Downscaling using multi source data

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Earth observation satellites offer great potential for monitoring urban environmental conditions, providing information on surface physical properties, measuring urban morphology and supporting urban planning.

Land surface temperature, extracted from remotely sensed data in the thermal infrared part of the spectrum, is a primary indicator of the urban thermal environment and can be used for surface urban heat island (SUHI) studies, the detection of areas within the city with the highest thermal stress (hot spots) and the estimation of urban energy fluxes.

Daily satellite images with the required in many applications fine spatial scale are not currently available, due to the **trade-off between a satellite's temporal and spatial resolution**.

Specifically, high spatial resolution sensors have typically a low revisit time of one or two weeks, whereas satellites with high temporal frequency provide data at low resolution. The latter results in a thermal mixture effect, where the resolution cells are larger than the thermal elements.

Thus, downscaling low-resolution imagery is necessary to bridge the existing gap and make available frequent thermal data at a finer resolution.

Some definitions

Zhan, W., Y. Chen, J. Zhou, J. Wang, W. Liu, J. Voogt, and J. Li. 2013. "Disaggregation of Remotely Sensed Land Surface Temperature: Literature Survey, Taxonomy, Issues, and Caveats." *Remote Sensing of Environment* 131: 119–139. doi:10.1016/j.rse.2012.12.014.

Disaggregation of LST

We define disaggregation of LST as a generic term that combines **thermal sharpening** (TSP) and **temperature unmixing** (TUM).

The verb disaggregate means to separate (something) into its component parts, an expression that is suitable for both TSP and TUM, in which subcomponents of regular subgrids (for TSP) and arbitrary subareas (for TUM) are individually separated.

Thermal sharpening (TSP)

TSP refers to any procedure through which thermal images are enhanced or made clearer for the purpose of interpretation.

A narrower definition of TSP is the enhancement of low-resolution LSTs using spatially distributed auxiliary data that are statistically correlated to LSTs pixel by pixel, block by block, or region by region.

Temperature unmixing (TUM)

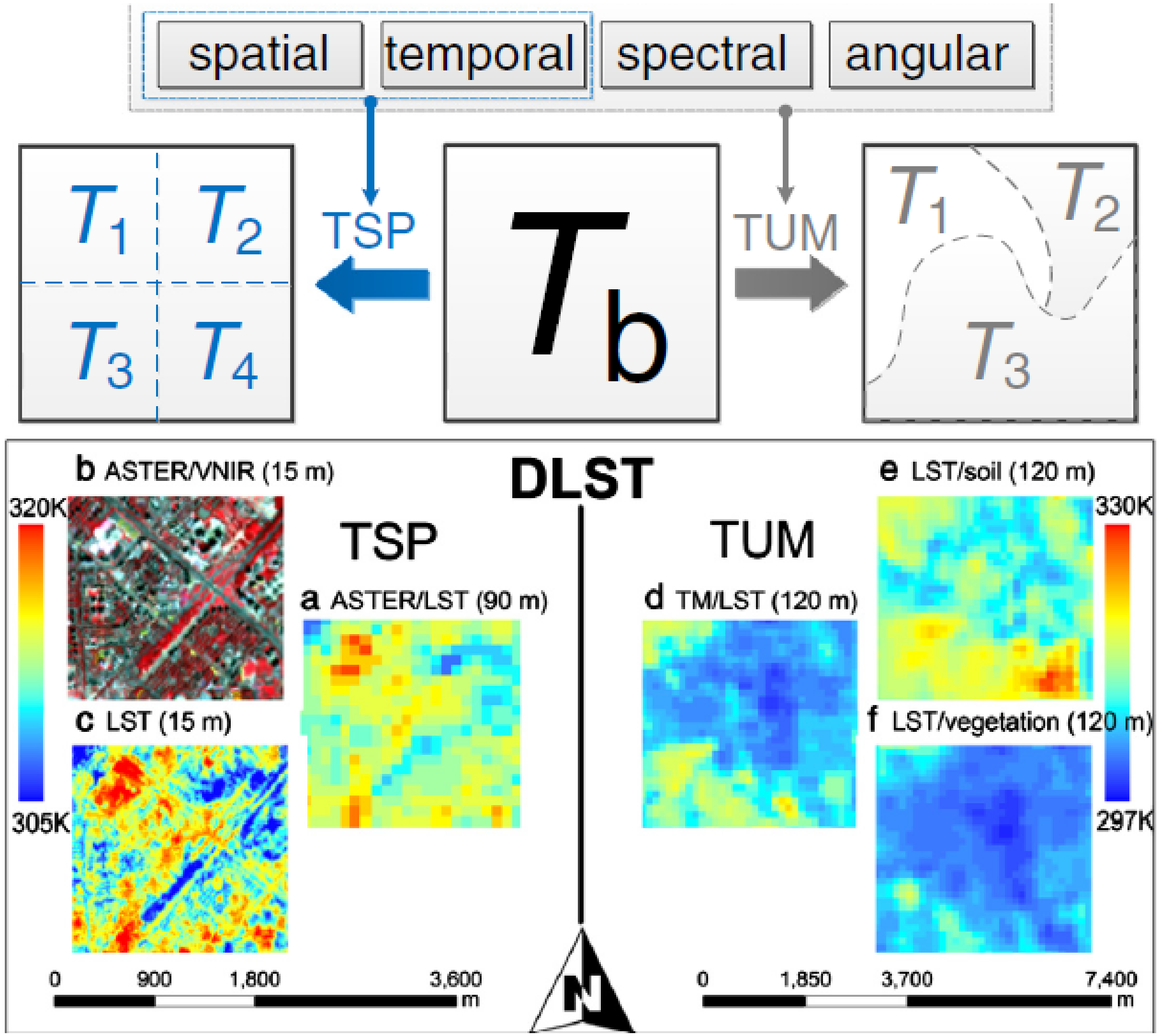
We characterize TUM as a group of generic processes by which component temperatures inside a pixel are decomposed based on multi-temporal, spatial, spectral, or angular observations.

This indicates that component temperatures, rather than component fractions and emissivity, are the main theme of TUM.

The classification of disaggregation of LST into TSP and TUM becomes apparent in the remote estimation of surface fluxes.

The downscaling of regional fluxes caused by subpixel heterogeneity is examined using TSP.

In TUM, the component temperatures are emphasized because they play a crucial role in energy flux estimations over areas occupied by sparsely distributed vegetation canopies.



A representation of disaggregation of land surface temperature (DLST). Tb is the background LST. T1, T2, T3, and T4 are subpixel LSTs.

In TSP, Tb is disaggregated into subgrid LSTs, whereas Tb is disaggregated into subcomponent LSTs in TUM.

(a), (b), and (c) illustrate a typical TSP performed over urban areas using ASTER data. (a) ASTER/LST with a resolution of 90 m;
(b) ASTER/VNIR (visible and near infrared) image (15 m) with bands 3, 2, and 1 designated as the red, green, and blue channels, respectively;
and (c) sharpened ASTER/LST(15 m).

(d), (e), and (f) represent a typical TUM process performed over rural areas (using TM data, where only soil and vegetation are used as components.

(d) TM/LST (120 m); (e) soil temperatures (120 m); and (f) vegetation temperatures (120 m).

from Zhan, W., Y. Chen, J. Zhou, J. Wang, W. Liu, J. Voogt, and J. Li. 2013. “Disaggregation of Remotely Sensed Land Surface Temperature: Literature Survey, Taxonomy, Issues, and Caveats.” *Remote Sensing of Environment* 131: 119–139. doi:10.1016/j.rse.2012.12.014.

Statistical downscaling

The most prevalent technique in enhancing the spatial resolution of satellite-derived surface temperatures is **statistical downscaling (also called thermal sharpening)** where a parametric relationship between land surface temperature (LST) and ancillary spatial data is used.

Kustas et al. (2003) used normalized difference vegetation index (NDVI) data and derived a relationship between the vegetation index and the surface temperature [referred as the Disaggregation Procedure for Radiometric Surface Temperature (DisTrad) method].

The thermal image sharpening algorithm (TsHARP) (Agam et al. 2008) was a modification of DisTrad, where different methods using NDVI and vegetation fraction were used.

Kustas, W. P., J. M. Norman, M. C. Anderson, and A. N. French. 2003. "Estimating Subpixel Surface Temperatures and Energy Fluxes from the Vegetation Index–Radiometric Temperature Relationship." *Remote Sensing of Environment* 85 (4): 429–440. doi:10.1016/S0034-4257(03)00036-1.

Agam, N., W. P. Kustas, M. C. Anderson, F. Li, and P. D. Colaizzi. 2008. "Utility of Thermal Image Sharpening for Monitoring Field Scale Evapotranspiration over Rainfed and Irrigated Agricultural Regions." *Geophysical Research Letters* 35 (2). doi:10.1029/2007GL032195.

Pixel modulation techniques (Nichol 2009; Stathopoulou and Cartalis 2009) using high-resolution emissivity data and/or season-coincident LST have also been applied in urban areas.

Another application in downscaling is the thermal sharpening of data derived from geostationary satellites, e.g. the Meteosat Second Generation-Spinning Enhanced Visible and InfraRed Imager (MSG-SEVIRI), using multiple predictor variables (Zaksek & Ostir, 2012) and including thermal information such as the LST Annual Cycle Parameters (Bechtel et al., 2012).

The importance of emissivity values

Emissivity values influence considerably the accuracy of the LST downscaled product, when compared to in-situ measurements or remotely sensed LST from a different sensor.

High errors in emissivity retrieval may arise due to urban pixels non-homogeneity; therefore, high-resolution airborne data or pixel unmixing techniques are often used.

Downscaling methods use (mostly the ones based on Modis Imaging Spectroradiometer LST product - MOD11A1), use emissivity data derived from a global land cover classification.

The literature on remotely sensed emissivity shows a variety of different approaches.

A widely used technique is the NDVI threshold method, according to which emissivity is estimated presuming that pixels are a combination of soil and vegetation, and then employing different formulas on specific NDVI ranges (Sobrino et al. 2008).

Sobrino, J. A., J. C. Jiménez-Muñoz, G. Sòria, M. Romaguera, L. Guanter, J. Moreno, A. Plaza, and P. Martínez. 2008. "Land Surface Emissivity Retrieval from Different VNIR and TIR Sensors." *IEEE Transactions on Geoscience and Remote Sensing* 46 (2): 316–327. doi:10.1109/TGRS.2007.904834.

Emissivity maps derived from a high-resolution land cover classification are considered of high importance so as to improve the final accuracy of the downscaling model.

Using **the 10 m VNIR bands** of the Sentinel-2 satellite and ancillary data (land use information and normalized surface elevation) results in identifying different surface cover types with relatively high accuracy, and thus support the downscaling method.

Methodology for Statistical downscaling

Sentinel-3 or MODIS thermal data are disaggregated from a spatial resolution of 1000 m to a fine scale of 100 m using a set of predictor variables, with LST subsequently being estimated employing high-resolution land cover-based emissivity data.

Predictors include visible and near-infrared (NIR) reflectances, vegetation indices, built-up and bare land indices, static topographic data and the solar incidence angle.

The land cover map is derived using a joint analysis of Sentinel-2 imagery, existing land use information and digital elevation models. Only the 10 m resolution channels of Sentinel-2 are used, ensuring a high degree of pixel homogeneity.

Agathangelidis, E. and Cartalis, C., 2018, Improving the disaggregation of MODIS land surface temperatures in an urban environment, International Journal for Remote Sensing, 5261-5286, https://doi.org/10.1080/01431161.2019.1579386.

Step 1. Define the set of predictors (tip. LST is primarily dependent on the thermal and radiative properties of surface materials)

Surface reflectances: Blue, green, red, NIR and the short-wave infrared bands.

Vegetation indices: NDVI (Tucker et al., 1979), EVI (Liu and Huete 1995), Soil Adjusted Vegetation Index (SAVI), (Huete 1988) and the Leaf Area Index (LAI) (Vanino et al. 2015).

Built-up and bare land indices: the Normalized Difference Built-up Index (NDBI), (Zha, Gao, and Ni 2003), the Enhanced Built-Up and Bareness Index (EBBI), (As- Syakur et al. 2012), the New Built-Up Index (NBUI) (Sinha, Verma, and Ayele 2016), the Bare Soil Index (BI) (Rikimaru et al., 1997) and the Modified Normalized Difference Water Index (MNDWI) (Xu 2006).

Topographic variables: elevation (DSM) and the slope angle.

The solar incident angle calculated from Allen, Trezza, and Tasumi (2006) (used only for daytime cases).

Caution

Due to the correlation between some of the selected predictors, the regression model may be sensitive to multicollinearity, which is addressed in the selection of regression techniques.

Step 2:

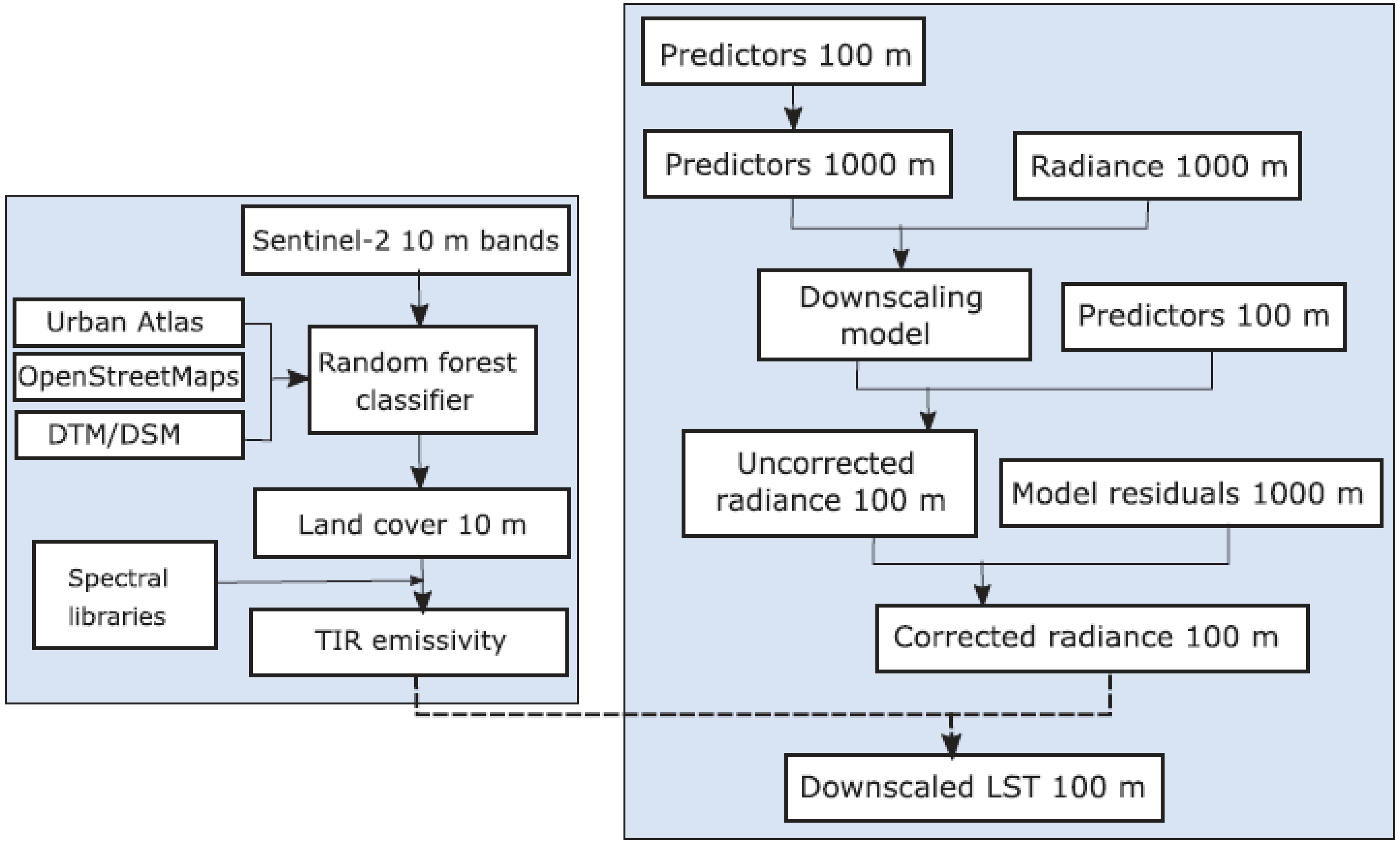
The predictors are initially estimated at a high resolution (HR) grid of 100 m × 100 m, are then aggregated to a low resolution (LR) spatial scale (1000 m). Multiple regression models are subsequently developed at LR between MODIS radiance bands 31, 32 and the predictor variables.

***Step 3*: ** The fitted regression that is obtained at LR is initially reapplied to the coarse scale dataset, and the residuals between the original scene and the model predicted radiance are estimated.

Following, the regression relationship is used with HR predictor variables to derive radiance at a fine scale (100 m). The downscaled values are finally adjusted by residual correction, i.e. by adding the derived residuals.

One common residual value is used for all HR pixels included within the corresponding LR pixel; **in this way, the radiometric content of the original image is preserved**.

***Step 4*: ** For the LST estimation from radiance values, the latter are first transformed to brightness temperatures using the inverse Planck function and then LST is derived taking into account the emissivity values.



Flowchart of the applied methodology.

Application for Sentinel 2 and 3

Goal: Daily thermal monitoring of urban areas at enhanced spatial resolution (100 m)

– Statistical downscaling of thermal data using ridge regression, multiple predictors and high resolution land cover based emissivity as deduced from Sentinel-2 (Agathangelidis & Cartalis, 2019)

Statistical downscaling steps:

-Develop parametric relationship between radiances and predictors at coarse scale.

-Apply relationship at fine scale, plus use residual correction.

-Calculate LST using split window algorithm and land cover based emissivity.

LST downscaling – Case study

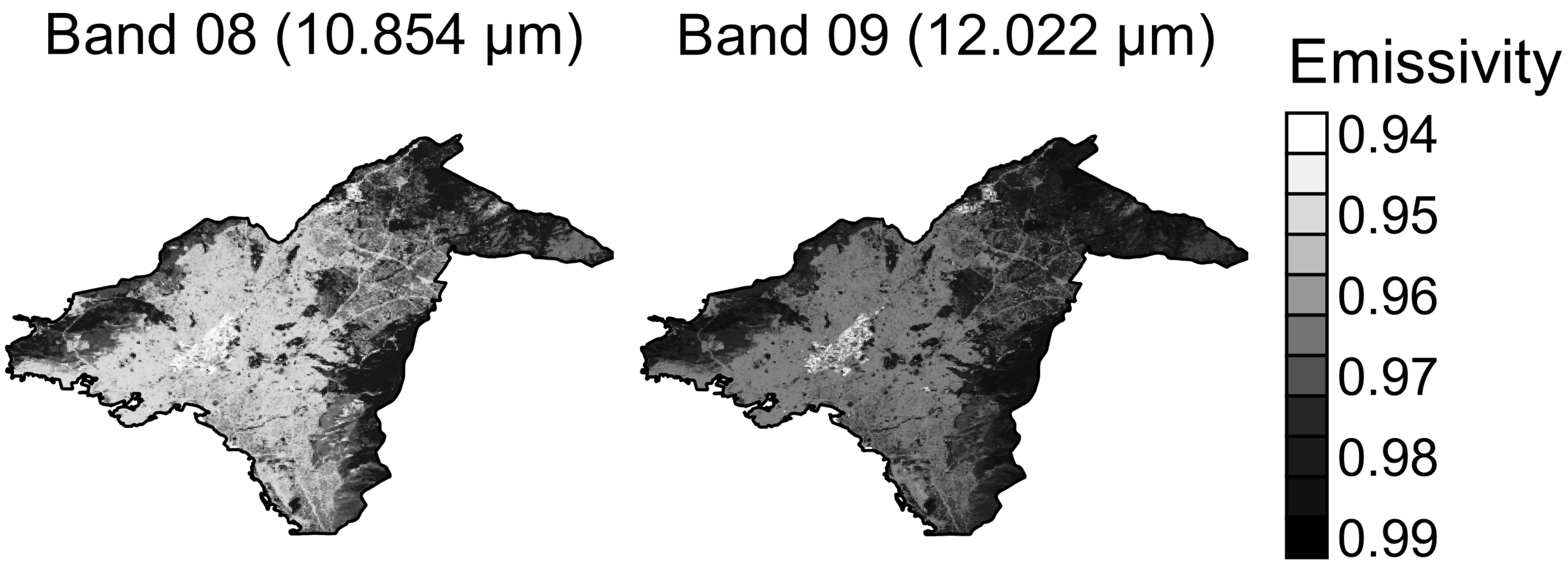
– **Sentinel-2** (28 Sep. 2016 – 12:10 local time)
VIS, NIR and SWIR bands
Vegetation and built-up indices
+ elevation, slope and solar incident angle

Downscaling predictors

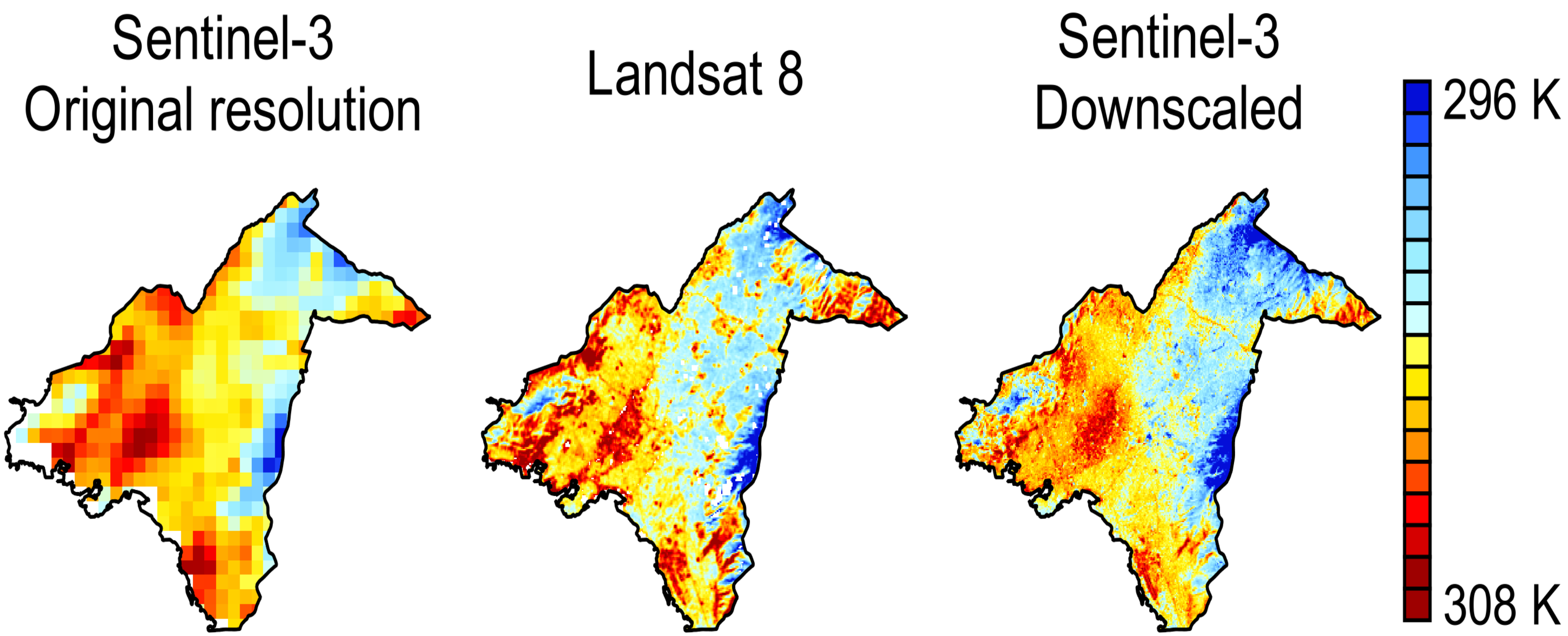
– **Sentinel-3** (29 Sep. 2016 – 11:57 local time)
Radiances / Brightness temperatures (S3A_SL_1_RBT)

– **Landsat 8** (29 Sep. 2016 – 12:05 local time)
Validation of downscaled LST

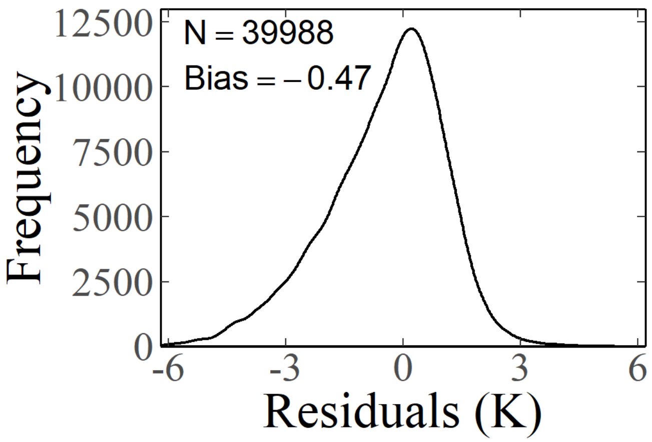
Land cover based emissivity for Sentinel-3

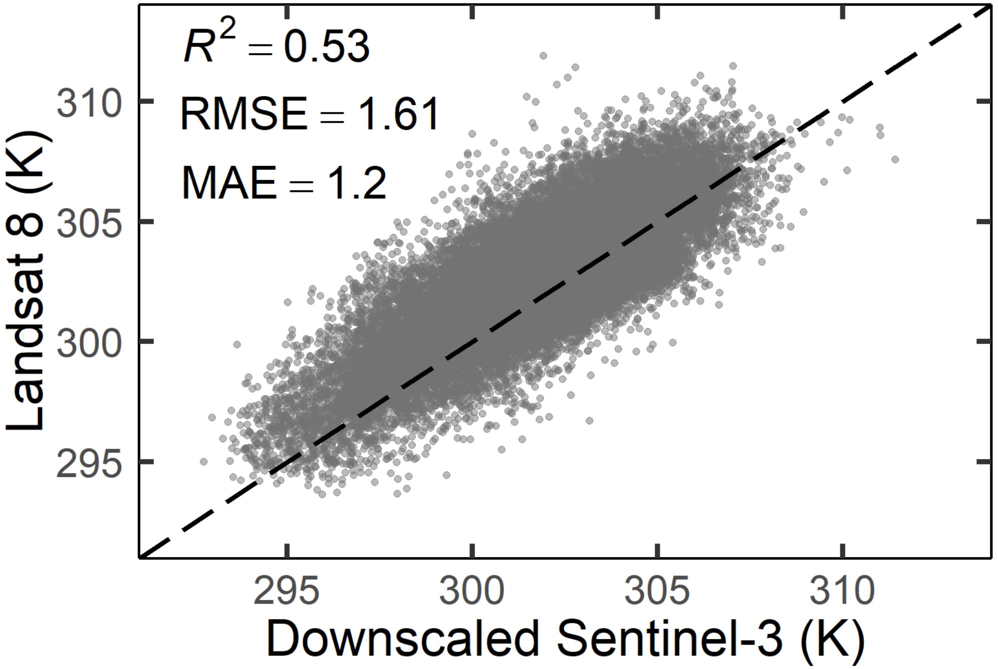


Downscaling Results (100 m)

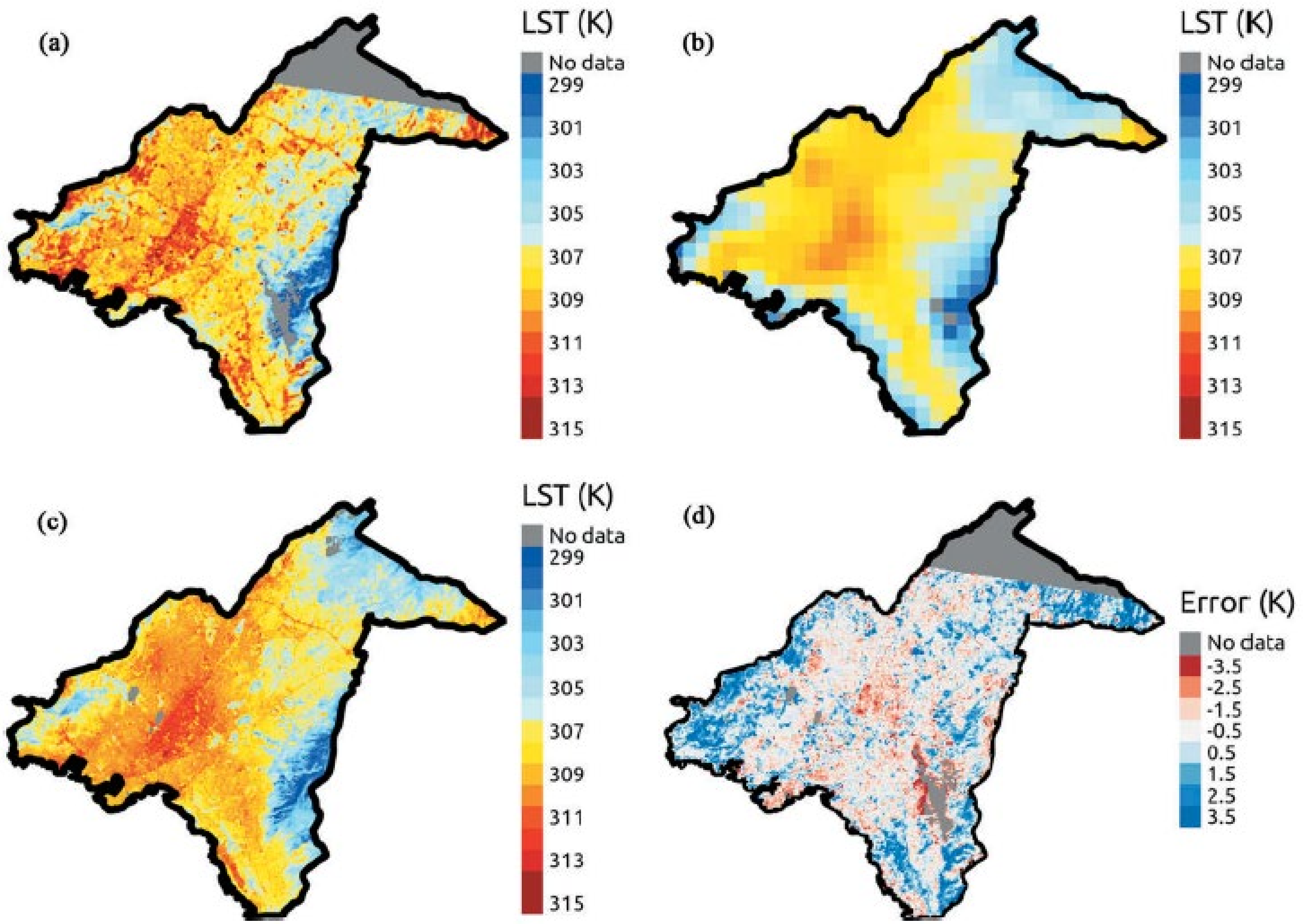


Downscaling Results (100 m)

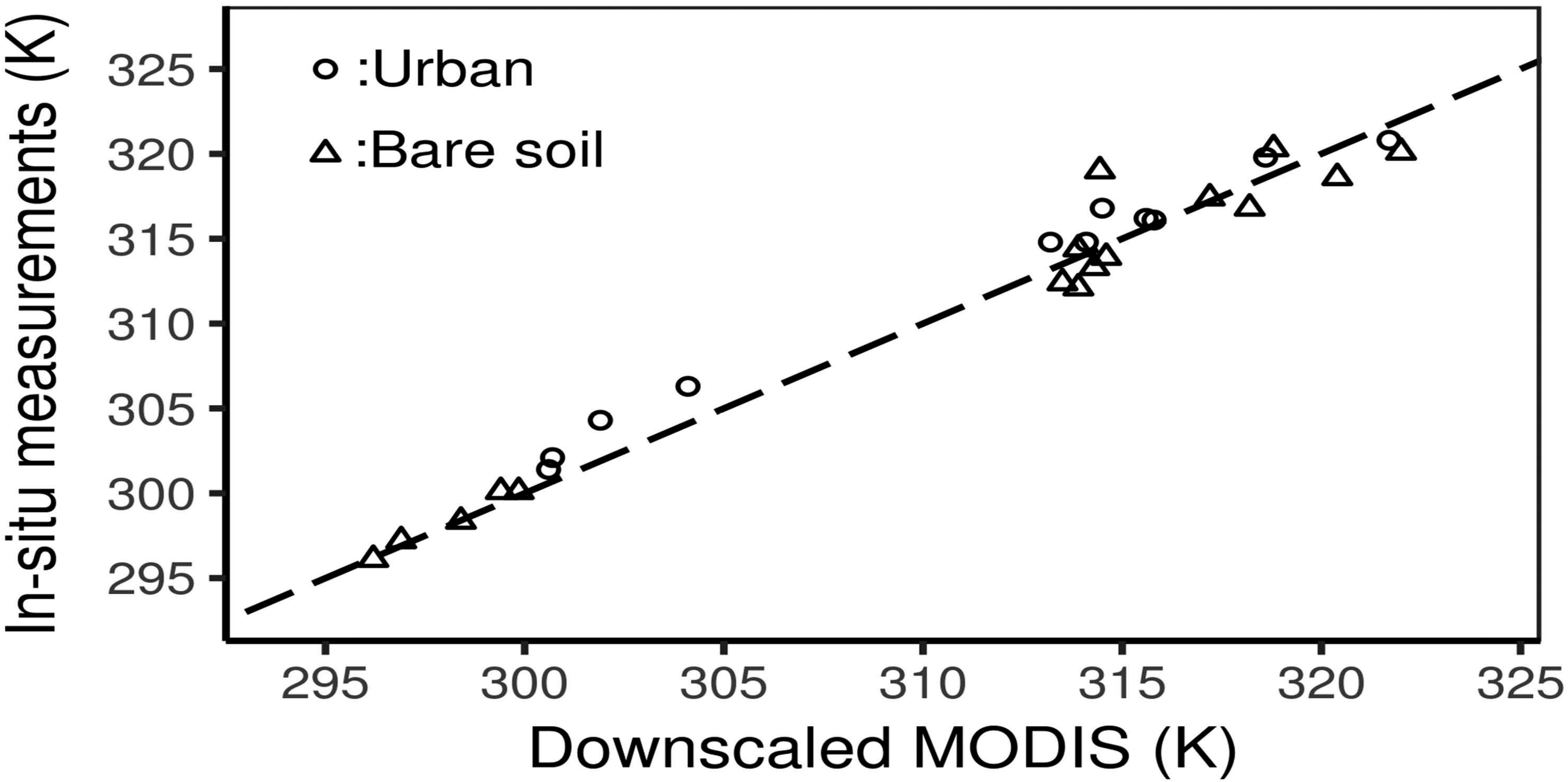




ASTER and MODIS



(a) ASTER LST, (b) MODIS LST, (c) downscaled LST using the Radiance-RR model, (d) Prediction error: difference between ASTER LST and downscaled LST.



:Urban
:Bare soil
325
320
315
310
305
300
295
In-situ measurements (K)
295
300
305
310
315
320
325
Downscaled MODIS (K)

The DisTrad method

Essa, W., B. Verbeiren, J. van der Kwast, and O. Batelaan. 2017. “Improved DisTrad for Downscaling Thermal MODIS Imagery over Urban Areas.” *Remote Sensing* 9 (12): 1243. doi:10.3390/rs9121243.

The different steps to downscale MODIS/Terra land surface temperature products from 960 to 60 m resolution using the original DisTrad method are as follows:

(1) A least-squares fit is performed between the MODIS/Terra land surface temperature product MOD_LST_{960} (dependent variable) and the upscaled impervious percentage map I_{960} (independent variable), which was derived by spatial averaging of the 30 m impervious percentage map:

$$MOD\_LST_{960} = a_0 + a_1 I_{960} \tag{1}$$

where a_0 and a_1 are, respectively, the intercept and regression coefficient of the least square regression.

(2) Calculate the estimated land surface temperature at the low resolution $\overline{T}_{960}$ (the resolution of the observed land surface temperature product—MODIS resolution) and the estimated land surface temperature at the high resolution $\overline{T}_{60}$ (target resolution for downscaling). The overbar symbol of T is used to indicate an estimated temperature based on a least-squares equation:

$$\overline{T}_{960} = a_0 + a_1 I_{960} \tag{2}$$

$$\overline{T}_{60} = a_0 + a_1 I_{60} \tag{3}$$

whereby I_{960} and I_{60} are the impervious percentage derived from the Landsat 7 ETM+ bands at 30 m resolution and aggregated to 960 m and 60 m resolution respectively; a_0 and a_1 are the regression coefficients of Equation (1).

(3) Calculate the temperature estimation residuals ($\Delta\overline{T}_{960}$), as the difference between the observed (original) MODIS/Terra land surface temperatures product (MOD_LST_{960}) and the estimated temperature ($\overline{T}_{960}$) at the low resolution, resulting from Equation (2):

$$\Delta\overline{T}_{960} = MOD\_LST_{960} - \overline{T}_{960} \quad (4)$$

The temperature estimation residuals represent the divergence of the estimated temperatures from the observed temperatures in urban areas, due to spatial variability in land surface temperature.

(4) The final step is to add the temperature estimation residuals at 960 m resolution (Equation (4)) to the estimated land surface temperature at the high resolution $\overline{T}_{60}$. Therefore, these residuals are resampled to match the sharpening target resolution (in this example, 60 m), represented by $\Delta\overline{T}_{60}$ in Equation (5). The sharpened temperature image $\overline{T}_{60}$ sharp is finally obtained using Equation (5):

$$\overline{T}_{60}\text{sharp} = \overline{T}_{60} + \Delta\overline{T}_{60} \quad (5)$$

Statistical downscaling with vegetation (NDVI)

The main steps of the statistical downscaling procedure include:

a) Developing a simple linear regression model using the Sentinel-3 data:

$$\boldsymbol{LST_{1000} = a + bNDVI_{1000} + \varepsilon = f(NDVI_{1000}) + \varepsilon} \qquad \textbf{EQUATION 1}$$

where a, b are the regression coefficients and ε the regression residuals.

b) Applying the regression model to the low resolution NDVI image:

$$\boldsymbol{\widehat{LST}_{1000} = f(NDVI_{1000})} \quad \{\boldsymbol{\widehat{LST}} \text{ mean modeled LST}\} \qquad \textbf{EQUATION 2}$$

in order to calculate the residual values per pixel:

$$\boldsymbol{\Delta\widehat{LST}_{1000} = LST_{1000} - \widehat{LST}_{1000} = \varepsilon} \qquad \textbf{EQUATION 3}$$

c) Using the regression model with the high resolution NDVI image (Sentinel-2), applying at the same time a local correction through the previously calculated residuals:

$$\boldsymbol{\widehat{LST}_{10} = f(NDVI_{10}) + \Delta\widehat{LST}_{1000}} \qquad \textbf{EQUATION 4}$$

Disaggregation of Radiometric Temperature

The DisTrad method focuses on the inverse relationship between temperature and NDVI, with a 2nd order polynomial regression [6]. The disaggregation step of the algorithm is expressed by the following equations:

$$\hat{T}_{LR} = f(NDVI_{LR}) = a_0 + a_1 NDVI_{LR} + a_2 {NDVI_{LR}}^2 \quad (1)$$

$$\Delta\hat{T}_{LR} = T_{LR}^{obs} - \hat{T}_{LR} \quad (2)$$

$$\hat{T}_{HR} = f(NDVI_{HR}) + \Delta\hat{T}_{LR} \quad (3)$$

where $\hat{T}_{LR}$ is predicted temperature at low resolution, T_{LR}^{obs} is observed temperature from satellite platform, and $\hat{T}_{HR}$ is predicted temperature at high resolution. A linear least square regression was applied between low resolution temperature imagery (T_{LR}) and NDVI data ($NDVI_{LR}$), and the residual term ($\Delta\hat{T}_{LR}$) obtained by Equations (1) and (2). The low resolution regression, then, is applied to the high resolution NDVI data to estimate disaggregated temperature imagery. Finally, to reduce thermal sharpening error, the residual term from the regression at the low resolution case is applied to the estimated temperature imagery at high resolution in Equation (3).

Statistical downscaling with Pixel Block Intensity Modulation (PBIM)

$$T_{\text{Sentinel, 30}} = T_{\text{Sentinel, 1000}} * T_{\text{Landsat, 30}} / T_{\text{Landsat 30} \rightarrow 1000}$$

$$T_{\text{Sentinel, 30}} = T_{\text{Sentinel, 1000}} * \varepsilon_{\text{Landsat, 30}} / \varepsilon_{\text{Landsat 30} \rightarrow 1000}$$

Stathopoulou, M., and C. Cartalis. 2009. "Downscaling AVHRR Land Surface Temperatures for Improved Surface Urban Heat Island Intensity Estimation." *Remote Sensing of Environment* 113 (12): 2592–2605. doi:10.1016/j.rse.2009.07.017.

Differences Method

$$\frac{\sum_{i=1}^{10}\left(Landsat_{60m_i} - MODIS_{1km_i}\right)}{10} = \overline{\Delta}_{60m}$$

Adjustment Factor Development

$$MODIS_{1km_j} + \overline{\Delta}_{60m} = MODIS_{60m_j}$$

Model Application/Validation

Statistical Normalization Method

$$\frac{\frac{\sum_{i=1}^{10} Landsat_{60m_i}}{10} - \overline{Landsat_{1km}}}{\sigma_{Landsat_{1km}}} = Z_{60m}$$

Adjustment Factor Development

Model Application/Validation

$$MODIS_{1km_j} + \left(Z_{60m} \times \sigma_{Landsat_{1km}}\right) = MODIS_{60m_j} \Rightarrow MODIS_{1km_j} + \left(\frac{\sum_{i=1}^{10} Landsat_{60m_i}}{10} - \overline{Landsat_{1km}}\right) = MODIS_{60m_j}$$