



A new thermal fusion method to downscale Land Surface Temperature to finer spatial resolution using Sentinel-MSI and Landsat-OLI/TIRS imagery

Hicham Bahi^{a,*}, Lahouari Bounoua^b, Anas Sabri^a, Abderrazak Bannari^c,
Anass Malah^a, Hassan Rhinane^d

^a Mohammed VI Polytechnic University, Benguerir, Morocco

^b Biospheric Sciences Laboratory, NASA GSFC, Greenbelt, MD, 20771, USA

^c Space Pix-Map International Inc., Gatineau, (Quebec), Canada

^d Sciences Ain Chock, University Hassan II, Casablanca, Morocco

ARTICLE INFO

Keywords:

Downscaling
High-resolution thermal fusion (HRTF)
Landsat-OLI/TIRS
Sentinel-MSI
Thermal data fusion
Thermal remote sensing
Urban and rural thermal environment
Land surface temperature (LST)

ABSTRACT

Land surface Temperature (LST) is an important observation when investigating environmental processes and is a characteristic signature of surface climate change at various scales. It is even more crucial to urban thermal structures studies, especially the urban heat islands (UHI), which impacts the urban energy demand and human health. However, high spatial resolution LST data is not available at a scale resolving the urban metabolism. To address this need, this research attempts to create synergy between the European Space Agency (ESA) and NASA satellite observations to enhance the spatial resolution of LST retrieval. The Multispectral Instruments (MSI) onboard the Sentinel 2A and 2B satellites provide observations with high and medium spatial and spectral resolutions, respectively. Although these instruments provide more spatial details than the Landsat-OLI/TIRS, useful at the city scale, they lack observations in the thermal infrared (TIR) spectral region. The main objective of this paper is to fuse Landsat-OLI/TIRS data to Sentinel-MSI to compensate for the lack of TIR information of the MSI and retrieve higher resolution LST. Accordingly, a new innovative High-Resolution Thermal Fusion (HRTF) approach has been developed, based on two steps: 1) a statistical downscaling of the brightness temperature (BT) to 10-m spatial resolution, and 2) retrieving LST based on an atmospheric correction of the fused BT using the split-window algorithm. The performance of the HRTF approach was cross-validated using independent data derived from MOD11A1 product and inter-compared with the most efficient machine learning algorithms of downscaling. The results show that the derived high spatial resolution (10-m) LST map using HRTF correlates significantly ($R^2 = 0.94$) with the original LST retrieved from the OLI/TIRS products with an RMSE of 0.88 K, outperforming the five ML methods for which the RMSE ranges from 1.39 to 1.86 K. This HRTF proposed approach is undoubtedly promising, particularly for the urban and rural thermal environmental applications at a large territorial scale.

* Corresponding author. Lot 660, Hay Moulay Rachid Ben Guerir, 43150, Morocco.

E-mail address: hicham.bahi@um6p.ma (H. Bahi).

1. Introduction

Thermal remote sensing is a powerful method to extract various biophysical and physiological parameters to study the interaction at the land-atmosphere interface. For many applications, the land surface temperature (LST) is considered the most important variable that affects the human thermal comfort and health in urban settlements, and their energy demand. Furthermore, it is also important for climate change studies (Ahmed, 2018; Chen and Zhang, 2022; Eleftheriou et al., 2018; Jin et al., 2005; Kulsum and Moniruzzaman, 2022), urban micro-climate (Bahi et al., 2017, 2019a, 2019b, 2019c; Mushore et al., 2017; Perera et al., 2022), as well as for sustainable urban development (Bounoua et al., 2023; Malah et al., 2022; Malah and Bahi, 2022). Theoretically, many thermal sensors with high to very high spatial resolutions are needed to retrieve accurate thermal environmental characteristics at territorial scale, including both urban and surrounding rural areas. Unfortunately, currently available thermal sensors do not allow for such spatial resolution. For instance, Landsat thermal sensors offer data with medium to low spatial resolutions, such as 60 m for the Enhanced Thematic Mapper Plus (ETM+), 100 m for the Thermal Infrared Sensor (TIRS) and 120 m for the Thematic Mapper (TM). In contrast, the most widely used sensors with daily global coverage for long-term monitoring provide data with much coarser resolution of 1 km. The Moderate Resolution Imaging Spectroradiometer (MODIS), Sea and Land Surface Temperature Radiometer (SLSTR) and the legacy Advanced Very High-Resolution Radiometer (AVHRR) produce data with a ground spatial resolution of 1 km, whereas the Spinning Enhanced Visible and Infra-Red Imager (SEVIRI) and the Geostationary Operational Environmental Satellite (GOES) Imager provide data at 3×3 km and 4×4 km at nadir direction, respectively. SEVIRI and GOES imagers provide the best temporal resolutions with ground track repeat cycle of 15 min and 3 h, respectively, compared to twice daily revisit times for MODIS and AVHRR, greater than 1.5 days for SLSTR, and 16 days for Landsat sensor series.

In addition, the problem of covering large territories with a high spatial resolution is constrained by the low temporal resolution (Wu et al., 2014) which limits the short-term variations such as the diurnal change. Although the Landsat series and the Advanced Spatial Thermal Emission and Reflection Radiometer (ASTER) sensors meet some requirements for certain applications (e.g. forestry, agriculture, soil moisture), finer thermal spatial details are still required for analyzing heterogeneous and complex environments characterized by small and fragmented features, such as in urban areas (Gao et al., 2012). This is more evident when studying the variation of surface urban heat islands within settlements, where roads and building blocks are typically only a few meters in size.

Currently, drone or unmanned vehicles with onboard TIR imaging cameras and control subsystems allow the extraction of LST with a very high spatial resolution (Dominguez et al., 2011a; Lo et al., 1997; Ren et al., 2015; Z. Wang et al., 2022; Wei et al., 2021; Y. Wu et al., 2022). However, this new technology is still too costly and requires logistical means, and hence does not provide the advantage of extended coverage compared to satellite remote sensing. Therefore, developing a new fusion approach between satellite data of high and moderate spatial resolutions is a necessary step and innovation to capture the fine scale thermal structure to study urban scales environments with more spatial details.

Technically, the MSIs onboard the Sentinel suite remain the best sensors for this purpose, offering high spatial and temporal resolutions data that can be fused with the Landsat-TIRS medium spatial resolution. In this regard, the current research attempts to exploit the potential for combining the Sentinel-MSI high spatial resolution data with the thermal capabilities of Landsat-OLI/TIRS data to enhance LST retrieval for several environmental applications, including urban studies, climate change and sustainability studies. This is an important initiative (El Ghazouani et al., 2021) that may enhance and extend the use of long timeseries of Landsat-OLI/TIRS data and allow assessment of high resolution urban thermal structure in dense cities and neighborhoods (e.g., El Ghazouani et al., 2021) as well as large territorial studies (R. Li et al., 2023).

The idea of harmonizing and enhancing the use of existing long term coarse or medium resolution satellite observations by fusing them with short-term high-resolution data is of paramount importance in land characterization, which is the basis for land-atmosphere interactions, as well as many environmental studies. At the same level of importance, data harmonization is also required when series of sensors of about the same spatial resolution are launched in succession. In this case a data temporal continuity and coherence process must be developed to take advantage of the historic observations and assess the changes.

This endeavor is challenging, and several studies have been conducted to investigate it based, in large part, on statistical downscaling (Pu and Bonafoni, 2023a). However, only few attempts have been made to ensure the spatial continuity between the fused data (Masek, 2015), while others approached the issue based on potential linear correlations (Onáčillová et al., 2022).

There is a general agreement that the most accurate techniques used for data fusion are geo-statistical approaches (Wang et al., 2016a) and modulation based fusion techniques (Alparone et al., 2004). In general, these techniques offer the possibility to obtain and preserve accurate spectral information and physical properties (Wang et al., 2016a, 2016b; Ribeiro Sales et al., 2013) and deliver sharper results compared to other traditional fusion methods (Jiang et al., 2011; Wang et al., 2016b). These techniques were used for LST retrieval and estimates of the Surface Urban Heat Island (SUHI) intensity prediction (Jung and Park, 2014; Liu and Pu, 2008; Rodríguez-Galiano et al., 2012; Rodríguez-Galiano et al., 2011; Stathopoulou and Cartalis, 2009; Zakšek and Ostir, 2012).

On the other hand, Machine and Deep Learning regression-based algorithms were also used between explanatory variables, such as Normalized Difference Vegetation Index (NDVI), the impervious Surface Area (ISA), emissivity (Sattari et al., 2018; Yuan and Bauer, 2007), and target variable LST. Machine learning models are still most used methods in the field compared to deep learning techniques because of their efficiency and simplicity (Bonafoni and Tosi, 2017). However, the accuracy of LST retrieval using these models is often limited by different environmental and geographical conditions, especially for heterogeneous areas with varying land covers and complex elevation structure (J. Wu et al., 2022).

Overcoming the challenges associated with data fusion requires sophisticated techniques and approaches, but the benefits of improved environmental monitoring and analysis make it a critical area of research and development. The various methodologies, including statistical downscaling, machine learning, physical downscaling, and hybrid methods, have been developed to address these

challenges, each leveraging unique strengths to improve the accuracy of environmental monitoring. Our proposed method, which involves fusion in the spectral domain before LST retrieval, offers a promising approach. By focusing on the spectral characteristics of the data, we preserve the physical aspect of the landscape and its spatial continuity which provides an advanced base to extract a more accurate LST, hence a detailed and reliable picture of environmental changes.

2. Study area and used data

2.1. Study area

The proposed fusion method was tested over the city of Brussels (Belgium) and its surrounding areas (Fig. 1) (Pelgrims et al., 2021). The region has a generally temperate and humid climate (Amaripadath and Attia, 2023; Beck et al., 2018), with average annual temperature and rainfall total of 10.5 °C and 852.4 mm, respectively (Bruffaerts et al., 2018). The choice of Brussels as a study area is strategic since it includes a complex and heterogeneous area with spatial disparities. According to the Administration of the Environment and Energy in the Brussels-Capital Region, there is a vast disparity the population density, ranging from less than 500 persons/km² to 40,000 persons/km², and the overcrowding of 70 % of population in less than 30 % of the city space (Fricke and Wolff, 2002). In addition, our study area encompasses different land uses and land cover classes such as artificial surfaces, agricultural lands, forest, vegetation, wetland, water bodies, and bare lands. Obviously, this high disparity and the heterogeneity of surfaces make our proposed approach extendable to other regions of the world.

2.2. Data

To improve LST at finer spatial resolution, Sentinel-MSI and Landsat-OLI/TIRS raw data were used (Table 1). The two scenes were acquired in the morning at approximately the same period with a time difference not exceeding 17 min. Both images were projected in the Universal Transverse Mercator (UTM) zone 31 N based on the international datum (WGS84).

The MSI records information in the electromagnetic spectrum region ranging from the visible to the SWIR, similar to Landsat-OLI, and spans over 13 bands. The spectral and spatial resolutions of Sentinel-MSI have 4 VNIR bands at 10-m, 6 bands at 20-m, and 3 bands

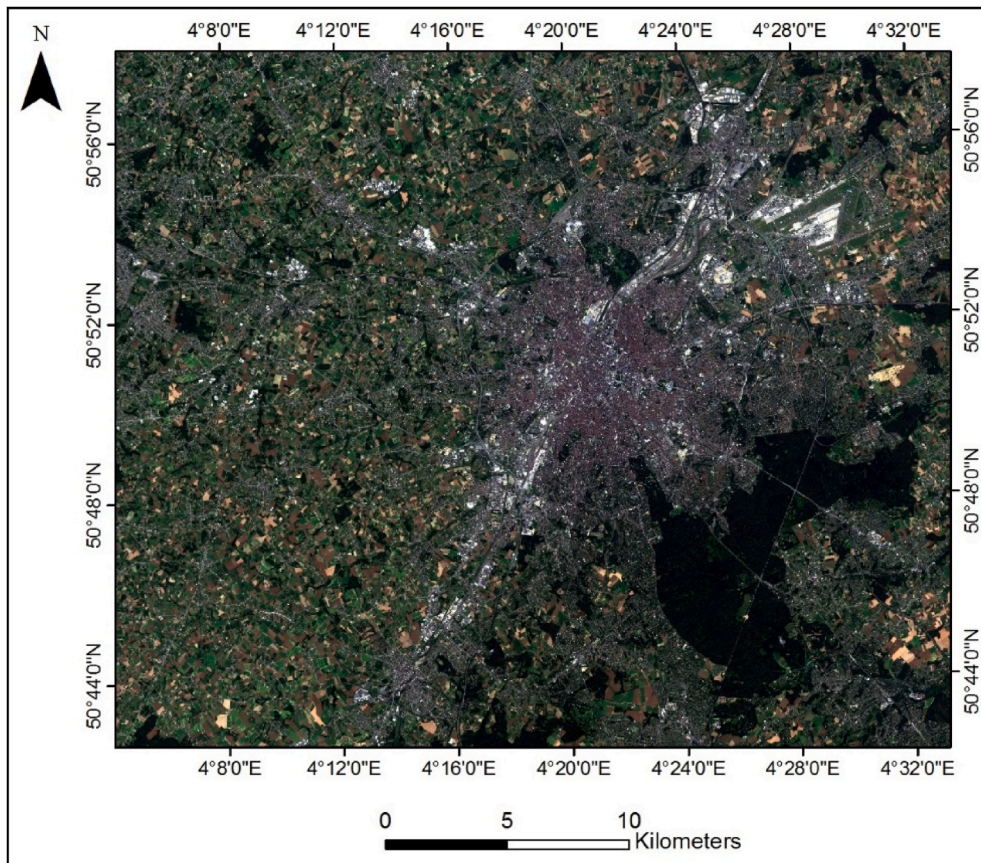


Fig. 1. Overview of the study area (Brussels city) spreading over an area of 988.58 km² and showing disparate landscapes.

Table 1
Satellite images used.

Products	Acquisition Date	Center latitude	Center longitude	Covered city
Sentinel-MSI	July 20, 2016	50.95490	3.78135	Brussels
Landsat-OLI	July 20, 2016	50.28118	4.49555	Brussels
MOD11A1	July 20, 2016	55.2079	8.9287	Brussels

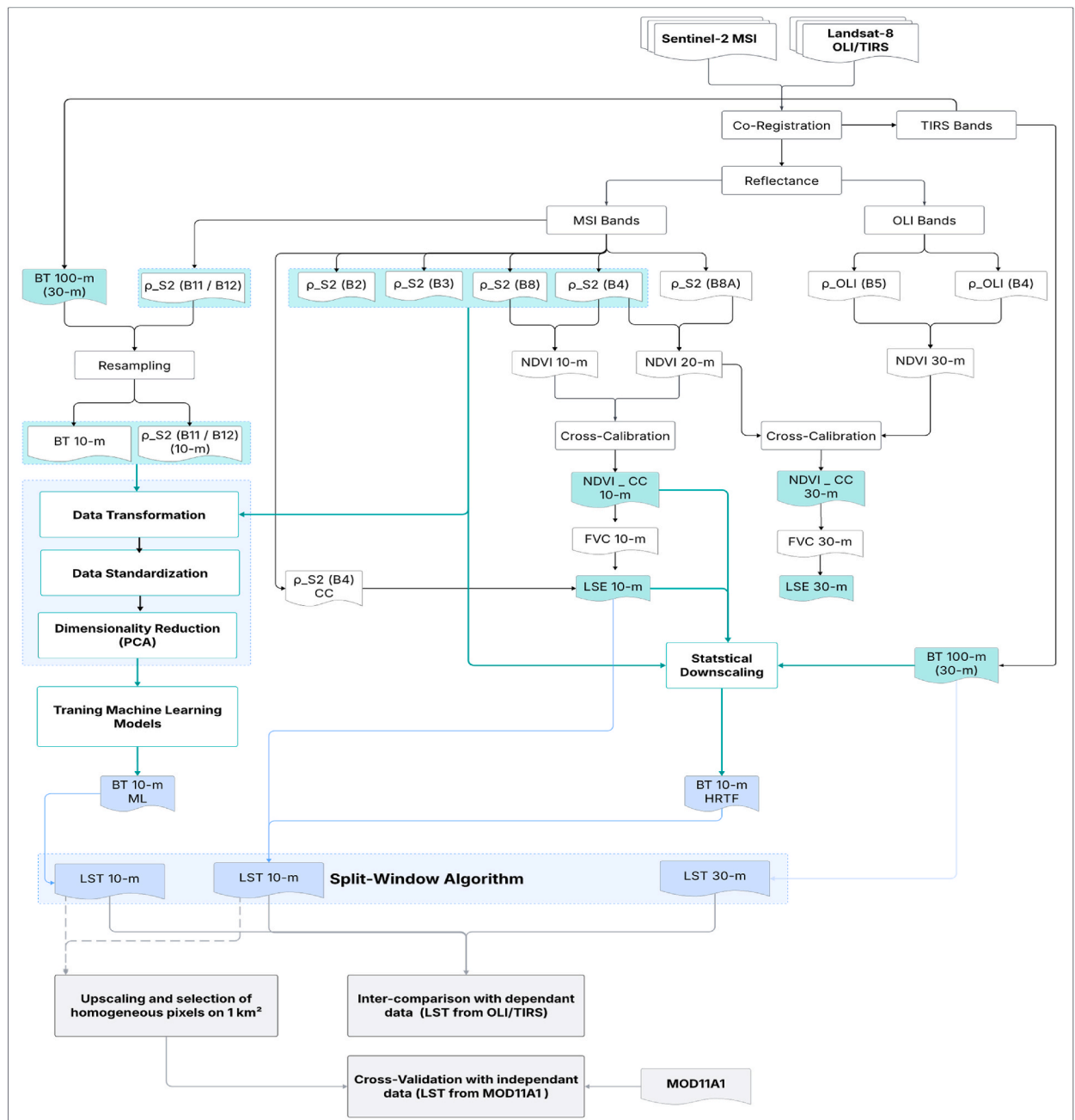


Fig. 2. Flowchart of the proposed HRTF algorithm and the Machine Learning models (ρ_{S2} : TOA reflectance of Sentinel-MSI band; ρ_{OLI} : TOA reflectance of OLI band; $\rho_{S2}(\text{Red})_{CC}$: TOA reflectance of Sentinel-MSI red band Cross-calibrated with its homologous band of OLI; $\rho_{S2}(\text{NIR } 8A)$: TOA reflectance of band 8A of Sentinel-MSI; BT: brightness temperature; NDVI; LSE: land surface emissivity; FVC: fraction vegetation cover). The machine learning models used include Random Forest Regression (RF), Lasso Regression (L1R), Ridge Regression (L2R), Polynomial Regression (PR), and Linear Regression (LR).

at 60-m compared to 8 bands at 30-m and a panchromatic band at 15-m for OLI. Compared to OLI, the MSI is richer in terms of spectral bands, with 4 additional bands, 3 of which are in Red-Edge and one in NIR.

The Sentinel-MSI revisit frequency (10 days) was an improvement when compared to those of Landsat (16 days) and SPOT (26 days) and it has been further improved to a 2.9 day temporal resolution with the Sentinel-MSI 2B, launched in March 2017 (Immitzer et al., 2016; Martimort et al., 2007; Wang et al., 2016c). While, the Thermal Infrared Sensor (TIRS) of Landsat-8 incorporates 2 TIR bands with an original spatial resolution of 100-m, resampled to 30-m to make it compatible with the 30-m OLI spectral bands (Roy et al., 2014). Furthermore, the MOD11A1 product was used as independent data for the cross-validation of the fused LST. This product provides precise and comprehensive measurements of LST, drawing upon data collected by the MODIS instrument aboard NASA's Terra and Aqua satellites.

3. Methodology

Fig. 2 summarizes the methodology used in this research. The first step consists of developing a new and innovative statistical downscaling method between the co-registered and the cross-calibrated Sentinel-MSI and Landsat-OLI/TIRS to compensate for the lack of details in the brightness temperature (BT) extracted from TIRS bands. The second step consists of applying atmospheric corrections on the downscaled BT using the water vapor content and the emissivity extracted the MSI bands, cross-calibrated with their homologous bands of OLI.

3.1. Co-registration

As illustrated in Fig. 2, the first step of our approach is the sub-pixel co-registration of satellite data. To resolve the problem of misalignment between the 30-m (OLI) and the 10-m (MSI) data, we applied geometric aligning between base data (Sentinel-MSI) and warp data (Landsat-OLI/TIRS) using a control point set well distributed and modeling the relationship based on a second order polynomial function transformation through the Landsat-OLI image (Hemati et al., 2021). This co-registration process shows an excellent Root Mean Square Error (RMSE) of less than one-third of the original pixel dimensions (0.185 pixels).

3.2. Data preprocessing and radiometric cross-calibration

We proceeded with the computation of the Top of Atmosphere (TOA) reflectance of red and NIR bands of OLI, followed by the correction of the solar elevation angle. TIRS bands were then converted to the at-sensor spectral radiance and afterward to the at-sensor BT by inverting Planck's blackbody equation. The level-1C preprocessing of the Sentinel-MSI data takes advantage of supplying an ortho-rectified image derived from a Digital Elevation Model (DEM) and provides pixel radiometric values in the TOA reflectance (Baillarin et al., 2012), which is converted to 16-bit radiometric dynamic range similar to OLI data. The true values of TOA reflectance of sentinel-MSI were computed by dividing the values of the digital numbers by the quantification value reported in the header file, a standard procedure ("Empirical cross sensor comparison of Sentinel-2A and 2B MSI, Landsat-8 OLI, and Landsat-7 ETM + top of atmosphere spectral characteristics over the conterminous United States - ScienceDirect," n.d.).

For the radiometric cross-calibration, three NDVIs at 10-m, 20-m, and 30-m spatial resolutions were computed from the TOA

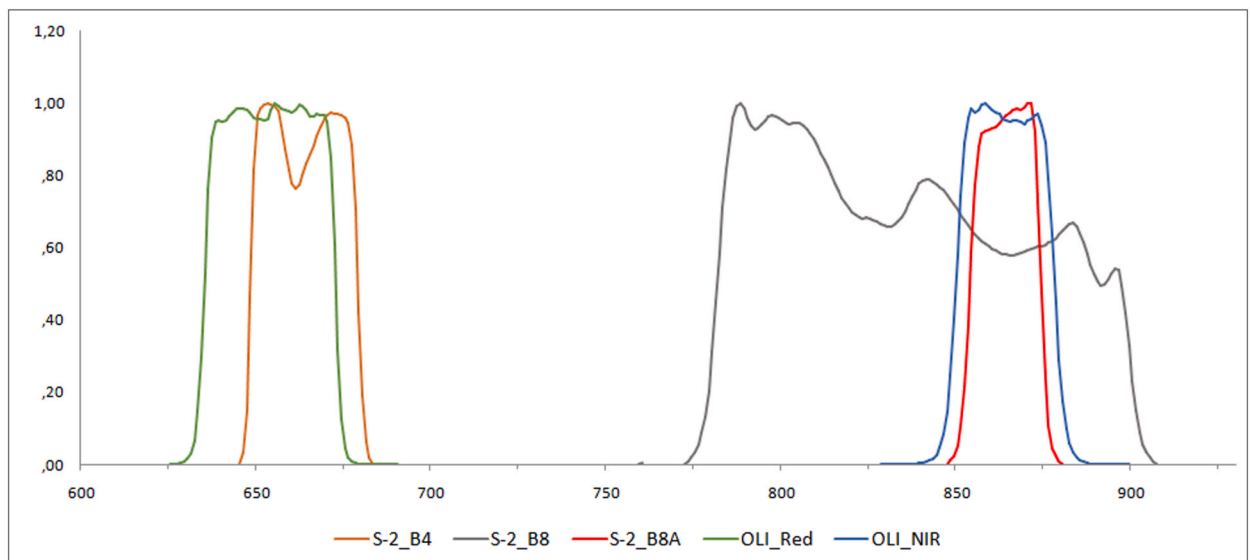


Fig. 3. Red and near-infrared bands spectral responses profiles of Sentinel-MSI and Landsat-OLI sensors.

reflectance of band-4/band-8 of Sentinel-MSI, band-4/band8A of Sentinel-MSI and band-4/band-5 of OLI respectively. We then proceeded with the cross-calibration (based on regression analysis) between NDVI retrieved from the narrower bands (bands 4 and 8A of MSI) (Fig. 3) and those computed respectively from the 30-m OLI (bands 4 and 5) and the 10-m MSI bands (bands 4 and 8) as shown in Fig. 2.

The inter-calibration of NDVI, rather than the reflectance values of individual bands, is promising because it allows us to obtain the best fits with R^2 exceeding 0.9, versus 0.7 for reflectance values (Roy et al., 2016) and more than 0.8 for improving the temporal continuity of the sensors (Bahi et al., 2016). The radiometric cross-calibration step is primordial since band-8 of Sentinel-MSI is more affected by the atmospheric effect, which includes a wavelength interval in the neighborhood of 825-nm that induces a water vapor absorption feature (Irons et al., 2012; Mishra et al., 2014; Roy et al., 2016). The inter-calibration process is further developed in Bahi et al. (2016).

3.3. Retrieving of land surface emissivity

The Land Surface Emissivity (LSE) is an essential parameter in LST estimation algorithms. However, unlike ocean emissivity, it varies according to soil types, surface moisture, heterogeneity of vegetation, and viewing angles (Ren et al., 2011; Salisbury and D'Aria, 1992). Three different methods were proposed in the literature to retrieve LSE from remote sensing data: classification-based emissivity (Snyder et al., 1998), NDVI-based emissivity (Sobrino et al., 2008; Valor, 1996), and a physics-based method (Wan and Li, 1997). We apply the method described by Li et al. (2016) (Eq. (1)) that uses an approximation of vegetation and urban soil surface emissivity values that are adapted from Sobrino et al. (2008). This technique is accurate in different areas, from the mid-latitudes to the tropics, with an error of 0.6 %, which is an acceptable error level for LST estimate using the Split-Window algorithm (Valor, 1996; Ye et al., 2022).

This study computed the emissivity in two pairs of pixel sizes, 30-m and 10-m. Each pair contains emissivity referring to bands 10 and 11 of TIRS. The first pair was calculated from the fraction of vegetation cover extracted from the cross-calibrated NDVI (NDVI_CC 30-m in Fig. 1) and the red band of the OLI sensor. Regarding the second pair, it was calculated according to the fraction of vegetation cover, extracted from the cross-calibrated NDVI of MSI (NDVI_CC 10m in Fig. 1), and the red band of Sentinel-MSI product cross-calibrated with its homologous band of OLI ($\rho S2(\text{Red})_{\text{CC}}$ in Fig. 1). The cross-calibration of the MSI red band was done because the “a, and b” coefficients in (Eq. (1)) refer to those of the OLI red band. The emissivity equation used in this study is more detailed in (Sobrino et al., 2004, 2008; Yu et al., 2014).

$$\varepsilon = \begin{cases} a + b\rho_{\text{red}} & \text{when NDVI} < 0.2 \\ \varepsilon_v P_v + \varepsilon_s (1 - P_v) + d\varepsilon & \text{when } 0.2 \leq \text{NDVI} \leq 0.5 \\ \varepsilon_v + d\varepsilon & \text{when NDVI} > 0.5 \end{cases} \quad (1)$$

Where ε_v is the vegetation canopy emissivity; ε_s is the bare soil emissivity; $d\varepsilon$ is the internal reflection emissivity due to cavity effect; and P_v is the vegetation proportion achieved that can be calculated using the following equation (Carlson and Ripley, 1997; Dis-sanayake et al., 2020):

$$P_v = \left[\frac{\text{NDVI} - \text{NDVI}_{\min}}{\text{NDVI}_{\max} - \text{NDVI}_{\min}} \right]^2 \quad (2)$$

Where $\text{NDVI}_{\min}$ and $\text{NDVI}_{\max}$ refer, respectively, to non-vegetated and fully vegetated land covers.

3.4. High resolution thermal fusion method

3.4.1. Statistical downscaling

To improve the spatial details of BT at 10-m resolution, we applied the model presented in (eq. (3)) based on the resampled BT of the TIRS bands to 10-m and 10-m MSI bands, taking into consideration NDVI and emissivity. We first applied multiple statistical analysis between all variables to extract the multivariate polynomial function in (eq. (3)), constraining the retrieval to the sought after magnitude at 10-m. A calibration is applied by combining the resampled BT and F function and applying a weight for each part (i and j used as exponent in (eq. (3)) and considering different possible iterations for i and j ranging from 0 to 2. This analysis showed an interplay between the preservation of the thermal characteristics of the original image at the expense of spatial details. Imposing the condition that allows the enhancement of spatial details while preserving the thermal characteristics, led to (eq. (4)) with i and j taking the values of 2 and 1, respectively.

$$\hat{Z}_{10}^{BT_k} = \sum_{i=0}^{i=n} \sum_{j=0}^{j=n} \lambda_{ij} \times \left(Z_{10}^{L8-BT_k} \right)^i \times F \left(Z_{10}^{S2-\rho(B_1)}, Z_{10}^{S2-NDVI}, Z_{10}^{S2-\varepsilon} \right)^j \quad (3)$$

$$\hat{Z}_{10}^{BT_k} = \lambda_{00} + \lambda_{ij} \times \left(Z_{10}^{L8-BT_k} \right)^i \times F \left(Z_{10}^{S2-\rho(B_1)}, Z_{10}^{S2-NDVI}, Z_{10}^{S2-\varepsilon} \right)^j \text{ With } 0 < j \leq i \quad (4)$$

Where Z is a pixel value; the superscript of Z indicates the data or the spectral band; the subscript of Z indicates the pixel size. The circumflex sign on Z indicates that the image has been predicted using the proposed statistical downscaling. BT_k indicates the BT of

band k with $k = \{10, 11\}$; n equal to 2; λ_{ij} are coefficients for the n order; and the tilde on BT indicates that the BT have been resampled to the subscript of Z spatial resolution using the nearest neighbor assignment. $L8_BT$ indicates the BT extracted from Landsat-8; $S2_p(B_l)$ indicates the reflectance of the l bands of Sentinel-MSI with $l = \{2, 3, 4, 8\}$; $S2_NDVI$ is the NDVI extracted from Sentinel-MSI; $S2_e$ is the land surface emissivity extracted from Sentinel-MSI; and F is a function that allows to predict BT according to the images mentioned in brackets. Once the BT is predicted, we perform the cross-calibration with that extracted from TIRS bands. Fig. 4 shows an example of the BT fusion result for the Brussels Airport and its neighborhood areas obtained from the proposed method (Eq. (4)).

3.4.2. Retrieving LST

An accurate LST estimate requires the selection of appropriate thermal bands and the most suitable algorithm for each sensor. Fortunately, the TIRS instrument incorporates two thermal bands defined in two complementary wavelengths (10.6 and 12.51 μm) that are spectrally similar to those of MODIS. Therefore, allowing for a more accurate LST retrieval than that acquired from previous Landsat sensors data using the Split-Window algorithm (Roy et al., 2014). Indeed, according to García-Santos et al. (2018); Yu et al. (2014), retrieving LST from both bands 10 and 11 using the Split-Window algorithm yields better results compared to the Single Channel algorithm using only the most accurate thermal band (band 10). The former is almost as accurate as the Radiative Transfer Equation-Based method using the same band 10 with a difference of 0.122 $^{\circ}\text{C}$ (Yu et al., 2014). The Split-Window algorithm used in this study is expressed as follows:

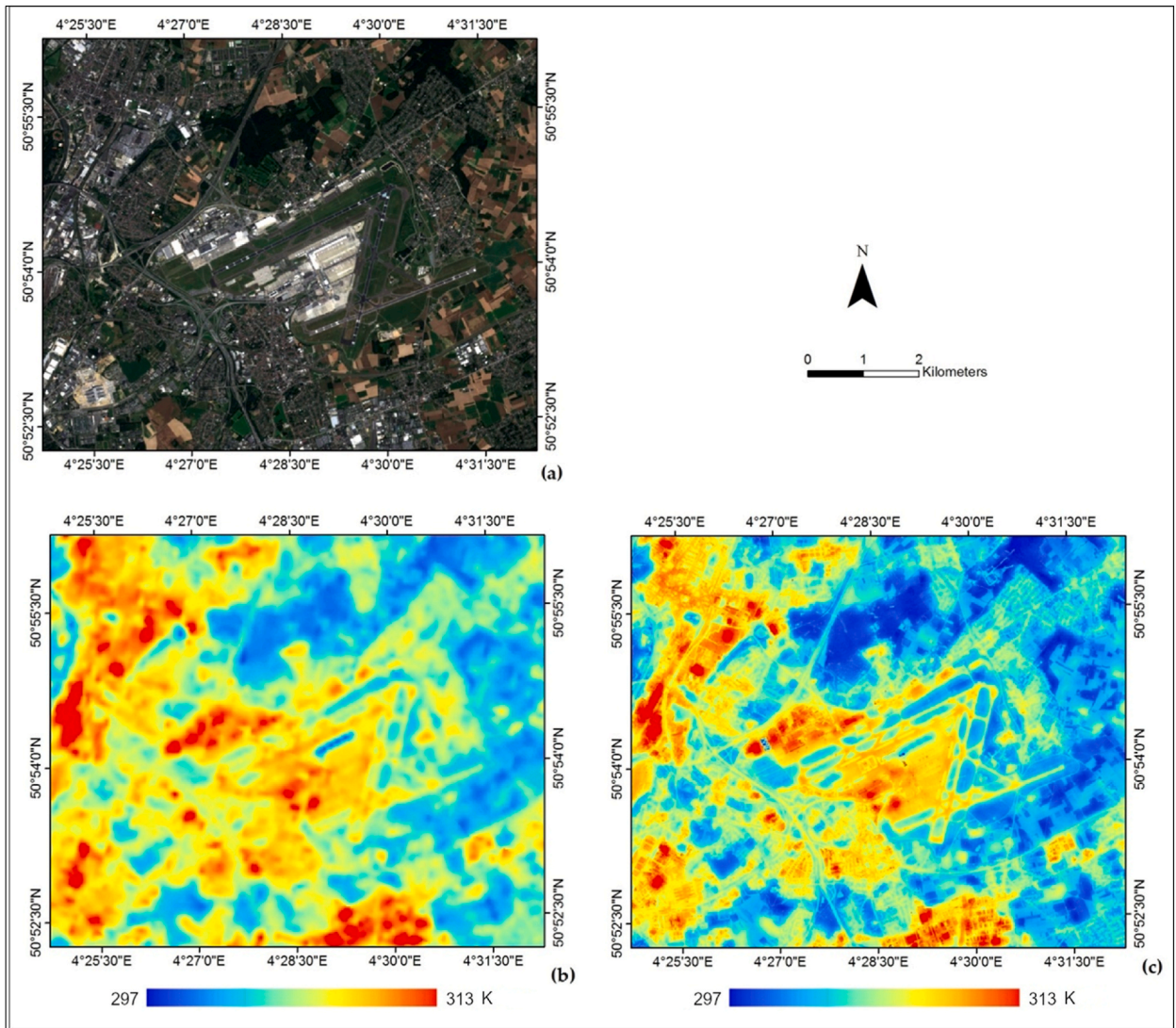


Fig. 4. Brightness temperature fusion example expressed in Kelvin: (a) true color of Brussels Airport and its neighborhood areas extracted from Sentinel-MSI bands; (b) original brightness temperature extracted from band 10 of Landsat-TIRS; and (c) fused brightness temperature at 10-m.

$$LST_{10m} = \hat{Z}_{10}^{BT_{10}} + c_1 \times (\hat{Z}_{10}^{BT_{10}} - \hat{Z}_{10}^{BT_{11}}) + c_2 \times (\hat{Z}_{10}^{BT_{10}} - \hat{Z}_{10}^{BT_{11}})^2 + c_0 + (c_3 + c_4 \times \omega) \times (1 - LSE_{10m}) + (c_5 + c_6 \times \omega) \times \Delta LSE_{10m} \quad (5)$$

Where LST_{10m} is the land surface temperature at 10-m spatial resolution in Kelvin; c_0 to c_6 are the Split-Window coefficients, which were initially derived from existing literature. The values of these coefficients for TIRS of Landsat 8 are given by [Zhao et al. \(2009\)](#); [Du et al. \(2015\)](#); [Li and Jiang \(2018\)](#); and [Rongali et al. \(2018\)](#). $\hat{Z}_{10}^{BT_{10}}$ and $\hat{Z}_{10}^{BT_{11}}$ are the downscaled at-sensor BT at bands 10 and 11; LSE_{10m} is the mean of land surface emissivity retrieved from the bands 10 and 11 extracted from Sentinel-MSI. ΔLSE_{10m} is the difference between land surface emissivity extracted from bands 10 and 11 of Sentinel-MSI, and ω is the atmospheric water vapor content. In this study, two LST datasets were computed: the first from Landsat-8 product and the second from the derived brightness temperature at 10-m spatial resolution and MSI data.

To obtain the best fit, the downscaled LST was cross-calibrated to the original one retrieved from Landsat 8 followed by error compensation.

3.5. Comparison and cross-validation of the results

3.5.1. Comparison with LST from TIRS

Since no measured reference of LST from a space-borne instrument at 10-m spatial resolution exists, we proceeded by upscaling the high spatial resolution data and original images by the same factor LR/HR (low resolution/high resolution). Then, we applied our proposed method to the up-scaled images of medium spatial resolution, followed by validation with original data as suggested by [\(Wang et al., 2016b\)](#). Five indices were used to evaluate our approach namely Correlation Coefficient (CC), Mean Absolute Error (MAE), RMSE, ERGAS (Erreur Relative Globale Adimensionnelle de Synthèse), and the Image Quality Index (Q). The ERGAS index is expressed as follows [\(Ranchin and Wald, 2000\)](#):

$$ERGAS = 100 \frac{HR}{LR} \sqrt{\frac{1}{N} \sum_{k=1}^N \frac{(RMSE(B_k))^2}{M_k^2}} \quad (6)$$

Where HR/LR is the ratio between the spatial resolution of the fused LST and the original one; N is the number of spectral bands (B_k) of the fused image; M_k is the mean value of each spectral band; and the RMSE calculated between the fused LST and the original one. The ideal value of the ERGAS index is 0 and remains satisfactory if it does not exceed 3 [\(Rodriguez-Galiano et al., 2012; Wald, 1999\)](#).

As an alternative to the RMSE, another index called the image quality index (Q) was developed [\(Prashanth et al., 2009\)](#). This index models any distortion between the original and fused images as a combination of three factors: loss of correlation, luminance distortion, and contrast distortion [\(Prashanth et al., 2009; Wang and Bovik, 2002\)](#). The Q index can be expressed as a product of three components [\(Wang and Bovik, 2002\)](#):

$$Q = \frac{\sigma_{OF}}{\sigma_O \sigma_F} \cdot \frac{2\overline{OF}}{(\overline{O})^2 + (\overline{F})^2} \cdot \frac{2\sigma_O \sigma_F}{\sigma_O^2 + \sigma_F^2} \quad (7)$$

Where $\overline{O}$ and $\overline{F}$ are the means of the original and the fused images; σ_O^2 and σ_F^2 are their variances; σ_{OF} is the covariance between the original image and the fused image. The first component in (Eq. (7)) measures the degree of linear correlation between the original and the fused images. The second component measures the mean luminance difference between O and F . While, the third component measures the contrast similarity between the original and the fused images [\(Wang and Bovik, 2002\)](#).

3.5.2. Cross-validation with LST from MODIS

The cross validation of retrieved LST is also performed based on independent observation as proposed by [\(Arabi Aliabad et al., 2021; Duan et al., 2018\)](#). The MODIS product (MOD11A1) acquired simultaneously on the same date was used as a reference. The validation was done on large homogenous areas of approximately 1 km² corresponding to the size of the MOD11A1. The cross-validation was performed by computing the deviation between the derived LST and the MOD11A1 for each tie point, the MAE and the RMSE for each of the farmland, forest, peri-urban and urban class as well as the global RMSE and MAE of the whole study area were also computed.

3.5.3. Overview of machine learning models for LST estimation

3.5.3.1. Linear regression. Linear regression is the most fundamental regression technique in order to establish a linear relationship between the dependent variable y and single or multiple independent variables x_i [\(Hastie et al., 2009; Schmidt, 2005\)](#). For a dataset (e. g., image of x^*x pixels) with $m = x^*x$ observations and n independent or predictor variables, the linear regression can be expressed as:

$$y_i = \beta_0 + \sum_{j=1}^n \beta_j x_{ij} + \varepsilon_i, i = 1, \dots, m$$

Where: y_i is the dependant variable for observation i ; x_{ij} represents the value of j^{th} independent variable for the i^{th} observation; β_0 is the intercept and β_j is the coefficient or the regression slope for the j^{th} independent variable; ε_i is the error term. The parameters $\beta_0, \beta_1, \dots$

β_n are estimated through minimizing the error function, typically the Residual Sum of Squares (RSS): $\min_{\beta} \sum_{i=1}^{n \times x} (y_i - \beta_0 - \sum_{j=1}^n \beta_j x_{ij})^2$. This approach, known as Ordinary Least Squares (OLS), can be optimized using gradient descent.

3.5.3.2. Polynomial Regression. Polynomial regression is an extension of the linear regression model, where higher-degree polynomial terms ($d \geq 2$) are added to introduce non-linearity while maintaining the foundational structure of linear models (Hastie et al., 2009; Schmidt, 2005). This approach enables the model to capture more complex relationships that a simple linear model cannot. Mathematically, it is expressed as:

$$y_i = \beta_0 + \sum_{j=1}^n \sum_{d=1}^D \beta_j x_{ij}^d + \varepsilon_i, i = 1, \dots, m$$

Where: y_i is the dependent variable for observation i ; x_{ij} represents the value of j^{th} independent variable for the i^{th} observation; β_0 is the intercept and β_j is the coefficient or the regression slope for the j^{th} independent variable; ε_i is the error term; D is the highest polynomial degree.

3.5.3.3. Lasso and ridge regression. Lasso and Ridge Regression are linear models (Hastie et al., 2009), that incorporates regularization techniques to reduce the risk of overfitting especially dealing with high-dimensional data or when the independent variable exhibits multicollinearity. Regularization helps by adding penalties terms preventing weights from becoming large and making model generalized in terms of estimation (Schmidt, 2005). Mathematically, both lasso and ridge regression can be expressed as linear model but differs in how the error function is formulated. For instance, for Lasso/Ridge linear regression, error function can be expressed as follows:

$$\min_{\beta} \sum_{i=1}^m \left(y_i - \beta_0 - \sum_{j=1}^n \beta_j x_{ij} \right)^2 + \lambda R(\beta)$$

Where λ controls the regularization strengths: For lasso (L1 Regularization) $R(\beta) = \sum_{j=1}^n |\beta_j|$ which is preferable for feature selection. In other words, effectively performing when irrelevant predictive features need removal. For Ridge (L2 Regularization) $R(\beta) = \sum_{j=1}^n \beta_j^2$ which is particularly useful when all independent variables contribute to the estimation of the Land Surface Temperature (LST) but multicollinearity exists among them. The L2 penalty shrinks all coefficients β_j toward zero while retaining all variables, effectively reducing the impact of multicollinearity without eliminating predictors.

3.5.3.4. Random Forest Regression. Random Forest is an ensemble learning method that builds multiple decision trees and aggregates their outputs to improve prediction accuracy and robustness (Hastie et al., 2009). It captures complex, non-linear relationships, handles high-dimensional data, and reduce multicollinearity among predictors (He et al., 2016; Hutengs and Vohland, 2016). Additionally, it can be a good alternative for overcoming overfitting issues commonly found in linear models (Legasa et al., 2022). By averaging predictions from many individual trees that are trained on different bootstrap samples of the training data and use only a random subset of the available predictors (Breiman, 2001). Mathematically, given a dataset with m observations and n features, Random Forest creates B independent decision trees. Each tree $T_b(X)$ is trained on a bootstrap sample, with predictions averaged for regression:

$$\hat{y}_i = \frac{1}{B} \sum_{b=1}^B T_b(X_i), X_i = (x_{i1}, x_{i2}, \dots, x_{in})$$

Where: $\hat{y}_i$ is the final predicted value at observation i ; B is the number of decision trees; $T_b(X_i)$ represent the prediction from the b -th tree.

3.5.4. Inter-comparison with machine learning models

To evaluate the accuracy and performance of the HRTF algorithm, five machine learning models were used for inter-comparison purposes. These are Random Forest Regression (RF) (Li et al., 2018; Wu and Li, 2019), Lasso Regression (L1R) (He et al., 2019; Ilghami Kkhosroshahi et al., 2023), Ridge Regression (L2R) (Agathangelidis and Cartalis, 2019a), Polynomial Regression (PR) (Kim et al., 2018; Zuo et al., 2019), and Linear Regression (LR) (Wang et al., 2020; Zhou et al., 2016) were selected due to their efficiency in handling complex relationships between input variables and output predictions (Panigrahi et al., 2023; Putri et al., 2023; Sharma et al., 2023). These set of machine learning algorithms have been widely used in remote sensing image classification and feature recognition (Jomthanachai et al., 2022; P. Wang et al., 2022; Yu et al., 2019), and have achieved high accuracy in spatial downscaling of LST (Agathangelidis and Cartalis, 2019b; Mukherjee et al., 2014; Wu and Li, 2019; Xu et al., 2021; Yang et al., 2019; Yoo et al., 2022).

These five machine learning models were used to predict the fine resolution of Brightness Temperature (BTs), which were subsequently used to estimate the LST with SWA. These estimated results BTs and LST were resampled to meet spatial resolution of Landsat-30m in order to enable consistent accuracy assessment with original data. Afterward, same accuracy metrics that were applied

for the developed model were used to compute the error and accuracy between original and predicted data (BTs and LST) at the pixel level across the whole scene.

4. Results analysis

4.1. Visual analysis

The visual comparison is an important phase of the analysis when implementing fusion methods as it allows immediate detection of chromatic distortions between the fused and the reference images. Figs. 5–8 confirm the contribution of the proposed method allowing a strong improvement of the spatial details of the merged thermal data compared to the original ones. Indeed, some details that are not detected by the original LST are properly identified and detected in the fused data. For instance, streets and most of the building blocks, and especially industrial zones, are well identified and delineated in the urban areas and are, generally, finer and brighter than the original LST images (Fig. 5).

In peripheral areas, we observe an important distinction of roads, vegetation, forest blocks (as is the case of forest blocks of the

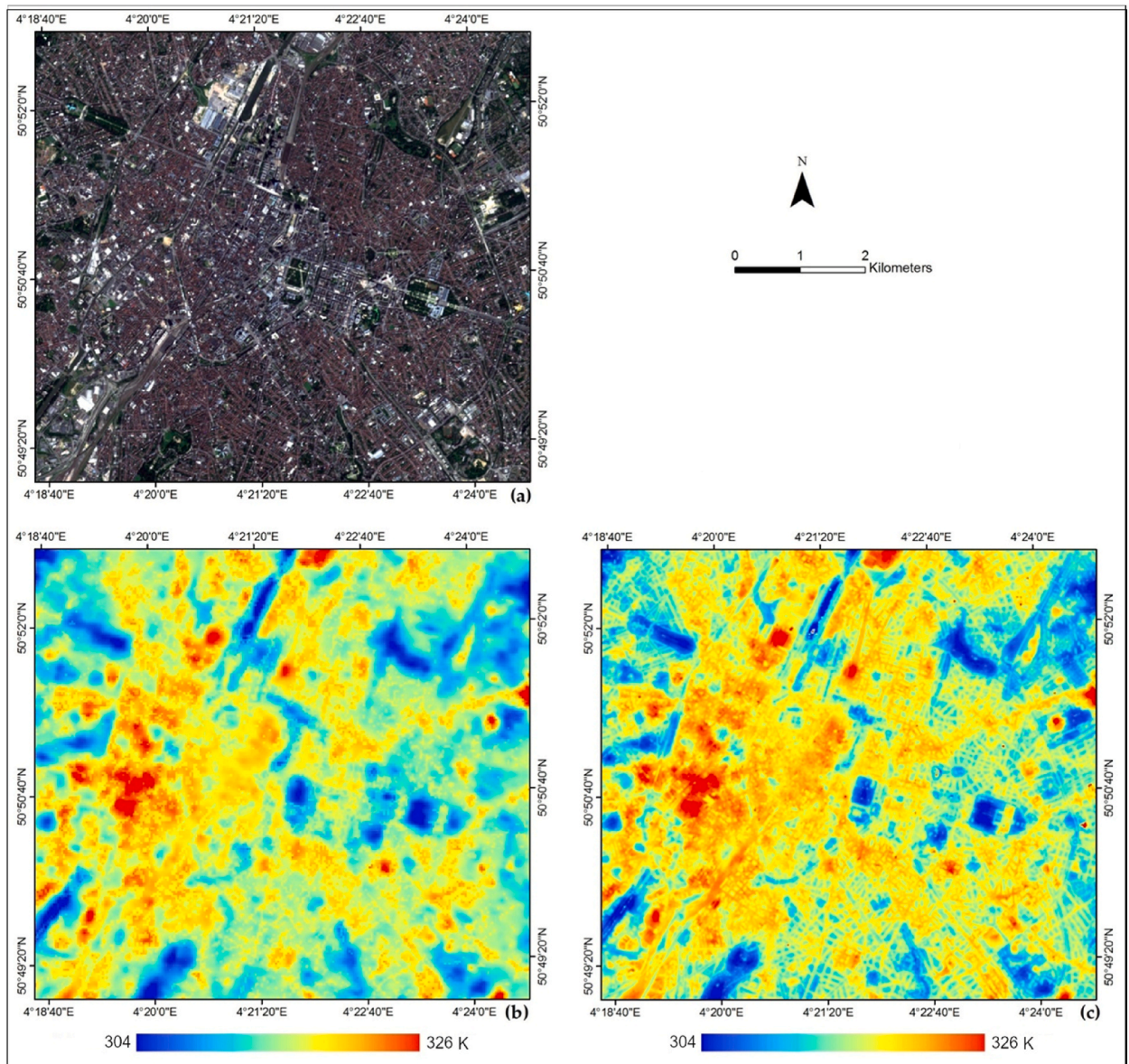


Fig. 5. Example of LST fusion in the center of Brussels city expressed in ° Kelvin: (a) true color of urban core of Brussels extracted from Sentinel-MSI bands; (b) original LST extracted from Landsat-OLI/TIRS (30-m); and (c) downscaled LST at 10-m.

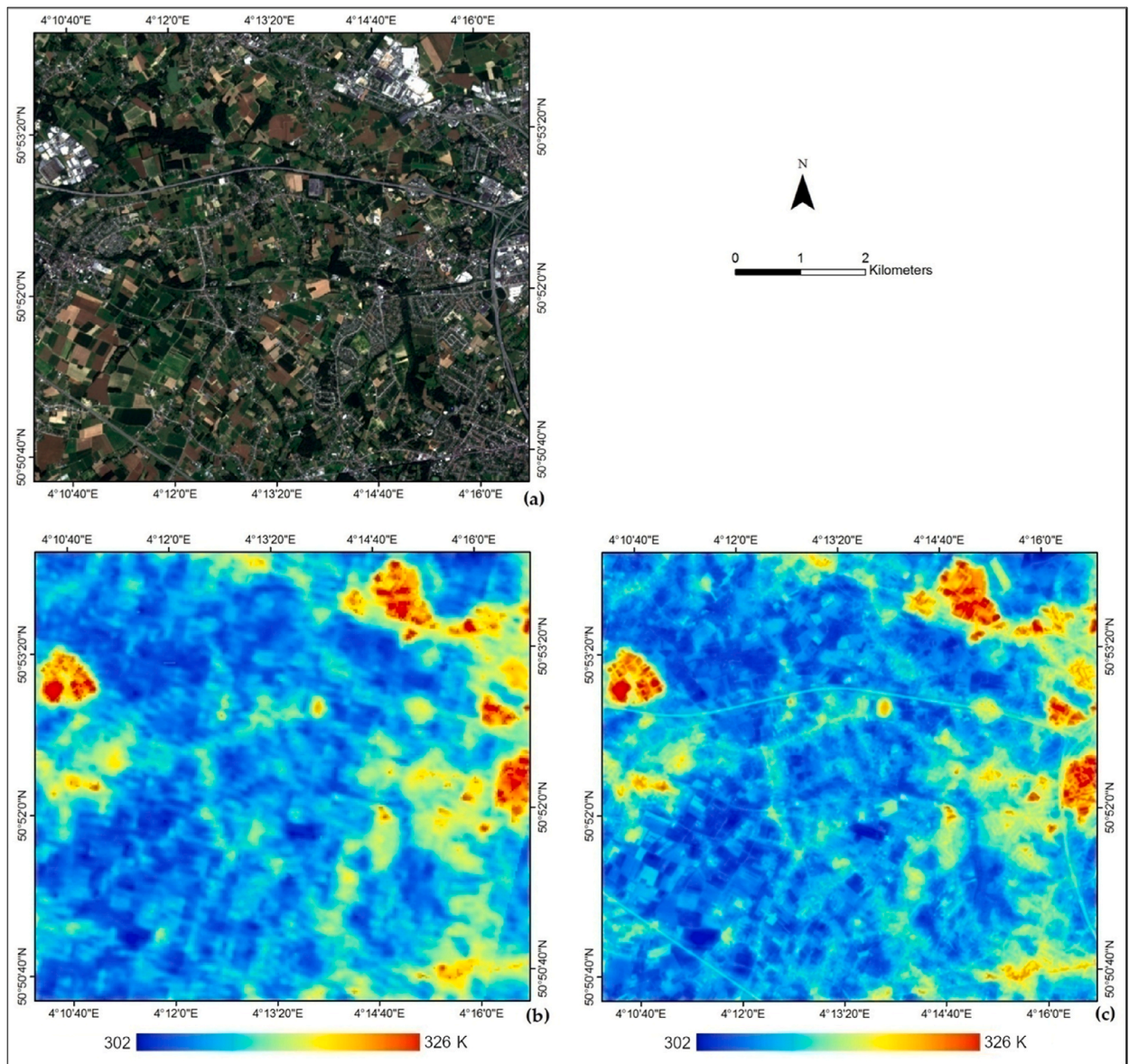


Fig. 6. Example of LST fusion in remote area of Brussels city expressed in ° Kelvin (Part of municipality of Ternat): (a) true color of remote areas of Brussels extracted from Sentinel-MSI bands; (b) original LST extracted from Landsat-OLI/TIRS at (30-m); and (c) downscaled LST at 10-m.

Sonian forest illustrated in Fig. 8) and the partial vegetation covers (Figs. 6 and 8). Around the airport, the proposed fusion approach allows sharper detection of the runway and significantly sharper definition of building structure (Fig. 7) masking the HRTF a better tool to delineate boundaries of different objects such as roads, buildings, vegetation, farmland, water bodies and forests.

The difference between the downscaled and the original LST (Fig. 9) shows a better accuracy in the rural areas compared to urban zones. The proposed approach highlighted most forests and vegetated areas with an error less than 0.5 K. While the building blocks remain the major class affected by error estimates that do not exceed 2.25 K with the presence of negligible pixels where the error values are less than 6 K.

We further examined the spatial distribution of the results obtained using the five machine learning models in order to compare them with the HRTF result over four typical areas in Brussels (Fig. 10). This comparison reveals interesting remarks. Across the urban core of the city, distant areas (Part of the municipality of Ternat), Brussels Airport and its surrounding areas, and the Sonian Forest, distinct differences emerged in the representation of landscape structures such as roads, vegetation, and forest blocks. On the one hand, the machine learning models provide suitable results in representing the spatial details of these areas. Conversely, the nuanced thermal anomalies in these areas are not well captured compared to the HRTF method. For example, 95 % of pixel values error between observed and predicted LST of Lasso Regression (L1R), Ridge Regression (L2R), Polynomial Regression (PR), and Linear Regression

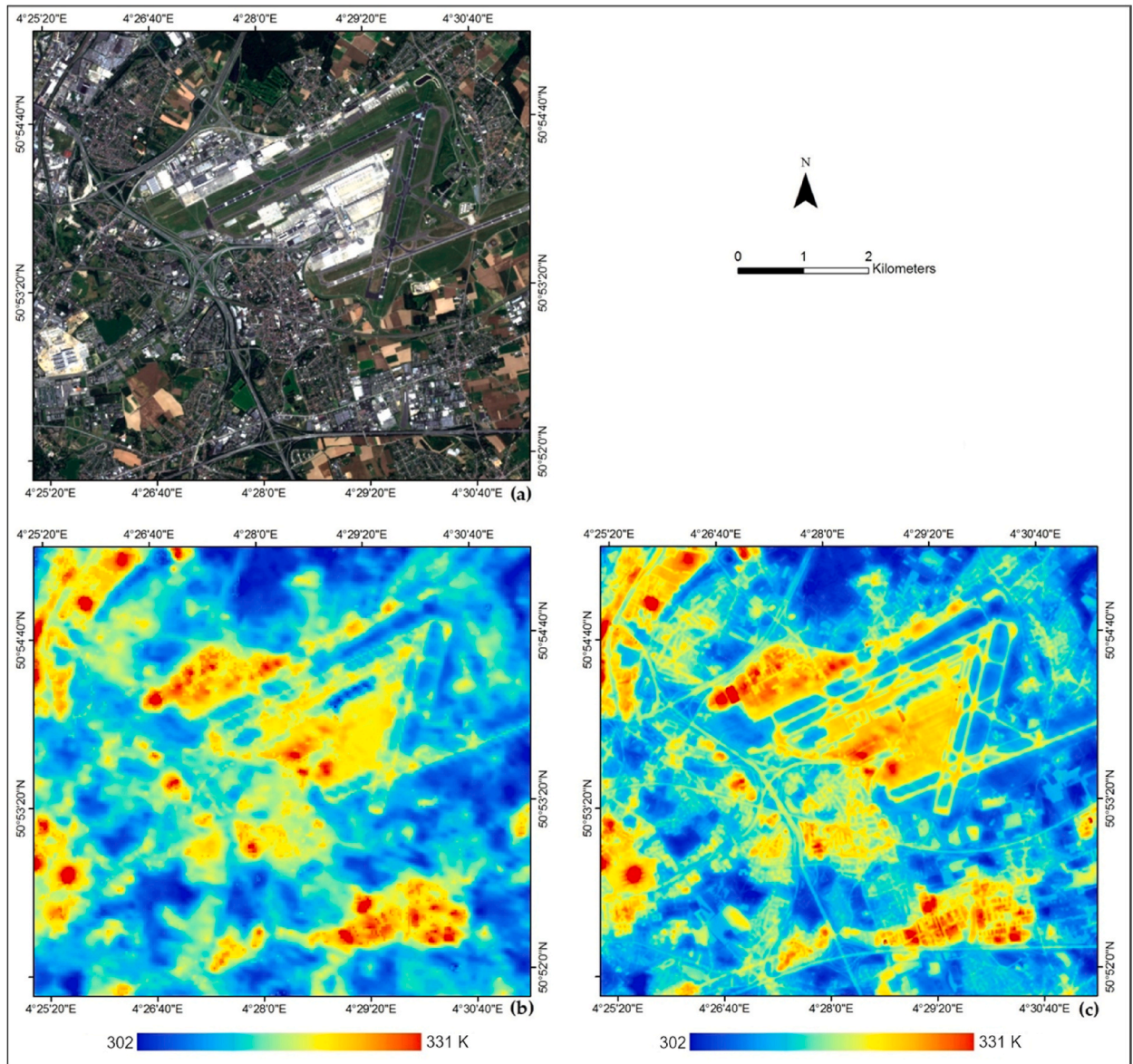


Fig. 7. Example of LST fusion in Brussels Airport and its surrounding areas expressed in ° Kelvin: (a) true color of the Brussels Airport and its surrounding areas extracted from Sentinel-MSI bands; (b) original LST extracted from Landsat-OLI/TIRS (30-m); and (c) downscaled LST at 10-m.

(LR) models was 3.38K. In contrast, the error of the remaining pixels has reached 21.1K, this includes the extreme temperature values, either unusually high or low (e.g. thermal anomalies). Regarding Random Forest Regression (RF) the 95 percentile error was 2.77K, and thermal anomalies exceeded 13.9K.

4.2. Statistical analysis

4.2.1. Statistical analysis

The derived LST map was evaluated using statistical analysis over the urban and the rural areas of Brussels based on the original Landsat-OLI/TIRS surface temperature. Five indices were calculated to evaluate the qualitative outcome, including CC, MAE, RMSE, ERGAS and Q. This evaluation was done considering the whole region spreading over 988-km² (Figs. 1 and 9) and including 6192 control points. The sample was designed to maximize the number of control points while ensuring they are evenly distributed across the study area. Including homogeneous areas, urban areas, peri-urban areas, agricultural zones, areas with thermal anomalies, and areas with fine spatial structure. Moreover to minimize potential biases in the evaluation process. The analysis was carried out for both the BT and the LST. The results are reported in Table 2 accompanied by scatter plots between the original and the fused data as

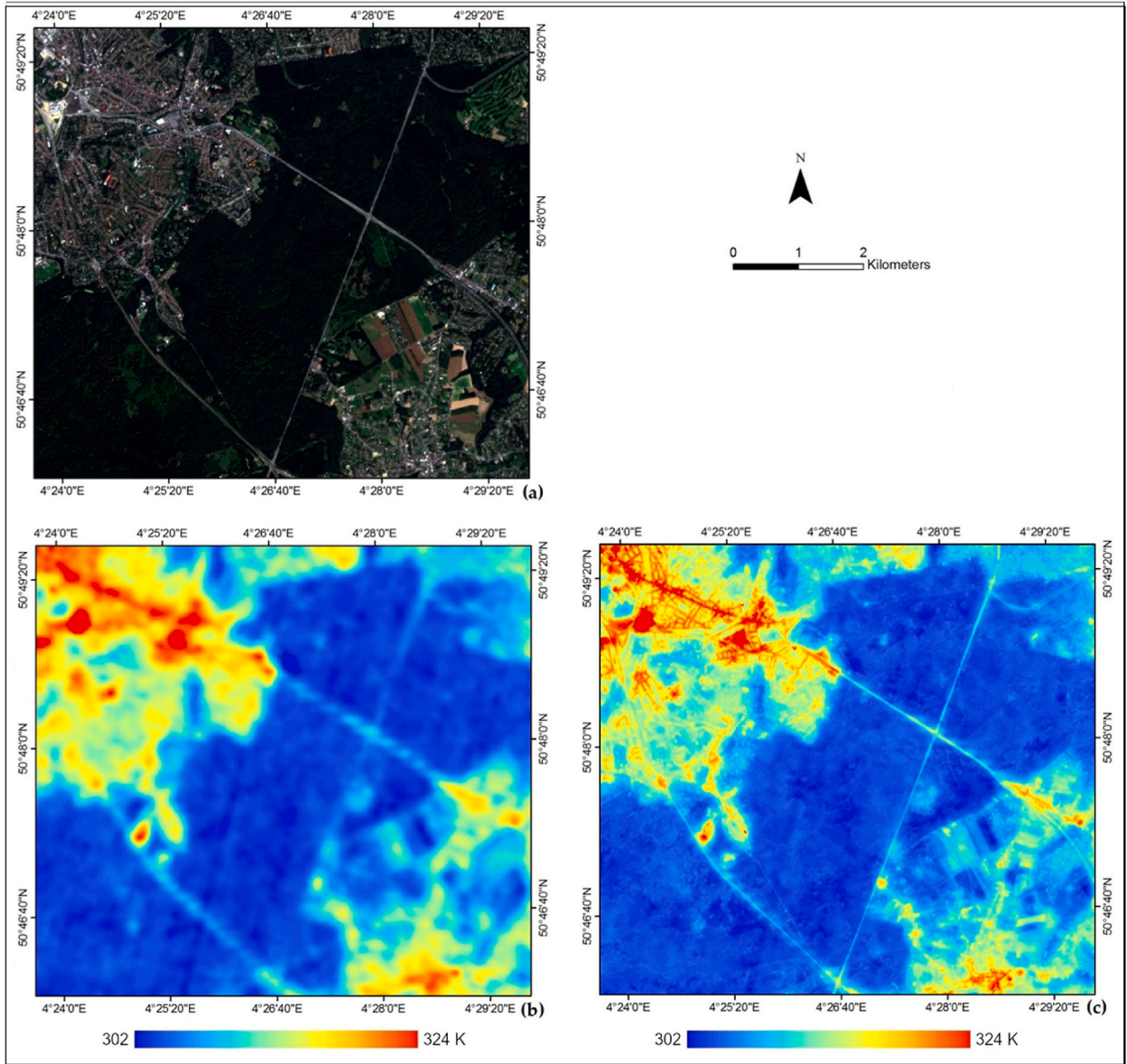


Fig. 8. Example of LST fusion in Sonian Wood (La forêt de Soignes), expressed in ° Kelvin, showing the forest blocks: (a) true color of the Sonian forest extracted from Sentinel-MSI bands; (b) original LST extracted from Landsat-OLI/TIRS (30-m); and (c) downscaled LST at 10-m.

illustrated in Fig. 11.

The results show that the downscaled data are highly correlated with the original images. The proposed approach resulted in downscaling the BT with an RMSE of 0.48 K, MAE of 0.37, and CC of 0.96 (Table 2). The results also show that the fused LST has an acceptable RMSE of 0.88K. The ERGAS index is close to its ideal value (0) indicating the fused data is of high quality. Finally, the Q index values suggest that the difference between the two monochromatic images is highly satisfactory.

The results confirm that the proposed approach captures the essence of the thermal structure when downscaling the BT from 30m to 10m spatial resolution achieving a very strong correlation coefficient of 97.4 % and showing a good linear fit to the 1:1 line suggesting quasi-proportionality. However, a slight overestimation of the fused LST is obtained compared to the original as shown by the 1:1 line (Fig. 11c). The strong correlation between the BT at the two resolutions suggests that the underlying physical processes (e.g., surface emissivity, vegetation cover, or soil moisture) are continuous and consistent across scales. However, atmospheric conditions (e.g., water vapor, aerosols) may vary with spatial resolution, leading to slight discrepancies in surface temperature estimates despite the strong correlation. Nevertheless, the proposed scaling algorithms does not seem to have introduced large errors, affecting the surface temperature estimates (Fig. 11c).

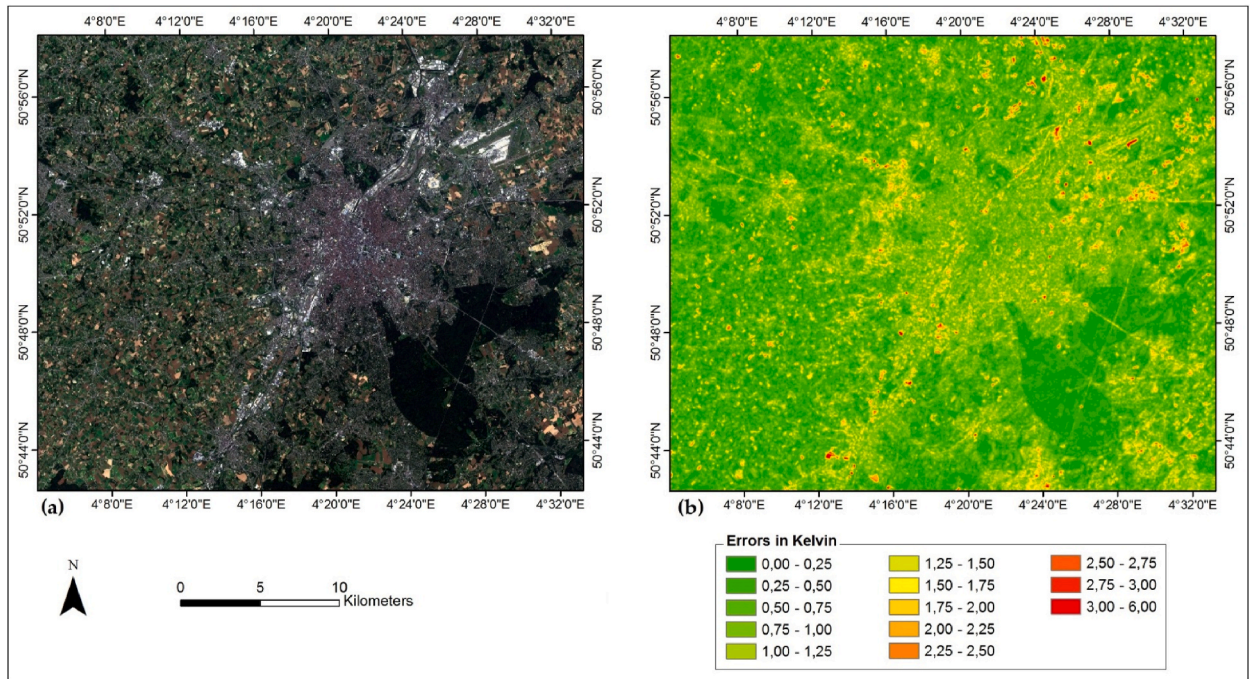


Fig. 9. Spatial distribution of fused LST errors: (a) true color of the study area, and (b) spatial distribution of errors through the same study area.

4.2.2. Statistical analysis with independent data

In order to verify the strength of the proposed algorithm, and considering the lack of LST in-situ measurements, a comparison was conducted between the fused LST and the MODIS product as proposed by [Arabi Aliabad et al. \(2021\)](#). To overcome the disparity in spatial resolution between the MODIS product and the downscaled LST, we focused on homogeneous surfaces that extend over an area of about 1 km² or those including more than 80 % of a MODIS 1kmx1km pixel. [Table 3](#) shows the cross-validation using the MOD11A1 as reference, while [Table A.1](#) in the appendix illustrates the LST estimation errors between the downscaled LST and that extracted from MOD11A1 at the level of each tie point respecting the aforementioned condition with related geographic coordinates, pixel class, LST values of downscales LST and those of MODIS as well as the quality control of MODIS pixel.

The statistical analyses obtained from the results of the cross-validation procedure based on MODIS observations show that the most accurate class is forest with an RMSE of 0.85 K, followed by farmland and suburban areas. While a significant increase in errors is observed in the urban core with a MAE of 2.24 K and an RMSE of approximately 2.77 K. This increased error can be caused by the moderate quality of MODIS LST in the urban core which is affected by an average error better than 2 K ([Table A.1 and A.2](#) in the Appendix).

[Fig. 12](#) shows some overestimation of the high resolution LST compared to MOD11A1 and similar to that shown in [Fig. 11c](#). Again, the cause may reside in atmospheric conditions at different scales. On the other hand, if we consider only rural areas covered mainly by dense vegetation, farmlands and forest trees, which represent a good LST quality (QC = 0), an MAE of 1.13 K and an RMSE of 1.48 K was achieved when cross-validated against MOD11A1. Overall a strong correlation exists between the data as evidenced by the R-square of 0.84.

4.2.3. Statistical analysis with machine learning models

[Table 4](#) shows the error metrics (CC, MAE, RMSE, ERGAS, and Q) between the downscaled images using the five machine learning models and the original images over the city of Brussels. The results demonstrate that the Polynomial, Lasso, and Ridge models were performing similarly for the given dataset and parameters (BT10, BT11, and LST). These models outperform the linear model, however, the Random Forest Model showed better performance for the three parameters, with the highest CC, lower RMSE and MAE, and an ERGAS index of 0.155, indicating high-quality of the downscaled images. The Q index for the LST of the Random Forest model was 0.902, which reflects a high similarity between the predicted and the original data.

However, the proposed approach significantly outperforms the five machine learning models across all metrics. The HRTF algorithm achieves higher Correlation Coefficient (CC) values, with 0.974 for BT10 and BT11 and 0.966 for LST, indicating better predictive accuracy than the best-performing ML model (Random Forest model). Overall, the HRTF method provided more accurate and better results of the downscaled LST.

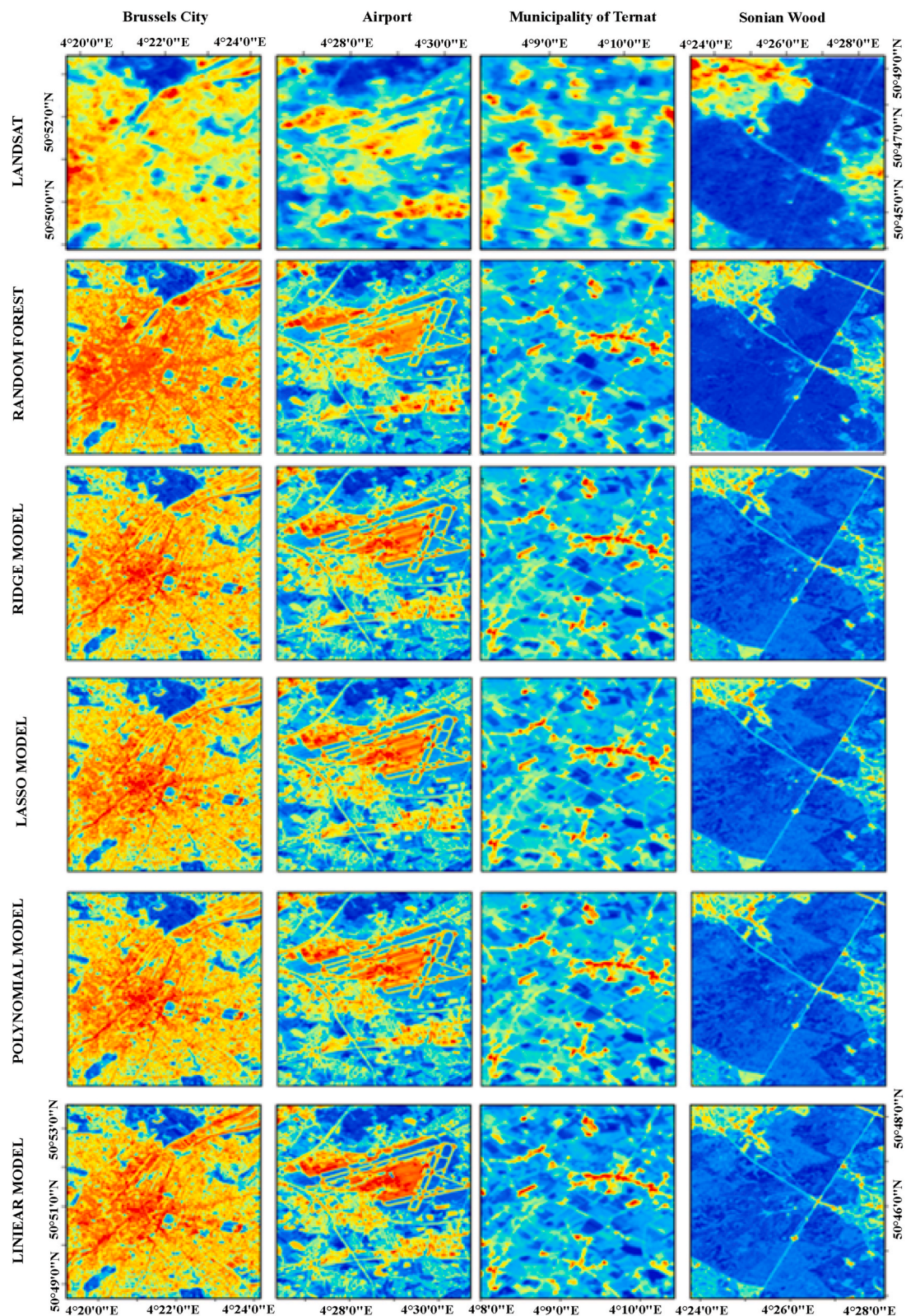


Fig. 10. The downscaled LSTs using the five machine learning models and the original LST extracted from Landsat-OLI/TIRS over four typical areas in Brussels city.

Table 2

Statistic parameters of the inter-comparison between downscaled and original data (BT: brightness temperature; LST: Land Surface Temperature; N: number of control points).

Indices	CC	MAE (K)	RMSE (K)	ERGAS	Q
BT10	0.974	0.371	0.480	0.018	0.971
BT11	0.974	0.331	0.426	0.016	0.971
LST	0.966	0.667	0.876	0.095	0.961
(N)	6192				
Covered surface	988.58 Km ²				

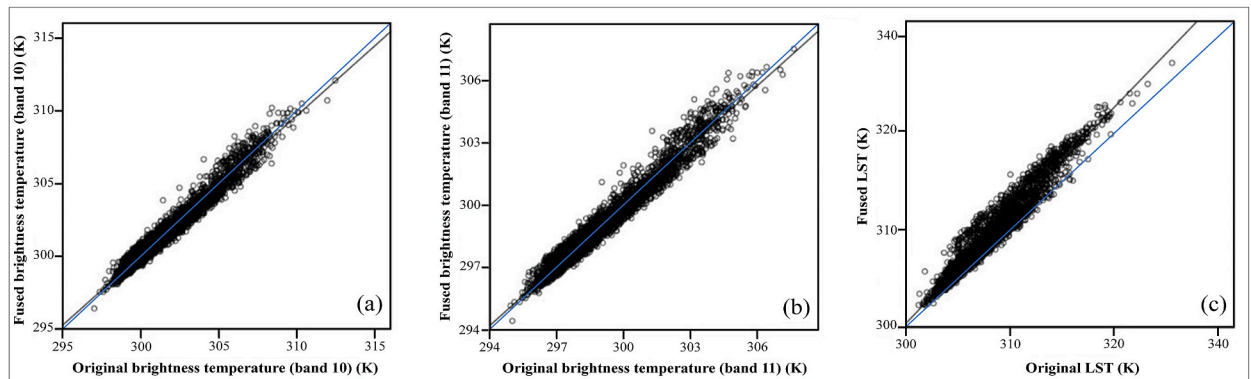


Fig. 11. Scatter plots of the downscaled versus the original data: for (a) original and downscaled BT of band 10; (b) original and downscaled BT of band 11; and (c) original and downscaled LST.

Table 3

Validation of downscaled LST extracted from the HRTF method using the MOD11A1 product as reference.

Classes	MAE (K)	RMSE (K)
Farmland	1.06	1.25
Forest	0.63	0.85
Peri-urban	1.22	1.40
Urban	2.24	2.77

MAE = 1.43 K RMSE = 1.92 K (for the whole classes' selected tie points).

5. Discussion

According to several studies (Rodriguez-Galiano et al., 2012; Stathopoulou and Cartalis, 2009; Dominguez et al., 2011b), the conventional fusion methods consist of applying the downscaling technique directly to the LST. The proposed approach is innovative and advantageous especially when applied to heterogeneous surfaces spreading over important extents and allowing the enhancement of the spatial details of the original LST with an excellent RMSE, less than 0.88K. The results obtained from this fusion method are promising compared to other methods in terms of spatial resolution and accuracy.

One of the main challenges in the present research is the lack of in-situ measurement for LST validation which was similarly presented in Pu and Bonafoni (2023a) and Dong et al. (2020). In addition, Pu and Bonafoni (2023b) highlight the issue related to field LST measurements that do not precisely describe the spatial distribution pattern of a large heterogeneous area at the pixel level. To address this, two cross-validation techniques of the downscaled LST from HRTF model were employed across both urban and rural areas of Brussels; firstly, comparative analysis with the original LST data from Landsat-OLI/TIRS (Bonafoni, 2016; Dong et al., 2020); secondly, with independent data from the MODIS temperature sensor product (Arabi Aliabad et al., 2021; Dong et al., 2020; Li et al., 2018; Zhang et al., 2019). It is important to note that the broad swath width of MODIS (2330 km), could lead to significant temporal inconsistencies across large study areas (Li et al., 2023, 2024). According to Li et al. (2023), the swath width of MODIS can result in more than a 1-h difference in local solar time from West to East. However, the present research focuses on Brussels City and its outskirts with a width of 31.42 Km which is relatively small compared to the 2330 km swath width of MODIS. Therefore, the impact of such temporal differences on LST measurements would possibly be negligible. In view of that, the MODIS data provides a reliable cross-validation for evaluating the accuracy of downscaled LST.

Concerning the validation with the original LST, the latter was retrieved using the Split Window Algorithm, which offers accuracy in the neighborhood of 1 K and an RMSE of about 1.025 K (Yu et al., 2014). Therefore, we can conclude that the HRTF method allows

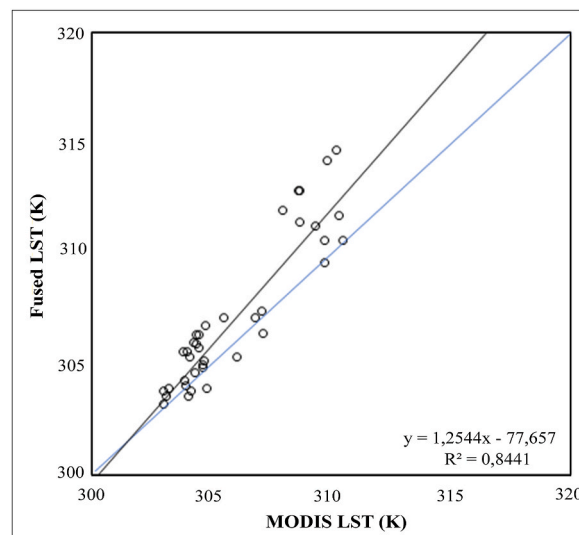


Fig. 12. Scatter plots of the MODIS LST versus downscaled LST.

Table 4

Statistic parameters of the five machine learning models (BT: Brightness Temperature, LST: Land Surface Temperature).

City	Brussels					
Model	Indices	CC	MAE (K)	RMSE (K)	ERGAS	Q
Linear Model	BT10	0.798	1.125	1.477	0.163	0.770
	BT11	0.780	1.062	1.374	0.153	0.748
	LST	0.778	1.674	2.222	0.240	0.766
Polynomial Model	BT10	0.824	1.062	1.389	0.153	0.802
	BT11	0.806	1.008	1.300	0.145	0.780
	LST	0.800	1.605	2.125	0.229	0.790
Lasso Model	BT10	0.824	1.062	1.389	0.153	0.802
	BT11	0.806	1.009	1.300	0.145	0.779
	LST	0.800	1.605	2.125	0.229	0.790
Ridge Model	BT10	0.824	1.062	1.389	0.153	0.802
	BT11	0.806	1.008	1.300	0.145	0.780
	LST	0.800	1.605	2.125	0.229	0.790
Random Forest Model	BT10	0.963	0.479	0.678	0.075	0.958
	BT11	0.950	0.412	0.642	0.071	0.951
	LST	0.910	1.097	1.440	0.155	0.902

us to retrieve precise information about the LST at 10-m spatial resolution with an approximate accuracy of about 1.905 K (1.025 + 0.88). Moreover, the result obtained from the validation with MODIS, as reported in Table 3, confirms the credibility and the reliability of this accuracy (1.905 k) since it shows an RMSE of about 1.92 K, close to that obtained previously (1.905 K), which is evidence of the performance of the proposed model.

Furthermore, as an additional evaluation this research has used five machine learning models of downscaling to compare and evaluate the accuracy and performance of the HRTF technique. The HRTF approach demonstrates better results in LST downscaling for the city of Brussels compared to the five machine learning models. Therefore, the proposed HRTF approach is highly recommended for the LST downscaling to the finer spatial resolution. It can be used to detect more spatial details in a wide range of applications, such as: surface urban heat island, thermal discomfort, health, heat-related death, soil moisture (Bannari et al., 2020), agriculture or urban microclimate monitoring.

6. Conclusions

Many research studies require high resolution data of land surface temperatures which is not readily available over long period of time. In this paper, we propose a new approach to downscale LST to 10-m spatial resolution based on Sentinel-MSI images. This approach differs from previous studies by the fact that the downscaling is done as a first step on the brightness temperature which conserves the continuity of the landscape, then atmospheric corrections based on the downscaled BT, atmospheric water vapor

content, and land surface emissivity is performed. This method has been tested in heterogeneous surfaces (including rural, urban, water, airport, roads, and forest cover) over the city of Brussels. Both the fused BT and LST were evaluated and verified using visual comparison and statistical metrics. The downscaled results generated with this method reached high spatial accuracy compared to the original data extracted from OLI/TIRS with an RMSE ranging from 0.63 to 0.88 K for LST, and less than 0.37K for BT. The cross-validation of the results using independent products, such as MOD11A1, shows an acceptable RMSE of 1.92 K. Comparison of the results with those obtained from machine learning models, shows better accuracy across all statistical metrics. Results obtained using this method are promising as they are able to capture the spatial details such as roads and buildings. It also shows the potential to create harmonization between high and medium spatial and spectral resolution data such as Sentinel-MSI data and Landsat-OLI/TIRS and provide an opportunity to use the Landsat data long series of observation and perform retrospective analysis. Finally, outputs from the proposed method can be used as input in several applications in the environmental field.

CRedit authorship contribution statement

Hicham Bahi: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lahouari Bounoua:** Writing – review & editing, Investigation, Conceptualization. **Anas Sabri:** Writing – review & editing, Methodology. **Abderrazak Bannari:** Writing – review & editing. **Anass Malah:** Writing – review & editing. **Hassan Rhinane:** Writing – review & editing.

Ethical statement

- 1) This material is the authors' own original work, which has not been previously published elsewhere.
- 2) The paper is not currently being considered for publication elsewhere.
- 3) The paper reflects the authors' own research and analysis in a truthful and complete manner.
- 4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
- 5) The results are appropriately placed in the context of prior and existing research.
- 6) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference.
- 7) All authors have been personally and actively involved in substantial work leading to the paper and will take public responsibility for its content.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.rsase.2025.101519>.

Data availability

The authors do not have permission to share data.

References

- Agathangelidis, I., Cartalis, C., 2019a. Improving the disaggregation of MODIS land surface temperatures in an urban environment: a statistical downscaling approach using high-resolution emissivity. *Int. J. Rem. Sens.* 40, 5261–5286. <https://doi.org/10.1080/01431161.2019.1579386>.
- Agathangelidis, I., Cartalis, C., 2019b. Improving the disaggregation of MODIS land surface temperatures in an urban environment: a statistical downscaling approach using high-resolution emissivity. *Int. J. Rem. Sens.* 40, 5261–5286. <https://doi.org/10.1080/01431161.2019.1579386>.
- Ahmed, S., 2018. Assessment of urban heat islands and impact of climate change on socioeconomic over Suez Governorate using remote sensing and GIS techniques. *Egypt. J. Remote Sens. Space Sci.* 21, 15–25. <https://doi.org/10.1016/j.ejrs.2017.08.001>.
- Alparone, L., Baronti, S., Garzelli, A., Nencini, F., 2004. Landsat ETM+ and SAR image fusion based on generalized intensity Modulation. *IEEE Trans. Geosci. Rem. Sens.* 42, 2832–2839. <https://doi.org/10.1109/TGRS.2004.838344>.
- Amaripadath, D., Attia, S., 2023. Performance dataset on a nearly zero-energy office building in temperate oceanic climate based on field measurements. *Data Brief* 48, 109217. <https://doi.org/10.1016/j.dib.2023.109217>.
- Arabi Aliabad, F., Zare, M., Ghafarian Malamiri, H., 2021. Comparison of the accuracy of daytime land surface temperature retrieval methods using Landsat 8 images in arid regions. *Infrared Phys. Technol.* 115, 103692. <https://doi.org/10.1016/j.infrared.2021.103692>.
- Bahi, H., Rhinane, H., Bensalmia, A., Fehrenbach, U., Scherer, D., 2016. Effects of urbanization and seasonal cycle on the surface urban heat island patterns in the coastal growing cities: a case study of casablanca, Morocco. *Remote Sens.* 8, 829. <https://doi.org/10.3390/rs8100829>.
- Bahi, H., Rhinane, H., Bensalmia, A., Fehrenbach, U., Scherer, D., et al., 2017. Reply to lofgren, B.M.: comment on Hicham Bahi effects of urbanization and seasonal cycle on the surface urban heat island patterns in the coastal growing cities: ACase study of casablanca, Morocco. *Remote Sens.* 9, 115. <https://doi.org/10.3390/rs9020115>. *Remote Sens.* 2016, 8, 829.

- Bahi, H., Radoine, H., Mastouri, H., 2019a. Spatio-temporal evaluation of urban thermal environment using smart spatial data. In: 2019 7th International Renewable and Sustainable Energy Conference (IRSEC). Presented at the 2019 7th International Renewable and Sustainable Energy Conference (IRSEC), pp. 1–6. <https://doi.org/10.1109/IRSEC48032.2019.9078272>. IEEE, Agadir, Morocco.
- Bahi, H., Radoine, H., Mastouri, H., 2019b. Urban heat island: state of the art. In: 2019 7th International Renewable and Sustainable Energy Conference (IRSEC). Presented at the 2019 7th International Renewable and Sustainable Energy Conference (IRSEC), pp. 1–7. <https://doi.org/10.1109/IRSEC48032.2019.9078329>. IEEE, Agadir, Morocco.
- Bahi, H., Radoine, H., Mastouri, H., 2019c. Spatio-temporal evaluation of urban thermal environment using smart spatial data. In: 2019 7th International Renewable and Sustainable Energy Conference (IRSEC). Presented at the 2019 7th International Renewable and Sustainable Energy Conference (IRSEC), pp. 1–6. <https://doi.org/10.1109/IRSEC48032.2019.9078272>. IEEE, Agadir, Morocco.
- Baillarin, S.J., Meygret, A., Dechoz, C., Petrucci, B., Lacherade, S., Tremas, T., Isola, C., Martimort, P., Spoto, F., 2012. Sentinel-2 level 1 products and image processing performances. IEEE 7003–7006. <https://doi.org/10.1109/IGARSS.2012.6351959>.
- Bannari, A., Bahi, H., Rhinane, H., 2020. Evaluating land surface moisture conditions before and after flash-flood storm from optical and thermal data: models comparison and validation. In: IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium. Presented at the IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium, pp. 5038–5041. <https://doi.org/10.1109/IGARSS39084.2020.9323655>. IEEE, Waikoloa, HI, USA.
- Beck, H.E., Zimmermann, N.E., McVicar, T.R., Vergopolan, N., Berg, A., Wood, E.F., 2018. Present and future Köppen-Geiger climate classification maps at 1-km resolution. Sci. Data 5, 180214. <https://doi.org/10.1038/sdata.2018.214>.
- Bonafoni, S., 2016. Downscaling of Landsat and MODIS land surface temperature over the heterogeneous urban area of milan. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 9, 2019–2027. <https://doi.org/10.1109/JSTARS.2016.2514367>.
- Bonafoni, S., Tosi, G., 2017. Downscaling of land surface temperature using airborne high-resolution data: a case study on aprilia, Italy. Geosci. Rem. Sens. Lett. IEEE 14, 107–111. <https://doi.org/10.1109/LGRS.2016.2630798>.
- Bounoua, L., Bachir, N., Souidi, H., Bahi, H., Lagmiri, S., Khebeza, M.Y., Nigro, J., Thome, K., 2023. Sustainable development in Algeria's urban areas: population growth and land consumption. Urban Science 7, 29. <https://doi.org/10.3390/urbansci7010029>.
- Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32. <https://doi.org/10.1023/A:1010933404324>.
- Bruffaerts, N., De Smedt, T., Delcloc, A., Simons, K., Hoebeke, L., Verstraeten, C., Van Nieuwenhuysse, A., Packeu, A., Hendrickx, M., 2018. Comparative long-term trend analysis of daily weather conditions with daily pollen concentrations in Brussels, Belgium. Int. J. Biometeorol. 62, 483–491. <https://doi.org/10.1007/s00484-017-1457-3>.
- Carlson, T.N., Ripley, D.A., 1997. On the relation between NDVI, fractional vegetation cover, and leaf area index. Rem. Sens. Environ. 62, 241–252. [https://doi.org/10.1016/S0034-4257\(97\)00104-1](https://doi.org/10.1016/S0034-4257(97)00104-1).
- Chen, Z., Zhang, Y., 2022. Quantitative identification of temporal-spatial variations of urban heat island (UHI) effects in changchun, China. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 15, 3052–3060. <https://doi.org/10.1109/JSTARS.2022.3167831>.
- Dissanayake, K., Kurugama, K., Ruwanthi, C., 2020. Ecological evaluation of urban heat island effect in colombo city, Sri Lanka based on Landsat 8 satellite data. In: 2020 Moratuwa Engineering Research Conference (MERCon). Presented at the 2020 Moratuwa Engineering Research Conference (MERCon), pp. 531–536. <https://doi.org/10.1109/MERCon50084.2020.9185277>.
- Dominguez, A., Kleissl, J., Luvall, J.C., Rickman, D.L., 2011a. High-resolution urban thermal sharpener (HUTS). Rem. Sens. Environ. 115, 1772–1780. <https://doi.org/10.1016/j.rse.2011.03.008>.
- Dominguez, A., Kleissl, J., Luvall, J.C., Rickman, D.L., 2011b. High-resolution urban thermal sharpener (HUTS). Rem. Sens. Environ. 115, 1772–1780. <https://doi.org/10.1016/j.rse.2011.03.008>.
- Dong, P., Gao, L., Zhan, W., Liu, Z., Li, J., Lai, J., Li, H., Huang, F., Tamang, S.K., Zhao, L., 2020. Global comparison of diverse scaling factors and regression models for downscaling Landsat-8 thermal data. ISPRS J. Photogrammetry Remote Sens. 169, 44–56. <https://doi.org/10.1016/j.isprsjprs.2020.08.018>.
- Du, C., Ren, H., Qin, Q., Meng, J., Zhao, S., 2015. A practical split-window algorithm for estimating land surface temperature from Landsat 8 data. Remote Sens. 7, 647–665. <https://doi.org/10.3390/rs70100647>.
- Duan, S.-B., Li, Z.-L., Wu, H., Leng, P., Gao, M., Wang, C., 2018. Radiance-based validation of land surface temperature products derived from Collection 6 MODIS thermal infrared data. Int. J. Appl. Earth Obs. Geoinf. 70, 84–92. <https://doi.org/10.1016/j.jag.2018.04.006>.
- El Ghazouani, L., Bounoua, L., Nigro, J., Mansour, M., Radoine, H., Souidi, H., 2021. Combining satellite data and spatial analysis to assess the UHI amplitude and structure within urban areas: the case of Moroccan cities. Urban Science 5, 67. <https://doi.org/10.3390/urbansci5030067>.
- Eleftheriou, D., Kiachidis, K., Kalmintzis, G., Kalea, A., Bantasis, C., Koumadoraki, P., Spathara, M.E., Tsolaki, A., Tzampazidou, M.I., Gemitzi, A., 2018. Determination of annual and seasonal daytime and nighttime trends of MODIS LST over Greece - climate change implications. Sci. Total Environ. 616–617, 937–947. <https://doi.org/10.1016/j.scitotenv.2017.10.226>.
- Hemati, M., Hasanlou, M., Mahdianpari, M., Mohammadimanesh, F., 2021. A systematic review of landsat data for change detection applications: 50 years of monitoring the earth. Remote Sens 13 (15), 2869–2902. <https://doi.org/10.3390/rs13152869>.
- Empirical cross sensor comparison of Sentinel-2A and 2B MSI, Landsat-8 OLI, and Landsat-7 ETM+ top of atmosphere spectral characteristics over the conterminous United States - ScienceDirect [WWW Document], n.d. URL <https://www.sciencedirect.com/science/article/pii/S0034425718305212> (accessed 7.24.24).
- Fricke, R., Wolff, E., 2002. The MURBANDY Project: development of land use and network databases for the Brussels area (Belgium) using remote sensing and aerial photography. Int. J. Appl. Earth Obs. Geoinf. 4, 33–50. [https://doi.org/10.1016/S0303-2434\(02\)00010-7](https://doi.org/10.1016/S0303-2434(02)00010-7).
- Gao, F., Kustas, W., Anderson, M., 2012. A data mining approach for sharpening thermal satellite imagery over land. Remote Sens. 4, 3287–3319. <https://doi.org/10.3390/rs4113287>.
- García-Santos, V., Cuxart, J., Martínez-Villagrana, D., Jiménez, M., Simó, G., 2018. Comparison of three methods for estimating land surface temperature from Landsat 8-TIRS sensor data. Remote Sens. 10, 1450. <https://doi.org/10.3390/rs10091450>.
- Hastie, T., Tibshirani, R., Friedman, J., 2009. The Elements of Statistical Learning. Springer Series in Statistics. Springer, New York, NY. <https://doi.org/10.1007/978-0-387-84858-7>.
- He, X., Chaney, N.W., Schleiss, M., Sheffield, J., 2016. Spatial downscaling of precipitation using adaptable random forests. Water Resour. Res. 52, 8217–8237. <https://doi.org/10.1002/2016WR019034>.
- He, R.-R., Chen, Y., Huang, Q., Kang, Y., 2019. LASSO as a tool for downscaling summer rainfall over the Yangtze River Valley. Hydrol. Sci. J. 64, 92–104. <https://doi.org/10.1080/02626667.2019.1570210>.
- Hutengs, C., Vohland, M., 2016. Downscaling land surface temperatures at regional scales with random forest regression. Rem. Sens. Environ. 178, 127–141. <https://doi.org/10.1016/j.rse.2016.03.006>.
- Ilghami Kkshosroshahi, A., Bejani, M., Pourali, H., Hosseinpour Salehi, A., 2023. Comparing regression techniques for temperature downscaling in different climate classifications. Eng. Proc. 56, 291. <https://doi.org/10.3390/ASEC2023-15256>.
- Immitzer, M., Vuolo, F., Atzberger, C., 2016. First experience with sentinel-2 data for crop and tree species classifications in central europe. Remote Sens. 8, 166. <https://doi.org/10.3390/rs8030166>.
- Irons, J.R., Dwyer, J.L., Barsi, J.A., 2012. The next Landsat satellite: the Landsat data continuity mission. Rem. Sens. Environ. 122, 11–21. <https://doi.org/10.1016/j.rse.2011.08.026>.
- Jiang, W., Yan, Y., Zhang, F., Wang, H., 2011. Image fusion based on modulation method with resolution degradation and interpolation. IEEE 1–6. <https://doi.org/10.1109/GeoInformatics.2011.5980849>.
- Jin, M., Dickinson, R.E., Zhang, D., 2005. The footprint of urban areas on global climate as characterized by MODIS. J. Clim. 18 (1), 1551–1565. <https://doi.org/10.1175/JCLI3334>.
- Jomthanachai, S., Wong, W.P., Khaw, K.W., 2022. An application of machine learning regression to feature selection: a study of logistics performance and economic attribute. Neural Comput. Appl. 34, 15781–15805. <https://doi.org/10.1007/s00521-022-07266-6>.

- Jung, H.-S., Park, S.-W., 2014. Multi-sensor fusion of Landsat 8 thermal infrared (TIR) and panchromatic (PAN) images. *Sensors* 14, 24425–24440. <https://doi.org/10.3390/s141224425>.
- Kim, D., Moon, H., Kim, H., Im, J., Choi, M., 2018. Intercomparison of downscaling techniques for satellite soil moisture products. *Adv. Meteorol.* 2018, 4832423. <https://doi.org/10.1155/2018/4832423>.
- Kulsum, U., Moniruzzaman, M., 2022. Exploring the relationship of climate change and land-use dynamics with satellite-derived surface indices and temperature in greater Dhaka, Bangladesh. *J. Earth Syst. Sci.* 131, 117. <https://doi.org/10.1007/s12040-022-01841-0>.
- Legasa, M.N., Manzanar, R., Calvino, A., Gutiérrez, J.M., 2022. A posteriori random forests for stochastic downscaling of precipitation by predicting probability distributions. *Water Resour. Res.* 58, e2021WR030272. <https://doi.org/10.1029/2021WR030272>.
- Li, S., Jiang, G.-M., 2018. Land surface temperature retrieval from landsat-8 data with the generalized split-window algorithm. *IEEE Access* 6, 18149–18162. <https://doi.org/10.1109/ACCESS.2018.2818741>.
- Li, X., Li, W., Middel, A., Harlan, S.L., Brazel, A.J., Turner, B.L., 2016. Remote sensing of the surface urban heat island and land architecture in Phoenix, Arizona: combined effects of land composition and configuration and cadastral-demographic-economic factors. *Rem. Sens. Environ.* 174, 233–243. <https://doi.org/10.1016/j.rse.2015.12.022>.
- Li, W., Ni, L., Li, Z.-L., Wu, H., 2018. Downscaling land surface temperature by using random forest regression algorithm. In: *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*. Presented at the IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium, pp. 2527–2530. <https://doi.org/10.1109/IGARSS.2018.8518393>.
- Li, R., Li, H., Hu, T., Bian, Z., Liu, F., Cao, B., Du, Y., Sun, L., Liu, Q., 2023. Land surface temperature retrieval from sentinel-3A SLSTR data: comparison among split-window, dual-window, three-channel, and dual-angle algorithms. *IEEE Trans. Geosci. Rem. Sens.* 61, 1–14. <https://doi.org/10.1109/TGRS.2023.3288584>.
- Li, Z.-L., Wu, H., Duan, S.-B., Zhao, W., Ren, H., Liu, X., Leng, P., Tang, R., Ye, X., Zhu, J., Sun, Y., Si, M., Liu, M., Li, J., Zhang, X., Shang, G., Tang, B.-H., Yan, G., Zhou, C., 2023. Satellite remote sensing of global land surface temperature: definition, methods, products, and applications. *Rev. Geophys.* 61, e2022RG000777. <https://doi.org/10.1029/2022RG000777>.
- Li, Z.-L., Liu, X., Zhao, E., Si, M., Gao, C., Wu, H., Ren, H., Duan, S.-B., Tang, R., Tang, B.-H., Leng, P., Liu, M., Yan, G., Sobrino, J.A., Zhao, W., 2024. Reflections on developments and opportunities of thermal infrared remote sensing. *TIG (Trends Genet.)* 2. <https://doi.org/10.59717/j.xinn-geo.2024.100104>, 100104–2.
- Liu, D., Pu, R., 2008. Downscaling thermal infrared radiance for subpixel land surface temperature retrieval. *Sensors* 8, 2695–2706. <https://doi.org/10.3390/s8042695>.
- Lo, C.P., Quattrochi, D.A., Luvall, J.C., 1997. Application of high-resolution thermal infrared remote sensing and GIS to assess the urban heat island effect. *Int. J. Rem. Sens.* 18, 287–304. <https://doi.org/10.1080/014311697219079>.
- Malah, A., Bahi, H., 2022. Integrated multivariate data analysis for Urban Sustainability Assessment, a case study of Casablanca city. *Sustain. Cities Soc.* 86, 104100. <https://doi.org/10.1016/j.scs.2022.104100>.
- Malah, A., Bahi, H., Radoine, H., Maanan, M., Mastouri, H., 2022. Assessment of urban environmental quality: a case study of casablanca, Morocco. *Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci.* 205–210. <https://doi.org/10.5194/isprs-archives-XLVI-4-W3-2021-205-2022>.
- Martimort, P., Arino, O., Berger, M., Biasutti, R., Carnicero, B., Del Bello, U., Fernandez, V., Gascon, F., Greco, B., Silvestrin, P., Spoto, F., Sy, O., 2007. Sentinel-2 Optical High Resolution Mission for GMES Operational Services. *IEEE*, pp. 2677–2680. <https://doi.org/10.1109/IGARSS.2007.4423394>.
- Masek, J., 2015. Sentinel-2/Landsat Collaboration. *NASA Goddard Space Flight Center, Greenbelt, United States. Building 34, Room W150*.
- Mishra, N., Haque, M., Leigh, L., Aaron, D., Helder, D., Markham, B., 2014. Radiometric cross calibration of Landsat 8 operational land imager (OLI) and Landsat 7 enhanced thematic mapper Plus (ETM+). *Remote Sens.* 6, 12619–12638. <https://doi.org/10.3390/rs61212619>.
- Mukherjee, S., Joshi, P.K., Garg, R.D., 2014. A comparison of different regression models for downscaling Landsat and MODIS land surface temperature images over heterogeneous landscape. *Adv. Space Res.* 54, 655–669. <https://doi.org/10.1016/j.asr.2014.04.013>.
- Mushore, T.D., Odindi, J., Dube, T., Matongera, T.N., Mutanga, O., 2017. Remote sensing applications in monitoring urban growth impacts on in-and-out door thermal conditions: a review. *Remote Sens. Appl.: Soc. Environ.* 8, 83–93. <https://doi.org/10.1016/j.rsase.2017.08.001>.
- Onáčillová, K., Gallay, M., Paluba, D., Pélková, A., Tokarcík, O., Laubertová, D., 2022. Combining Landsat 8 and sentinel-2 data in google Earth engine to derive higher resolution land surface temperature maps in urban environment. *Remote Sens.* 14, 4076. <https://doi.org/10.3390/rs14164076>.
- Panigrahi, B., Kathala, K.C.R., Sujatha, M., 2023. A machine learning-based comparative approach to predict the crop yield using supervised learning with regression models. *Procedia Comput. Sci. Intern. Confer. Mach. Learn Data Eng.* 218, 2684–2693. <https://doi.org/10.1016/j.procs.2023.01.241>.
- Pelgrims, I., Devleeschauwer, B., Guyot, M., Keune, H., Nawrot, T.S., Remmen, R., Saenen, N.D., Trabelsi, S., Thomas, I., Aerts, R., De Clercq, E.M., 2021. Association between urban environment and mental health in Brussels, Belgium. *BMC Public Health* 21, 635. <https://doi.org/10.1186/s12889-021-10557-7>.
- Perera, T.A.N.T., Nayanajith, T.M.D., Jayasinghe, G.Y., Premasiri, H.D.S., 2022. Identification of thermal hotspots through heat index determination and urban heat island mitigation using ENVimet numerical micro climate model. *Model. Earth Syst. Environ.* 8, 209–226. <https://doi.org/10.1007/s40808-021-01091-x>.
- Prashanth, H.S., Shashidhara, H.L., Balasubramanya Murthy, K.N., 2009. Image scaling comparison using universal image quality index. *IEEE* 859–863. <https://doi.org/10.1109/ACT.2009.218>.
- Pu, R., Bonafoni, S., 2023a. Thermal infrared remote sensing data downscaling investigations: an overview on current status and perspectives. *Remote Sens. Appl.: Soc. Environ.* 29, 100921. <https://doi.org/10.1016/j.rsase.2023.100921>.
- Pu, R., Bonafoni, S., 2023b. Thermal infrared remote sensing data downscaling investigations: an overview on current status and perspectives. *Remote Sens. Appl.: Soc. Environ.* 29, 100921. <https://doi.org/10.1016/j.rsase.2023.100921>.
- Putri, M.R., Wijaya, I.G.P.S., Praja, F.P.A., Hadi, A., Hamami, F., 2023. The comparison study of regression models (multiple linear regression, ridge, lasso, random forest, and polynomial regression) for house price prediction in west nusua tenggara. In: *2023 International Conference on Advancement in Data Science, E-Learning and Information System (ICADEIS)*. Presented at the 2023 International Conference on Advancement in Data Science, E-Learning and Information System (ICADEIS), pp. 1–6. <https://doi.org/10.1109/ICADEIS58666.2023.10270916>.
- Ranchin, T., Wald, L., 2000. Fusion of high spatial and spectral resolution images: the ARSIS concept and its implementation. *Photogramm. Eng. Rem. Sens.* 66, 49–61.
- Ren, H., Yan, G., Chen, L., Li, Z., 2011. Angular effect of MODIS emissivity products and its application to the split-window algorithm. *ISPRS J. Photogrammetry Remote Sens.* 66, 498–507. <https://doi.org/10.1016/j.isprsjprs.2011.02.008>.
- Ren, P., Meng, Q., Zhang, Y., Zhao, L., Yuan, X., Feng, X., 2015. An unmanned airship thermal infrared remote sensing system for low-altitude and high spatial resolution monitoring of urban thermal environments: integration and an experiment. *Remote Sens.* 7, 14259–14275. <https://doi.org/10.3390/rs71014259>.
- Ribeiro Sales, M.H., Souza, C.M., Kyriakidis, P.C., 2013. Fusion of MODIS images using kriging with external drift. *IEEE Trans. Geosci. Rem. Sens.* 51, 2250–2259. <https://doi.org/10.1109/TGRS.2012.2208467>.
- Rodríguez-Galiano, V.F., Pardo-Igúzquiza, E., Chica-Olmo, M., Rigol-Sánchez, J.P., 2011. Increasing the spatial resolution of thermal infrared images using cokriging. *Proce. Environ. Sci.* 3, 117–122. <https://doi.org/10.1016/j.proenv.2011.02.021>.
- Rodríguez-Galiano, V., Pardo-Igúzquiza, E., Sanchez-Castillo, M., Chica-Olmo, M., Chica-Rivas, M., 2012. Downscaling Landsat 7 ETM+ thermal imagery using land surface temperature and NDVI images. *Int. J. Appl. Earth Obs. Geoinf.* 18, 515–527. <https://doi.org/10.1016/j.jag.2011.10.002>.
- Rongali, G., Keshari, A.K., Gosain, A.K., Khosa, R., 2018. Split-window algorithm for retrieval of land surface temperature using Landsat 8 thermal infrared data. *J. Geovis Spat. Anal.* 2, 14. <https://doi.org/10.1007/s41651-018-0021-y>.
- Roy, D.P., Wulder, M.A., Loveland, T.R.C.E.W., Allen, R.G., Anderson, M.C., Helder, D., Irons, J.R., Johnson, D.M., Kennedy, R., Scambos, T.A., Schaaf, C.B., Schott, J. R., Sheng, Y., Vermote, E.F., Belward, A.S., Bindaschadler, R., Cohen, W.B., Gao, F., Hipple, J.D., Hostert, P., Huntington, J., Justice, C.O., Kilic, A., Kovalsky, V., Lee, Z.P., Lyburner, L., Masek, J.G., McCorkel, J., Shuai, Y., Trezza, R., Vogelmann, J., Wynne, R.H., Zhu, Z., 2014. Landsat-8: science and product vision for terrestrial global change research. *Rem. Sens. Environ.* 145, 154–172. <https://doi.org/10.1016/j.rse.2014.02.001>.
- Roy, D.P., Kovalsky, V., Zhang, H.K., Vermote, E.F., Yan, L., Kumar, S.S., Egorov, A., 2016. Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. *Rem. Sens. Environ.* 185, 57–70. <https://doi.org/10.1016/j.rse.2015.12.024>.

- Salisbury, J.W., D'Aria, D.M., 1992. Emissivity of terrestrial materials in the 8–14 μm atmospheric window. *Rem. Sens. Environ.* 42, 83–106. [https://doi.org/10.1016/0034-4257\(92\)90092-X](https://doi.org/10.1016/0034-4257(92)90092-X).
- Sattari, F., Hashim, M., Pour, A.B., 2018. Thermal sharpening of land surface temperature maps based on the impervious surface index with the TsHARP method to ASTER satellite data: a case study from the metropolitan Kuala Lumpur, Malaysia. *Measurement* 125, 262–278. <https://doi.org/10.1016/j.measurement.2018.04.092>.
- Schmidt, M., 2005. *Least Squares Optimization with L1 Norm Regularization*.
- Sharma, U., Gupta, N., Verma, M., 2023. Prediction of compressive strength of GGBFS and Flyash-based geopolymer composite by linear regression, lasso regression, and ridge regression. *Asian J. Civ. Eng.* 24, 3399–3411. <https://doi.org/10.1007/s42107-023-00721-2>.
- Snyder, W.C., Wan, Z., Zhang, Y., Feng, Y.-Z., 1998. Classification-based emissivity for land surface temperature measurement from space. *Int. J. Rem. Sens.* 19, 2753–2774. <https://doi.org/10.1080/014311698214497>.
- Sobrino, J.A., Jiménez-Muñoz, J.C., Paolini, L., 2004. Land surface temperature retrieval from LANDSAT TM 5. *Rem. Sens. Environ.* 90, 434–440. <https://doi.org/10.1016/j.rse.2004.02.003>.
- Sobrino, J.A., Jimenez-Muoz, J.C., Soria, G., Romaguera, M., Guanter, L., Moreno, J., Plaza, A., Martinez, P., 2008. Land surface emissivity retrieval from different VNIR and TIR sensors. *IEEE Trans. Geosci. Rem. Sens.* 46, 316–327. <https://doi.org/10.1109/TGRS.2007.904834>.
- Stathopoulou, M., Cartalis, C., 2009. Downscaling AVHRR land surface temperatures for improved surface urban heat island intensity estimation. *Rem. Sens. Environ.* 113, 2592–2605. <https://doi.org/10.1016/j.rse.2009.07.017>.
- Valor, E., 1996. Mapping land surface emissivity from NDVI: application to European, African, and South American areas. *Rem. Sens. Environ.* 57, 167–184. [https://doi.org/10.1016/0034-4257\(96\)00039-9](https://doi.org/10.1016/0034-4257(96)00039-9).
- Wald, L., 1999. Some terms of reference in data fusion. *IEEE Trans. Geosci. Rem. Sens.* 37, 1190–1193. <https://doi.org/10.1109/36.763269>.
- Wan, Zhengming, Li, Zhao-Liang, 1997. A physics-based algorithm for retrieving land-surface emissivity and temperature from EOS/MODIS data. *IEEE Trans. Geosci. Rem. Sens.* 35, 980–996. <https://doi.org/10.1109/36.602541>.
- Wang, Z., Bovik, A.C., 2002. A universal image quality index. *IEEE Signal Process. Lett.* 9, 81–84. <https://doi.org/10.1109/97.995823>.
- Wang, Q., Shi, W., Atkinson, P.M., Pardo-Iguzquiza, E., 2016a. A new geostatistical solution to remote sensing image downscaling. *IEEE Trans. Geosci. Rem. Sens.* 54, 386–396. <https://doi.org/10.1109/TGRS.2015.2457672>.
- Wang, Q., Shi, W., Li, Z., Atkinson, P.M., 2016b. Fusion of sentinel-2 images. *Rem. Sens. Environ.* 187, 241–252. <https://doi.org/10.1016/j.rse.2016.10.030>.
- Wang, Q., Shi, W., Li, Z., Atkinson, P.M., 2016c. Fusion of sentinel-2 images. *Rem. Sens. Environ.* 187, 241–252. <https://doi.org/10.1016/j.rse.2016.10.030>.
- Wang, R., Gao, W., Peng, W., 2020. Downscale MODIS land surface temperature based on three different models to analyze surface urban heat island: a case study of hangzhou. *Remote Sens.* 12, 2134. <https://doi.org/10.3390/rs12132134>.
- Wang, P., Tan, S., Zhang, G., Wang, S., Wu, X., 2022. Remote sensing estimation of forest aboveground biomass based on lasso-SVR. *Forests* 13, 1597. <https://doi.org/10.3390/f13101597>.
- Wang, Z., Zhou, J., Liu, S., Li, M., Zhang, X., Huang, Z., Dong, W., Ma, J., Ai, L., 2022. A land surface temperature retrieval method for UAV broadband thermal imager data. *Geosci. Rem. Sens. Lett. IEEE* 19, 1–5. <https://doi.org/10.1109/LGRS.2021.3100586>.
- Wei, L., Wu, H., Jiang, X.-G., Ru, C., Jiang, Y.-Z., Gao, C.-X., 2021. A modified single-Channel algorithm for estimating land surface temperature from UAV TIR imagery. In: 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS. Presented at the 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, pp. 8185–8188. <https://doi.org/10.1109/IGARSS47720.2021.9553704>.
- Wu, H., Li, W., 2019. Downscaling land surface temperatures using a random forest regression model with multitype predictor variables. *IEEE Access* 7, 21904–21916. <https://doi.org/10.1109/ACCESS.2019.2896241>.
- Wu, H., Ye, L.-P., Shi, W.-Z., Clarke, K.C., 2014. Assessing the effects of land use spatial structure on urban heat islands using HJ-1B remote sensing imagery in Wuhan, China. *Int. J. Appl. Earth Obs. Geoinf.* 32, 67–78. <https://doi.org/10.1016/j.jag.2014.03.019>.
- Wu, J., Xia, L., On Chan, T., Awange, J., Zhong, B., 2022. Downscaling land surface temperature: a framework based on geographically and temporally neural network weighted autoregressive model with spatio-temporal fused scaling factors. *ISPRS J. Photogrammetry Remote Sens.* 187, 259–272. <https://doi.org/10.1016/j.isprsjprs.2022.03.009>.
- Wu, Y., Shan, Y., Lai, Y., Zhou, S., 2022. Method of calculating land surface temperatures based on the low-altitude UAV thermal infrared remote sensing data and the near-ground meteorological data. *Sustain. Cities Soc.* 78, 103615. <https://doi.org/10.1016/j.scs.2021.103615>.
- Xu, S., Zhao, Q., Yin, K., He, G., Zhang, Z., Wang, G., Wen, M., Zhang, N., 2021. Spatial downscaling of land surface temperature based on a multi-factor geographically weighted machine learning model. *Remote Sens.* 13, 1186. <https://doi.org/10.3390/rs13061186>.
- Yang, C., Zhan, Q., Lv, Y., Liu, H., 2019. Downscaling land surface temperature using multiscale geographically weighted regression over heterogeneous landscapes in wuhan, China. *IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens.* 12, 5213–5222. <https://doi.org/10.1109/JSTARS.2019.2955551>.
- Ye, X., Ren, H., Zhu, J., Fan, W., Qin, Q., 2022. Split-window algorithm for land surface temperature retrieval from landsat-9 remote sensing images. *Geosci. Rem. Sens. Lett. IEEE* 19, 1–5. <https://doi.org/10.1109/LGRS.2022.3184980>.
- Yoo, C., Im, J., Cho, D., Lee, Y., Bae, D., Sismanidis, P., 2022. Downscaling MODIS nighttime land surface temperatures in urban areas using ASTER thermal data through local linear forest. *Int. J. Appl. Earth Obs. Geoinf.* 110, 102827. <https://doi.org/10.1016/j.jag.2022.102827>.
- Yu, X., Guo, X., Wu, Z., 2014. Land surface temperature retrieval from Landsat 8 TIRS—comparison between radiative transfer equation-based method, split window algorithm and Single Channel method. *Remote Sens.* 6, 9829–9852. <https://doi.org/10.3390/rs6109829>.
- Yu, X., Ge, H., Lu, D., Zhang, M., Lai, Z., Yao, R., 2019. Comparative study on variable selection approaches in establishment of remote sensing model for forest biomass estimation. *Remote Sens.* 11, 1437. <https://doi.org/10.3390/rs11121437>.
- Yuan, F., Bauer, M.E., 2007. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Rem. Sens. Environ.* 106, 375–386. <https://doi.org/10.1016/j.rse.2006.09.003>.
- Zakšek, K., Ostir, K., 2012. Downscaling land surface temperature for urban heat island diurnal cycle analysis. *Rem. Sens. Environ.* 117, 114–124. <https://doi.org/10.1016/j.rse.2011.05.027>.
- Zhang, X., Zhao, H., Yang, J., 2019. Spatial downscaling of land surface temperature in combination with TVDI and elevation. *Int. J. Rem. Sens.* 40, 1875–1886. <https://doi.org/10.1080/01431161.2018.1489164>.
- Zhao, S., Qin, Q., Yang, Y., Xiong, Y., Qiu, G., 2009. Comparison of two split-window methods for retrieving land surface temperature from MODIS data. *J. Earth Syst. Sci.* 118, 345–353. <https://doi.org/10.1007/s12040-009-0027-4>.
- Zhou, J., Liu, S., Li, M., Zhan, W., Xu, Z., Xu, T., 2016. Quantification of the scale effect in downscaling remotely sensed land surface temperature. *Remote Sens.* 8, 975. <https://doi.org/10.3390/rs8120975>.
- Zuo, J., Xu, J., Chen, Y., Wang, C., 2019. Downscaling precipitation in the data-scarce inland river basin of northwest China based on Earth system data products. *Atmosphere* 10, 613. <https://doi.org/10.3390/atmos10100613>.