef]
79. Du, J.; Kimball, J.S.; Jones, L.A. Satellite Microwave Retrieval of Total Precipitable Water Vapor and Surface Air Temperature Over Land From AMSR2. *IEEE Trans. Geosci. Remote Sens.* **2015**, *53*, 2520–2531. [CrossRef]
80. Hongyu, D.; Xuejun, S.; Hong, J.; Zenghui, K.; Zhibao, W.; Yongli, C. Research on the cooling island effects of water body: A case study of Shanghai, China. *Ecol. Indic.* **2016**, *67*, 31–38. [CrossRef]
81. Yu, R.; Lyu, M.; Lu, J.; Yang, Y.; Shen, G.; Li, F. Spatial coordinates correction based on multi-sensor low-altitude remote sensing image registration for monitoring forest dynamics. *IEEE Access* **2020**, *8*, 18483–18496. [CrossRef]
82. Mia, M.B.; Nishijima, J.; Fujimitsu, Y. Exploration and monitoring geothermal activity using Landsat ETM+images. A case study at Aso volcanic area in Japan. *J. Volcanol. Geotherm. Res.* **2014**, *275*, 14–21. [CrossRef]
83. Feizizadeh, B.; Blaschke, T. Examining Urban heat Island relations to land use and air pollution: Multiple endmember spectral mixture analysis for thermal remote sensing. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2013**, *6*, 1749–1756. [CrossRef]
84. Xu, L.Y.; Xie, X.D.; Li, S. Correlation analysis of the urban heat island effect and the spatial and temporal distribution of atmospheric particulates using TM images in Beijing. *Environ. Pollut.* **2013**, *178*, 102–114. [CrossRef]
85. Zhou, J.; Hu, D.; Qihao, W. Analysis of surface radiation budget during the summer and winter in the metropolitan area of Beijing, China. *J. Appl. Remote Sens.* **2010**, *4*, 043513. [CrossRef]
86. Bande, L.; Manadhar, P.; Marpu, P. Definition of local climate zones in relation to envi-met and site data in the city of Al Ain, UAE. *WIT Trans. Ecol. Environ.* **2019**, *238*, 209–220. [CrossRef]
87. Zaki, S.A.; Azid, N.S.; Shahidan, M.F.; Hassan, M.Z.; Md Daud, M.Y.; Abu Bakar, N.A.; Ali, M.S.M.; Yakub, F. Analysis of urban morphological effect on the microclimate of the urban residential area of Kampung Baru in Kuala Lumpur using a geospatial approach. *Sustainability* **2020**, *12*, 7301. [CrossRef]
88. Wong, M.S.; Lee, K.H.; Shaker, A. Integrating Biophysical and Socioeconomic Data to Support Land Surface Temperature Analysis: An Example in Hong Kong. *Int. J. Geoinf.* **2010**, *6*, 1–10.
89. Tang, J.; Di, L.; Xiao, J.; Lu, D.; Zhou, Y. Impacts of land use and socioeconomic patterns on urban heat island. *Int. J. Remote Sens.* **2017**, *38*, 3445–3465. [CrossRef]

90. Rajasekar, U.; Weng, Q. Application of Association Rule Mining for Exploring the Relationship between Urban Land Surface Temperature and Biophysical/Social Parameters. *Photogramm. Eng. Remote Sens.* **2009**, *75*, 385–396. [CrossRef]
91. Cai, G.; Liu, Y.; Du, M. Impact of the 2008 Olympic Games on urban thermal environment in Beijing, China from satellite images. *Sustain. Cities Soc.* **2017**, *32*, 212–225. [CrossRef]
92. Zemtsov, S.; Shartova, N.; Varentsov, M.; Konstantinov, P.; Kidyayeva, V.; Shchur, A.; Timonin, S.; Grischchenko, M. Intraurban social risk and mortality patterns during extreme heat events: A case study of Moscow, 2010–2017. *Health Place* **2020**, *66*, 102429. [CrossRef]
93. *Elsevier Content Coverage Guide*; Elsevier: Amsterdam, The Netherlands, 2010; pp. 1–24.
94. Web of Science Platform: Web of Science: Summary of Coverage. Available online: <https://clarivate.libguides.com/webofscienceplatform/coverage> (accessed on 5 January 2021).
95. Guzzo, R.A.; Jackson, S.E.; Katzell, R.A. Meta-Analysis Analysis. *Res. Organ. Behav.* **1987**, *9*, 407–442.
96. Lovatto, P.A.; Lehnen, C.R.; Andretta, I.; Carvalho, A.D.; Hauschild, L. Meta-análise em pesquisas científicas: Enfoque em metodologias. *Rev. Bras. Zootec.* **2007**, *36*, 285–294. [CrossRef]
97. Viana, J.; Santos, J.V.; Neiva, R.M.; Souza, J.; Duarte, L.; Teodoro, A.C.; Freitas, A. Remote Sensing in Human Health: A 10-Year Bibliometric Analysis. *Remote Sens.* **2017**, *9*, 1225. [CrossRef]
98. Leiden University. VOSviewer. Available online: <https://www.vosviewer.com> (accessed on 5 March 2021).
99. Esri. ArcMap. Available online: <https://www.esri.com/en-us/arcgis/products/arcgis-desktop/resources> (accessed on 5 March 2021).
100. Köppen, W. Versuch einer Klassifikation der Klimate, vorzugsweise nach ihren Beziehungen zur Pflanzenwelt. *Geogr. Z.* **1900**, *6*, 593–611. Available online: <http://www.jstor.org/stable/27803924> (accessed on 5 September 2021).
101. Chen, D.; Chen, H.W. Using the Köppen classification to quantify climate variation and change: An example for 1901–2010. *Environ. Dev.* **2013**, *6*, 69–79. [CrossRef]
102. Padmanaban, R.; Bhowmik, A.K.; Cabral, P. Satellite image fusion to detect changing surface permeability and emerging urban heat islands in a fast-growing city. *PLoS ONE* **2019**, *14*, e208949. [CrossRef] [PubMed]
103. Zha, Y.; Gao, J.; Ni, S. Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *Int. J. Remote Sens.* **2003**, *24*, 583–594. [CrossRef]
104. Feng, Y.; Du, S.; Myint, S.W.; Shu, M. Do urban functional zones affect land surface temperature differently? A case study of Beijing, China. *Remote Sens.* **2019**, *11*, 1802. [CrossRef]
105. Bokaie, M.; Shamsipour, A.; Khatibi, P.; Hosseini, A. Seasonal monitoring of urban heat island using multi-temporal Landsat and MODIS images in Tehran. *Int. J. Urban Sci.* **2019**, *23*, 269–285. [CrossRef]
106. Cai, M.; Ren, C.; Xu, Y.; Lau, K.K.L.; Wang, R. Investigating the relationship between local climate zone and land surface temperature using an improved WUDAPT methodology—A case study of Yangtze River Delta, China. *Urban Clim.* **2017**, *24*, 485–502. [CrossRef]
107. Connors, J.P.; Galletti, C.S.; Chow, W.T.L. Landscape configuration and urban heat island effects: Assessing the relationship between landscape characteristics and land surface temperature in Phoenix, Arizona. *Landsc. Ecol.* **2013**, *28*, 271–283. [CrossRef]
108. Van Nguyen, O.; Kawamura, K.; Trong, D.P.; Gong, Z.; Suwandana, E. Temporal change and its spatial variety on land surface temperature and land use changes in the Red River Delta, Vietnam, using MODIS time-series imagery. *Environ. Monit. Assess.* **2015**, *187*, 464. [CrossRef]
109. Weng, Q. Fractal analysis of satellite-detected urban heat island effect. *Photogramm. Eng. Remote Sens.* **2003**, *69*, 555–566. [CrossRef]
110. Peres, L.d.F.; Lucena, A.J.d.; Rotunno Filho, O.C.; França, J.R.d.A. The urban heat island in Rio de Janeiro, Brazil, in the last 30 years using remote sensing data. *Int. J. Appl. Earth Obs. Geoinf.* **2018**, *64*, 104–116. [CrossRef]
111. Karakuş, C.B. The Impact of Land Use/Land Cover (LULC) Changes on Land Surface Temperature in Sivas City Center and Its Surroundings and Assessment of Urban Heat Island. *Asia-Pac. J. Atmos. Sci.* **2019**, *55*, 669–684. [CrossRef]
112. Tomaszewska, M.; Henebry, G.M. Urban-rural contrasts in Central-Eastern European cities using a MODIS 4 micron time series. *Remote Sens.* **2016**, *8*, 924. [CrossRef]
113. Du, H.; Ai, J.; Cai, Y.; Jiang, H.; Liu, P. Combined effects of the surface urban heat Island with landscape composition and configuration based on remote sensing: A case study of Shanghai, China. *Sustainability* **2019**, *11*, 2890. [CrossRef]
114. Alavipanah, S.; Schreyer, J.; Haase, D.; Lakes, T.; Qureshi, S. The effect of multi-dimensional indicators on urban thermal conditions. *J. Clean. Prod.* **2018**, *177*, 115–123. [CrossRef]
115. Zhao, C.; Jensen, J.L.R.; Weng, Q.; Currit, N.; Weaver, R. Use of Local Climate Zones to investigate surface urban heat islands in Texas. *GISci. Remote Sens.* **2020**, *57*, 1083–1101. [CrossRef]
116. Hereher, M.E. Effects of land use/cover change on regional land surface temperatures: Severe warming from drying Toshka lakes, the Western Desert of Egypt. *Nat. Hazards* **2017**, *88*, 1789–1803. [CrossRef]
117. Li, M.; Song, Y.; Huang, X.; Li, J.; Mao, Y.; Zhu, T.; Cai, X.; Liu, B. Improving mesoscale modeling using satellite-derived land surface parameters in the Pearl River Delta region, China. *J. Geophys. Res. Atmos.* **2014**, *119*, 6325–6346. [CrossRef]
118. Mpakairi, K.S.; Muvengwi, J. Night-time lights and their influence on summer night land surface temperature in two urban cities of Zimbabwe: A geospatial perspective. *Urban Clim.* **2019**, *29*, 100468. [CrossRef]
119. Pan, J. Analysis of human factors on urban heat island and simulation of urban thermal environment in Lanzhou city, China. *J. Appl. Remote Sens.* **2015**, *9*, 095999. [CrossRef]

120. Varentsov, M.; Konstantinov, P.; Baklanov, A.; Esau, I.; Miles, V.; Davy, R. Anthropogenic and natural drivers of a strong winter urban heat island in a typical Arctic city. *Atmos. Chem. Phys.* **2018**, *18*, 17573–17587. [\[CrossRef\]](#)
121. Min, M.; Lin, C.; Duan, X.; Jin, Z.; Zhang, L. Spatial distribution and driving force analysis of urban heat island effect based on raster data: A case study of the Nanjing metropolitan area, China. *Sustain. Cities Soc.* **2019**, *50*, 101637. [\[CrossRef\]](#)
122. Wang, J.; Huang, B.; Fu, D.; Atkinson, P.M. Spatiotemporal variation in surface urban heat island intensity and associated Determinants across major Chinese cities. *Remote Sens.* **2015**, *7*, 3670–3689. [\[CrossRef\]](#)
123. Amanollahi, J.; Tzani, C.; Ramli, M.F.; Abdullah, A.M. Urban heat evolution in a tropical area utilizing Landsat imagery. *Atmos. Res.* **2016**, *167*, 175–182. [\[CrossRef\]](#)
124. Wang, W.; Yao, X.; Shu, J. Air advection induced differences between canopy and surface heat islands. *Sci. Total Environ.* **2020**, *725*, 138120. [\[CrossRef\]](#)
125. Sussman, H.S.; Raghavendra, A.; Zhou, L. Impacts of increased urbanization on surface temperature, vegetation, and aerosols over Bengaluru, India. *Remote Sens. Appl. Soc. Environ.* **2019**, *16*, 100261. [\[CrossRef\]](#)
126. Zeng, Y.; Huang, W.; Zhan, F.; Zhang, H.; Liu, H. Study on the urban heat island effects and its relationship with surface biophysical characteristics using MODIS imageries. *Geo-Spat. Inf. Sci.* **2010**, *13*, 1–7. [\[CrossRef\]](#)
127. Sabrin, S.; Karimi, M.; Fahad, M.G.R.; Nazari, R. Quantifying environmental and social vulnerability: Role of urban Heat Island and air quality, a case study of Camden, NJ. *Urban Clim.* **2020**, *34*, 100699. [\[CrossRef\]](#)
128. Bhang, K.J.; Lee, J.D. Identification of the anthropogenic land surface temperature distribution by land use using satellite images: A case study for Seoul, Korea. *J. Korean Soc. Surv. Geod. Photogramm. Cartogr.* **2017**, *35*, 249–260. [\[CrossRef\]](#)
129. Tang, Y. Effect analysis of land-use pattern with landscape metrics on an urban heat island. *J. Appl. Remote Sens.* **2018**, *12*, 026004. [\[CrossRef\]](#)
130. Echevarria Icaza, L.; Van der Hoeven, F.; Van den Dobbelsteen, A. Surface thermal analysis of North Brabant cities and neighbourhoods during heat waves. *Tema* **2016**, *9*, 63–87. [\[CrossRef\]](#)
131. Mathew, A.; Khandelwal, S.; Kaul, N. Investigating spatial and seasonal variations of urban heat island effect over Jaipur city and its relationship with vegetation, urbanization and elevation parameters. *Sustain. Cities Soc.* **2017**, *35*, 157–177. [\[CrossRef\]](#)
132. Uddin, S.; Al Ghabban, A.N.; Al Dousari, A.; Al Murad, M.; Al Shamroukh, D. A remote sensing classification for land-cover changes and micro-climate in Kuwait. *Int. J. Sustain. Dev. Plan.* **2010**, *5*, 367–377. [\[CrossRef\]](#)
133. Miles, V.; Esau, I. Surface urban heat islands in 57 cities across different climates in northern Fennoscandia. *Urban Clim.* **2020**, *31*, 100575. [\[CrossRef\]](#)
134. Rosenzweig, C.; Solecki, W.D.; Parshall, L.; Chopping, M.; Pope, G.; Goldberg, R. Characterizing the urban heat island in current and future climates in New Jersey. *Environ. Hazards* **2005**, *6*, 51–62. [\[CrossRef\]](#)
135. Jiang, X.; Weidong, L. Numerical simulations of impacts of urbanization on heavy rainfall in Beijing using different land-use data. *Acta Meteorol. Sin.* **2007**, *21*, 245–255.
136. Jin, M.; Shepherd, J.M.; Peters-Lidard, C. Development of a parameterization for simulating the urban temperature hazard using satellite observations in climate model. *Nat. Hazards* **2007**, *43*, 257–271. [\[CrossRef\]](#)
137. Kamruzzaman, M.; Deilami, K.; Yigitcanlar, T. Investigating the urban heat island effect of transit oriented development in Brisbane. *J. Transp. Geogr.* **2018**, *66*, 116–124. [\[CrossRef\]](#)
138. Sagris, V.; Sepp, M. Landsat-8 TIRS Data for Assessing Urban Heat Island Effect and Its Impact on Human Health. *IEEE Geosci. Remote Sens. Lett.* **2017**, *14*, 2385–2389. [\[CrossRef\]](#)
139. Pearsall, H. Staying cool in the compact city: Vacant land and urban heating in Philadelphia, Pennsylvania. *Appl. Geogr.* **2017**, *79*, 84–92. [\[CrossRef\]](#)
140. Liu, Y.; Fang, X.; Xu, Y.; Zhang, S.; Luan, Q. Assessment of surface urban heat island across China's three main urban agglomerations. *Theor. Appl. Climatol.* **2018**, *133*, 473–488. [\[CrossRef\]](#)
141. Martin, P.; Baudouin, Y.; Gachon, P. An alternative method to characterize the surface urban heat island. *Int. J. Biometeorol.* **2015**, *59*, 849–861. [\[CrossRef\]](#)
142. Mirzaei, M.; Verrelst, J.; Arbabi, M.; Shaklabadi, Z.; Lotfizadeh, M. Urban heat island monitoring and impacts on citizen's general health status in Isfahan metropolis: A remote sensing and field survey approach. *Remote Sens.* **2020**, *12*, 1350. [\[CrossRef\]](#)
143. Wang, W.; Zhou, W.; Ng, E.Y.Y.; Xu, Y. Urban heat islands in Hong Kong: Statistical modeling and trend detection. *Nat. Hazards* **2016**, *83*, 885–907. [\[CrossRef\]](#)
144. Dong, W.; Liu, Z.; Zhang, L.; Tang, Q.; Liao, H.; Li, X. Assessing heat health risk for sustainability in Beijing's urban heat island. *Sustainability* **2014**, *6*, 7334–7357. [\[CrossRef\]](#)
145. Maithani, S.; Nautiyal, G.; Sharma, A. Investigating the Effect of Lockdown During COVID-19 on Land Surface Temperature: Study of Dehradun City, India. *J. Indian Soc. Remote Sens.* **2020**, *48*, 1297–1311. [\[CrossRef\]](#)
146. Li, S.; Zhao, Z.; Miaomiao, X.; Wang, Y. Investigating spatial non-stationary and scale-dependent relationships between urban surface temperature and environmental factors using geographically weighted regression. *Environ. Model. Softw.* **2010**, *25*, 1789–1800. [\[CrossRef\]](#)
147. Guo, J.; Han, G.; Xie, Y.; Cai, Z.; Zhao, Y. Exploring the relationships between urban spatial form factors and land surface temperature in mountainous area: A case study in Chongqing city, China. *Sustain. Cities Soc.* **2020**, *61*, 102286. [\[CrossRef\]](#)
148. Brunson, C.; Fotheringham, A.S.; Charlton, M.E. Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Int. Encycl. Hum. Geogr.* **1996**, *28*, 281–298. [\[CrossRef\]](#)

149. Fotheringham, A.S.; Brunson, C.; Charlton, M. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*; John Wiley: Chichester, UK, 2002; ISBN 0-471-49616-2.
150. Kumari, M.; Singh, C.K.; Bakimchandra, O.; Basistha, A. Geographically weighted regression based quantification of rainfall–topography relationship and rainfall gradient in Central Himalayas. *Int. J. Climatol.* **2017**, *37*, 1299–1309. [\[CrossRef\]](#)
151. Leong, Y.Y.; Yue, J.C. A modification to geographically weighted regression. *Int. J. Health Geogr.* **2017**, *16*, 1–18. [\[CrossRef\]](#) [\[PubMed\]](#)
152. Borthakur, M.; Saikia, A.; Sharma, K. Swelter in the city: Urban greenery and its effects on temperature in Guwahati, India. *Singap. J. Trop. Geogr.* **2020**, *41*, 341–366. [\[CrossRef\]](#)
153. Wang, X.; Zhou, T.; Tao, F.; Zang, F. Correlation Analysis between UBD and LST in Hefei, China, Using LuoJia1-01 Night-Time Light Imagery. *Appl. Sci.* **2019**, *9*, 5224. [\[CrossRef\]](#)
154. Jia, S.Q.; Wang, Y.H. Effects of land use and land cover pattern on urban temperature variations: A case study in Hong Kong. *Urban Clim.* **2020**, *34*, 100693. [\[CrossRef\]](#)
155. Li, C.; Zhao, J.; Thinh, N.X.; Yang, W.; Li, Z. Analysis of the spatiotemporally varying effects of urban spatial patterns on land surface temperatures. *J. Environ. Eng. Landsc. Manag.* **2018**, *26*, 216–231. [\[CrossRef\]](#)
156. Buyantuyev, A.; Wu, J. Urban heat islands and landscape heterogeneity: Linking spatiotemporal variations in surface temperatures to land-cover and socioeconomic patterns. *Landsc. Ecol.* **2010**, *25*, 17–33. [\[CrossRef\]](#)
157. Luo, X.; Peng, Y. Scale effects of the relationships between urban heat islands and impact factors based on a geographically-weighted regression model. *Remote Sens.* **2016**, *8*, 760. [\[CrossRef\]](#)
158. Zhao, H.; Ren, Z.; Tan, J. The spatial patterns of land surface temperature and its impact factors: Spatial non-stationarity and scale effects based on a Geographically-Weighted regression model. *Sustainability* **2018**, *10*, 2242. [\[CrossRef\]](#)
159. Majkowska, A.; Kolendowicz, L.; Półrolniczak, M.; Hauke, J.; Czernecki, B. The urban heat island in the city of Poznań as derived from Landsat 5 TM. *Theor. Appl. Climatol.* **2017**, *128*, 769–783. [\[CrossRef\]](#)
160. Sarkar Chaudhuri, A.; Singh, P.; Rai, S.C. Assessment of impervious surface growth in urban environment through remote sensing estimates. *Environ. Earth Sci.* **2017**, *76*, 541. [\[CrossRef\]](#)
161. Mohan, M.; Kikegawa, Y.; Gurjar, B.R.; Bhati, S.; Kolli, N.R. Assessment of urban heat island effect for different land use-land cover from micrometeorological measurements and remote sensing data for megacity Delhi. *Theor. Appl. Climatol.* **2013**, *112*, 647–658. [\[CrossRef\]](#)
162. Chen, X.; Xu, Y.; Yang, J.; Wu, Z.; Zhu, H. Remote sensing of urban thermal environments within local climate zones: A case study of two high-density subtropical Chinese cities. *Urban Clim.* **2020**, *31*, 100568. [\[CrossRef\]](#)
163. Konstantinov, P.I.; Grishchenko, M.Y.; Varentsov, M.I. Mapping urban heat islands of arctic cities using combined data on field measurements and satellite images based on the example of the city of Apatity (Murmansk Oblast). *Izv.—Atmos. Ocean Phys.* **2015**, *51*, 992–998. [\[CrossRef\]](#)
164. Zhang, P.; Bounoua, L.; Imhoff, M.L.; Wolfe, R.E.; Thome, K. Comparison of MODIS Land Surface Temperature and Air Temperature over the Continental USA Meteorological Stations. *Can. J. Remote Sens.* **2014**, *40*, 110–122. [\[CrossRef\]](#)
165. Hu, L.; Brunsell, N.A. A new perspective to assess the urban heat island through remotely sensed atmospheric profiles. *Remote Sens. Environ.* **2015**, *158*, 393–406. [\[CrossRef\]](#)
166. Geletič, J.; Lehnert, M.; Dobrovolný, P. Land surface temperature differences within local climate zones, Based on two central European cities. *Remote Sens.* **2016**, *8*, 788. [\[CrossRef\]](#)
167. Tomlinson, C.J.; Chapman, L.; Thornes, J.E.; Baker, C.J. Derivation of Birmingham’s summer surface urban heat island from MODIS satellite images. *Int. J. Climatol.* **2012**, *32*, 214–224. [\[CrossRef\]](#)
168. Li, M.; Wang, T.; Xie, M.; Zhuang, B.; Li, S.; Han, Y.; Cheng, N. Modeling of urban heat island and its impacts on thermal circulations in the Beijing–Tianjin–Hebei region, China. *Theor. Appl. Climatol.* **2017**, *128*, 999–1013. [\[CrossRef\]](#)
169. Bounoua, L.; Zhang, P.; Nigro, J.; Lachir, A.; Thome, K. Regional Impacts of Urbanization in the United States. *Can. J. Remote Sens.* **2017**, *43*, 256–268. [\[CrossRef\]](#)
170. Barat, A.; Kumar, S.; Kumar, P.; Parth Sarthi, P. Characteristics of Surface Urban Heat Island (SUHI) over the Gangetic Plain of Bihar, India. *Asia-Pac. J. Atmos. Sci.* **2018**, *54*, 205–214. [\[CrossRef\]](#)
171. Huang, H.; Deng, X.; Yang, H.; Li, S.; Li, M. Spatial evolution of the effects of urban heat island on residents’ health. *Teh. Vjesn.* **2020**, *27*, 1427–1435. [\[CrossRef\]](#)
172. Mitchell, B.C.; Chakraborty, J. Exploring the relationship between residential segregation and thermal inequity in 20 U.S. cities. *Local Environ.* **2018**, *23*, 796–813. [\[CrossRef\]](#)
173. Mushore, T.D.; Odindi, J.; Dube, T.; Mutanga, O. Understanding the relationship between urban outdoor temperatures and indoor air-conditioning energy demand in Zimbabwe. *Sustain. Cities Soc.* **2017**, *34*, 97–108. [\[CrossRef\]](#)
174. Kim, J.P.; Guldman, J.M. Land-Use planning and the urban heat island. *Environ. Plan. B Plan. Des.* **2014**, *41*, 1077–1099. [\[CrossRef\]](#)
175. Kumari, P.; Kapur, S.; Garg, V.; Kumar, K. Effect of surface temperature on energy consumption in a calibrated building: A case study of Delhi. *Climate* **2020**, *8*, 71. [\[CrossRef\]](#)
176. Ullah, S.; Tahir, A.A.; Akbar, T.A.; Hassan, Q.K.; Dewan, A.; Khan, A.J.; Khan, M. Remote sensing-based quantification of the relationships between land use land cover changes and surface temperature over the lower Himalayan region. *Sustainability* **2019**, *11*, 5492. [\[CrossRef\]](#)

177. Lee, T.W.; Ho, A. Scaling of the urban heat island effect based on the energy balance: Nighttime minimum temperature increase vs. urban area length scale. *Clim. Res.* **2010**, *42*, 209–216. [\[CrossRef\]](#)
178. Fan, C.; Wang, Z. Spatiotemporal characterization of land cover impacts on urban warming: A spatial autocorrelation approach. *Remote Sens.* **2020**, *12*, 1631. [\[CrossRef\]](#)
179. Wu, Z.; Yao, L.; Ren, Y. Characterizing the spatial heterogeneity and controlling factors of land surface temperature clusters: A case study in Beijing. *Build. Environ.* **2020**, *169*, 106598. [\[CrossRef\]](#)
180. Pan, Z.; Wang, G.; Hu, Y.; Cao, B. Characterizing urban redevelopment process by quantifying thermal dynamic and landscape analysis. *Habitat Int.* **2019**, *86*, 61–70. [\[CrossRef\]](#)
181. Zhang, Y.; Zhan, Y.; Yu, T.; Ren, X. Urban green effects on land surface temperature caused by surface characteristics: A case study of summer Beijing metropolitan region. *Infrared Phys. Technol.* **2017**, *86*, 35–43. [\[CrossRef\]](#)
182. Zhao, M.; Cai, H.; Qiao, Z.; Xu, X. Influence of urban expansion on the urban heat island effect in Shanghai. *Int. J. Geogr. Inf. Sci.* **2016**, *30*, 2421–2441. [\[CrossRef\]](#)
183. Deilami, K.; Kamruzzaman, M.; Hayes, J.F. Correlation or causality between land cover patterns and the urban heat island effect? Evidence from Brisbane, Australia. *Remote Sens.* **2016**, *8*, 716. [\[CrossRef\]](#)
184. Zhang, H.; Jing, X.M.; Chen, J.Y.; Li, J.J.; Schwegler, B. Characterizing urban fabric properties and their thermal effect using QuickBird image and Landsat 8 thermal infrared (tir) data: The case of downtown Shanghai, China. *Remote Sens.* **2016**, *8*, 541. [\[CrossRef\]](#)
185. Wu, C.; Li, J.; Wang, C.; Song, C.; Chen, Y.; Finka, M.; La Rosa, D. Understanding the relationship between urban blue infrastructure and land surface temperature. *Sci. Total Environ.* **2019**, *694*, 133742. [\[CrossRef\]](#) [\[PubMed\]](#)
186. Cai, Z.; Han, G.; Chen, M. Do water bodies play an important role in the relationship between urban form and land surface temperature? *Sustain. Cities Soc.* **2018**, *39*, 487–498. [\[CrossRef\]](#)
187. Xue, Z.; Hou, G.; Zhang, Z.; Lyu, X.; Jiang, M.; Zou, Y.; Shen, X.; Wang, J.; Liu, X. Quantifying the cooling-effects of urban and peri-urban wetlands using remote sensing data: Case study of cities of Northeast China. *Landsc. Urban Plan.* **2019**, *182*, 92–100. [\[CrossRef\]](#)
188. Rasul, A.; Balzter, H.; Smith, C. Spatial variation of the daytime Surface Urban Cool Island during the dry season in Erbil, Iraq. *Urban Clim.* **2015**, *14*, 176–186. [\[CrossRef\]](#)
189. Kumar, S.; Ghosh, S.; Hooda, R.S.; Singh, S. Monitoring and prediction of land use land cover changes and its impact on land surface temperature in the central part of hisar district, Haryana under semi-arid zone of India. *J. Landsc. Ecol.* **2019**, *12*, 117–140. [\[CrossRef\]](#)
190. Dai, Z.; Guldman, J.M.; Hu, Y. Thermal impacts of greenery, water, and impervious structures in Beijing's Olympic area: A spatial regression approach. *Ecol. Indic.* **2019**, *97*, 77–88. [\[CrossRef\]](#)
191. Soto-Estrada, E.; Correa-Echeverri, S.; Posada-Posada, M.I. Thermal analysis of urban environments in Medellin, Colombia, using an unmanned aerial vehicle (UAV). *J. Urban Environ. Eng.* **2017**, *11*, 142–149. [\[CrossRef\]](#)
192. Arghavani, S.; Malakooti, H.; Ali Akbari Bidokhti, A.A. Numerical assessment of the urban green space scenarios on urban heat island and thermal comfort level in Tehran Metropolis. *J. Clean. Prod.* **2020**, *261*, 121183. [\[CrossRef\]](#)
193. Dong, J.; Lin, M.; Zuo, J.; Lin, T.; Liu, J.; Sun, C.; Luo, J. Quantitative study on the cooling effect of green roofs in a high-density urban Area—A case study of Xiamen, China. *J. Clean. Prod.* **2020**, *255*, 120152. [\[CrossRef\]](#)
194. Asadi, A.; Arefi, H.; Fathipour, H. Simulation of green roofs and their potential mitigating effects on the urban heat island using an artificial neural network: A case study in Austin, Texas. *Adv. Sp. Res.* **2020**, *66*, 1846–1862. [\[CrossRef\]](#)
195. Zhao, Q.; Myint, S.W.; Wentz, E.A.; Fan, C. Rooftop surface temperature analysis in an Urban residential environment. *Remote Sens.* **2015**, *7*, 12135–12159. [\[CrossRef\]](#)
196. Herrera-Gomez, S.S.; Quevedo-Nolasco, A.; Pérez-Urrestarazu, L. The role of green roofs in climate change mitigation. A case study in Seville (Spain). *Build. Environ.* **2017**, *123*, 575–584. [\[CrossRef\]](#)
197. Tsunematsu, N.; Yokoyama, H.; Honjo, T.; Ichihashi, A.; Ando, H.; Shigyo, N. Relationship between land use variations and spatiotemporal changes in amounts of thermal infrared energy emitted from urban surfaces in downtown Tokyo on hot summer days. *Urban Clim.* **2016**, *17*, 67–79. [\[CrossRef\]](#)
198. Gábor, P.; Jombach, S. The relation between the biological activity and the land surface temperature in Budapest. *Appl. Ecol. Environ. Res.* **2010**, *7*, 241–251. [\[CrossRef\]](#)
199. Gao, M.; Chen, F.; Shen, H.; Barlage, M.; Li, H.; Tan, Z.; Zhang, L. Efficacy of possible strategies to mitigate the urban heat island based on urbanized high-resolution land data assimilation system (U-HRLDAS). *J. Meteorol. Soc. Jpn.* **2019**, *97*, 1075–1097. [\[CrossRef\]](#)
200. Mutani, G.; Todeschi, V. The Effects of Green Roofs on Outdoor Thermal Comfort, Urban Heat Island Mitigation and Energy Savings. *Atmosphere* **2020**, *11*, 123. [\[CrossRef\]](#)
201. Alavipanah, S.; Wegmann, M.; Qureshi, S.; Weng, Q.; Koellner, T. The role of vegetation in mitigating urban land surface temperatures: A case study of Munich, Germany during the warm season. *Sustainability* **2015**, *7*, 4689–4706. [\[CrossRef\]](#)
202. Sodoudi, S.; Shahmohamadi, P.; Vollack, K.; Cubasch, U.; Che-Ani, A.I. Mitigating the Urban Heat Island Effect in Megacity Tehran. *Adv. Meteorol.* **2014**, *2014*. [\[CrossRef\]](#)
203. Yuan, C.; Chen, L. Mitigating urban heat island effects in high-density cities based on sky view factor and urban morphological understanding: A study of Hong Kong. *Archit. Sci. Rev.* **2011**, *54*, 305–315. [\[CrossRef\]](#)

204. Zhibin, R.; Haifeng, Z.; Xingyuan, H.; Dan, Z.; Xingyang, Y. Estimation of the Relationship Between Urban Vegetation Configuration and Land Surface Temperature with Remote Sensing. *J. Indian Soc. Remote Sens.* **2015**, *43*, 89–100. [\[CrossRef\]](#)
205. Greene, C.S.; Millward, A.A. Getting closure: The role of urban forest canopy density in moderating summer surface temperatures in a large city. *Urban Ecosyst.* **2017**, *20*, 141–156. [\[CrossRef\]](#)
206. Grover, A.; Singh, R.B. Monitoring Spatial patterns of land surface temperature and urban heat island for sustainable megacity: A case study of Mumbai, India, using landsat TM data. *Environ. Urban. Asia* **2016**, *7*, 38–54. [\[CrossRef\]](#)
207. Masoudi, M.; Tan, P.Y.; Liew, S.C. Multi-city comparison of the relationships between spatial pattern and cooling effect of urban green spaces in four major Asian cities. *Ecol. Indic.* **2019**, *98*, 200–213. [\[CrossRef\]](#)
208. Bao, T.; Li, X.; Zhang, J.; Zhang, Y.; Tian, S. Assessing the Distribution of Urban Green Spaces and its Anisotropic Cooling Distance on Urban Heat Island Pattern in Baotou, China. *ISPRS Int. J. Geo-Inf.* **2016**, *5*, 12. [\[CrossRef\]](#)
209. Cheng, X.; Wei, B.; Chen, G.; Li, J.; Song, C. Influence of Park Size and Its Surrounding Urban Landscape Patterns on the Park Cooling Effect. *J. Urban Plan. Dev.* **2015**, *141*, 1–10. [\[CrossRef\]](#)
210. Yuan, F.; Bauer, M.E. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sens. Environ.* **2007**, *106*, 375–386. [\[CrossRef\]](#)
211. Chen, X.-L.; Zhao, H.-M.; Li, P.-X.; Yin, Z.-Y. Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. *Remote Sens. Environ.* **2006**, *104*, 133–146. [\[CrossRef\]](#)
212. Li, J.; Song, C.; Cao, L.; Zhu, F.; Meng, X.; Wu, J. Impacts of landscape structure on surface urban heat islands: A case study of Shanghai, China. *Remote Sens. Environ.* **2011**, *115*, 3249–3263. [\[CrossRef\]](#)
213. Zhou, W.; Huang, G.; Cadenasso, M.L. Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes. *Landsc. Urban Plan.* **2011**, *102*, 54–63. [\[CrossRef\]](#)
214. Cao, X.; Onishi, A.; Chen, J.; Imura, H. Quantifying the cool island intensity of urban parks using ASTER and IKONOS data. *Landsc. Urban Plan.* **2010**, *96*, 224–231. [\[CrossRef\]](#)
215. Amiri, R.; Weng, Q.; Alimohammadi, A.; Alavipanah, S.K. Spatial-temporal dynamics of land surface temperature in relation to fractional vegetation cover and land use/cover in the Tabriz urban area, Iran. *Remote Sens. Environ.* **2009**, *113*, 2606–2617. [\[CrossRef\]](#)
216. Schwarz, N.; Lautenbach, S.; Seppelt, R. Exploring indicators for quantifying surface urban heat islands of European cities with MODIS land surface temperatures. *Remote Sens. Environ.* **2011**, *115*, 3175–3186. [\[CrossRef\]](#)
217. Parsaee, M.; Joybari, M.M.; Mirzaei, P.A.; Haghighat, F. Urban heat island, urban climate maps and urban development policies and action plans. *Environ. Technol. Innov.* **2019**, *14*, 100341. [\[CrossRef\]](#)
218. Pena Acosta, M.; Vahdatikhaki, F.; Santos, J.; Hammad, A.; Dorée, A.G. How to bring UHI to the urban planning table? A data-driven modeling approach. *Sustain. Cities Soc.* **2021**, *71*, 102948. [\[CrossRef\]](#)
219. Kotharkar, R.; Ramesh, A.; Bagade, A. Urban Heat Island studies in South Asia: A critical review. *Urban Clim.* **2018**, *24*, 1011–1026. [\[CrossRef\]](#)
220. National Weather Service JetStream Max: Addition Köppen-Geiger Climate Subdivisions. Available online: https://www.weather.gov/jetstream/climate_max (accessed on 10 September 2021).
221. Kottek, A.; Grieser, J.; Beck, C.; Rudolf, B.; Rubel, F. World Map of the Köppen-Geiger climate classification updated. *Meteorol. Z.* **2006**, *15*, 259–263. [\[CrossRef\]](#)
222. European Environment Agency European Environment Agency. Available online: <https://www.eea.europa.eu/> (accessed on 1 February 2021).
223. Gusso, A.; Cafruni, C.; Bordin, F.; Veronez, M.; Lenz, L.; Crijia, S. Multi-Temporal Patterns of Urban Heat Island as Response to Economic Growth Management. *Sustainability* **2015**, *7*, 3129–3145. [\[CrossRef\]](#)
224. Foissard, X.; Dubreuil, V.; Quénot, H. Defining scales of the land use effect to map the urban heat island in a mid-size European city: Rennes (France). *Urban Clim.* **2019**, *29*, 100490. [\[CrossRef\]](#)
225. Wilbanks, T.; Fernandez, S. (Coordinating Lead Authors). In *Climate Change and Infrastructure, Urban Systems, and Vulnerabilities*; Technical Report for the U.S. Department of Energy in Support of the National Climate Assessment; Island Press: Washington, DC, USA, 2013.

PROCEEDINGS OF SPIE

SPIDigitalLibrary.org/conference-proceedings-of-spie

Relationship between the land surface temperature and the vegetation proportion to identify heat islands: case study of Brasília (Brazil)

Rodrigues de Almeida, Cátia, Teodoro, Ana Claudia Moreira

Cátia Rodrigues de Almeida, Ana Claudia Moreira Teodoro, "Relationship between the land surface temperature and the vegetation proportion to identify heat islands: case study of Brasília (Brazil)," Proc. SPIE 11534, Earth Resources and Environmental Remote Sensing/GIS Applications XI, 1153411 (20 September 2020); doi: 10.1117/12.2572802

SPIE.

Event: SPIE Remote Sensing, 2020, Online Only

Relationship between the Land Surface Temperature and the Vegetation Proportion to identify Heat Islands. Case study of Brasília (Brazil)

Cátia Rodrigues de Almeida^{*a}, Ana Claudia Teodoro^{a,b}

^aDep. of Geosciences, Environment and Land Planning, Faculty of Sciences, University of Porto, Rua Campo Alegre, Porto, Portugal; ^bICT (Institute of Earth Sciences) – Porto pole (Portugal)

ABSTRACT

Anthropic changes resulting from urbanization contribute to the modification of surface materials, originating the suppression of vegetation, waterproofing of the soil and the variation of albedo, which can contribute to the formation of Heat Islands (HI). This phenomenon results from the higher absorption of electromagnetic energy by the buildings, when compared to vegetation, corroborating both the increase of surface temperature and the minimization of the relative humidity of the air. This effect is potentiated at night, when urbanized regions maintain higher average temperatures for a longer time, when compared to vegetation areas. Some impacts of this effect are: (i) thermal discomfort and influence on the local microclimate and; (ii) displacement of water bodies. This work aimed to analyze the relationship between the Land Surface Temperature (LST) and the Vegetation Proportion (Pv), derived from Normalized Difference Vegetation Index (NDVI), in the densely built area of Brasília (Brazil), in order to evaluate if its characteristics confirm the micro-scale climate change. Several images from Landsat 5 and 8 thermal sensors were processed between 1989 and 2019 and the results obtained point out that the LST is inversely proportional to Pv, i.e., the highest temperatures were observed in classified areas with scarce or no Pv, which corroborates with the hypothesis that anthropic altered regions can influence the local climate. Despite the phenomenon observed and the 50% increase in maximum temperature in 2019 when compared to the 1989 and the decrease in maximum Pv by 36% in the same years, it is mandatory additional studies to confirm these findings.

Keywords: Heat Islands, Climate change, Land Surface Temperature, Vegetation Proportion, Landsat.

1. INTRODUCTION

Remote Sensing (RS) consists of a set of techniques that aims to obtain target information without physical contact, by means of sensors arranged on platforms (satellites, airplanes, balloons) that record the electromagnetic radiation emitted or reflected, converting it into a signal that subsequently, it allows the generation of images [1].

There are several possibilities of applying RS techniques to understand phenomena that impact the health and well-being of the population, such as, for example, the use of data from thermal sensors to identify the surface temperature of a place, due on its use and characteristics land occupation [2].

Population occupation in specific regions can favor accessibility to different basic needs, such as transportation and sanitation. However, the anthropic changes necessary to support a high population density, especially in relation to land use adaptations, can influence the characteristics of local climatic conditions, for example, with an increase in surface temperature. In this context, the urbanization can corroborate with the imbalance of ecosystems, especially in of altering surface components of the soil and in the use of construction materials, in detriment of vegetation areas, resulting in a contrast between local and rural climate and in the formation of the phenomenon known as Heat Islands (HI) [3].

* up201600831@fc.up.pt; phone +351 936 291 306

The city in Brasília (Brazil) is an example of a place that undergoes superficial changes, although it was designed to be a city park with appreciation of vegetation areas. The growing urban expansion has contributed to the increase of agricultural areas and urban centers.

“Although planned, Brasília and the Federal District present themselves as a summary picture of the reality of developing countries. The swelling of the urban spot is one of those striking features. The capital's installation plan foresaw a population of 500 thousand inhabitants in the year 2000, but that number has already surpassed two million, creating serious urban problems. Periphery is one of those difficulties.” [3]

Scientific studies that assess the anthropic impacts due to urbanization are of paramount importance, as they promote discussions about the need for adequate and sustainable urban planning. In addition, it encourages rethinking about improvements in relation to the civil construction materials currently used and which can be improved to minimize the retention effects and localized heating, influencing the local climate.

1.1 Heat Islands

The surface temperature of a place is related to the reflective power of its components and to the diffusion of electromagnetic energy emitted by the Sun. This phenomenon is called albedo [4]. Figure 1 shows some of the materials used in civil construction, with their respective albedo rates.

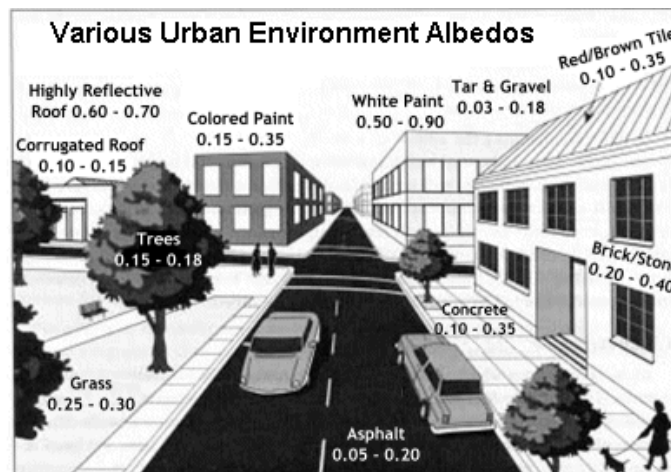


Figure 1. Albedo of urban materials [5].

Analyzing Fig 1, it is possible to verify that the albedo of these components presents high variability and, for the most part, absorbs more electromagnetic energy than vegetation, potentiating the formation of HI and resulting in surface temperature increasing, thermal discomfort and influence on the microclimate, such as displacement of water bodies and changes in local precipitation. In addition, it corroborates the contrast between the local and rural climate and the formation of the HI, as exemplified in Figure 2. The HI are more present in the urban centers because the latent heat flow is reduced and the sensitive heat is intensified due to the albedo change [3, [6].

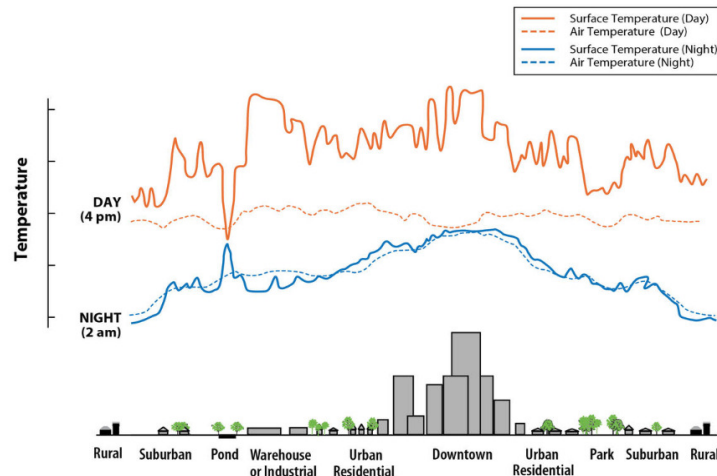


Figure 2. Profile of the urban HI in relation to suburban [7].

Despite being a subject explored by the scientific community and there are several option of civil construction materials with technologies that aim to mitigate its effects, such as permeable asphalt the areas classified as HI, still need improvements and mitigations [8].

The Earth's surface receives electromagnetic radiation emitted by the Sun, absorbing one part and reflecting another. Thermal sensors operate in the thermal infrared range - considered as an atmospheric window, because the absorption rate in this zone is minimal - and measure, at the top of the atmosphere, the radiation emitted by the terrestrial surface. This dynamic associated with remote sensing sensors is important for the development of scientific research, because it allows the analysis of different scales of the same site, as well as the use of data from thermal sensors to assess whether there are climate changes in urbanized areas [9].

The objective of this work was to evaluate the relationship between the presence of vegetation and its possible influences on surface temperature in Brasília, in Brazil, considering a region classified as densely urbanized, as well as to propose a discussion on the possibility of classify it as a HI, considering the Land Surface Temperature (LST) retrieved by remote sensing sensors.

1.2 Use of Satellite Images for HI studies

Considering that all bodies with a temperature greater than zero Kelvin emit electromagnetic radiation, it is possible to use remote sensors to record and convert them into an image relative to the target. The thermal sensors operate in the range of the atmospheric window of the thermal infrared (8 - 14 μm) which includes the emission portion of the terrestrial spectrum and allows the detection of heat, due to the sensitivity of the detectors to direct contact with photons, which are emitted by thermal radiation. In practice, the sensors are cooled to temperatures close to 0°, so that their emissions do not influence the measurements and record the surface temperature, as well as the thermal properties of the targets, relative to the thermal infrared. The measured radiation temperature is compared to the internal reference temperatures of the sensors, which are related to the absolute radiance temperature [6, 10].

It is important to mentioning that the collection of data by thermal sensors is associated with heat stroke: if the data is acquired on a day with low incidence, the materials will have lower temperatures and, consequently, emit lower intensities of radiant energy compared to a day of high heat stroke [11].

The data used in this work were acquired by the sensors available in Landsat 5, whose operation started on March 1st, 1984 until November 2011, and on Landsat 8, which has been active since 02/11/2013. The orbit of both satellites are heliosynchronous, almost polar, with nominal altitude of 705 km, an orbital inclination of 98.2° and a revisit time of 16 days [10].

The sensors on board the Landsat 5 are the Multispectral Scanner - MSS and Thematic Mapper - TM, which was used in this work. The TM is an advanced multispectral scanning sensor, with spectral resolution of 7 bands in the range of 0.45 to 12.5 μm and spatial resolution of 30 m (with the exception of band 6, which is 120 m, resampled to 30 m). The radiometric resolution, which consists of the sensor's ability to discriminate small variations in energy that, in images, refers to the number of shades of gray distinguishable between black and white, is related to the sensor bits. The TM has 8 bits, therefore, it records Digital Number - DN values between 0 and 255. The scanning area is 185 km and, with the exception of band 6, the sensor simultaneously scans 16 lines, using a rotating mirror, that captures information in both directions of the scan. Landsat 8 operates with Operational Land Imager - OLI and Thermal Infrared Sensor - TIRS sensors. OLI has 8 multispectral and 1 panchromatic bands, with 30 and 15 m resolution, respectively. The TIRS has two thermal bands, with a resolution of 100 m (resampling to 30 m). The band used in this work was band 10, relative to TIRS 1 (10.3 - 11.19 μm), with a radiometric resolution of 16 bits. The scanning system is pushbroom scanners, which use the movement of the satellite to scan several lines perpendicular to the flight line, successively [10].

1.3 State of the Art

LST is a variable in the physics of local and global surface processes, linked to radiant, latent heat flows and sensitive to the interface with the surface. Refers to the radiometric temperature aggregate of the surface, that is, the radiance measure of the set of components that is within the sensor's field of view. Understanding its dynamics and modeling its data can assist in predicting environmental changes, climatic variability, among other applications [12].

The methodology based on the production of LST maps to analyze the surface temperature in Brazil has been investigated previously. In a study about Brasília published in 2014, four images from Landsat 5, from 1987 to 2011 were processed, and identified places that intensify the HI phenomenon due to the presence of exposed soil and deforestation compared to the presence of vegetation, which rate milder surface temperature, as in the city park region. The authors reinforce the need for complementary studies, with greater detail of the thermal images, as well as the comparison of data from different sensors and correction of atmospheric effects to assist in the composition of public policies, to mitigate the effects of HI and impacts on society [13].

In 2015, a study was published about Maceió, in Brazil, relating LST maps to the presence of vegetation, using the Normalized Difference Vegetation Index (NDVI), considering Landsat 5 data. The methodology was efficient to identify the low concentration of vegetation in urban areas, in addition to enabling the inverse relationship between NDVI and LST, in which the places with the highest LST value corresponded to those with the lowest NDVI, with ranging between 35° C and 38° C and the values in vegetation areas ranging between 20° C and 29° C, corroborating for the statement that the vegetation operates as a softener for the HI effect [14].

In São Paulo, an study about HI was also carried out in 2016. Several variables were selected, such as the leaf area index, surface temperature, soil use patterns and the thermal classification of the HI. Two images of Landsat 5 were used. The results were compared to the cartographic data with territorial limits and hydrography, extracted and from the Environmental Atlas of the Municipality of São Paulo and the soil patterns. The authors identified that absent or low presence of vegetation is the main cause of the intensity and spatial distribution of HI. The surface that presents the greatest spatial relationship with the phenomenon corresponding to the warehouse / industry, commerce and service, characterized by the source of asphalt, zinc and concrete roofs, asbestos and aluminum, culminating in a surface temperature difference above 8° C, relative to rural areas. The study reinforces the importance of preserving vegetation in order to soften the surface temperature and the need to expand green areas in urbanized regions, since regions with this characteristic present milder temperature results when compared to those without any vegetation. The authors suggest methodological supplements due to the small variability of the types of cover, which focused on areas with different values of plant biomass or with its absence and disregarded other phenomena that may occur in the formation of HI, such as the concentration of pollutants and atmospheric gases, the conversion, flow and analysis of thermal amplitudes in more detail and their possible consequences in relation to morbidity and mortality from diseases affecting the circulatory system [15].

Another work focusing on LST was published in 2017, using data from Landsat 5 and Landsat 8 related to the city of Santa Maria -Rio Grande do Sul, in Brazil. The chosen images correspond to the period between 1994 and 2014. A supervised classification was performed with the MaxVer algorithm, in order to understand the dynamics of land use and occupation. The LST maps were and the HI were identified. The results were compared to the city's meteorological conditions, made available by the National Meteorological Institute (INMET). According to the results obtained, the

surface temperature was higher in urban areas. In this period, the urban areas increase in 70%, that explain the temperature comportment. Although the phenomenon was identified in all images, the ones with the highest intensity, with 6° C above the average, were those related to summer and spring. As in other studies, the results show milder temperatures in vegetated areas and the possibility of using remote sensing data for studies related to HI [16].

In 2018, a survey was carried out that, in addition to the LST processing, analyzed the relationships between surface materials and urban morphology in 12 sample areas of Brasília, using advantage of thermal images from February to August 2016 from the Landsat 8. The result supports a statement that the city has HI characteristics in a decentralized way, since the distribution of urban densities follows this same logic. [17]

In the same year, another study was carried out in São Paulo, with the aim of analyzing the spatial distribution of target temperatures and the frequency of HI intensities, considering areas with different uses, in Presidente Prudente. The authors processed 24 images of band 10 from the Landsat 8, between February 2013 and January 2016. The highest LST values were found in areas of the low-rise housing complex, followed by the region that includes a neighborhood of medium construction standard. The lowest recorded LST values are associated with areas with lower construction density and the presence of permeable soils, with trees and undergrowth [18].

It is possible to verify that, in all the aforementioned studies, the result corroborates for the affirmation that the anthropic alterations influence in the microclimate. It is worth mentioning that in all cases, the estimation of the LST was performed according to the methodology adopted in this study, except for the inclusion of the composition of the vegetation adopted in the final processing.

2. METHODOLOGY

Brasília was chosen as study area due to its topography, which, because it is flat area, are less sensitive to external influences when compared to areas with more irregular and/or severe topography.

A bibliographic survey on the use of satellite images to identify HI, as well as data available of the study site was also performed. The methodology adopted in this work for the process the satellite images, is presented in Figure 3.

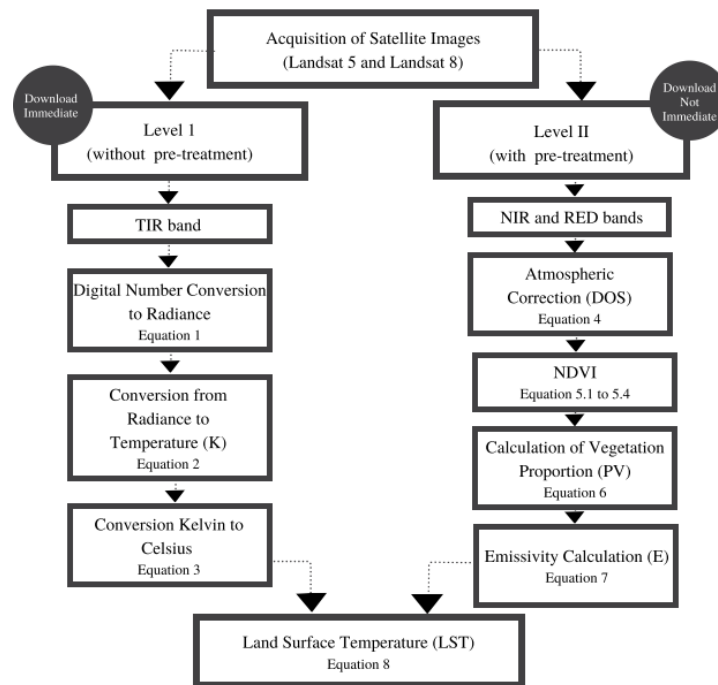


Figure 3. Steps for generating the LST map.

The acquisition of satellite images provided by USGS, at levels 1 and 2, with the absence and presence of pre-treatment, was done. The period chosen for analysis was the month of August, because in this month high levels of combination are not common. The only image that does not refer to that period is the 1994 image, which refers to July, as the August images presented high cloud cover. All the images were downloaded with the presence of clouds below 10%. The selected dates were: 08/12/1989, 07/25/1994, 08/08/1999, 08/03/2009, 08/21/2004, 08/31/2009, 08/01/2014 and 08/31/2019), the first five images are from Landsat 5 and the others are from Landsat 8 [19, 20].

Regarding data processing, the methodology was divided into two initial stages, one considers the NIR and RED bands and the other was applied to TIR band. For the image processing tasks, the QGIS software was used to apply the Atmospheric Correction (DOS algorithm) for the NIR and RED bands. The ArcMap software was also used, including: (i) reprojection for the SIRGAS_2000_UTM_Zone_23S system, (ii) the raster calculator function for mathematical calculations, (iii) generation of Normalized Vegetation Difference Index (NDVI) maps, Vegetation Proportion (Pv) and emissivity computation, and; (iv) conversion of values for surface temperatures, using the Spectral Radiance Scaling Method and cuts to delimit the study area. The Land Surface Temperature (LST), one of the final results of this work, was generated with the resulting maps produced in both stages.

It was necessary include a step of atmospheric correction because, when generating the first LST maps, no atmospheric correction was applied to the NIR and RED bands, as they were chosen on demand in the USGS. Therefore, they had already been pre-processed. However, the results obtained were not satisfactory, as the final temperatures varied between -400 and -200° C. Accordingly, Dark Object Subtraction (DOS) was applied. This technique assumes that the darkest objects in the image, which should be black and with digital values equal 0, receive reflectance values as a function of atmospheric scattering. The first map was corrected using the raster calculator function, in ArcMap, subtracting the value 2 (two) from the raster, which was added to the body of water and should be zero. The result obtained between this processing and the result of the Semi-Automatic Classification Plugin (SCP) of the QGIS software was compared and, as it was similar, the other maps were corrected directly with the SCP plugin [19, 21, 23].

A delimitation of the densely urbanized areas of Brasília was used and the generated LST was cut out considering this smaller area of approximately 25.7 km², with the presence of vegetation, which allows the evaluation of the relationship between its existence and the obtained surface temperature [3, 22].

After the generation of the maps, a color scale was defined for both temperature and Pv, to make it possible to compare the results obtained between the analyzed years;

Finally, a discussion was proposed regarding the relationship between the proportion of vegetation and the increase in surface temperature in the evaluated region.

The mathematical expressions as well, all the constants used in image processing are presented in the following equations. It is worth mentioning that they were used specific constants from the TM (Landsat 5) and TIRS (Landsat 8), available in their metadata file. All equations were applied using the ArcMap raster calculator, with the exception of Vegetation Index - VI, which refers to the SCP (Semi-Automatic Classification Plugin) command, available on QGIS.

The Digital Number (DN) conversion to radiance ($L\lambda$) was performed considering Equation (1).

$$L\lambda = (L_{\max\lambda} - L_{\min\lambda}) / (Q_{\text{calmax}} - Q_{\text{calmin}}) \times (Q_{\text{cal}} - Q_{\text{calmin}}) + L_{\min\lambda} \quad (1)$$

Where, $L\lambda$ is the spectral radiance at the sensor opening (watts/(m²* srad*μm)); Q_{cal} is the calibrated quantized value of a pixel; $L_{\min\lambda}$ is the spectral radiance scaled to Q_{calmin} (watts/(m²* srad*μm)); $L_{\max\lambda}$ is the pectral radiance scaled to Q_{calmax} (watts/(m²* srad *μm)); Q_{calmax} is the calibrated maximum quantized value of a pixel (corresponding to $L_{\max\lambda}$) (gray level); Q_{calmin} is the calibrated minimum quantized value of a pixel (corresponding to $L_{\min\lambda}$) (gray level).

The conversion from radiance ($L\lambda$) to temperature (Kelvin) was obtained byEquation (2).

$$TK = K_2 / \ln ((K_1 / L\lambda) + 1)) \quad (2)$$

Where, TK is the apparent brightness temperature (K); $L\lambda$ is the reflectance at the top of the atmosphere (Watts / (m² * srad * μm)) and; K_1 and K_2 are the specific thermal constants for each band, available in the metadata file.

After, it was necessary convert the temperature from Kelvin (K) to Celsius (° C) (Equation (3)).

$$TC = TK - 273.15 \quad (3)$$

In order to identify the presence of vegetation and fulfill the objective of the work, the NDVI computation was carried out in different stages, so that its proportion in the studied site was kept as coherently as possible, according to the following steps:

1st step: calculation of NDVI.

$$NDVI = (NIR - RED) / (NIR + RED) \quad (4)$$

{ values between -1, +1 }

2nd step: a mask was created to identify the values greater than 0 and the NDVI was multiplied with the generated mask, conditioning the NDVI to 0 and +1:

$$NDVI_+ = Mask \{0, 1\} * NDVI \quad (5)$$

{ values between 0, +1 }

3rd step: a mask was created to identify values greater than 0.5. In this step, the objective was to keep the values above 0.5 and to make a proportional estimate of the values between 0 and 0.5. Similar to the previous process, the $NDVI_{>0.5}$ was computed, multiplying the mask created with these values and the $NDVI_+$.

$$NDVI_{>0.5} = Mask \{0, 1\} * NDVI_+ \quad (6)$$

4th step: the NDVI values between 0 and 0.5 were computed by raising their value to the square, so that the proportion within the pixel, for the emissivity calculation was adequate:

$$NDVI_{0, 0.5} = Mask \{0, 1\} * (NDVI_{0, 0.5})^2 \quad (7)$$

The estimation of the P_v was performed considering Equation (7).

$$P_v = NDVI_{0, 0.5} + NDVI_{>0.5} \quad (8)$$

In Equation (8) is presented the emissivity estimation.

$$E = 0.004 * P_v + 0.986 \quad (9)$$

Finally, the LST was computed according to Equation (9).

$$LST = (TB / (1 + (L\lambda * TB / P) * \ln(E))) \quad (10)$$

Where, LST is the temperature corrected by emissivity, with K converted to ° C; TB is the temperature of the brightness in the sensor; $L\lambda$ is the wavelength of the emitted radiance; and P is given in Equation (10).

$$P = h \times c / \sigma (1.438 \times 10^{-2} \text{ mk}) \quad (11)$$

Where, σ is the Boltzmann constant (1.38×10^{-23} J/K), h is the Planck constant (6.626×10^{-34} Js) and; c is the speed of light ($2,998 \times 10^8$ m/s)

In Table 1 and Table 2 are presented the information about the images used (date and time of acquisition), and the constants used in the equations given above.

Table 1. Information about the images used [19].

LANDSAT_PRODUCT_ID	Date of acquisition	Time of acquisition
LT05_L1TP_221071_19890812_20170202_01_T1	8/12/1989	12:41:29
LT05_L1TP_221071_19940725_20170113_01_T1	07/25/1994	12:32:09
LT05_L1TP_221071_19990808_20161219_01_T1	8/08/1999	12:52:24
LT05_L1TP_221071_20040821_20161129_01_T1	08/21/2004	12:57:54
LT05_L1TP_221071_20090803_20161022_01_T1	8/03/2009	13:03:52
LC08_L1TP_221071_20140801_20170420_01_T1	08/01/2014	13:14:41
LC08_L1TP_221071_20190831_20190916_01_T1	8/31/2019	13:14:55

Table 2. Constants used in the processing steps [19].

Satellite	Maximum Radiance (Lmax λ)	Minimum Radiance (Lmin λ)	QUANTIZE_CAL_MAX (Qcalmax)	QUANTIZE_CAL_MIN (Qcalmin)	K ₁	K ₂	Spectral range (μ m)	Emitted radiance wavelength L λ
Landsat 5	15,303	1,238	255	1	607,76	1260,56	10,4 - 12,5	11,45
Landsat 8	0,0003342	0,1	65535	1	774,8853	1321,0789	10,60 - 11,19	10,90

3. RESULTS AND DISCUSSIONS

3.1 Characterization of the Study Area

Brasília is the federal capital of Brazil and the seat of the Federal District government. Located in the Midwest region of the country, in a geographical region called Planalto Central, it has 5 802 km² of area. The climate is tropical, with an average temperature of 22 °C and annual variations from 13 °C to 28 °C, in the averages of the last 30 years. Figure 4 shows the evolution of the resident population, with data estimated for 2019, making it the fourth most populous city in Brazil [22, 24].

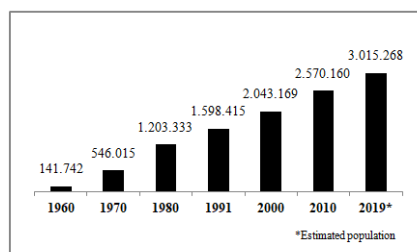


Figure 4. Number of resident population in Brasília – DF (adapted [22]).

With population growth at levels higher than planned, knowledge about anthropological impacts and changes in soil is necessary. Figure 5 shows the location of Brasília in Brazil, the identification of areas classified as densely urbanized and the delimited area for this study, in Natural and False Color Composition [22]. The composition was processed considering the most recent date, that is, 8/31/2019. This small area with approximately 25.7 km², contains distinct features: i) presence of vegetation, especially in a strip that connects the northeast to southeast of image, going through the center; and ii) mostly densely urbanized areas, distributed throughout the image, allowing the analysis of the behavior of the surface temperature in these different surfaces.

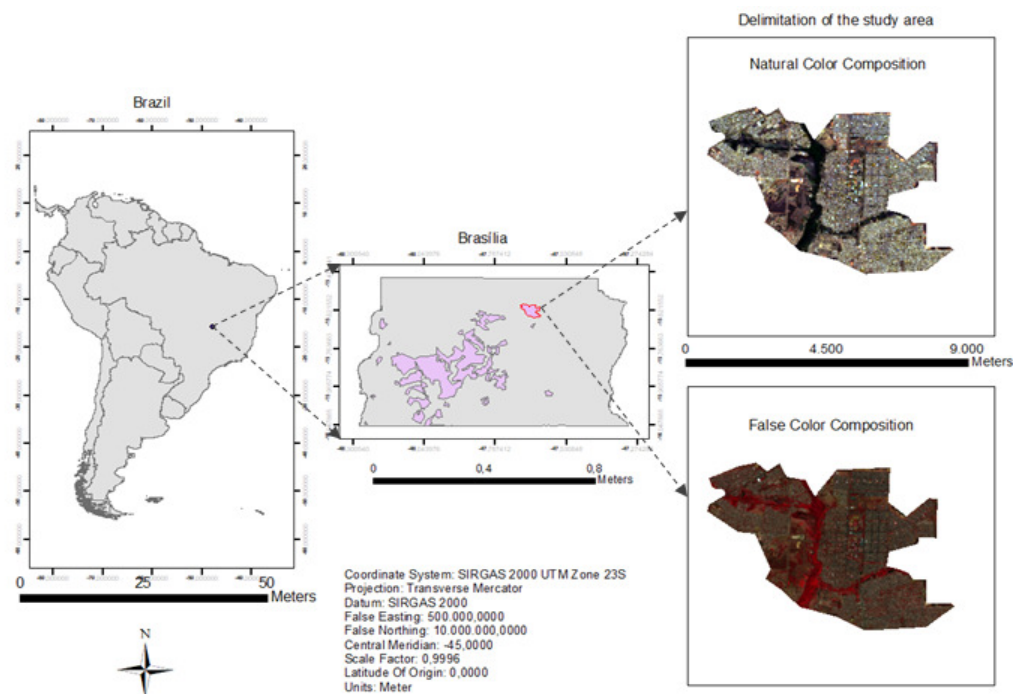


Figure 5. Delimitation of the study area.

After processing the images, the results obtained for both LST and the Pv were reclassified on the same scale, to allow a temporal analysis, in addition to the visual interpretation. Figure 6 shows the results obtained for the 30 years study for LST and the Figure 7 shows the results related to Pv. The LST scale was divided in 2.5 °C intervals, so that they could be identified as transition areas in a more specific way. The Pv was divided into five groups, following the next requirements: i) from 0 to 0.20: no or less Pv; ii) from 0.20 to 0.40: average Pv; iii) from 0.40 to 0.6: partial vegetation, iv) from 0.6 to 0.8: good concentration of vegetation and; v) above 0.8: great concentration of vegetation.

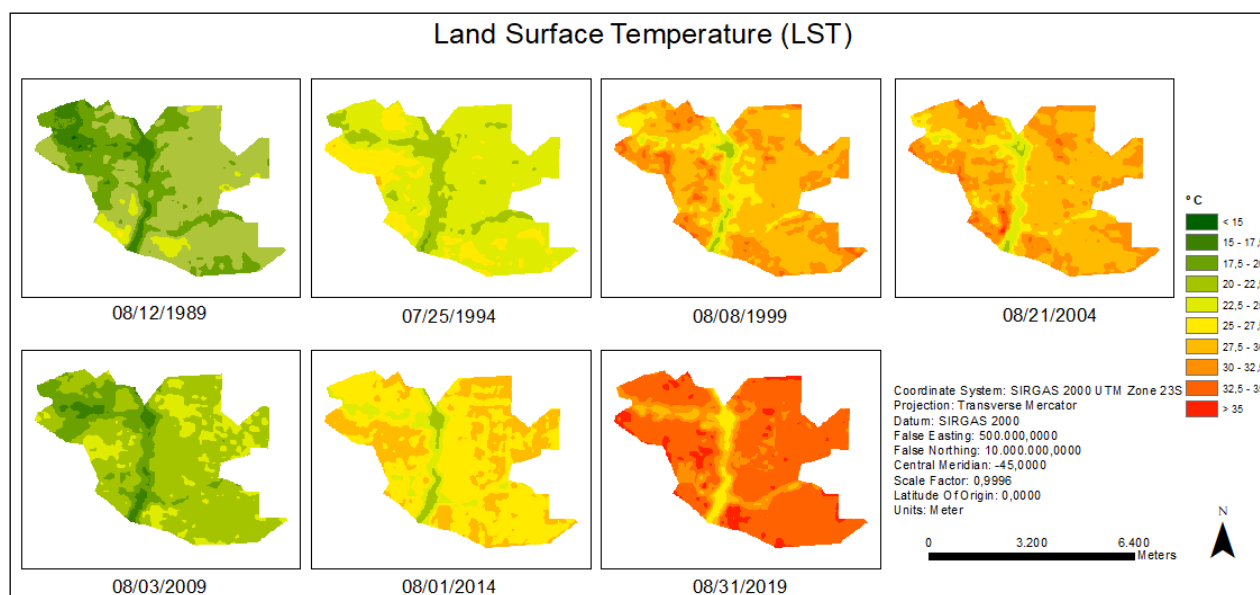


Figure 6. Results obtained for LST.

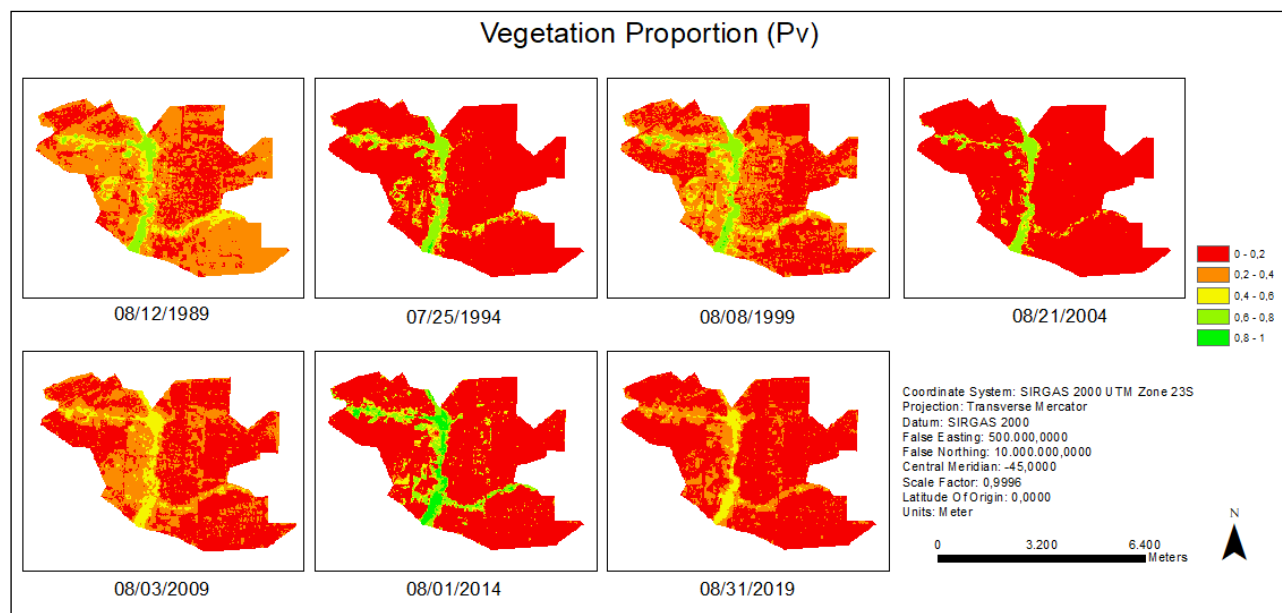


Figure 7. Results obtained for Pv.

The years 1989 and 2009 were the ones with the lowest LST temperatures in relation to the others and, in 2019, the surface temperatures were the highest in the analyzed period. Considering that there are external factors not processed in this first methodological approach and that can influence the results, such as the solar radiation rate relative to the day analyzed, it is not possible to conclude with the data obtained that there was a significant increase in surface temperature in the studied area. Thus, it is suggested that complementary research be made in the methodology, adding the application of statistical and geostatistical models, which take into account the constants that may influence the result. However, it is possible comparing the data obtained in the LST in relation to the Pv, for the same year. Visually, it is possible to verify that places with lower Pv and greater urban density increased in surface. The strip of vegetation in the area acts as an attenuator, minimizing the temperature along its strip, in all images. This behavior corroborates the capacity of green areas to attenuate the temperature, in comparison to the areas of civil and / or industrial construction. Table 3 shows the maximum, minimum and average values obtained for Pv and LST.

Table 3. Maximum and minimum of LST and Pv.

		08/12/1989	07/25/1994	08/08/1999	08/21/2004	08/03/2009	08/01/2014	08/31/2019
LST (°C)	Max	26	29	35	36	24	30	39
	Min	14	20	21	22	16	21	25
	Average	20	24	28	29	20	26	32
Pv	Max	0,80	0,84	0,82	0,80	0,69	0,90	0,52
	Min	0,01	0,00	0,00	0,00	0,00	0,00	0,00
	Average	0,41	0,42	0,41	0,40	0,35	0,45	0,26

Table 3 was intended to present the amplitude and mean of the data, but does not represent the possibility of direct comparison between the years, since the HI phenomenon must be analyzed spatially, according to the surface characteristic, and not by generalized data. Although a temporal analysis is not the most appropriate for the methodology adopted in this study, seen that the compared between the years was based to a day and external factors can influence the results, there is a reduction in the proportion of vegetation in the analyzed period.

The LST presents ascending data for maximum temperature when compared to 1989, with the exception of 2009, whose maximum temperature was lower than the other dates, which may be associated with external factors that were not included in this study.

4. CONCLUSIONS

RS data can be applied to understand several phenomena, including the effects related to surface temperatures, through the use of thermal sensors. The HI phenomenon consists of a change on a local scale, which generates effects on the microclimate and occurs mainly due to the anthropic changes of urbanization and civil construction, which influence the variation of the albedo of a place, mainly due to the suppression of vegetation and waterproofing of the ground. In addition to urbanization, other elements can corroborate HI, such as air pollution and the geographic location of the study site. In this sense, Brasília is one of the areas studied to assess the existence of HI. Although planned, urbanization has intensified in the region and publications address the effects of microclimate and thermal discomfort reported by the population. In this study, 7 images were processed from 1989 to 2019, delimited to an area classified as densely urbanized, with approximately 25.7 km². In the region, there is also the presence of vegetation, which allowed to analyze its effects on the surface temperature of the place. The resulting maps of LST and Pv of the study area show inversely proportional visual results, that is, in the areas with the highest concentration of vegetation, milder temperatures were observed. Although the results corroborate the assumption of its characterization as HI, this work does not allow to conclude that, since complementary analyzes and methodological adjustments, mainly quantitative, are necessary, such as: i) conducting statistical analyzes to assess the correlation between surface temperatures and the presence of vegetation; ii) evaluate the growth of urbanization in the region, on a microscale, so that it can make assumptions based on quantitative data, in addition to visual interpretation; iii) consider other variables, for example, the hypothesis of a possible generalized increase in temperature and; iv) process and analyze more images related to the analyzed period to decrease the time scale of the analyzed data. Finally, the use of RS data is very useful for research on the HI surface, as well as the presence of vegetation.

REFERENCES

- [1] Almeida, C. M., “Aplicação dos Sistemas de Sensoriamento Remoto por Imagens e o Planejamento Urbano Regional,” Arq.Urb, São Paulo. (3), 98-123 (2010), <<https://pepsic.emnuvens.com.br/arqurb/article/view/120/106>> (02 July 2020).
- [2] Amorim, M. C. de C. T., “Detecção remota de ilhas de calor superficiais: Exemplos de cidades de porte médio e pequeno do ambiente tropical, Brasil,” Finisterra, Lisboa. (105), 111-133 (2017), <<http://www.scielo.mec.pt/pdf/fin/n105/n105a07.pdf>> (02 May 2020).
- [3] Baptista, G.M.M., [Estudo Multitemporal do Fenômeno Ilhas de Calor no Distrito Federal], Revista Meio Ambiente. (02), 03-17 (2002).
- [4] EPA – Agência de Proteção Ambiental dos Estados Unidos., “Ilhas de calor,” <<http://www.epa.gov/heat-islands>> (29 January 2020).
- [5] Goodman, S. J., “Heat Island,” < https://weather.msfc.nasa.gov/urban/urban_heat_island.html> (29 January 2020).
- [6] Imhoff, M. L., Zhang, P., Wolfe, R. E. and Bounoua, L., [Remote Sensing of the Urban Heat Island Effect Across Biomes in the Continental USA], Remote Sensing of Environment 114 (3), 504- 513 (2010).
- [7] USGS - U.S. Geological Survey., “Urban Heat Islands,” <<https://www.usgs.gov/media/images/urban-heat-islands>> (29 January 2020).
- [8] Pires, R. A. G. and Carrilho, B. B., “Asfalto convencional ou permeável? Viabilidade técnica na prevenção de enchentes,” ISSN: 1984-8781 - Anais XVIII ENANPUR 2019, <<http://anpur.org.br/xviiienanpur/anaisadmin/capapdf.php?reqid=1744>> (29 January 2020).
- [9] Costa, D. F.; Peres, L. F; Silva, H. R., “Identificação de ilhas de calor na área urbana de Ilha Solteira-SP através da utilização de geotecnologias”, <<http://marte.sid.inpe.br/col/dpi.inpe.br/sbsr@80/2008/11.17.13.31/doc/647-653.pdf>> (29 January 2020).
- [10] Sousa, A. M. O. and Silva, J. R. M., “Fundamentos Teóricos de Detecção Remota. Évora: Universidade de Évora,” 2011, <http://www.rdp.uevora.pt/bitstream/10174/4822/1/Sebenta_DR_fundamentosTericos_2011.pdf> (25 July 2020).
- [11] Baptista, G. M. M., [Sensores Imageadores na Faixa do Termal (8 - 14 µm)], (2012).
- [12] NASA - National Aeronautics and Space Administration., “Committee on Earth Observation Satellites Working Group on Calibration and Validation: Land Surface Temperature Product Validation Best Practice

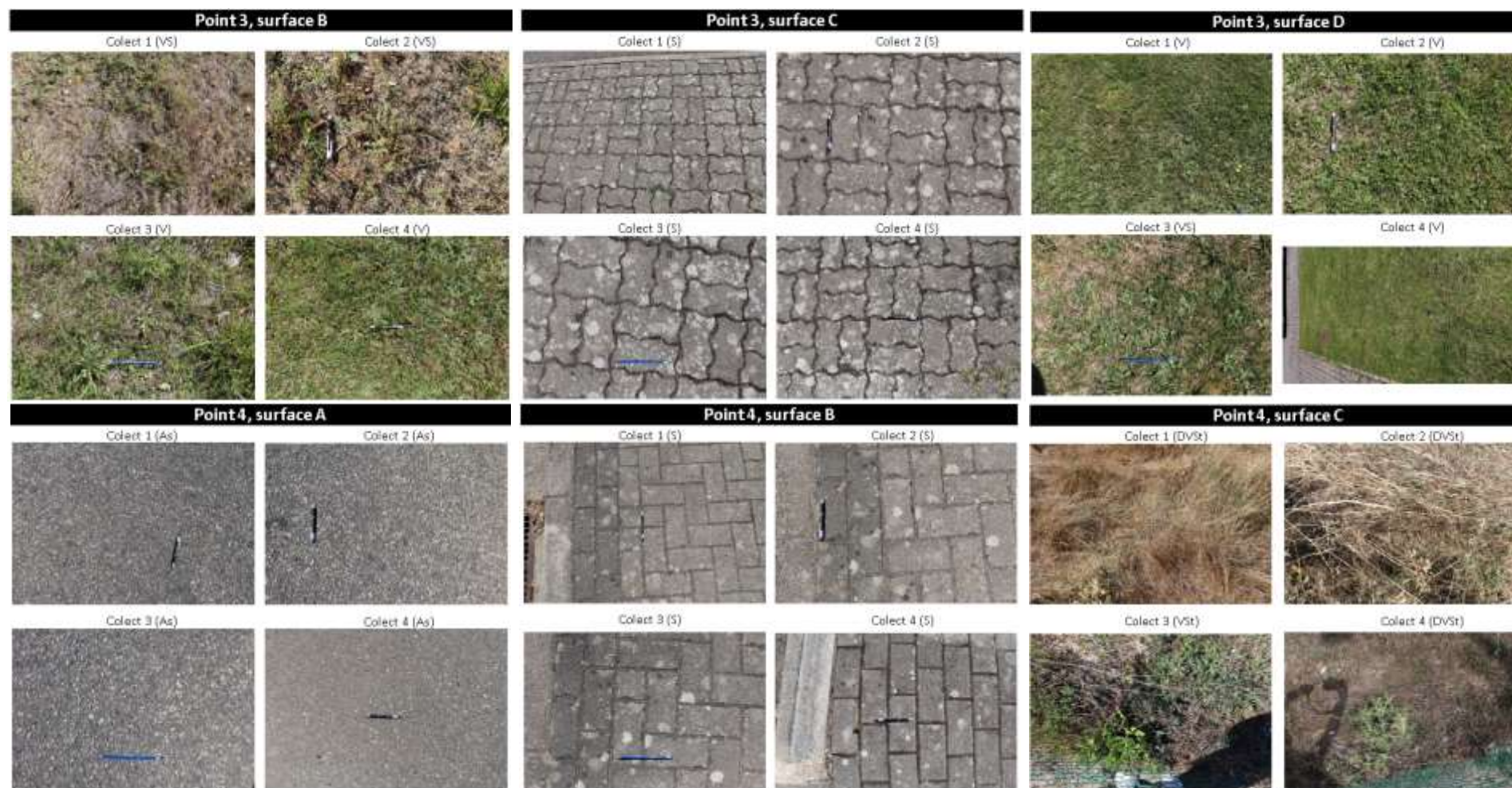
- Protocol,”. 72 (2018), <https://lpvs.gsfc.nasa.gov/PDF/CEOS_LST_PROTOCOL_Feb2018_v1.1.0_light.pdf> (04 August 2020).
- [13] Santana, N. C., “Investigação de Ilhas de Calor em Brasília: Análise Multitemporal com Enfoque na Cobertura do Solo,” ISSN: 1984-2295 - Revista Brasileira de Geografia Física <<https://periodicos.ufpe.br/revistas/rbgfe/article/view/233071/26991>> (25 July 2020).
- [14] Almeida, A. J. P., Junior, S. A. M. G. J., Andrade, E. L., and Neto, J. V. F., “Relação entre o Índice de Vegetação e a Temperatura de Superfície na estimativa e identificação das ilhas de calor na cidade de Maceió-AL,” Anais XVII Simpósio Brasileiro de Sensoriamento Remoto - SBSR, João Pessoa-PB, Brasil, (2015), INPE, <<http://www.dsr.inpe.br/sbsr2015/files/p0406.pdf>> (04 August 2020).
- [15] BARROS, H. R., and LOMBARDO, M. A., [A ilha de calor urbana e o uso e cobertura do solo em São Paulo-SP], Geosp – Espaço e Tempo, ISSN 2179-0892, 20 (1) 160-177 (2016).
- [16] Trindade, P. M. P., Saldanha, D. L., Filho, W. P., [Utilização do Infravermelho Termal naA Espaço Temporal da Temperatura de Superfície e Ilhas de Calor Urbanas], Revista Brasileira de Cartografia, 69 (4) (2017).
- [17] Vianna, E. O., “O Campo Térmico Urbano. Ilhas de Calor em Brasília – DF,” <<https://repositorio.unb.br/handle/10482/33012>> (25 July 2020).
- [18] AMORIM, M. C. C.T., “Ilhas de Calor Superficiais: Frequência da Intensidade e Variabilidade Espacial em Cidade de Clima Tropical Continental,” Geo UERJ, [S.l.] (34), p. e40959, abr. 2019. ISSN 1981-9021, <<https://www.e-publicacoes.uerj.br/index.php/geouerj/article/view/40959>> (25 July 2020). <https://doi.org/10.12957/geouerj.2019.40959>.
- [19] USGS - U.S. Geological Survey. “Dates Landsat 5 and Landsat 8”, <<https://www.usgs.gov/>> (30 December 2019).
- [20] INMET – Instituto Nacional de Meteorologia. <<http://www.inmet.gov.br/portal/index.php?r=clima/mesTempo>> (18 December 2019).
- [21] Chavez, JR, P. S., [An improved dark-object subtraction technique for atmospheric scattering correction of multispectral data], Remote Sensing of Environment 24 (3), 459-479. (1988)
- [22] IBGE – Instituto Brasileiro de Geografia e Estatística, “Panorama” <<https://cidades.ibge.gov.br/brasil/df/brasilia/panorama>> (29 January 2020).
- [23] Polidorio, A. M., *et al.* “Correção radiométrica de imagens multiespectrais CBERS e Landsat ETM usando atributos de reflectância e de cor”. Anais XII Simpósio Brasileiro de Sensoriamento Remoto, Goiânia, Brasil, 16-21 abril 2005, INPE, 4241-4248, <<http://marte.dpi.inpe.br/col/ltid.inpe.br/sbsr/2004/11.19.19.46/doc/4241.pdf>> (30 December 2019).
- [24] DF, “História – Brasília: a cidade-sonho. Distrito Federal,” <<http://www.df.gov.br/historia/>> (30 December 2019).

Appendix III

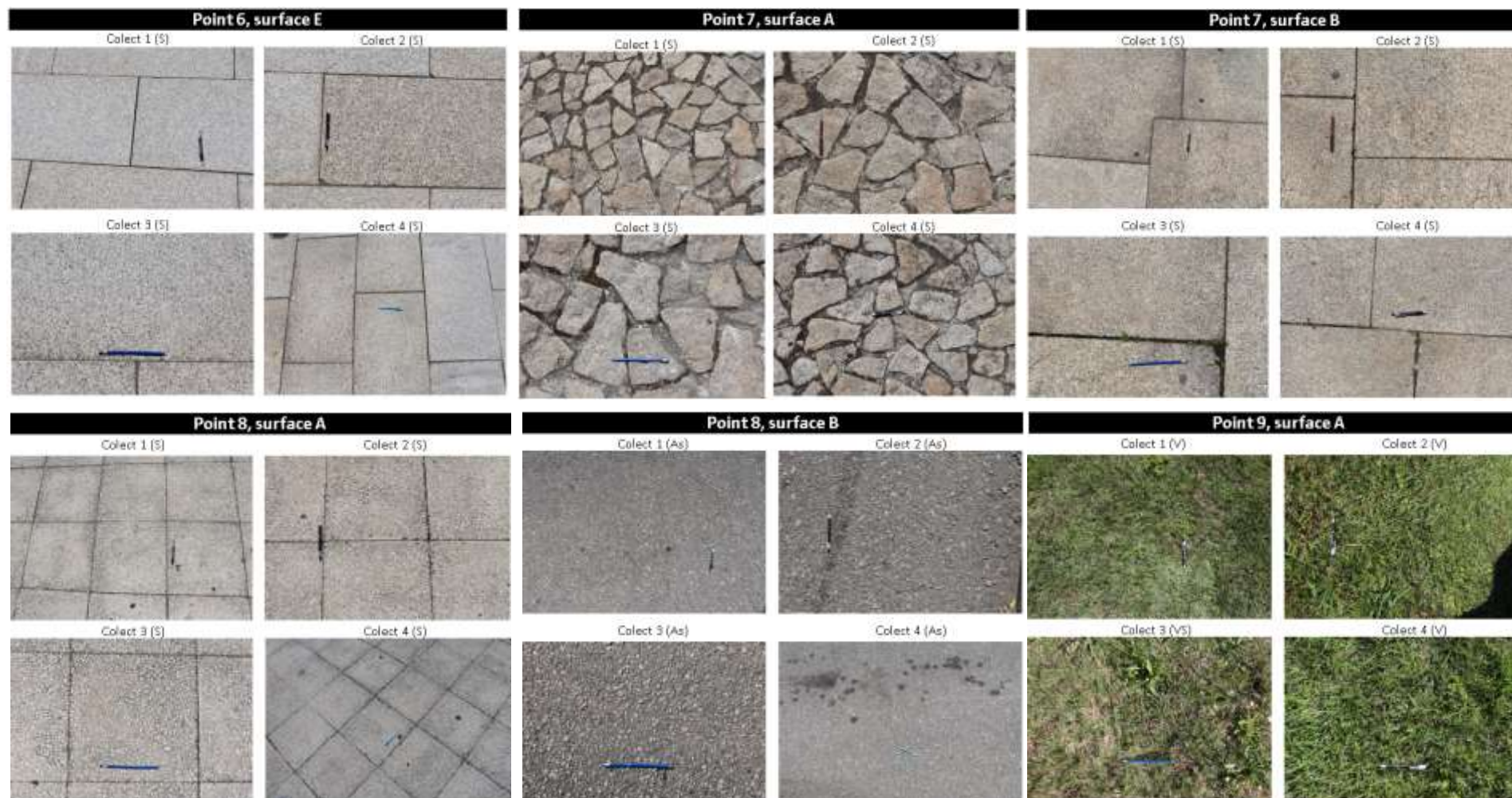
Surfaces sampled in the four field collections and their respective classifications.

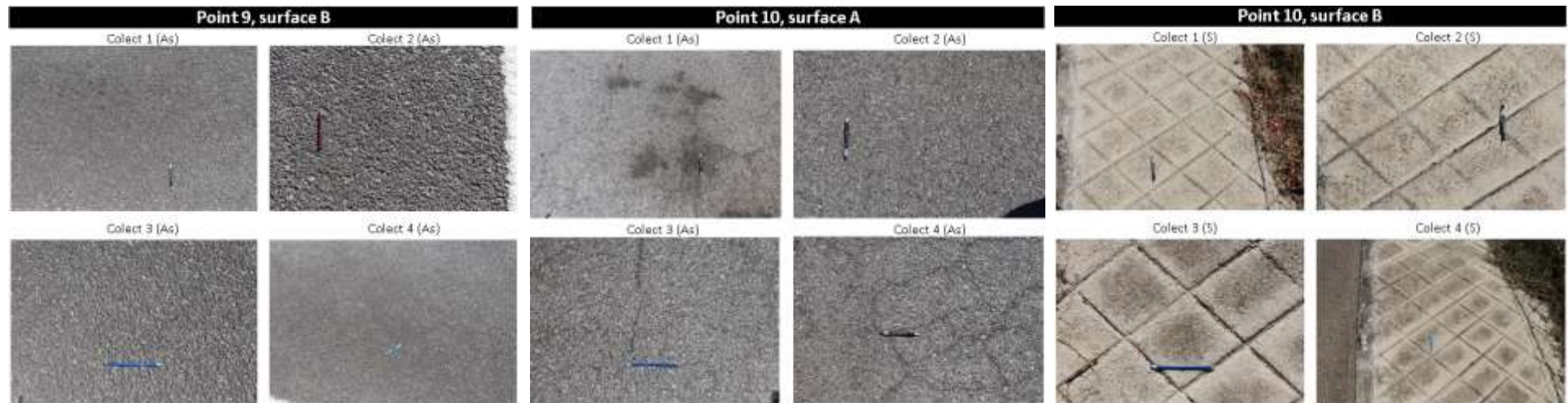
Where: Asphalt (As); Sidewalk (S); Vegetation (V); Vegetation with Soil (Vs); Dry Vegetation (DV); and Dry Vegetation and Rock (DVSt).











Appendix IV

Portable Weather stations and the surroundings involved.



Appendix V

Code used in GEE for processing Landsat 8 data.

```

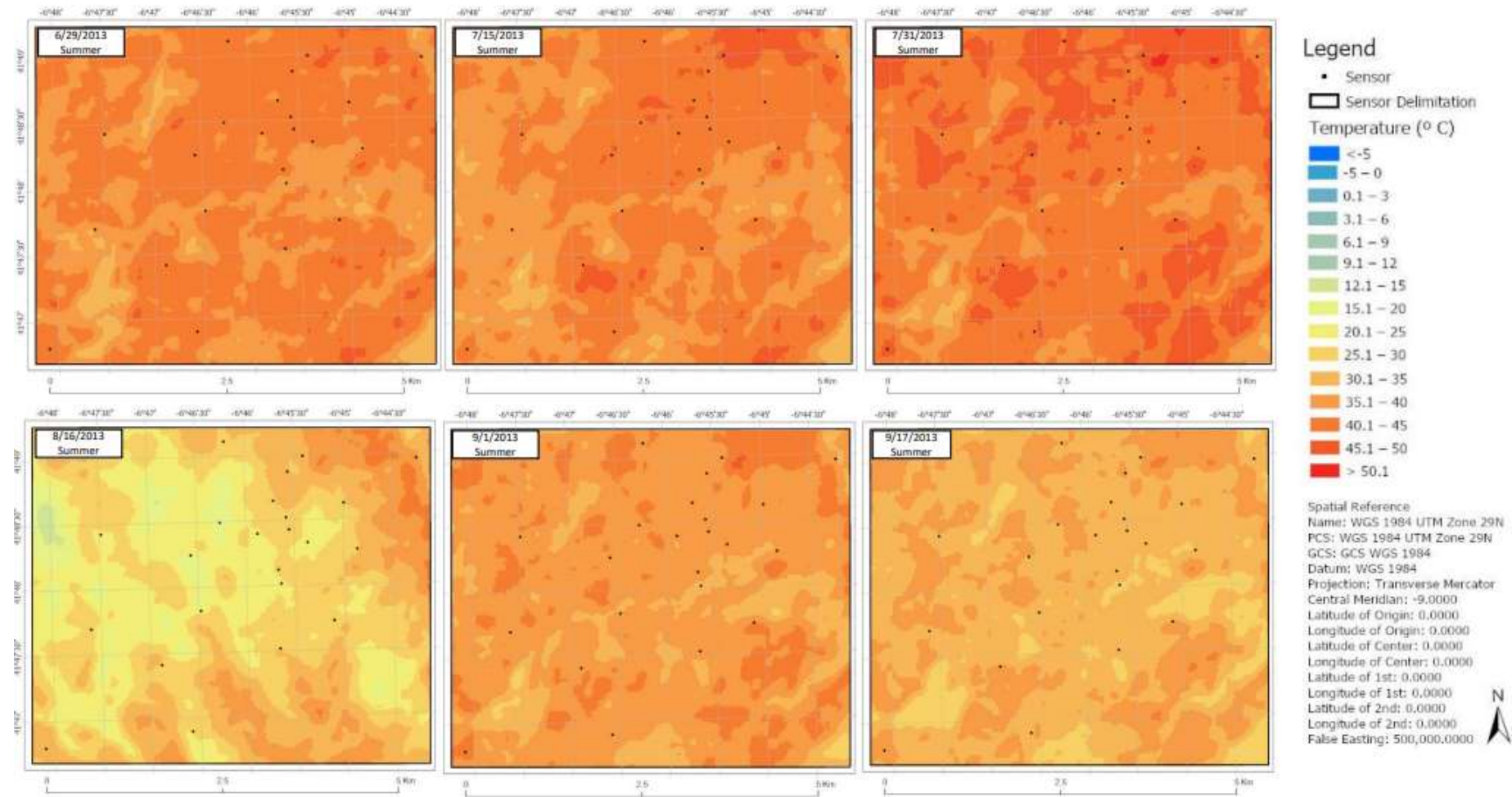
Imports (3 entries)
  var area: Table users/Catia/Concelho_Braganca_dissolve
  var braganca: Polygon, 4 vertices
  var pin: Table users/Catia/sensorsV2

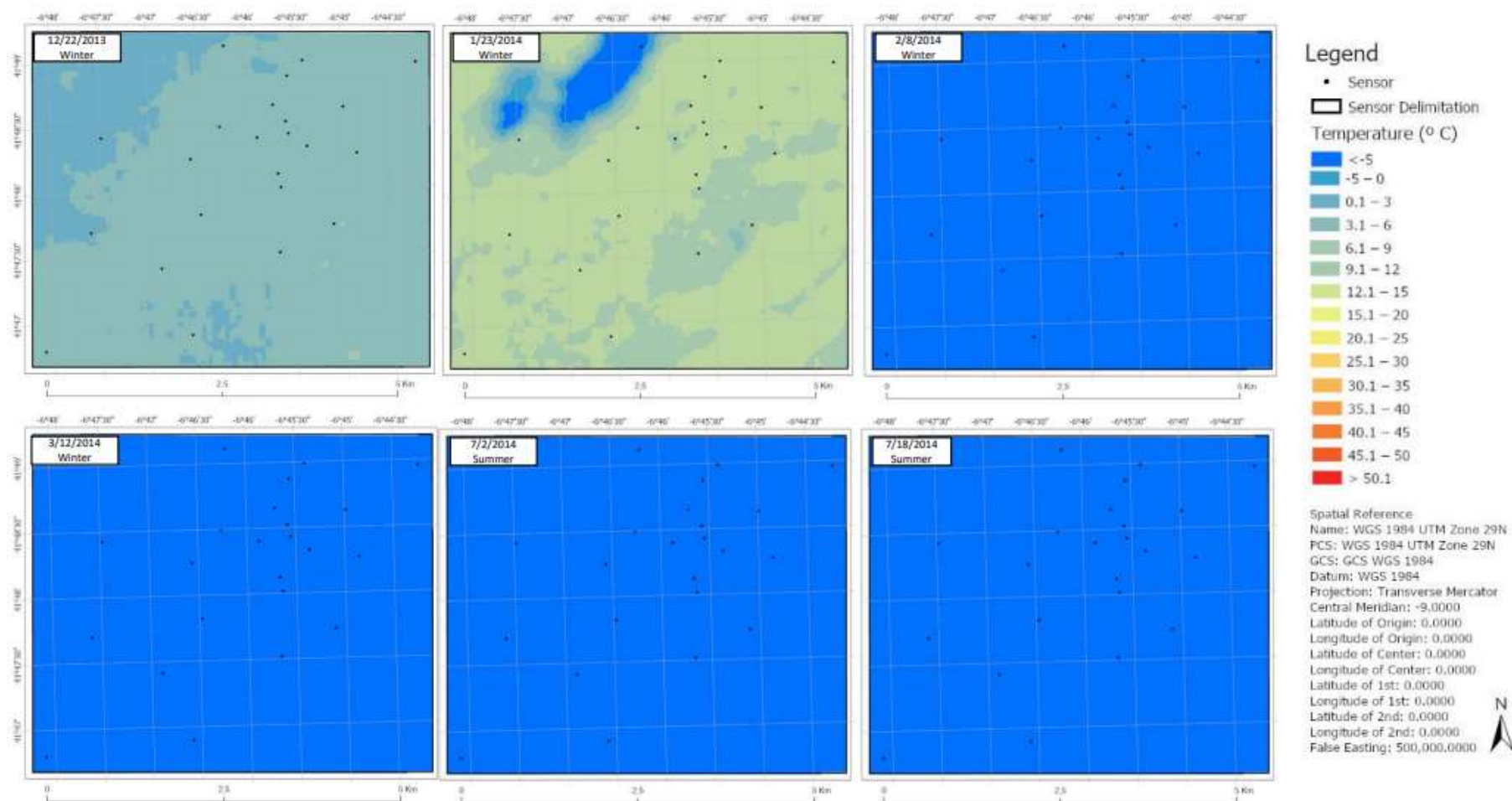
1  //////////////////////////////////////////////////BEGGING OF THE FUNCTION
2  function LST_L8 (col){
3  //SELECT THE FIRST IMAGE OF THE COLLECTION, CLIP THE AREA AND APPLY CLOUD MASK
4  {
5    var image = col.first().clip(area)
6    Map.addLayer(image);
7  }
8  /////////////////////////////////// THERMAL
9  //select thermal band 10 (with brightness temperature), no BT calculation
10 var thermal= image.select('ST_B10').multiply(0.00341802).add(149);
11 //LST in Celsius Degree bring -273.15
12 var LST = thermal.expression(
13 'Tb-273.15', {
14   'Tb': thermal.select('ST_B10'),
15 }).rename('LST');
16 Map.addLayer(LST, {min: 20.569706944223423, max:29.328077233404645, palette: [
17   '040274', '040281', '0502a3', '0502b8', '0502ce', '0502e6',
18   '0602ff', '235cb1', '307ef3', '269db1', '30c8e2', '32d3ef',
19   '3be285', '3ff38f', '86e26f', '3ae237', 'b5e22e', 'd6e21f',
20   'fff705', 'ffd611', 'ffb613', 'ff8b13', 'ff6e08', 'ff500d',
21   'ff0000', 'de0101', 'c21301', 'a71001', '911003'
22   ]}, 'LST');
23 {
24 var LSTmin = ee.Number(LST.reduceRegion({
25   reducer: ee.Reducer.min(),
26   geometry: area,
27   scale: 30,
28   maxPixels: 1e9
29 }).values().get(0));
30 print(LSTmin, 'LSTmin');
31 var LSTmax = ee.Number(LST.reduceRegion({
32   reducer: ee.Reducer.max(),
33   geometrv: area,
34   scale: 30,
35   maxPixels: 1e9
36 }).values().get(0));
37 print(LSTmax, 'LSTmax')
38 }
39 ////// .TIF
40 Export.image.toDrive({
41   image:LST,
42   description: "LSTdados15092018",
43   scale: 30,
44   region: area
45 })
46 }
47 /////////////////////////////////// SELECT COLLECTION - IMAGE
48 {
49 var col = ee.ImageCollection('LANDSAT/LC08/C02/T1_L2')
50 .filterDate('2018-9-14','2018-9-16')
51 .filterBounds(area);
52 }
53 print(col, 'coleccion'); //PRINT IMAGES
54 Map.addLayer(col, null, "col");
55 LST_L8(col)

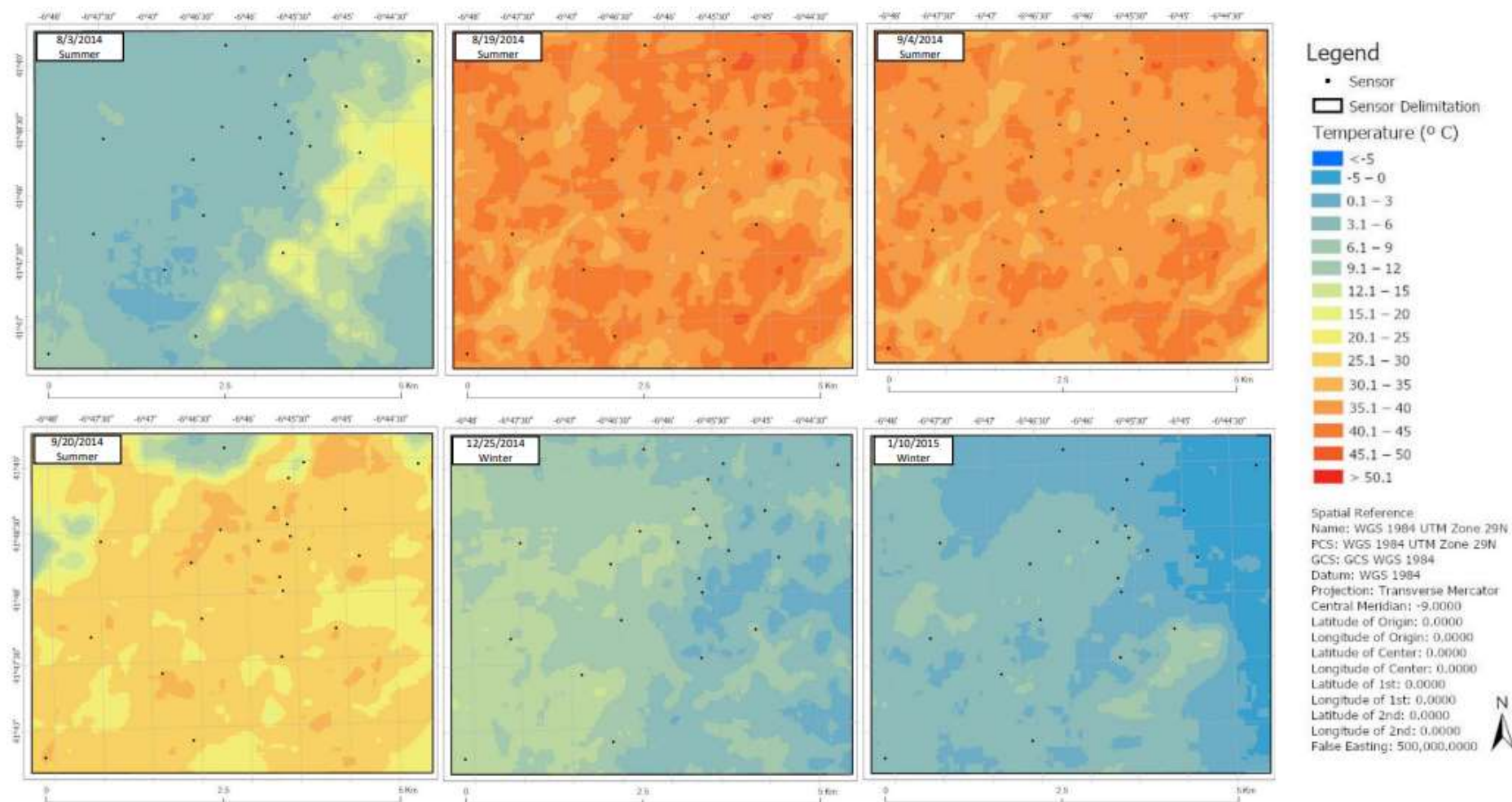
```

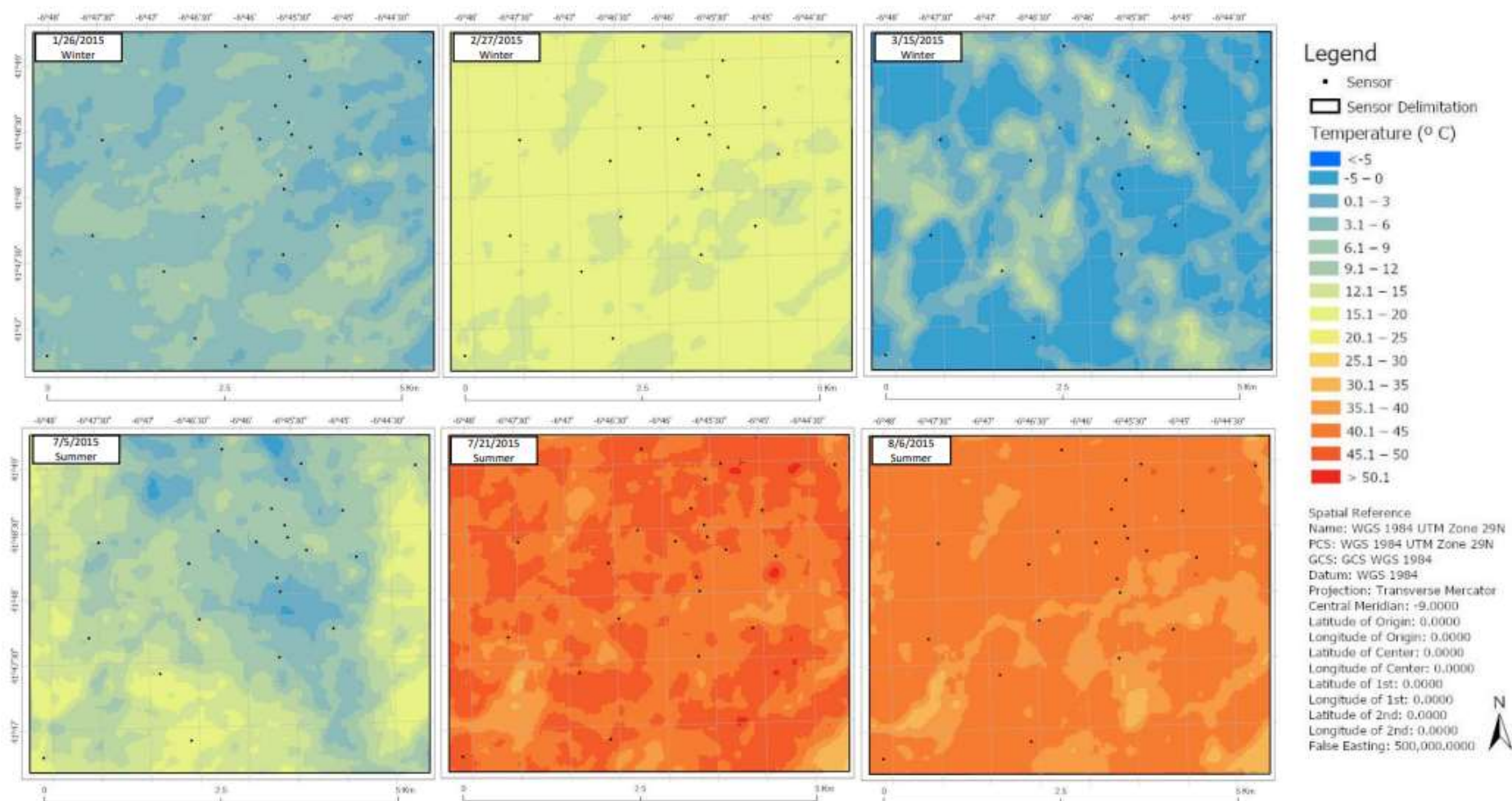
Appendix VI

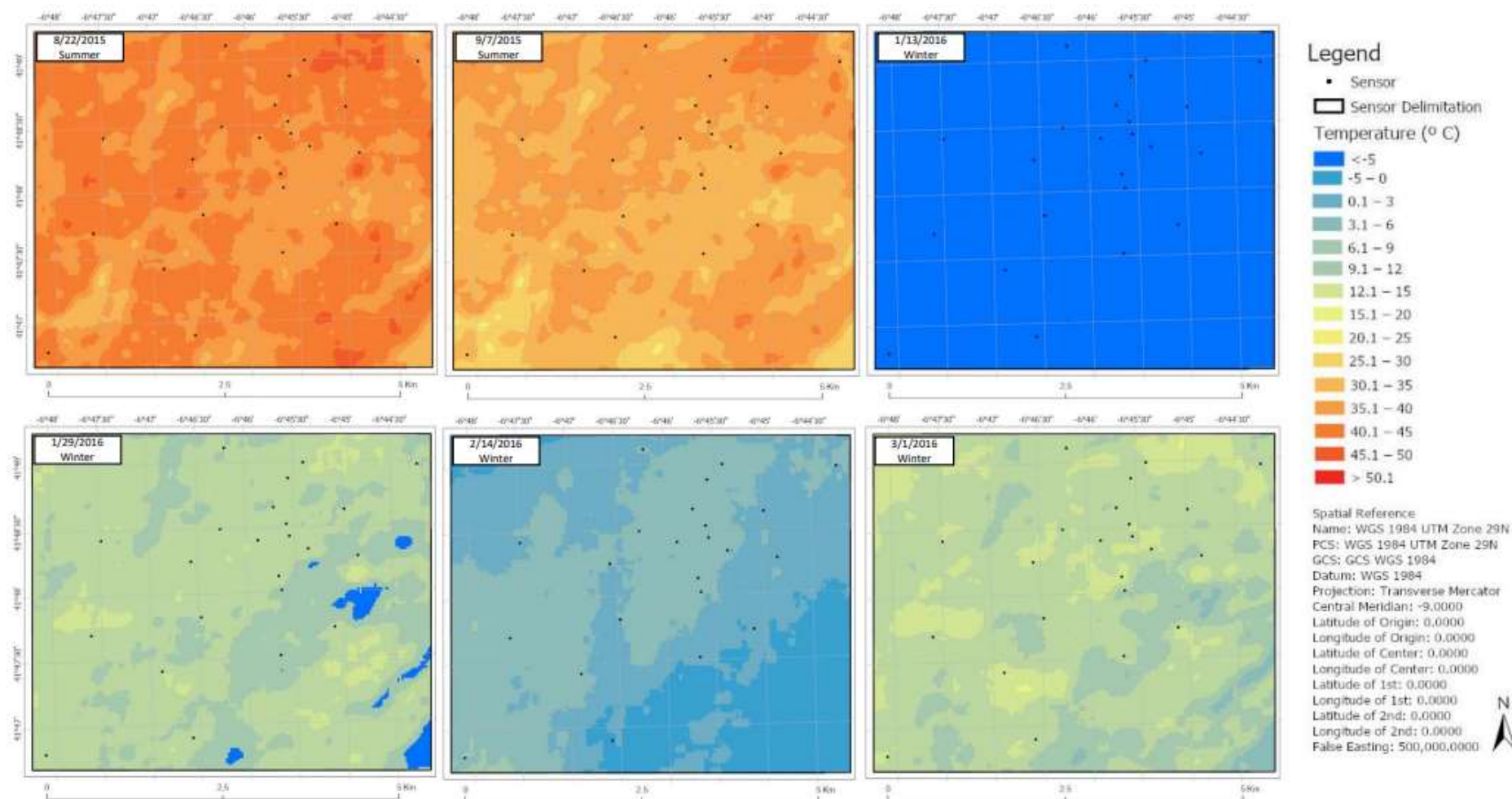
LST maps generated in GEE.

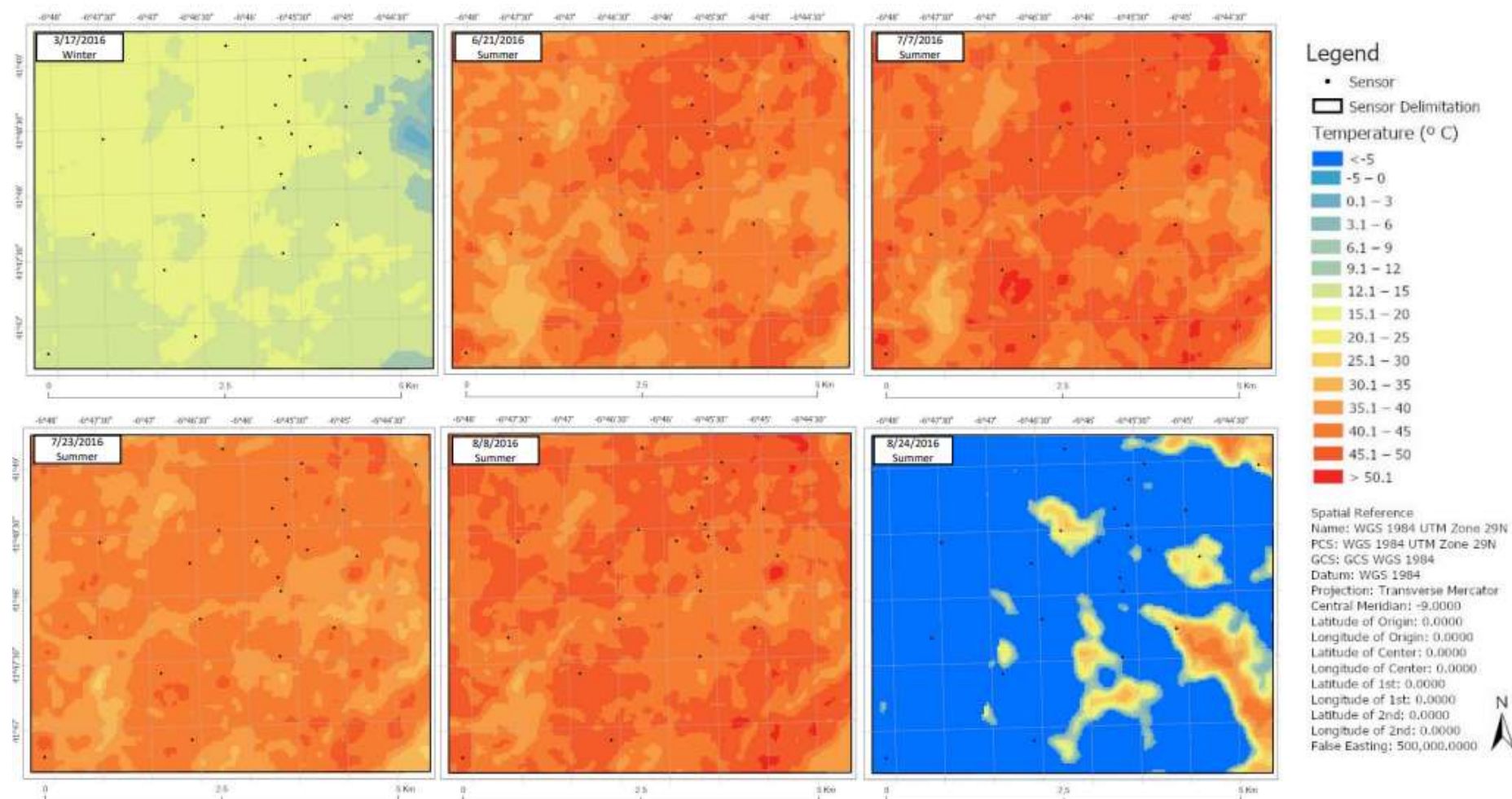


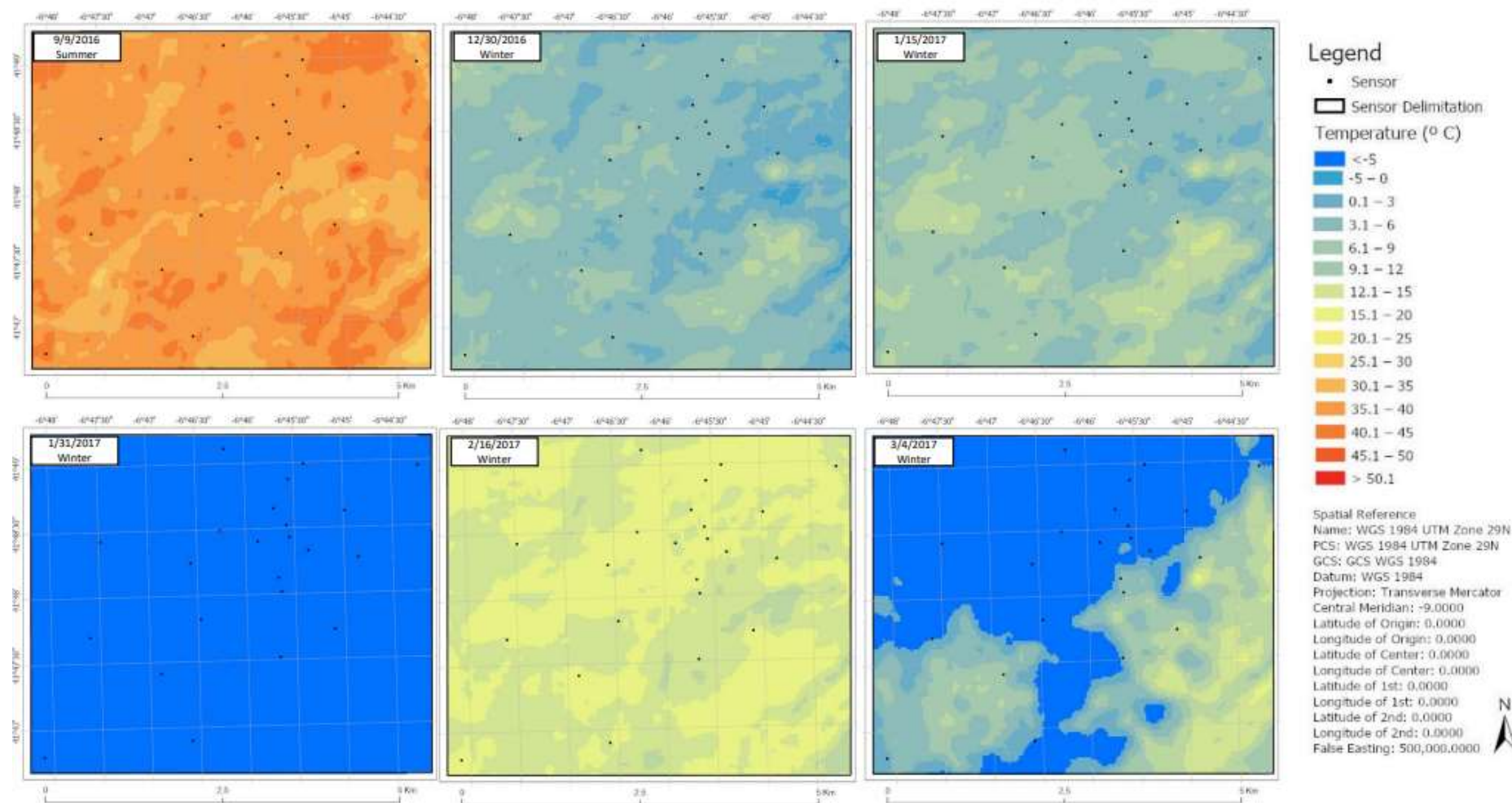


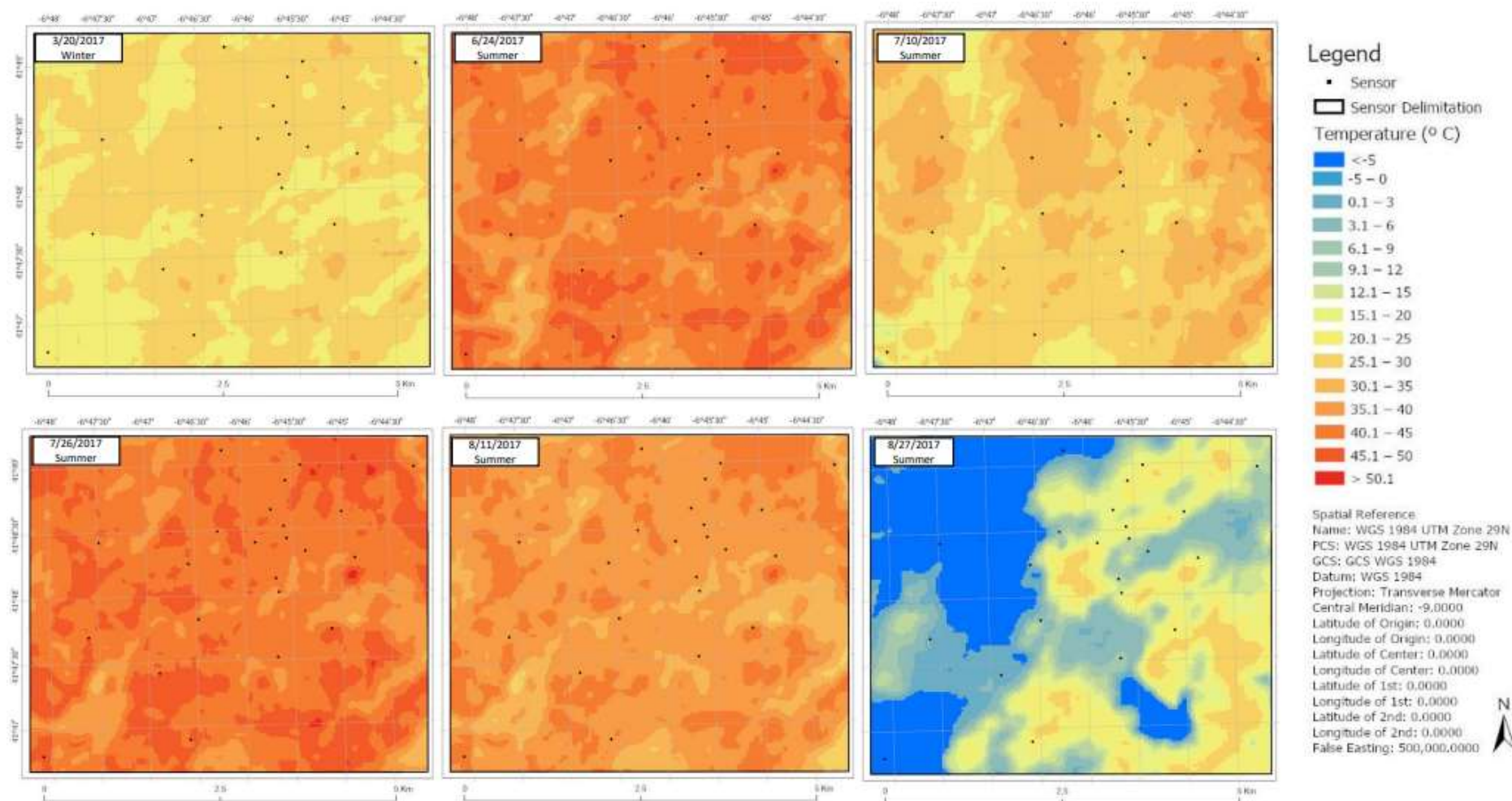


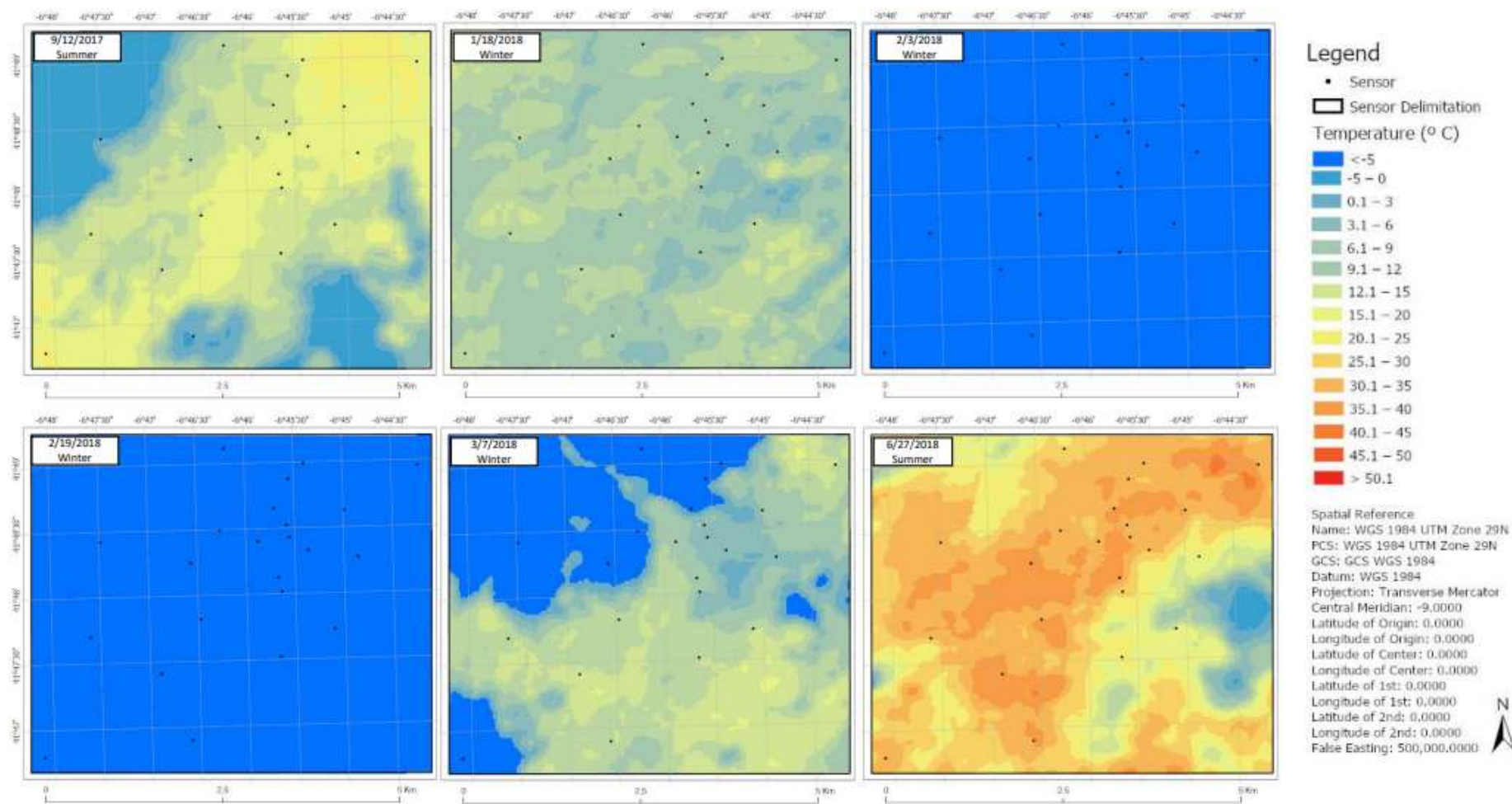


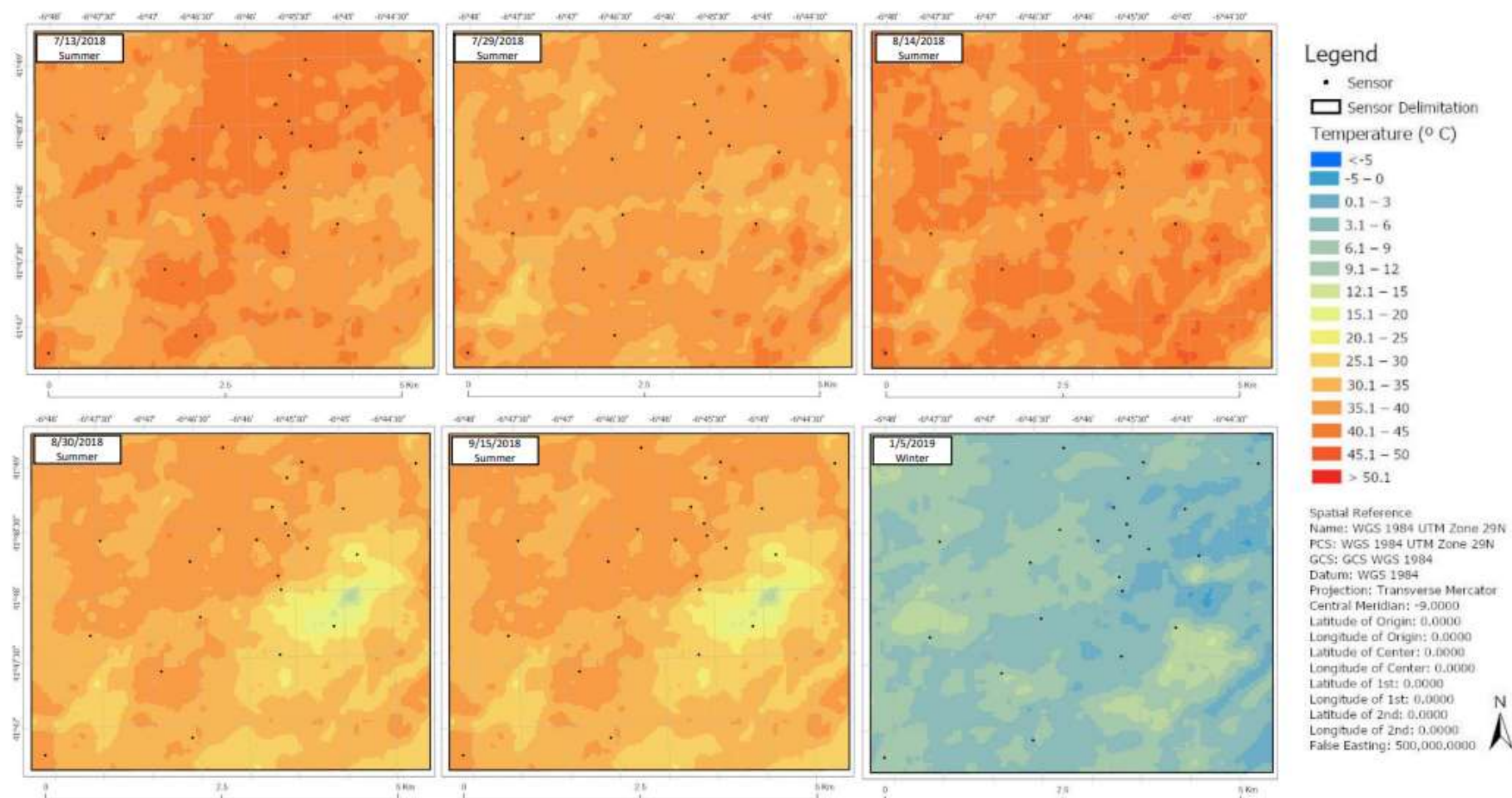


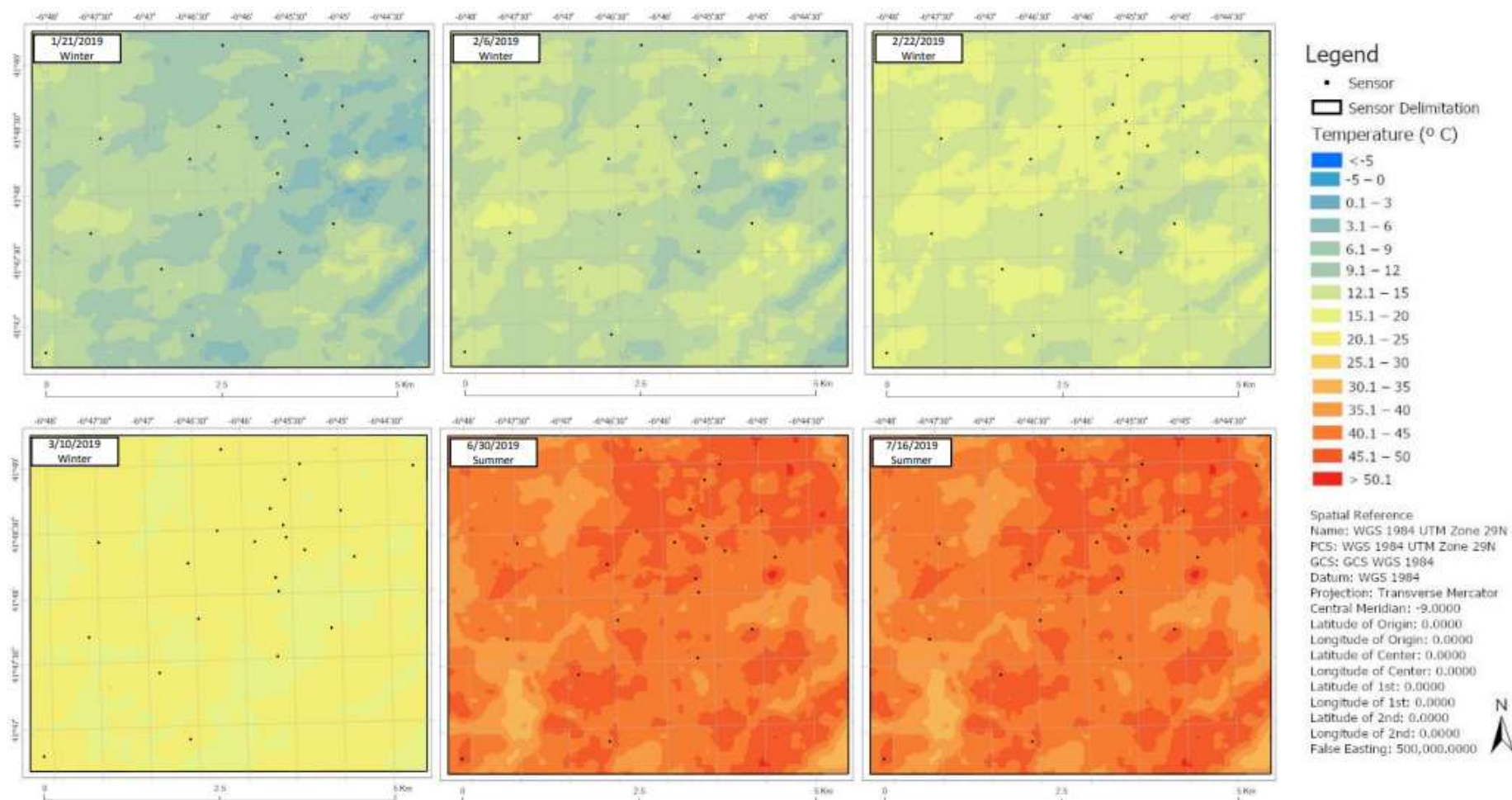


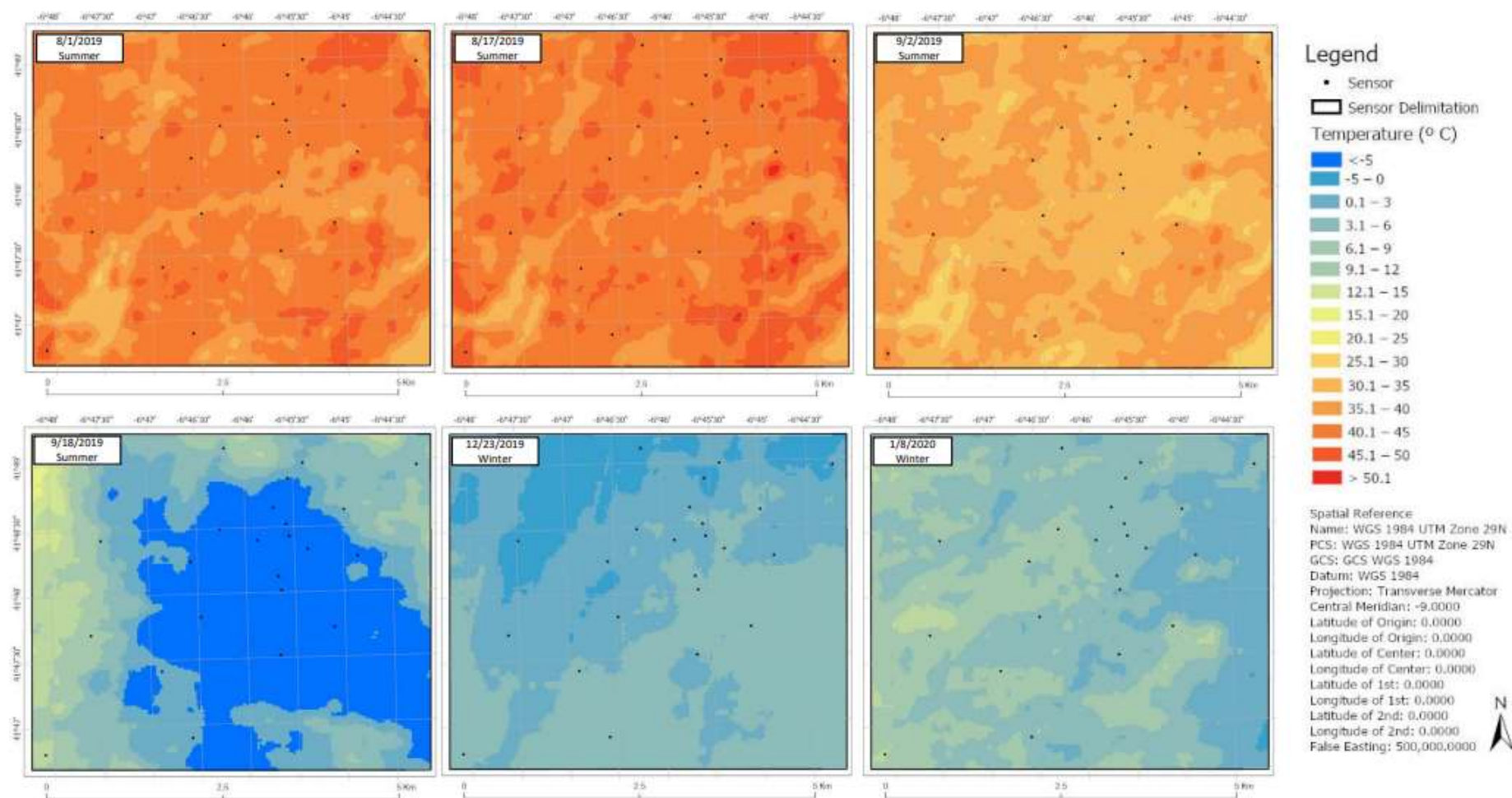


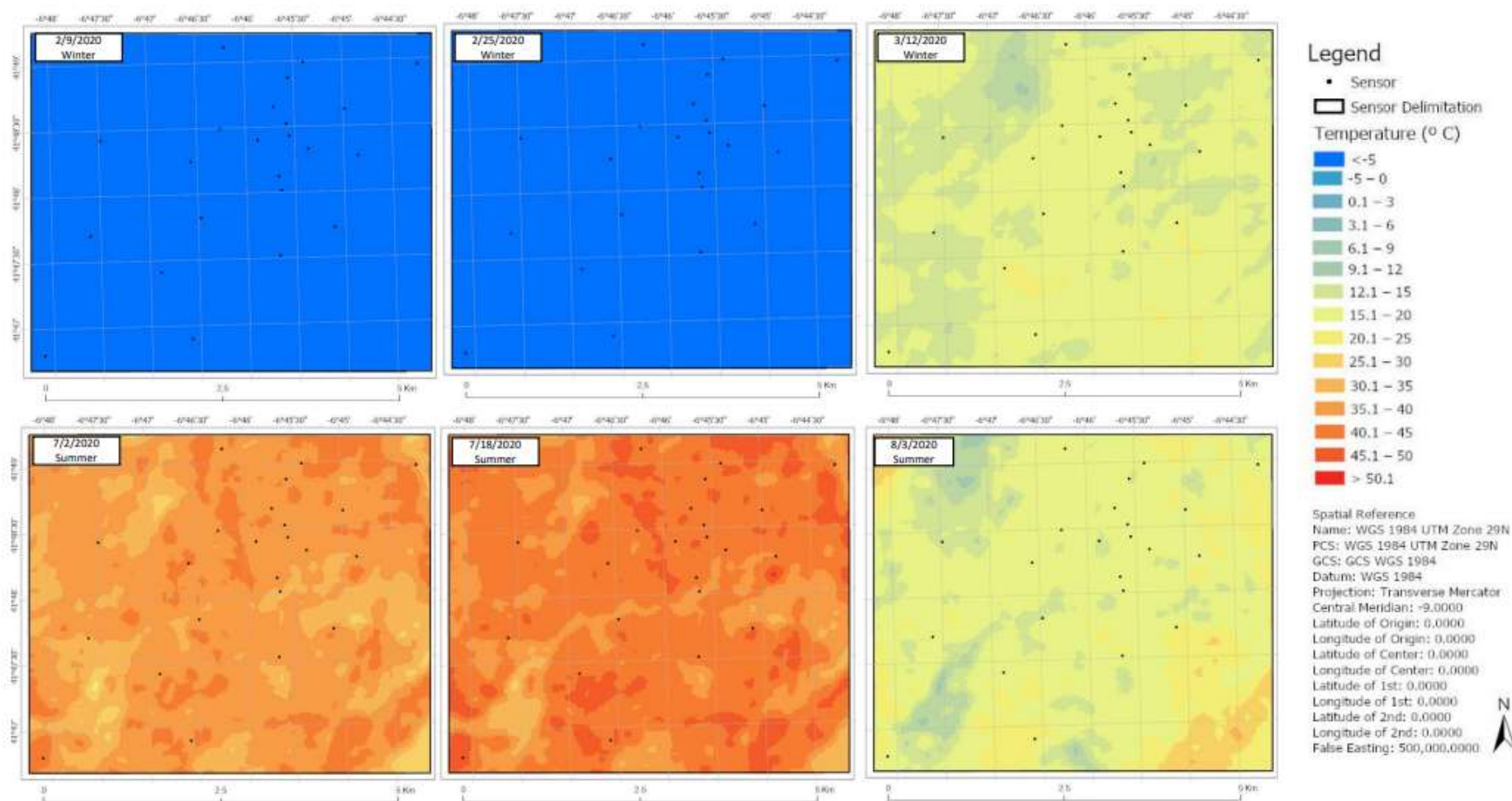




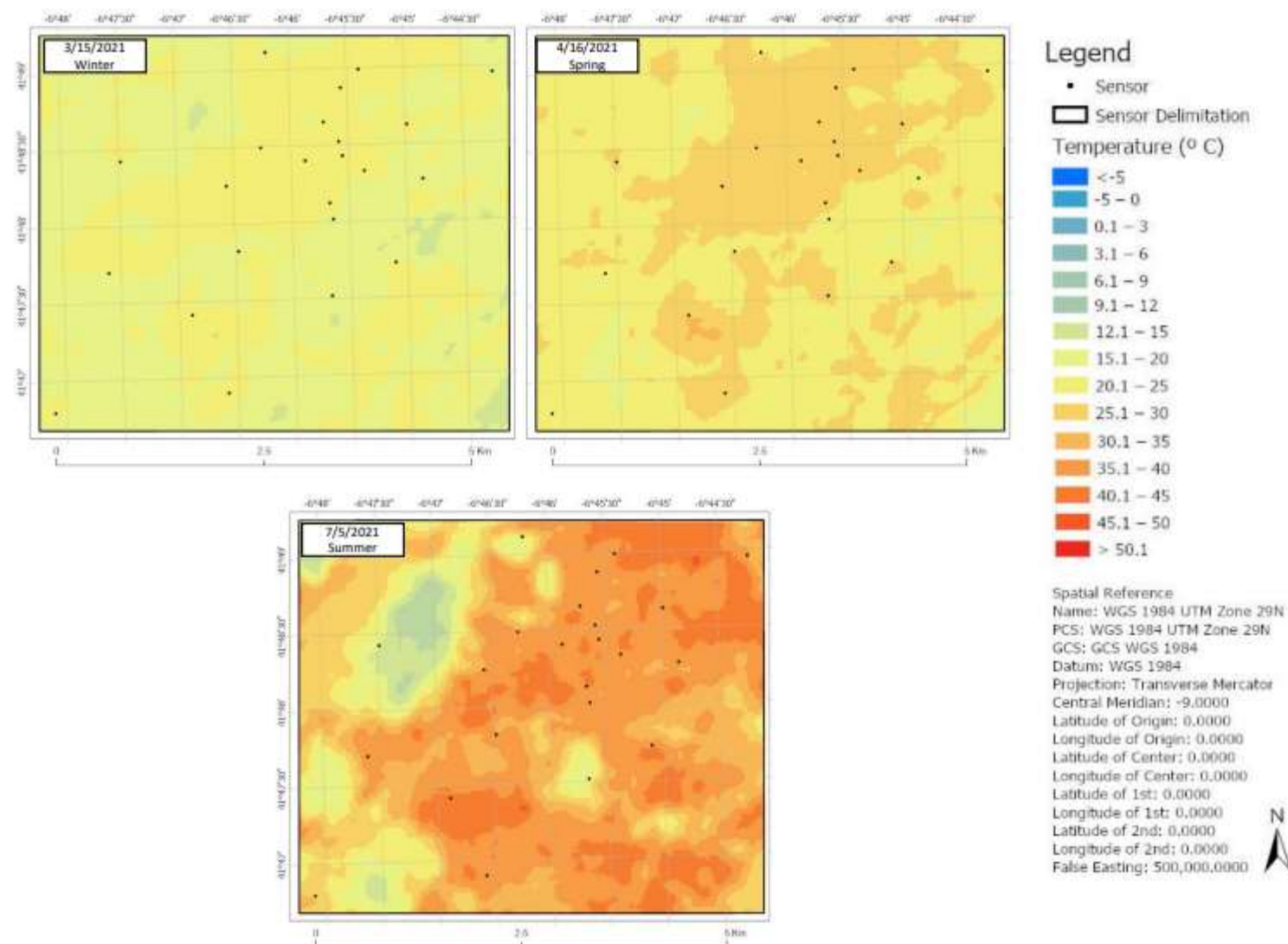












Appendix VII

List of 87 dates related to the passage of Landsat 8, with their respective observations (whether they were considered in the analysis or not).

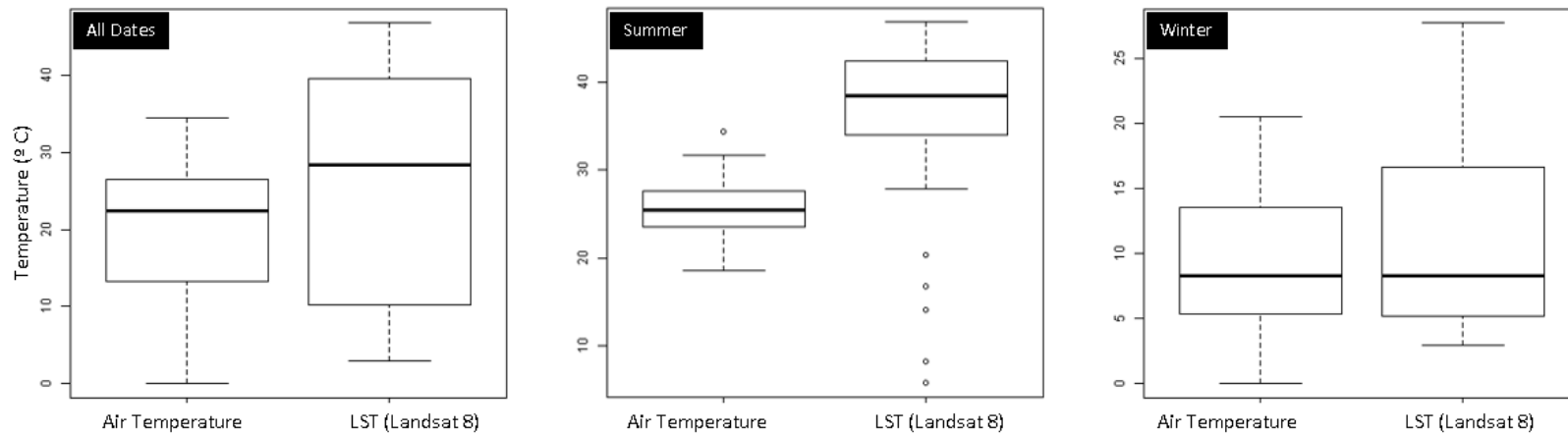
Date	Season	Observation
6/29/2013	Summer	Date considered.
7/15/2013	Summer	Date considered.
7/31/2013	Summer	Date considered.
8/16/2013	Summer	Date considered.
9/1/2013	Summer	Date considered.
9/17/2013	Summer	Date considered.
12/22/2013	Winter	Date considered.
1/23/2014	Winter	Date not considered.
2/8/2014	Winter	Date not considered.
3/12/2014	Winter	Date not considered.
7/2/2014	Summer	Date not considered.
7/18/2014	Summer	Date not considered.
8/3/2014	Summer	Date considered.
8/19/2014	Summer	Date considered.
9/4/2014	Summer	Date considered.
9/20/2014	Summer	Date considered.
12/25/2014	Winter	Date considered.
1/10/2015	Winter	Date considered.
1/26/2015	Winter	Date considered.
2/27/2015	Winter	Date considered.
3/15/2015	Winter	Date considered.
7/5/2015	Summer	Date considered.
7/21/2015	Summer	Date considered.
8/6/2015	Summer	Date considered.
8/22/2015	Summer	Date considered.
9/7/2015	Summer	Date considered.
1/13/2016	Winter	Date not considered.
1/29/2016	Winter	Date not considered.
2/14/2016	Winter	Date considered.
3/1/2016	Winter	Date considered.
3/17/2016	Winter	Date considered.
6/21/2016	Summer	Date considered.
7/7/2016	Summer	Date considered.
7/23/2016	Summer	Date considered.
8/8/2016	Summer	Date considered.
8/24/2016	Summer	Date not considered.
9/9/2016	Summer	Date considered.
12/30/2016	Winter	Date considered.
1/15/2017	Winter	Date considered.
1/31/2017	Winter	Date not considered.
2/16/2017	Winter	Date considered.
3/4/2017	Winter	Date not considered.
3/20/2017	Winter	Date considered.
6/24/2017	Summer	Date considered.

Date	Season	Observation
7/10/2017	Summer	Date considered.
7/26/2017	Summer	Date considered.
8/11/2017	Summer	Date considered.
8/27/2017	Summer	Date not considered.
9/12/2017	Summer	Date considered.
1/18/2018	Winter	Date considered.
2/3/2018	Winter	Date not considered.
2/19/2018	Winter	Date not considered.
3/7/2018	Winter	Date not considered.
6/27/2018	Summer	Date considered.
7/13/2018	Summer	Date considered.
7/29/2018	Summer	Date considered.
8/14/2018	Summer	Date considered.
8/30/2018	Summer	Date considered.
9/15/2018	Summer	Date considered.
1/5/2019	Winter	Date considered.
1/21/2019	Winter	Date considered.
2/6/2019	Winter	Date considered.
2/22/2019	Winter	Date considered.
3/10/2019	Winter	Date considered.
6/30/2019	Summer	Date considered.
7/16/2019	Summer	Date considered.
8/1/2019	Summer	Date considered.
8/17/2019	Summer	Date considered.
9/2/2019	Summer	Date considered.
9/18/2019	Summer	Date not considered.
12/23/2019	Winter	Date considered.
1/8/2020	Winter	Date considered.
2/9/2020	Winter	Date not considered.
2/25/2020	Winter	Date not considered.
3/12/2020	Winter	Date considered.
7/2/2020	Summer	Date considered.
7/18/2020	Summer	Date considered.
8/3/2020	Summer	The date considered/Data collection day.
8/19/2020	Summer	Date considered.
9/4/2020	Summer	The date considered/Data collection day.
9/20/2020	Summer	Date considered.
12/25/2020	Winter	Date considered.
1/10/2021	Winter	Date considered.
2/27/2021	Winter	Date considered.
3/15/2021	Winter	Date considered.
4/16/2021	Spring	The date is considered only in the qualitative data analysis/Data collection day.
7/5/2021	Summer	The date considered/Data collection day.

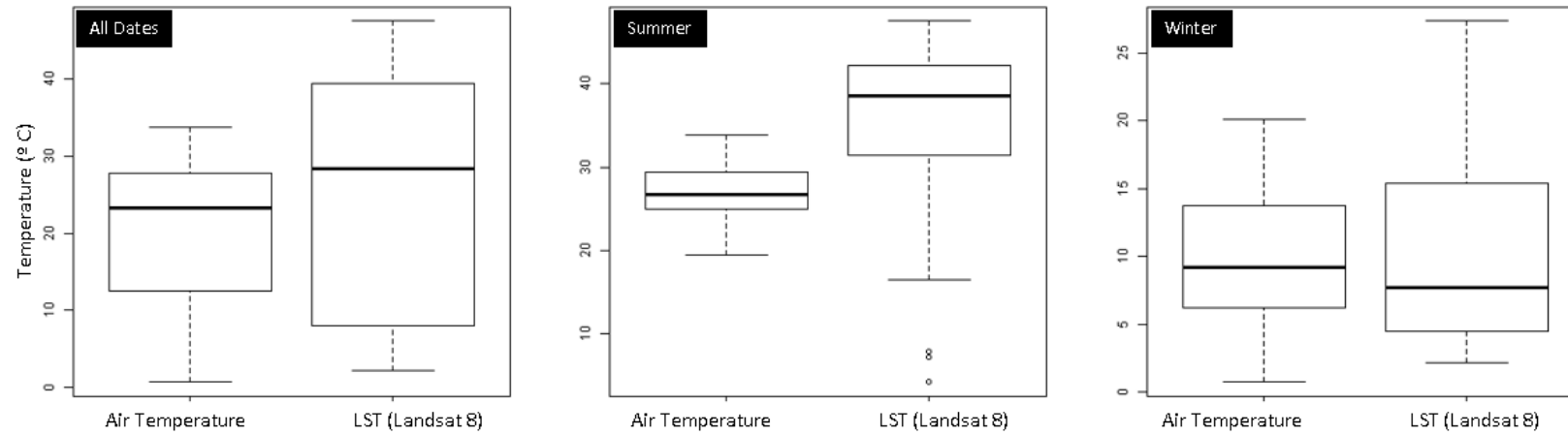
Appendix VIII

Boxplot generated with air temperature (measured by the fixed meteorological network) and LST (Landsat 8), for each sensor, ordered by UCZ, using data from all dates, those from summer and winter, respectively.

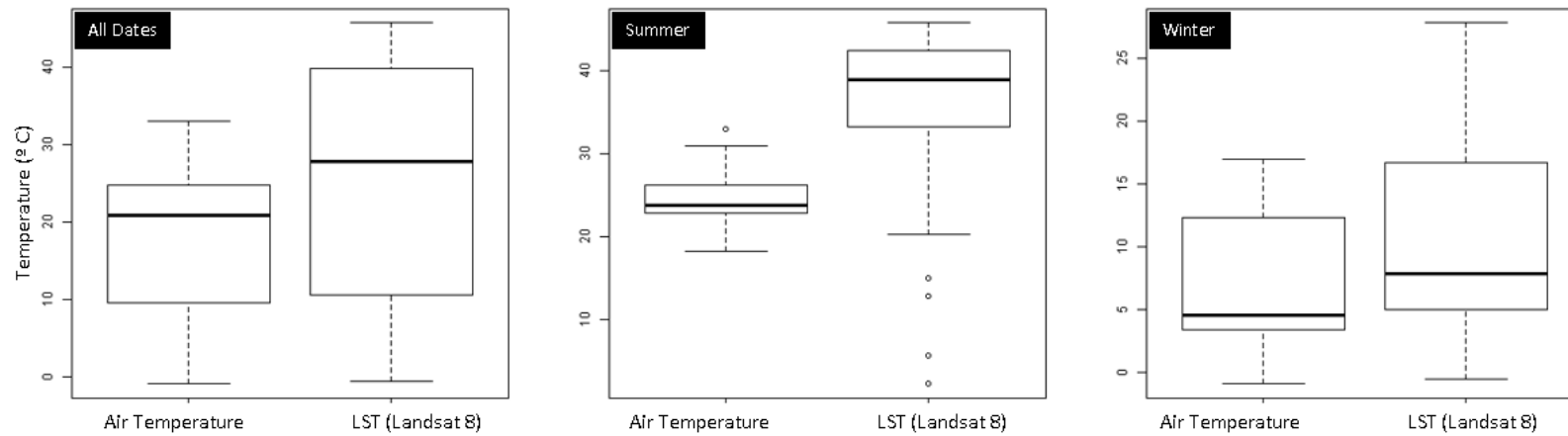
Sensor 4 (BDT)



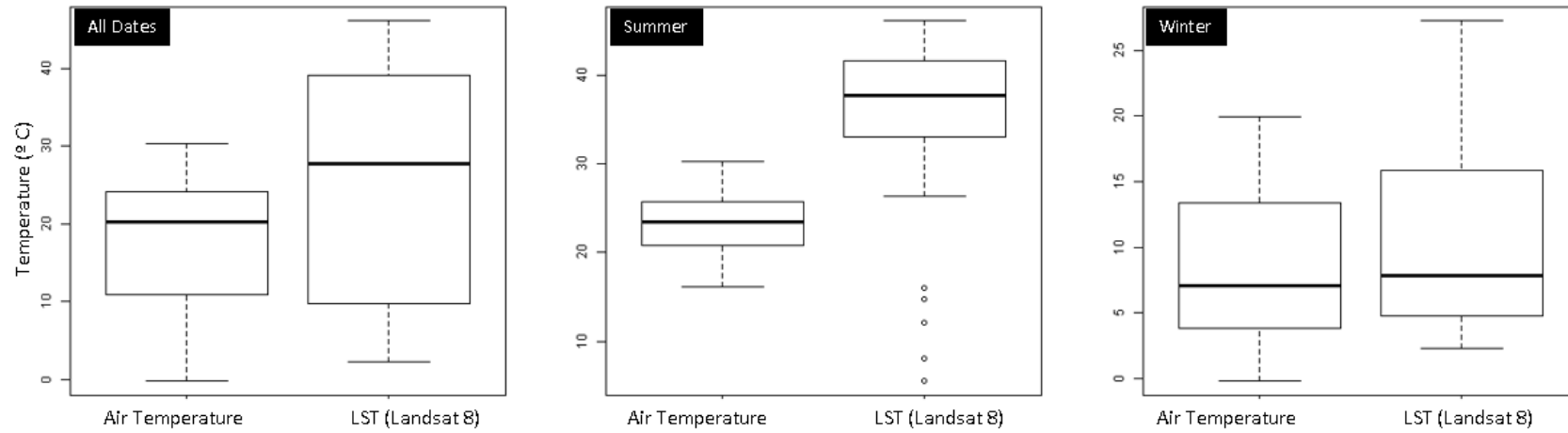
Sensor 6 (BDT)



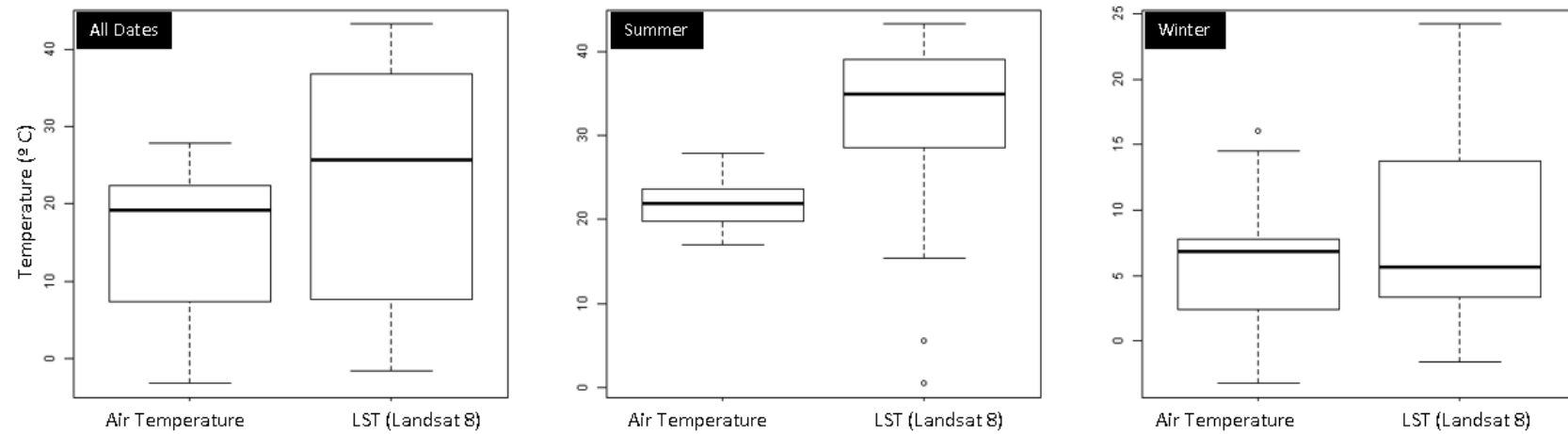
Sensor 2 (EVU)



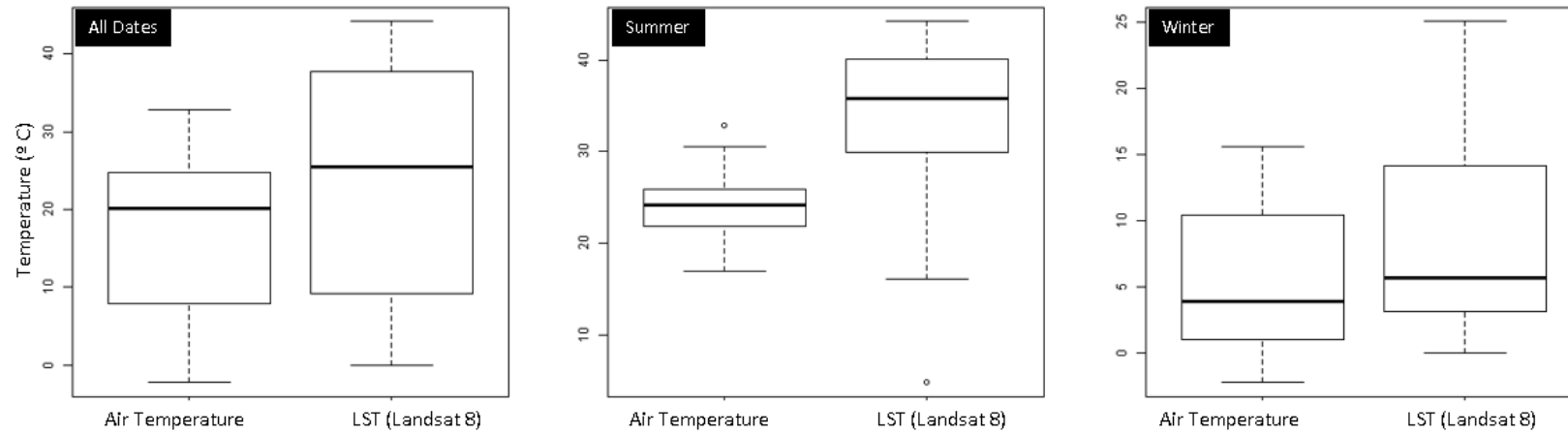
Sensor 8 (EVU)



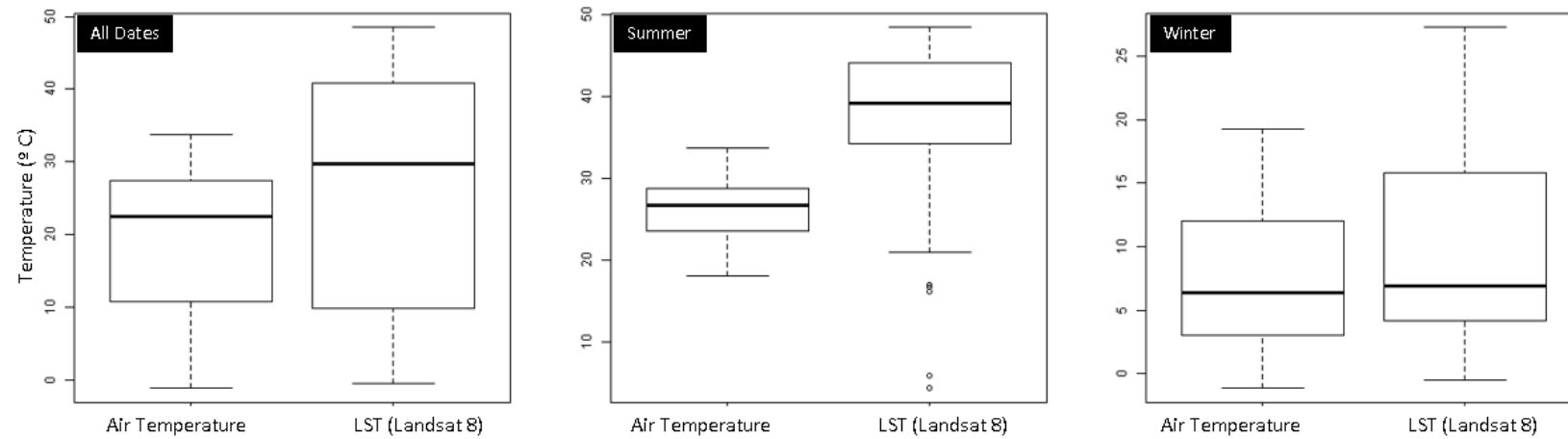
Sensor 9 (EVU)



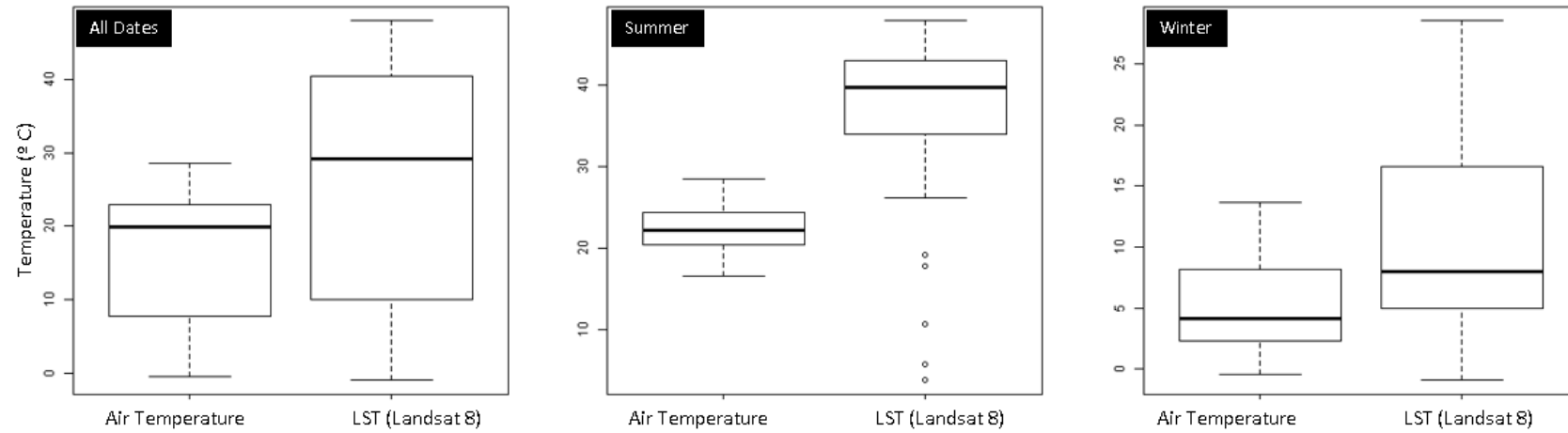
Sensor 11 (EVU)



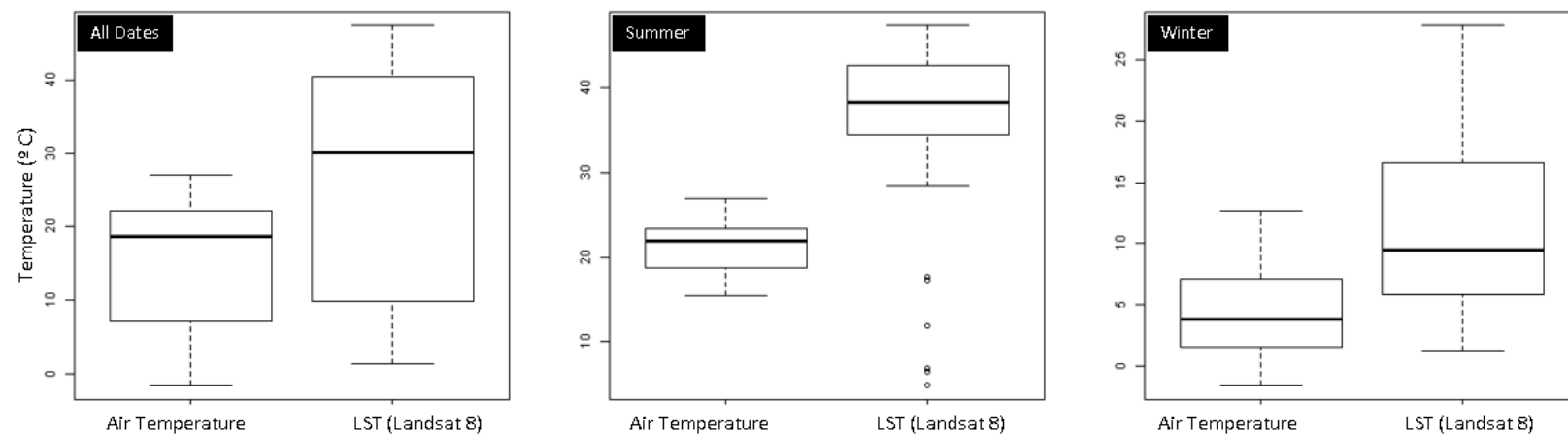
Sensor 3 (PMA)



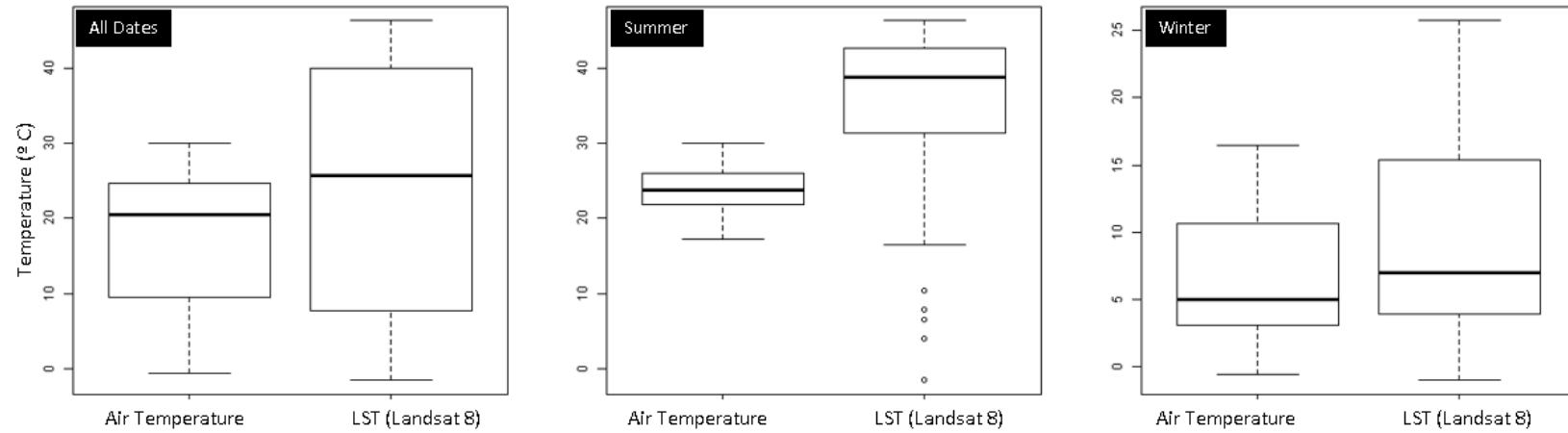
Sensor 7 (PMA)



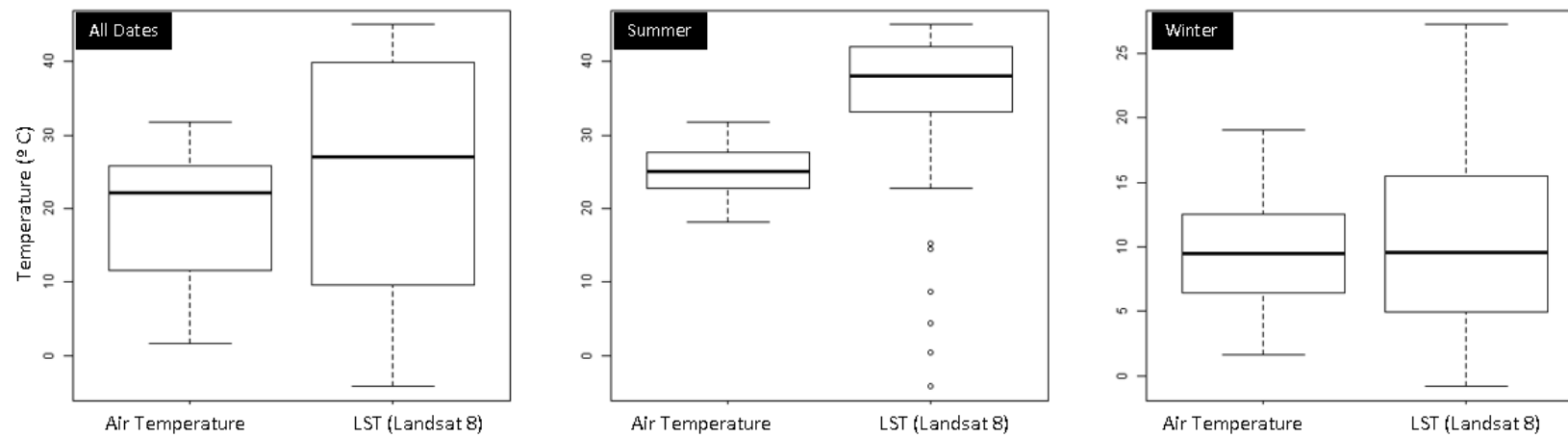
Sensor 13 (PMA)



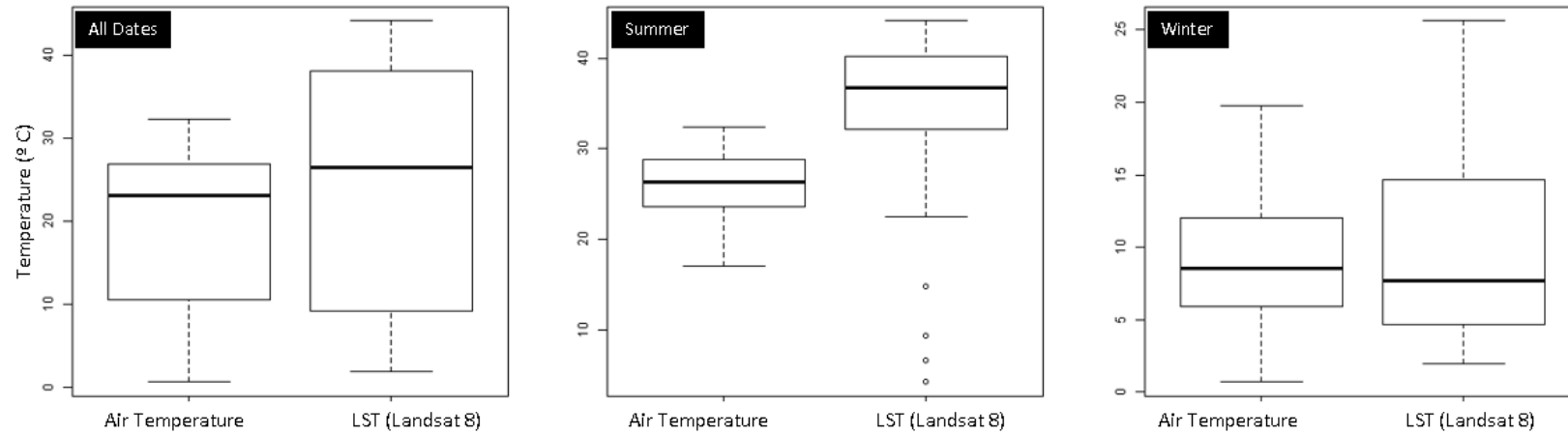
Sensor 1 (TUR)



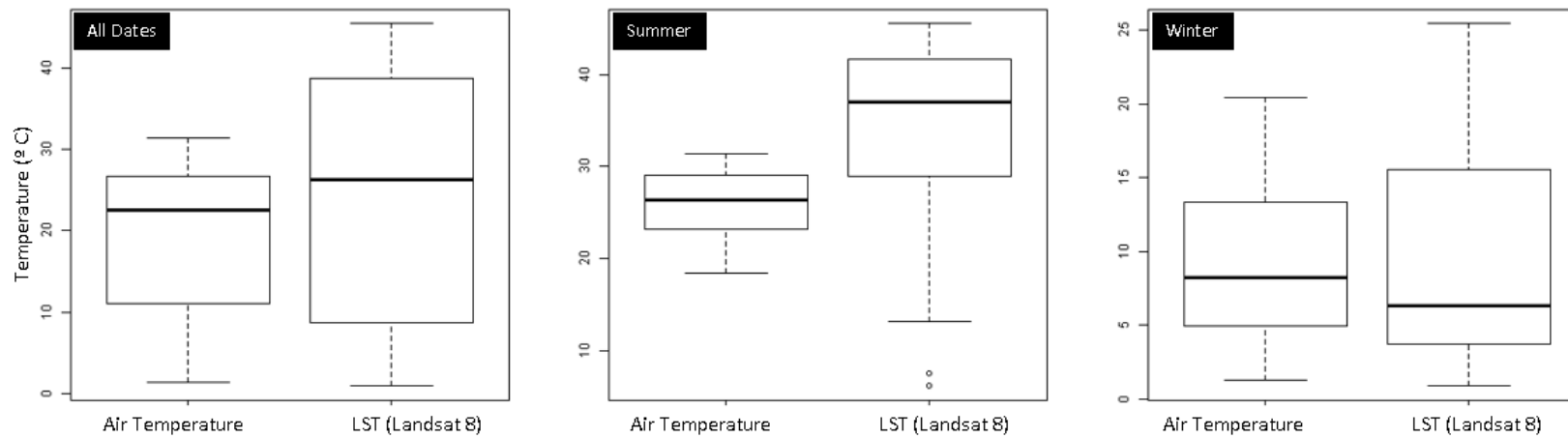
Sensor 14 (TUR)



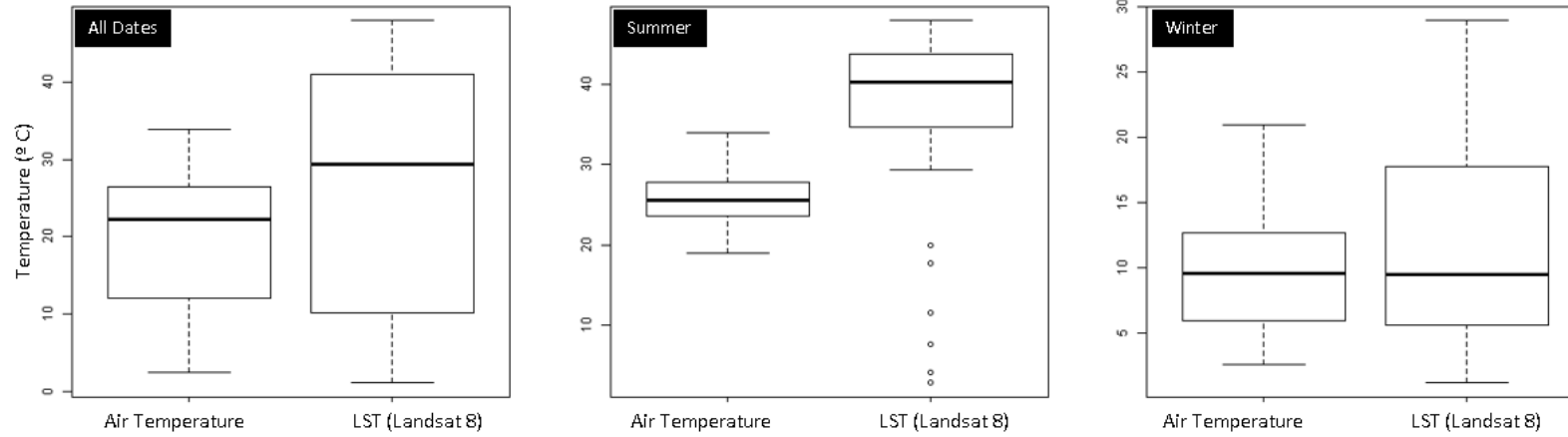
Sensor 15 (TUR)



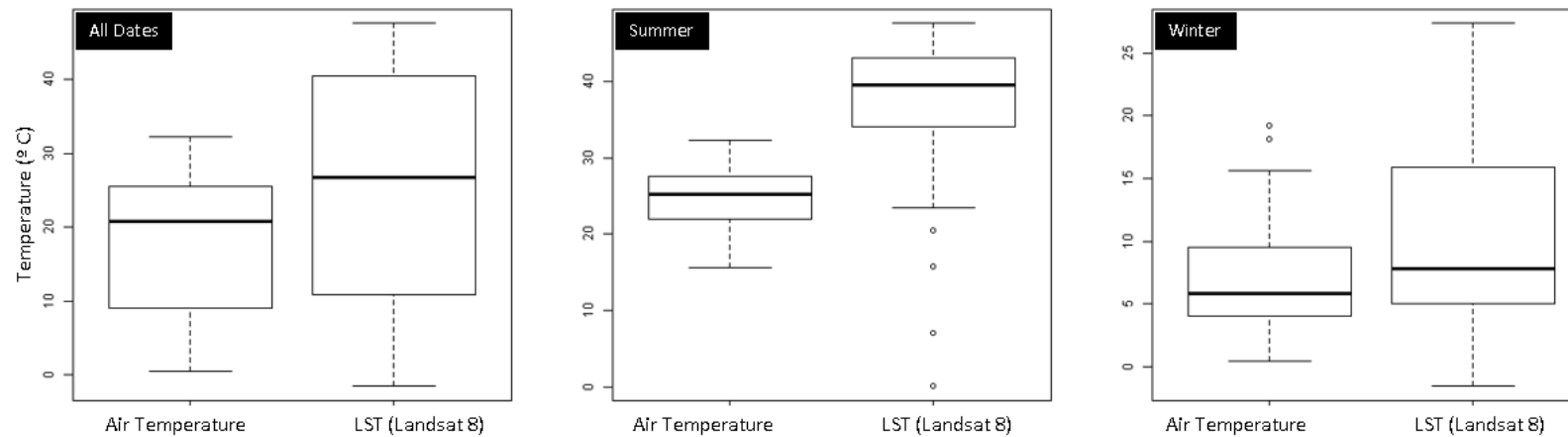
Sensor 10 (UMR)



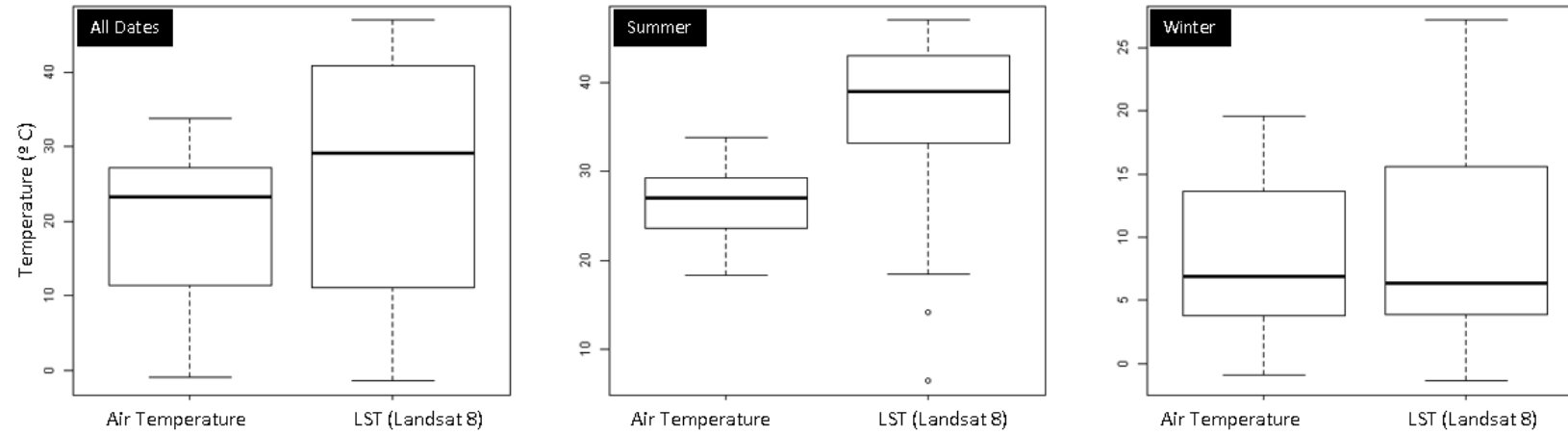
Sensor 12 (UMR)



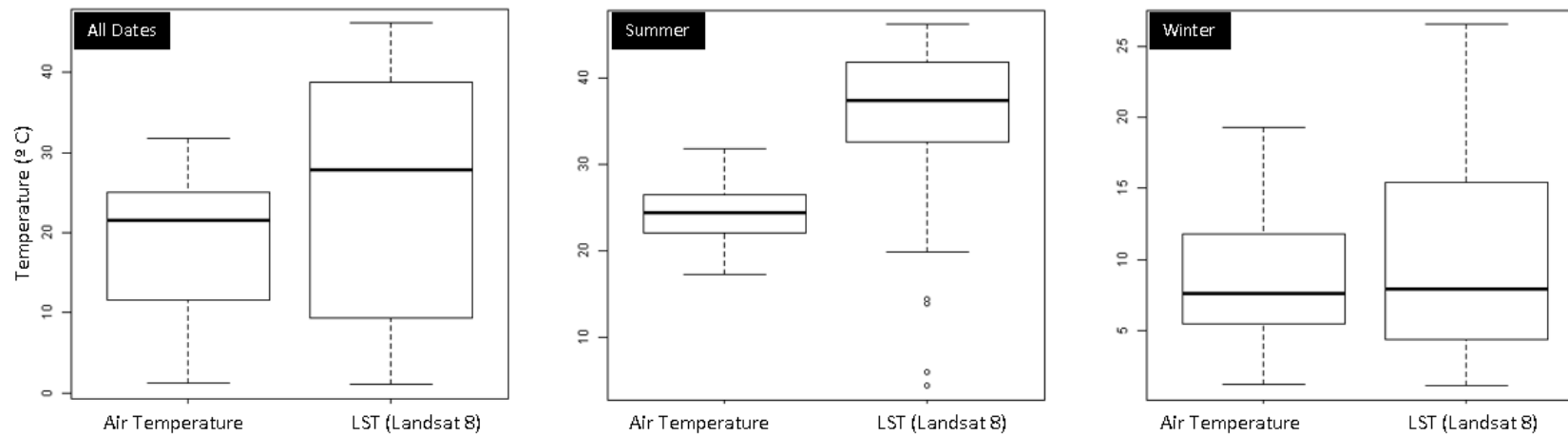
Sensor 18 (UMR)



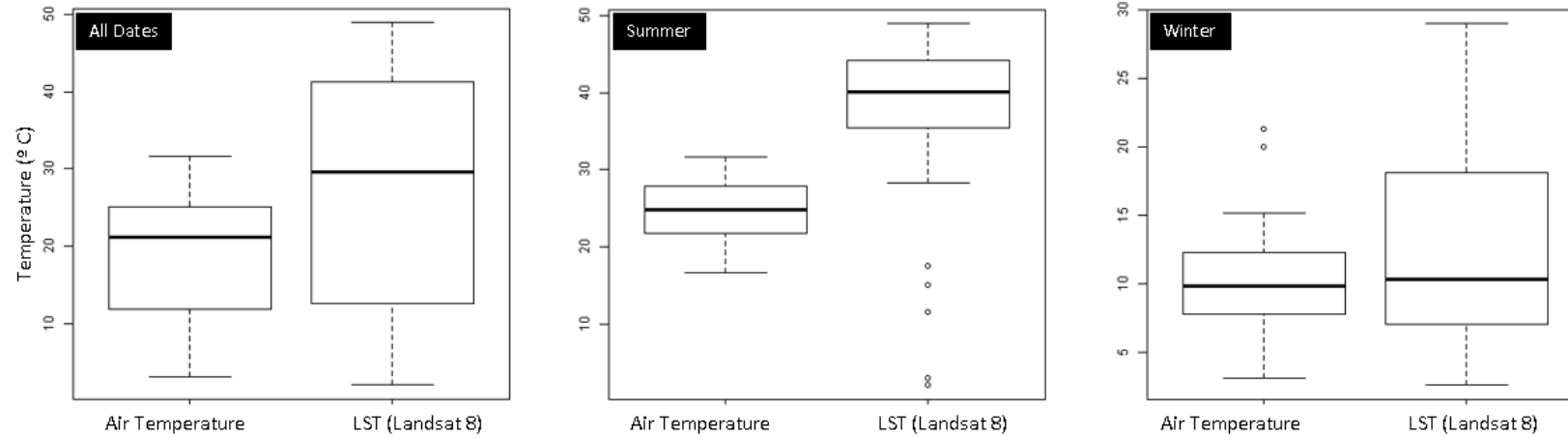
Sensor 22 (UMR)



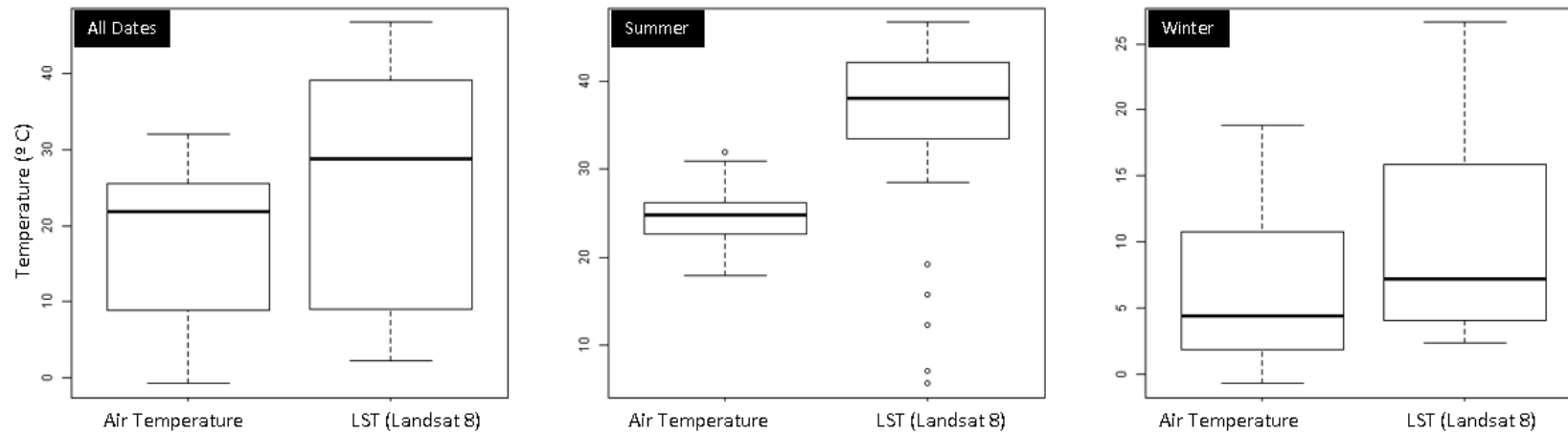
Sensor 5 (ZCS)



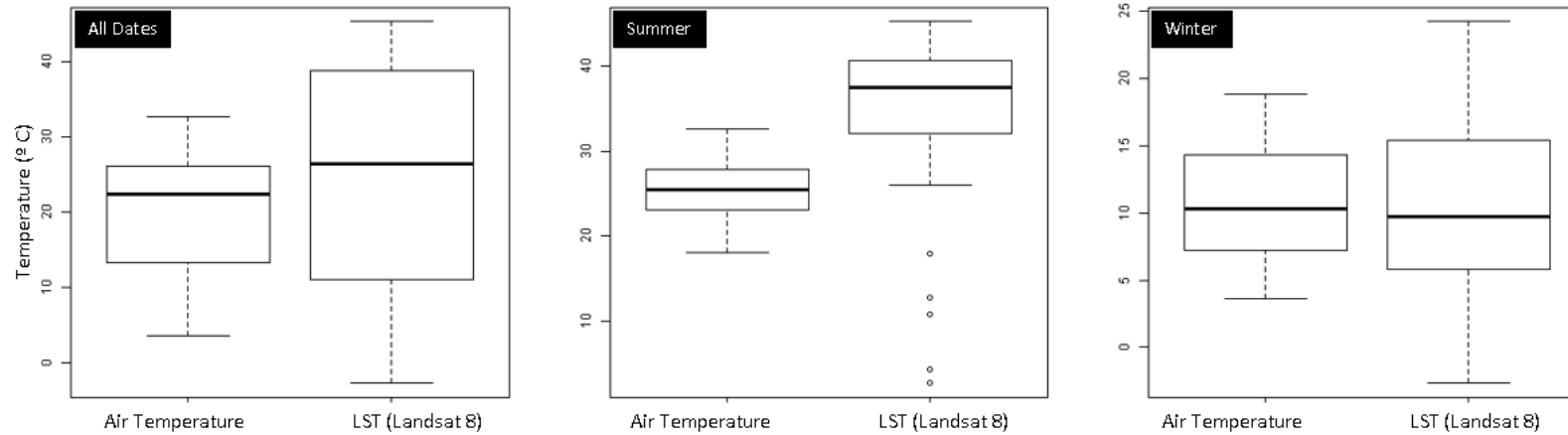
Sensor 17(ZCS)



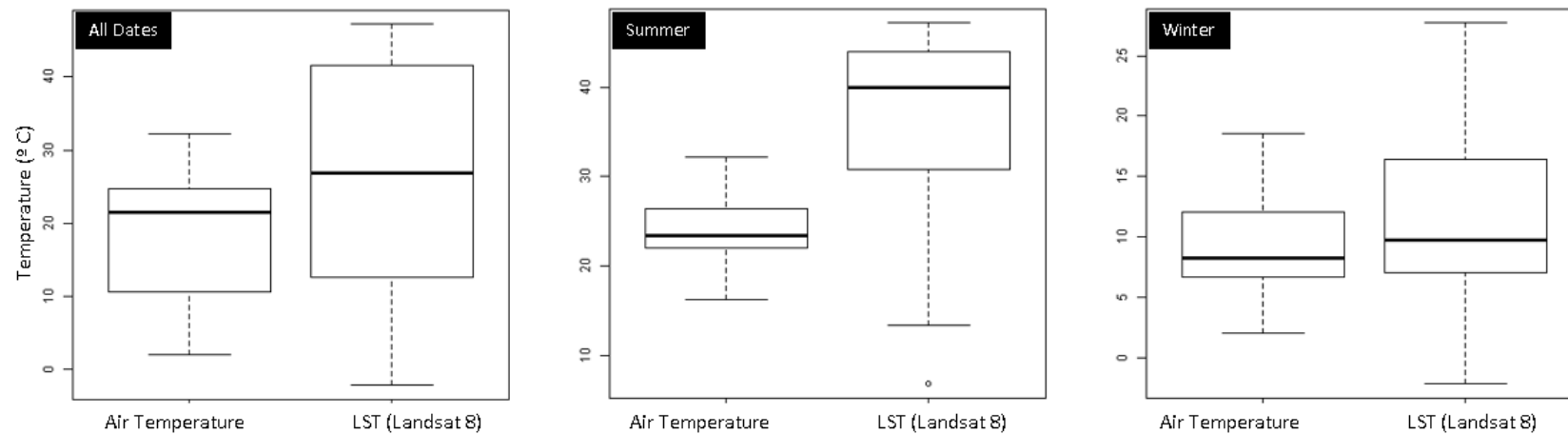
Sensor 21 (ZCS)



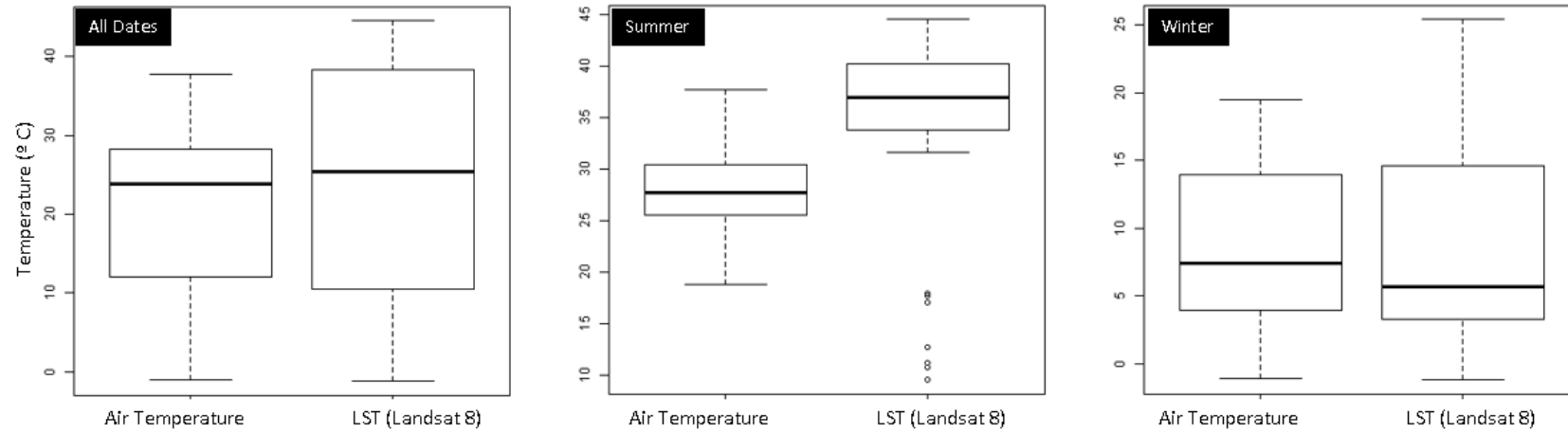
Sensor 16 (ZRE)



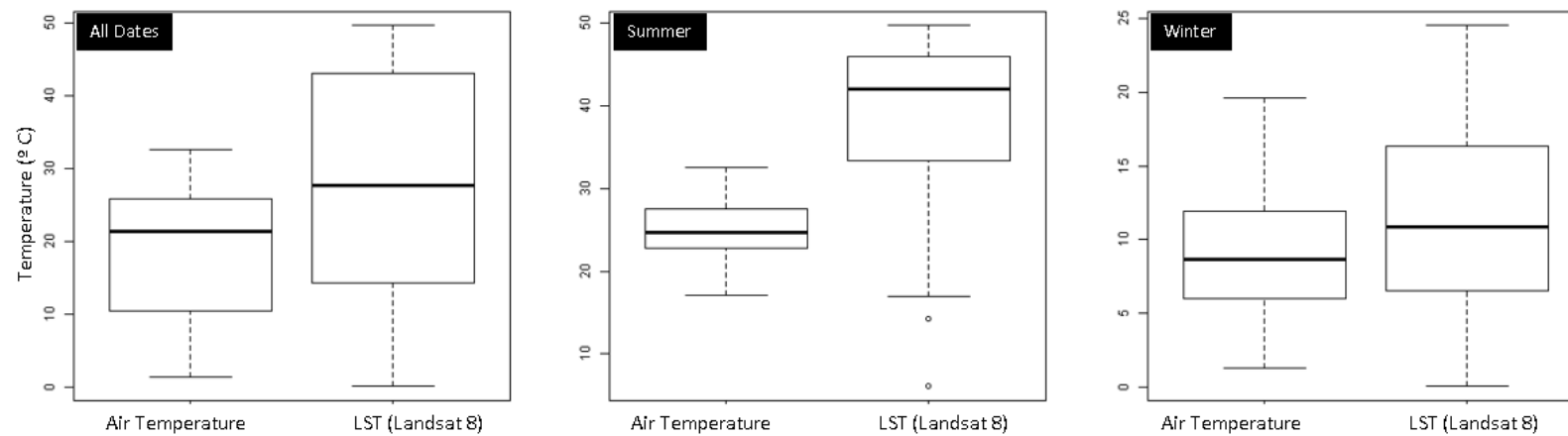
Sensor 19 (ZRE)



Sensor 20 (ZRE)



Sensor 23 (ZRE)



Appendix IX

Maximum, minimum, average, and standard deviation values of UHI_{int} (LST and air temperature).

UCZ	Sensor	Parameter	All dates		Summer		Winter	
			Air Temperature	Lst (Landsat 8)	Air Temperature	Lst (Landsat 8)	Air Temperature	Lst (Landsat 8)
BDT	4	Min.	-3.36	-3.88	-2.63	-3.88	-3.36	-2.41
		Máx.	7.53	8.38	1.73	8.38	7.53	7.11
		Average	0.08 ± 1.67	0.05 ± 2.44	0.08 ± 0.97	-0.10 ± 2.73	0.08 ± 2.46	0.29 ± 1.89
	6	Min.	-4.33	-10.45	-0.90	-10.45	-4.33	-3.46
		Máx.	4.91	8.80	4.19	7.79	4.91	8.80
		Average	0.93 ± 1.82	-0.64 ± 2.78	1.36 ± 1.17	-0.83 ± 2.99	0.24 ± 2.43	-0.32 ± 2.42
EVU	2	Min.	-7.49	-8.43	-4.04	-8.43	-7.49	-3.28
		Máx.	1.50	7.64	1.16	7.64	1.50	3.10
		Average	-1.64 ± 1.82	-0.42 ± 2.61	-1.04 ± 1.35	-0.68 ± 3.11	-2.63 ± 2.08	0.00 ± 1.44
	8	Min.	-5.24	-4.90	-5.24	-4.90	-4.41	-2.71
		Máx.	2.67	7.94	0.41	7.94	2.67	6.91
		Average	-1.66 ± 1.71	-0.73 ± 2.40	-2.05 ± 1.32	-1.04 ± 2.64	-1.01 ± 2.09	-0.21 ± 1.90
	9	Min.	-9.63	-6.99	-5.94	-6.99	-9.63	-4.50
		Máx.	0.34	6.26	0.34	6.26	0.04	1.81
		Average	-3.46 ± 2.03	-2.76 ± 2.27	-3.36 ± 1.67	-3.15 ± 2.55	-3.62 ± 2.53	-2.16 ± 1.59
	11	Min.	-9.54	-8.71	-4.71	-8.71	-9.54	-4.60
		Máx.	3.34	6.41	3.34	6.41	0.16	2.93
		Average	-2.31 ± 2.68	-2.25 ± 2.55	-1.17 ± 1.78	-2.44 ± 3.00	-3.97 ± 2.92	-1.97 ± 1.71

UCZ	Sensor	Parameter	All dates		Summer		Winter	
			Air Temperature	Lst (Landsat 8)	Air Temperature	Lst (Landsat 8)	Air Temperature	Lst (Landsat 8)
PMA	3	Min.	-6.04	-9.46	-2.83	-9.46	-6.04	-3.66
		Máx.	4.86	8.51	4.86	8.51	2.32	1.84
		Average	-0.11 ± 2.39	0.08 ± 2.83	0.91 ± 1.57	0.52 ± 3.31	-1.81 ± 2.57	-0.66 ± 1.58
	7	Min.	-7.64	-6.95	-5.14	-6.95	-7.64	-2.87
		Máx.	0.99	9.02	0.36	9.02	0.99	3.09
		Average	-3.32 ± 1.77	0.21 ± 2.61	-2.95 ± 1.48	0.13 ± 3.15	-3.92 ± 2.06	0.34 ± 1.35
	13	Min.	-8.49	-13.48	-8.49	-13.48	-7.95	-0.61
		Máx.	3.07	8.98	3.07	8.98	-0.68	3.24
		Average	-4.23 ± 2.05	-0.01 ± 2.97	-3.98 ± 2.02	-0.39 ± 3.63	-4.66 ± 2.07	0.62 ± 1.05
TUR	1	Min.	-6.57	-18.60	-4.19	-18.60	-6.57	-3.78
		Máx.	1.53	5.52	1.53	5.52	-0.39	3.78
		Average	-2.08 ± 1.41	-1.35 ± 3.65	-1.61 ± 1.01	-1.53 ± 4.45	-2.85 ± 1.64	-1.07 ± 1.69
	14	Min.	-3.97	-19.88	-3.97	-19.88	-1.74	-3.46
		Máx.	3.19	6.90	1.27	6.90	3.19	4.40
		Average	-0.11 ± 1.09	-1.21 ± 4.24	-0.42 ± 0.91	-1.91 ± 5.14	0.40 ± 1.19	-0.05 ± 1.48
	15	Min.	-2.64	-8.71	-2.54	-8.71	-2.64	-2.92
		Máx.	2.41	7.25	2.29	7.25	2.41	6.98
		Average	0.34 ± 1.08	-1.61 ± 2.63	0.55 ± 0.90	-2.02 ± 2.89	-0.01 ± 1.26	-0.94 ± 2.00

UCZ	Sensor	Parameter	All dates		Summer		Winter	
			Air Temperature	Lst (Landsat 8)	Air Temperature	Lst (Landsat 8)	Air Temperature	Lst (Landsat 8)
UMR	10	Min.	-3.89	-16.17	-1.94	-16.17	-3.89	-4.48
		Máx.	2.70	9.29	2.70	9.29	2.70	4.22
		Average	0.27 ± 1.40	-1.56 ± 2.97	0.62 ± 1.06	-1.76 ± 3.50	-0.30 ± 1.69	-1.24 ± 1.82
	12	Min.	-3.56	-11.84	-1.75	-11.84	-3.56	-1.60
		Máx.	3.52	9.88	1.70	9.88	3.52	4.47
		Average	0.38 ± 1.13	0.59 ± 3.29	0.29 ± 0.89	0.41 ± 4.01	0.52 ± 1.45	0.88 ± 1.53
	18	Min.	-5.37	-16.15	-2.95	-16.15	-5.37	-4.10
		Máx.	1.91	8.76	1.91	8.76	1.26	1.95
		Average	-1.12 ± 1.65	0.03 ± 3.17	-0.64 ± 1.33	0.43 ± 3.80	-1.91 ± 1.85	-0.62 ± 1.55
	22	Min.	-4.64	-4.23	-2.30	-4.23	-4.64	-3.53
		Máx.	2.65	6.41	2.65	6.41	1.66	1.70
		Average	0.24 ± 1.82	-0.06 ± 2.16	1.06 ± 0.99	0.54 ± 2.24	-1.11 ± 2.08	-1.06 ± 1.60
ZCS	5	Min.	-4.90	-7.24	-3.53	-7.24	-4.90	-2.79
		Máx.	1.54	7.98	0.50	7.98	1.54	4.98
		Average	-0.94 ± 1.24	-0.93 ± 2.52	-1.03 ± 0.94	-1.14 ± 2.93	-0.79 ± 1.63	-0.57 ± 1.61
	17	Min.	-3.92	-12.62	-3.92	-12.62	-3.56	-2.13
		Máx.	4.75	10.18	2.09	8.98	4.75	10.18
		Average	-0.14 ± 1.88	1.27 ± 3.18	-0.84 ± 1.50	0.97 ± 3.63	1.03 ± 1.90	1.76 ± 2.24
	21	Min.	-7.02	-4.05	-2.89	-4.05	-7.02	-3.24
		Máx.	1.50	8.98	1.50	8.98	0.88	5.50
		Average	-1.61 ± 2.08	-0.53 ± 2.55	-0.68 ± 1.16	-0.46 ± 2.89	-3.12 ± 2.36	-0.65 ± 1.93

Appendix X

Correlation values and p-value were obtained in each sensor sorted by UCZs, between air temperature (fixed weather station) and LST (Landsat 8), considering all dates, summer, and winter, respectively. The value in green is the “Strong” correlation (between 0.40 – 0.69), and in orange is the very strong correlation (≥ 0.70).

Sensor	ZCS	All dates		Summer		Winter	
		Statistical Value	p-value	Statistical Value	p-value	Statistical Value	p-value
4	BDT	0.876	0.00E+00	0.737	1.80E-08	0.800	9.11E-07
6	BDT	0.856	0.00E+00	0.671	8.45E-07	0.872	6.29E-09
2	EVU	0.829	0.00E+00	0.690	3.03E-07	0.830	1.53E-07
8	EVU	0.856	0.00E+00	0.641	3.68E-06	0.906	2.03E-10
9	EVU	0.886	0.00E+00	0.603	6.20E-05	0.866	4.44E-08
11	EVU	0.856	0.00E+00	0.618	3.60E-05	0.888	1.51E-09
3	PMA	0.863	0.00E+00	0.656	1.78E-06	0.915	6.14E-11
7	PMA	0.806	0.00E+00	0.620	9.25E-06	0.828	1.75E-07
13	PMA	0.801	0.00E+00	0.605	1.75E-05	0.771	3.98E-06
1	TUR	0.841	0.00E+00	0.708	1.12E-07	0.846	5.27E-08
14	TUR	0.842	0.00E+00	0.743	1.17E-08	0.829	1.70E-07
15	TUR	0.866	0.00E+00	0.670	8.93E-07	0.874	5.73E-09
10	UMR	0.903	0.00E+00	0.740	2.09E-08	0.913	8.09E-11
12	UMR	0.831	0.00E+00	0.686	3.91E-07	0.845	5.52E-08
18	UMR	0.877	0.00E+00	0.691	2.99E-07	0.874	5.69E-09
22	UMR	0.892	0.00E+00	0.693	2.66E-07	0.940	1.06E-12
5	ZCS	0.863	0.00E+00	0.687	3.57E-07	0.892	9.07E-10
17	ZCS	0.846	0.00E+00	0.708	1.09E-07	0.834	1.21E-07
21	ZCS	0.865	0.00E+00	0.650	3.23E-06	0.915	5.93E-11
16	ZRE	0.854	0.00E+00	0.708	1.10E-07	0.797	1.11E-06
19	ZRE	0.847	0.00E+00	0.665	1.16E-06	0.871	7.26E-09
20	ZRE	0.885	0.00E+00	0.679	5.59E-07	0.937	1.75E-12
23	ZRE	0.877	0.00E+00	0.680	5.44E-07	0.798	1.06E-06

Appendix XI

Resulting data from the linear regression model for all dates, for summer and winter, between air temperature (fixed weather station) and LST (Landsat 8).,

The formula in RStudio: $\text{lm}(\text{formula} = \text{SxLST} \sim \text{SxT})$, x corresponds to the number of each sensor.

Sensor	All dates		Summer		Winter	
	Intercept	ST	Intercept	ST	Intercept	ST
1	-0.6605	1.4594	-18.828	2.208	0.9885	1.2858
2	1.068	1.378	-7.042	1.708	2.305	1.208
3	-0.7548	1.3900	-7.687	1.652	0.7048	1.2012
4	-2.477	1.463	-6.296	1.627	1.148	1.014
5	-2.642	1.500	-0.765	1.432	-1.306	1.303
6	-3.208	1.404	-8.633	1.610	-1.018	1.159
7	2.669	1.462	-3.382	1.727	2.981	1.433
8	-1.737	1.521	-3.961	1.635	1.103	1.092
9	0.5216	1.4640	-1.778	1.584	2.298	1.066
10	-3.973	1.465	-8.994	1.660	-2.003	1.236
11	1.970	1.255	1.524	1.281	2.688	1.070
12	-3.468	1.518	-7.269	1.671	-1.054	1.251
13	4.434	1.420	1.048	1.579	5.176	1.250
14	-5.060	1.546	-19.352	2.108	-2.435	1.314
15	-3.442	1.408	-5.815	1.505	-1.252	1.149
16	-5.287	1.542	-5.493	1.558	-2.264	1.220
17	-4.714	1.659	-6.341	1.733	-1.736	1.341
18	-0.9136	1.4728	-3.331	1.576	0.7496	1.2174
19	-3.396	1.628	-0.2572	1.5054	-2.519	1.499
20	-2.137	1.293	3.315	1.103	-1.988	1.234
21	1.557	1.341	-1.597	1.472	2.485	1.170
22	-2.195	1.431	-4.205	1.512	-0.8254	1.2366
23	-3.297	1.639	-6.099	1.761	0.874	1.142