Algorithm for statistical downscaling of land surface temperature using ElasticNet
Алгоритм статистическо даунскейлинга температури на земната повърхност използвайки ElasticNet

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Nowadays there are many algorithms for statistical downscaling of land surface temperature (LST) that can improve the spatial resolution of this data (Zhan et al., 2013). The problem of existing algorithms is the necessity to select features and adjust the algorithm parameters depending on land surface classes present in the image. For example, DisTrad algorithm, based on the assumption about unambiguous relationship between Normalized Difference Vegetation Index (NDVI) and LST, shows good results when observing agricultural areas, but has worse performance for urban areas (Kustas et al., 2003).

The objective was to develop an algorithm for downscaling land surface temperature with parameters minimally dependent on the land surface classes.

Brightness temperature (BT) was calculated for cloudless Landsat-8 TIR images and then it was downscaled to spatial resolution of Landsat-8 OLI VNIR bands (30 m). Since the Landsat-8 TIR data disseminated by the USGS EROS Archive (eros.usgs.gov) is of 30 m spatial resolution derived from the original 100 m resolution by means of cubic convolution (Roy et al., 2014), 90 m resolution images generated by aggregation with a factor 3 were used instead.

Downscaling was performed for test areas with prevailing land surface classes "vegetation", "urban" and "water".

The features for predictive model were Landsat-8 OLI spectral bands, excepting panchromatic band, $\{B_1, \dots, B_7, B_9\}$, as well as spectral indices: Normalized Difference Vegetation Index (*NDVI)*, Normalized Difference Water Index (*NDWI*) (Xu, 2006) and Normalized Difference Built-up Index (*NDBI*) (Landsat). Let denote raster feature stack as: $S = \{B_1, \dots, B_7, B_9, NDVI, NDWI, NDBI\}$.

The inputs to the algorithm are low-resolution brightness temperature BT_c and high-resolution feature stack $S_f = \{B_1, \dots, B_7, B_9, NDVI, NDWI, NDBI\}$.

Algorithm stages:

1. Build a regression model relating the initial low-resolution BT (BT_c) with low-resolution feature stack S_c (S_c is generated by spatial averaging of S_f):

$$\widehat{BT}_c = f(S_c).$$

The ElasticNet was used as regression method (Zou and Hastie, 2005). It retains the simplicity of linear regression and, due to the presence of regularization terms of the 1st and 2nd orders, allows to automatically remove features insignificant for a given area.

2. Calculate residuals R_c – difference between modelled and observed low-resolution BT:

$$R_c = BT_c - \widehat{BT}_c.$$

3. Approximate the residuals R_c using Random Forest method:

$$\hat{R}_c = f_R(S_c) + \varepsilon.$$

The residual approximation plays a smoothing role. Random Forest is used because it allows to approximate substantially nonlinear relations and select the most significant features.

4. Increase spatial resolution of residuals $\hat{R}_c$ from low to high ($\hat{R}_f$) using bilinear interpolation.

5. Generate simulated high-resolution BT ($\widehat{BT}_f$) using f model:

$$\widehat{BT}_f = f(S_f).$$

Add residuals $\hat{R}_f$ to the result and get the final high-resolution BT (BT_f):

$$BT_f = \widehat{BT}_f + \hat{R}_f.$$

To assess the quality of results, the mean absolute error (MAE) and root mean square error (RMSE) were calculated for the following situations (Cho et al., 2018):

1. Synthesis. The TIR and VNIR bands are proportionally upscaled, and downscaling is applied to the upscaled images. The VNIR resolution after upscaling is the same as the original TIR resolution (90 m). BT calculated from the original image (90 m resolution) is used as a reference.
2. Consistency. Downscaling is performed first, and then the resulting BT (30 m) is upscaled to initial resolution of 90 m. The original BT with 90m resolution is used as a reference.

   The results of the algorithm are shown in Fig. 1.

Figure 1.

The MAE and RMSE errors (in Kelvin) are shown in Table 1.

Table 1. MAE and RMSE errors (K) of LST statistical downscaling algorithm

	MAE (synthesis)	RMSE (synthesis)	MAE (consistency)	RMSE (consistency)
vegetation	0.98	1.29	0.83	1.10
urban	1.02	1.37	0.85	1.15
water	1.02	1.40	0.81	1.11

As can be seen, errors are stable for areas with different land surface classes.

The developed algorithm for land surface temperature downscaling from Landsat-8 OLI/TIR data based on the ElasticNet regression method minimally depends on the land surface classes with MAE up to 1.02 K and RMSE up to 1.40 K. The resulting temperature maps are characterized by the presence of fine details visually indistinguishable in the original images. In the future, the algorithm can be improved, for example, for downscaling Landsat-8 TIR data to the spatial resolution of Sentinel-2 VNIR bands (10 m).

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Figure 1. Fragments of LC08_L1TP_178026_20180511_20180517_01_T1 image (Kelvin) of different spatial resolution: a – urban area (90 m); b – vegetation area (90 m); c – water area (90 m); d – urban area (30 m); e – vegetation area (30 m); f – water area (30 m).