Assessment and synergy analysis of outdoor thermal comfort and thermal infrared remote sensing for urban heat island studies

Safae Ahsissene*, *Fatima Zahrae* Rhziel, and *Naoufal* Raissouni

RS&GIS Research Unit, National School for Applied Sciences of Tetuan, University Abdelmalek Essaadi, Tetuan, Morocco

Abstract. The aim of this research is to explore the potentialities and limits of the integration of remote sensing biophysical data (land surface temperature) in the outdoor thermal comfort studies. Accordingly, by examining correlations between land surface temperature and air temperature, and using respectively remote sensing satellite data MODIS and different weather stations archives alongside questionnaire surveys. Currently, the parameters of thermal comfort indices are usually calculated using the data from one, or few permanent or portable ground-based weather stations. Due to the lack of adequate distribution of weather stations, those calculations generally do not accurately represent the alteration of thermal comfort, through time and space. Nevertheless, it has been essentially proved that despite strong tendencies between in-situ measured parameters and remotely sensed ones, various elements need to be studied (e.g., location, land surface type, vegetation, and elevation). Finally, preliminary results confirm that the proposed linear approaches are providing considerable and promising performance suitable for future specific situations and studies purposes.

1 Introduction

Growing populations have resulted in the construction of high-rise buildings that can house more than one family in cities, resulting in cities that are densely packed with multiple tall buildings in small areas. As a result temperatures in cities are usually significantly higher than in rural areas, a phenomenon called Urban Heat Island (UHI) [1].

One of the most significant consequences of UHI is that it imposes thermal stress on the local climate [2-3], affecting the environment and affecting the quality of life by increasing thermal discomfort in urban areas [4-5].

There are four types of UHI and they can only be distinguished by either the observation method or the definition of the surface [6-7].

Urban heat island can be categorized into different types, surface, canopy, boundary layer…etc.

Surface urban heat island (SUHI) represents an urbanized change to the land surface temperature [8-9].

Urban heat island studies have used several satellite thermal infrared (TIR) sensors like Terra/Aqua MODIS, Landsat and Terra Aster to retrieve a variety of temporal and spatial data [10].

The process of remote sensing involves measuring the reflected and emitted radiation of an area in order to identify and track its physical characteristics; It can be used for observation of different temporal and geographic resolutions of surface parameters (type of land cover, vegetation, water surfaces...etc.) and environmental parameters (land surface temperature, water vapour…etc.). This makes it ideal for use in studying SUHI and outdoor thermal comfort variations and alterations [11-14].

The concept of thermal comfort expresses a general contentment with the thermal environment. Studies of outdoor thermal comfort refer to the identification of the preferences of individuals and how climate changes affect them and can affect different aspects of their urban life [15-16].

Thermal comfort in urban environments requires continuous assessment, monitoring, and prediction. In the coming decades, A growing population and an expansion in the physical area are predicted to alter the spatial and temporal patterns of thermal comfort [13-17].

A number of studies have been conducted to model outdoor thermal comfort in urban environments using data from synoptic stations [18-21].

Studies have examined outdoor thermal comfort using thermal remote sensing and meteorological data from weather stations [14], others used data from ground stations, Landsat and Sentinel satellite images to create outdoor thermal comfort maps [11], additionally a recent study used PCA (Principal component analysis) and LSA (Latent semantic analysis) models to analyse

* Corresponding author: safae.ahsissene@gmail.com

outdoor thermal comfort using remotely sensed reflected and emitted radiation [13].

In this study, we will be combining results obtained from a questionnaire survey and comparing them to results from weather stations and MODIS (Moderate Resolution Imaging Spectroradiometer).

2 Methods

2.1 Study area

Our study area is the Mediterranean city of Tetuan (Fig.1); it is a city located in northern Morocco bordered to the east by the Mediterranean Sea.

Fig. 1. Map of area of study.

Questionnaire surveys were conducted in Feddan Park that is located in the ancient Medina part of Tetuan, and is one of the city's few urban open spaces.

The survey was carried on four seasons and resulted in the collection of 1167 questionnaires.

The questionnaire had twelve questions inquiring about age, sex, time spent outdoors, clothes, and finally a question about thermal sensation vote (TSV): "dressed as you are at the moment, please pick which option indicates how you currently feel":

- Cold (-3).
- Cool (-2).
- Slightly cool (-1).
- Neutral (0).
- Slightly warm (1).
- Warm (2).
- Hot (3).

2.2 Land surface data

The MOD11A1 Version 6 products were used for land surface temperature. It provides Land Surface Temperature and Emissivity (LST&E) data daily per-pixel with a spatial resolution of one kilometer (km).

Daily land surface data was collected in all the five months in which the surveys were conducted, October, January, February, June and August.

Air temperature was extracted from Sania Ramel Airport Station for those same months (www.wunderground.com).

Correlation between the two sets of data LST and $Tair$ was calculated and an equation was established that predicts $Tair$.

2.3 Discomfort index

As a physiological thermal stress indicator, the Thom discomfort index DI uses air temperature and humidity and measures their effect on human thermal comfort.

Based on Thom's formula [22], the DI is calculated as follows:

$$DI = Tair - (0.55 - 0.0055 \times RH)(Tair - 14.5) \quad (1)$$

where $Tair$ is air temperature and RH is relative humidity.

Values of discomfort index can be interpreted as follows [23]:

- $DI \leq 14.9$ or $DI \geq 26.5$ Uncomfortable.
- $15.0 \leq DI \leq 19.9$ Comfortable.
- $20.0 \leq DI \leq 26.4$ Partially Comfortable.

3 Results and discussion

Land surface temperature and air temperature are locally correlated (Fig. 2).

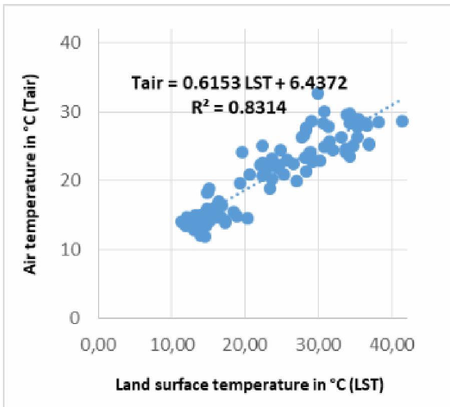

Fig. 2. Regression model and correlation between air temperature $Tair$ and land surface temperature LST .

Comparison between $Tair$ and LST found strong tendencies between the two variables (Table 1), which led us to extract an equation expressing $Tair$ from the measurements of LST . The linear regression between air temperature and land surface temperature can be expressed as follows:

$$Tair = 0.6153\, LST + 6.4372 \quad (2)$$

where $Tair$ is air temperature and LST is land surface temperature.

Table 1. Comparison between *LST* (land surface temperature) and *Tair* (air temperature), SD = Standard Deviation.

	LST	*Tair*
SD	7.29	4.76
Mean	21.21	19.23
Minimum	11.33	11.84
Maximum	36.93	30.08
Root mean square	4.187	

3.1 Discomfort index results

The linear equation resulting from the correlation between air temperature and land surface temperature has helped us in modifying the formula used to calculate discomfort index by replacing *Tair* with *LST* as the following:

$$DI = 0.6153LST + 6.4372 - (0.55 - 0.0055RH)(0.6153LST - 8.0628) \quad (3)$$

where the land surface temperature and was extracted from MODIS (MOD06) and the daily mean relative humidity was calculated from Sania Ramel Airport station.

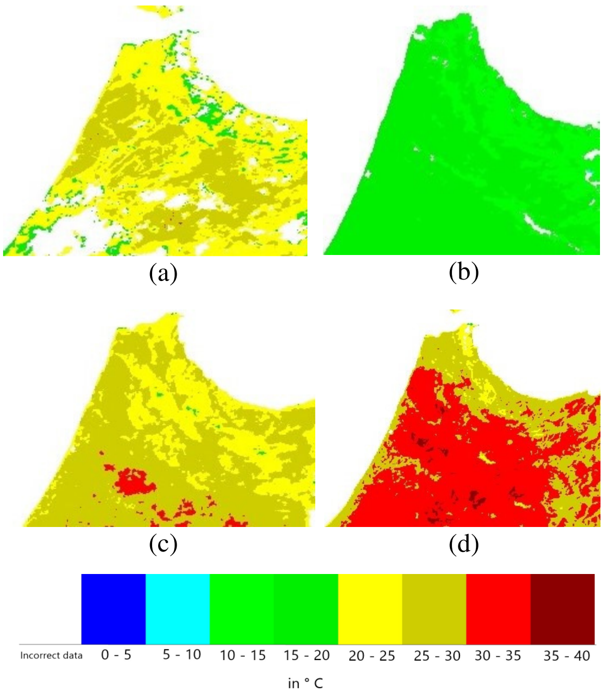

Fig. 3. Discomfort index maps for the four seasons: (a) autumn (10 October 2021), (b) winter (19 January 2021=2), (c) spring (05 June 2022), (d) summer (19 august 2022).

Discomfort index was then calculated for multiple days of each season. Fig.3 shows the calculations made on days in which *LST* images were clear and can easily be interpreted and compared.

Comparing discomfort index between different seasons can be easily made by just looking at the maps (Fig. 3), it is clear that autumn and spring are generally more comfortable than summer and winter.

Table 2 presents discomfort index results on days of the surveys.

Table 2. Discomfort index results: Min= Minimum, Max= maximum, SD = standard deviation, NA = Not applicable (for clouded data).

Discomfort index	**Min**	**Max**	**Mean**	**SD**
09 October 2021	19.28	23.79	21.33	1.27
10 October 2021	17.20	24.17	20.11	1.61
18 January 2022	11.87	17.19	15.09	1.32
05 February 2022	NA	NA	NA	NA
11 February 2022	15.16	20.07	17.60	1.24
01 June 2022	23.60	27.92	25.74	1.01
03 June 2022	22.04	26.23	24.14	0.88
13 June 2022	NA	NA	NA	NA
20 august 2022	19.55	25.68	21.88	1.23
22 august 2022	NA	NA	NA	NA

The following dates: 5 February, 13 June, and 22 August could not be calculated due to clouded pictures of LST.

3.2 Comparisons between Thermal sensation votes and discomfort index

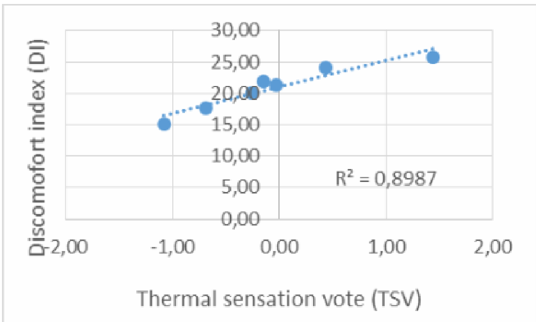

Fig. 4. Correlation between thermal sensation vote (TSV) and discomfort index (DI).

After the calculation of discomfort index, the results were then compared with the questionnaire results (Fig.4). There was a high correlation between the two.

4 Conclusion

Air temperature and LST are locally correlated.

Discomfort Index was highly correlated with TSV on the days of the study.

This method could be used in determining outdoor thermal comfort.

Some days of the study couldn't be added due to unclear MODIS pictures.

Remote sensing data can and should be used for future studies.

The Preliminary results of the proposed linear approaches are providing considerable and promising performance suitable for future specific situations and studies purposes.

Despite strong tendencies between in-situ measured parameters and remotely sensed ones, various elements need to be studied (e.g., location, land surface type, vegetation, and elevation).

Further studies should be made on longer periods for better results.

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