Physically-based land surface temperature modeling in urban areas using 3D city models and multispectral satellite data

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Abstract:

Mitigation of urban heat islands (UHIs) requires understanding of the factors affecting the interaction of solar radiation and urban surfaces. The absorbed heat is manifested via land surface temperature and subsequently re-radiated into the surroundings thus increasing ambient temperatures. In this study, the land surface temperature was estimated by a novel algorithm combining map algebra in GRASS GIS, the Stefan Boltzmann Law and the Kirchhoff rule using raster input data derived from a virtual 3D city model and Sentinel 2 multispectral imagery. Airborne and terrestrial laser scanning and airborne photogrammetry were used to generate a high-resolution virtual 3D city model of the Košice City in Slovakia. The model was the source of the urban land surface geometry and land cover properties necessary for high-resolution modelling of solar radiation. The freely available Sentinel 2 data was used to estimate broad-band albedo, thermal emissivity and vegetation transmittance to assess the effects of various urban surfaces on UHIs. The proposed approach provides means for GIS specialists and urban planners to assess and communicate the impact of measures taken in order to mitigate the urban heat island or communicate the effect of greenery on cooling the urban climate.

**Keywords:** Land surface temperature; Urban heat islands; Solar radiation; GRASS GIS

# 1. Introduction

Mitigation of urban heat islands (UHI) requires understanding of factors affecting the interaction between solar radiation and urban surfaces. Their relationship is complex which results in distinguishing two types of UHI: surface and atmospheric UHI (Voogt and Oke, 2003, EPA, 2008). Surface UHI usually develop during hot, sunny summer days. The Sun heats dry, exposed urban surfaces, like roofs, roads and pavements, to temperatures 25 to 50°C higher than the temperature of the ambient air mass. Surface temperatures have a significant influence on air temperatures, especially in the canopy layer, which is closest to the surface where the most of the human activity concentrates, especially between the ground and the tops of trees and roofs. For example, parks and vegetated areas typically have cooler surface temperature which contributes to cooler air temperature (Estoque et al., 2017; Soltani and Sharifi, 2017). Dense, built-up areas, on the other hand, typically increase the air temperature. But in general, the temperature of air is less variable than the temperature of land surface across an area for high variability of land cover materials within urban space.

Over the past two decades, numerous studies were published analysing the associations between solar radiation, reflectance, emissivity and other heat transfer parameters of urban surface materials (Berdahl and Bretz, 1997; Mirsadeghi et al. 2013). The development and changes in UHIs may vary substantially throughout the day or year depending on radiative and thermal properties of urban surfaces and urban geometry (Soltani and Sharifi, 2017; Hu and Wendel, 2019). Land Surface Temperature (LST) is considered a reliable indicator of the UHI, as there is a strong correlation between the LST and near-surface air temperature for the heat radiating from the surface to the atmosphere (Nichol, 1994; Arrau and Pena, 2010). However, atmospheric mixing induces varying strength of the relationship between land surface and near-surface air temperatures which changes during the day and night (EPA, 2008; Chen et al., 2017). LST is generally defined as the radiative skin temperature of the ground. LST is the key parameter in physics of land surface processes, combining surface-atmosphere interactions and energy fluxes between the atmosphere and the ground. Properties of urban materials, in particular solar reflectance, thermal emissivity, and heat capacity influence the LST and subsequently development of UHI, as they determine how the Sun’s radiation energy is reflected, emitted, and absorbed.

Thermal variability of land surface can be efficiently observed and recorded on global scale by thermal remote sensing for which several spaceborne platforms were used since 1970s. Syed et al. (2018) provide a list of the thermal satellite sensors which became increasingly popular for assessing the UHI effect. Li et al. (2013) summarized the physical principles of satellite thermal remote sensing. Thermal sensors record radiance in spectral ranges associated with typical range of land surface temperature. The radiance is directly converted to brightness (radiometric) temperature (BT) by inversion of Planck’s equation. Despite the BT is a very close approximation of LST the two variables differ for not considering the atmospheric effects and thermal emissivity of the land surface causing the LST being few degrees Kelvin lower than BT. The important limitation for studying the LST in urban landscape by of the satellite thermal data is in their relatively low spatial resolution (60 m to 1000 m) and temporal resolution (several hours to days) in comparison with data from visible spectral range or 3-D lidar data (Mushore et al., 2017). Strong heterogeneity of urban land cover comprising complex patterns of various buildings, artificial surfaces and urban vegetation leads to strong spatial differentiation of LST over relatively small distances of several meters which remains satisfactorily unresolvable by contemporary thermal satellite sensors, such as MODIS, Sentinel 3, ASTER, Landsat 7 ETM+, Landsat 8 TIRS.

Recently, a more detailed representation of urban areas using 3-D city models is available that can improve ability to relate small-scale urban structures to remotely sensed thermal imagery and assess urban surfaces for a more precise parameterization of remotely sensed data (Hu and Wendel, 2019). The 3-D city models can be used to predict solar irradiance at any time moment and, in the next step, to predict LST assuming other significant properties of surface materials are known. Nakata-Osaki et al. (2018) developed a GIS tool for calculating the maximum intensity of urban heat island based on 3-D urban geometry data adopting the empirical model of Oke (1981).

The positive impact of urban vegetation on mitigation of UHIs is well known and documented (e.g., EPA, 2008; Yuan and Bauer, 2007; Gill et al., 2007). However, much less information is available on quantification of the impact in relation to urban vegetation parameters and temporal variation throughout the year depending on phenological phase of plants. The parameters of vegetation can be expressed by various metrics which can be derived from satellite data such as the percentage of canopy cover, leaf area index, or chlorophyll content. Undoubtedly, the normalized vegetation index (NDVI), and its refined form, enhanced vegetation index (EVI), are the most widely used for continental to global-scale vegetation monitoring because they can compensate for changing illumination conditions, surface slope, and viewing angle (Jensen, 2006). The principle of applying NDVI in vegetation mapping is that vegetation is highly reflective in the near infrared and highly absorptive in the visible red. The contrast between these channels can be used as an indicator of the status of the vegetation.

The use of LiDAR in estimating canopy cover of trees is supported by various studies based on a comparison of lidar-based canopy cover data to the metrics measured in the field (Morsdorf et al., 2006; Smith et al., 2009; Richardson et al., 2009). Canopy cover and gap fraction are commonly used metrics in forest ecology (Korhonen and Morsdorf, 2014). In canopy cover estimation the proportion of vertical gaps between tree crowns is needed for a specific area. Canopy gap fraction includes all gaps observed from a single point with some angular view range. Canopy cover can be estimated with high accuracy as the fraction of first echoes above a specified height threshold, because only the large gaps are considered. In gap fraction estimation, last echoes should also be used so that the effect of the smaller gaps within the crowns is considered. Leaf area index (LAI) can be estimated from the gap fraction using a logarithmic model with a single coefficient representing leaf orientation. However, sensor effects have a strong influence on the estimates, and therefore validation with high-quality field data is recommended.

Tooke et al. (2012) found that representation of trees as opaque objects substantially underestimates solar irradiance across urban landscape, leading up to an 18% underestimate of direct irradiance in residential areas with trees. Both atmospheric transmittance and geometric structure of urban space are also shown to be critical model parameters. Tooke et al. (2012) propose that opportunities exist for incorporating additional spectral data, especially for generating estimates of the reflected component of incoming solar radiation. The potential also exists for advancing estimates of radiation transmission by articulating the temporal, spectral and structural dynamics of the local vegetation (Onačillová and Gallay, 2018). This approach is also adopted in this study by using Sentinel 2 imagery having relatively high spatial, spectral and temporal resolution.

The goal of this paper is to present a methodology for calculation of LST in an open-source environment of GRASS GIS using the *r.sun* solar radiation model, a digital surface model derived from a virtual 3D city model and input data describing the varying properties of urban greenery derived from airborne and terrestrial LiDAR data and Sentinel 2 multispectral imagery.

# 2. Methods and data

## 2.1 The r.sun solar radiation model

The most important factor contributing to development of surface UHIs is the amount of solar irradiance. It consists of three components: beam (direct), diffuse and reflected irradiance. The most important component is beam irradiance because in average it represents about 50-60% of global irradiance and even more during summer sunny days. Beam irradiance depends on solar and local surface geometry and therefore it can be computed quite easily. Diffuse irradiance is anisotropic, i.e., it varies over the sky depending on the direction of solar rays. The ground-reflected component of solar irradiance is usually quite small (e.g., several percent of global irradiance). It depends on topography and ground reflectance (albedo).

The spatial distribution of solar irradiance at the land surface depends on many factors, such as the Earth's geometry, land surface morphology and atmospheric conditions. These factors can be described by a set of equations creating a complex model such as *r.sun* (Šúri and Hofierka, 2004) that is capable of estimating the amount of global solar irradiance in all its components for any point on land surface. The *r.sun* model is one of the most widely used GIS-based solar radiation models that is implemented in the open-source environment of GRASS GIS (Neteler et al., 2012; Neteler and Mitasova 2008). Originally developed as a clear-sky model (Hofierka, 1997), it was later further substantially improved by Šúri and Hofierka (2004) to include diffuse and reflected components of solar radiation for clear-sky and real-sky conditions. It has been used in a wide range of applications at various scales (e.g., Romero et al., 2008, Ruiz-Arias et al., 2009, Bergamasco and Asinari, 2011).

The *r.sun* module in GRASS GIS works in two modes (GRASS, 2018). Mode 1 is for instantaneous calculations, for which raster-based maps of solar irradiance (W.m-2) and solar incident angles (degrees) are obtained. In mode 2, the raster-based maps provide daily sums of solar irradiation (W.h.m-2) and daily direct-sun duration (min). These are computed from the integration of irradiance values (derived in mode 1) that are calculated at a user selected time step from sunrise to sunset. The computation can account for sky obstructions (shadowing) by local land surface features.

## 2.2 The calculation of land surface temperature of urban surfaces

The magnitude of surface UHIs varies with seasons, due to changes in solar irradiance as well as ground cover and weather conditions. Mitigating UHIs requires lowering the average surface temperature of the city so that there is less surface-to-air heat transfer. Urban vegetation is one of key components of this effort as the greenery maintains cooler surface temperatures, mainly by the process of evapotranspiration and shading. Generally, a built-up area exhibits a variable thermal pattern with hot and cold peaks corresponding to various thermal properties of urban surfaces. For building and pavement surfaces in the sun, surface characteristics such as albedo, emissivity, and roughness, are also relevant. For a surface under the sun and insulated underneath, the equilibrium surface temperature, *Ts* is obtained from the heat balance equation based on the Stefan-Boltzmann law which describes the total power radiated from a body in terms of its temperature (Bretz et al., 1998):

 (1)

where  is the unitless solar reflectivity or albedo of the surface varying from 0 to 1, *I* is the global solar irradiance incident on the surface in W.m-2,which is the output from the *r.sun* model, is the emissivity of the surface,  is the Stefan-Boltzmann constant, 5.6685 × 10-8W.m-2K-4, *Ts* is the equilibrium surface temperature in K, *Tsky* is the effective radiant sky temperature, *hc* is the convection heat transfer coefficient in Wm-2K-1 and finally *Ta* is the air temperature in K (ASHRAE, 1989).

Using this equation, the surface temperature *Ts* can be computed numerically using Newton's iteration method, which is the method of choice for non-linear problems with continuous, non-zero first derivatives due to its fast (quadratic) convergence. In GRASS GIS using a shell script our algorithm has the following form:

#!/bin/sh

#lst.stefan-boltzman.sh

echo "Global irradiance file"

read irr

g.copy --o rast=$irr,gi

echo "Albedo file"

read alb

g.copy --o rast=$alb,albedo

echo "Emissivity file"

read eps

g.copy --o rast=$eps,epsilon

echo "Convection coefficient file"

read cc

g.copy --o rast=$cc,h\_c

echo "Initial estimation of land surface temperature (e.g., 300)"

read temp0

echo "Ambient air temperature (e.g., 300)"

read T\_a

echo "Radiant sky temperature (e.g., 280)"

read T\_sky

echo " initialization of parameters..."

r.mapcalc --o "c = -epsilon \* 0.000000056685 \* $T\_sky \* $T\_sky \* $T\_sky \* $T\_sky - h\_c \* $T\_a - (1 - albedo) \* gi"

r.mapcalc --o "lst0 = $temp0" #initialization of LST

r.mapcalc --o "y = lst0\*lst0\*lst0"

r.mapcalc --o "lst = (3\*epsilon\*0.000000056685\*y\*lst0 - c)/(4\*epsilon\*0.000000056685\*y+h\_c)" #1st iteration

i=2

while [ $i -le 10 ]

do

echo "Iteration" $i

g.copy --o rast=lst,lst0

r.mapcalc --o "y = lst0\*lst0\*lst0"

r.mapcalc --o "lst = (3\*epsilon\*0.000000056685\*y\*lst0 - c)/(4\*epsilon\*0.000000056685\*y+h\_c)"

i=`expr $i + 1`

done

echo "Finished."

This algorithm requires an initial estimation of LST, which is based on the measured air temperature and the weather conditions (sunny, overcast day, etc.). Subsequent 10 iterations produce results with sufficient accuracy. Our GRASS GIS implementation assumes that the values of ambient air temperature *Ta* and radiant sky temperature *Tsky* are also known beforehand. The air temperature is usually measured by meteorological stations, often even within the city. The radiant sky temperature can be estimated using one of the available approximation methods published, e.g. in (Algarni, 2015), depending on the cloudiness. In this study, we use simple clear-sky and cloudy-sky direct temperature models where *Tsky = Ta - 20* under clear-sky conditions (Garg, 1982) and *Tsky = Ta* *- 6* under cloudy conditions (Whillier, 1967). Other temperature models can be used depending on available data to improve the accuracy of assessment. The dominant parameters which determine the maximum LST are the solar reflectance (albedo), thermal emissivity of the surface and convection heat transfer coefficient *hc*. In case that exact values are not avaílable, the emissivity can be very roughly approximated by . Berdahl and Bretz (1997) demonstrated a linear correlation between the reflectance (albedo) and thermal emissivity of the surface for typical metal roof coatings.

The relationship between albedo and thermal emissivity is generally called Kirchhoff's law of heat radiation: surfaces with high reflectivity (or, roughly, high albedo) have low emissivity and vice versa. Based on this law, we assume for an arbitrary freely radiating body in thermodynamic equilibrium with itself that its emissivity at a specific wavelength is equal to its absorptivity of the incoming radiation at the same wavelength (Baltes, 1976). Despite the fact that this does not rigidly hold for spectrally averaged quantities, it can be used for approximating the emissivity in case other more accurate data are not available. Moreover, emissivity can be calculated from Sentinel 2 data by deriving broad-band albedo as described by Vanino et al. (2018).

The convection coefficient *hc* is usually the most difficult parameter to estimate. It depends strongly on wind speed and direction, geometry of the building and surroundings objects, height of the roof above ground level, building material texture (roughness) and surface to air temperature difference (Mirsadeghi et al., 2013). In sunlight, with zero wind speed, *hc*, is determined by natural convection. It is a weakly increasing function of temperature difference, and almost independent of surface size. For example, for *Tsky* - *Ta* = 30 K, estimates give *hc* = 6.6 Wm-2K-1. For wind speeds above 1 m.s-1, the convection coefficient is determined by forced convection, and, *hc* rises from 2.5 to 3.0 W.m-2.K-1 at zero wind speed to about 15 to 20 W.m-2.K-1 at wind speeds of 7 m.s-1 with even higher values of *hc* for roofs and upwind surfaces (Liu et al., 2015). Mirsadeghi et al. (2013) provides an extensive overview of available models for *hc* estimation and concluded that there is considerable uncertainty in the prediction of this parameter. More accurate estimates of *hc* require complex modelling techniques using 3D city models, data on building materials and 3D wind simulations.

## 2.3 The study area and data

This study focuses on the Košice City in Eastern Slovakia as an example of urban space typical for a moderate climate of Central Europe. We selected a study area with a feasible size and sufficient diversity of urban greenery which would be suitable for ground-based mapping, airborne survey and large enough for monitoring by Earth observation satellites such as Sentinel 2A and Landsat 8. The area comprises 4 km2 of the central part of the Košice City as delineated in Figure 1. Within this area, we have selected a smaller site (Moyzesova street) representing a typical mixture of urban surfaces and greenery to show a detailed view of input and output data.

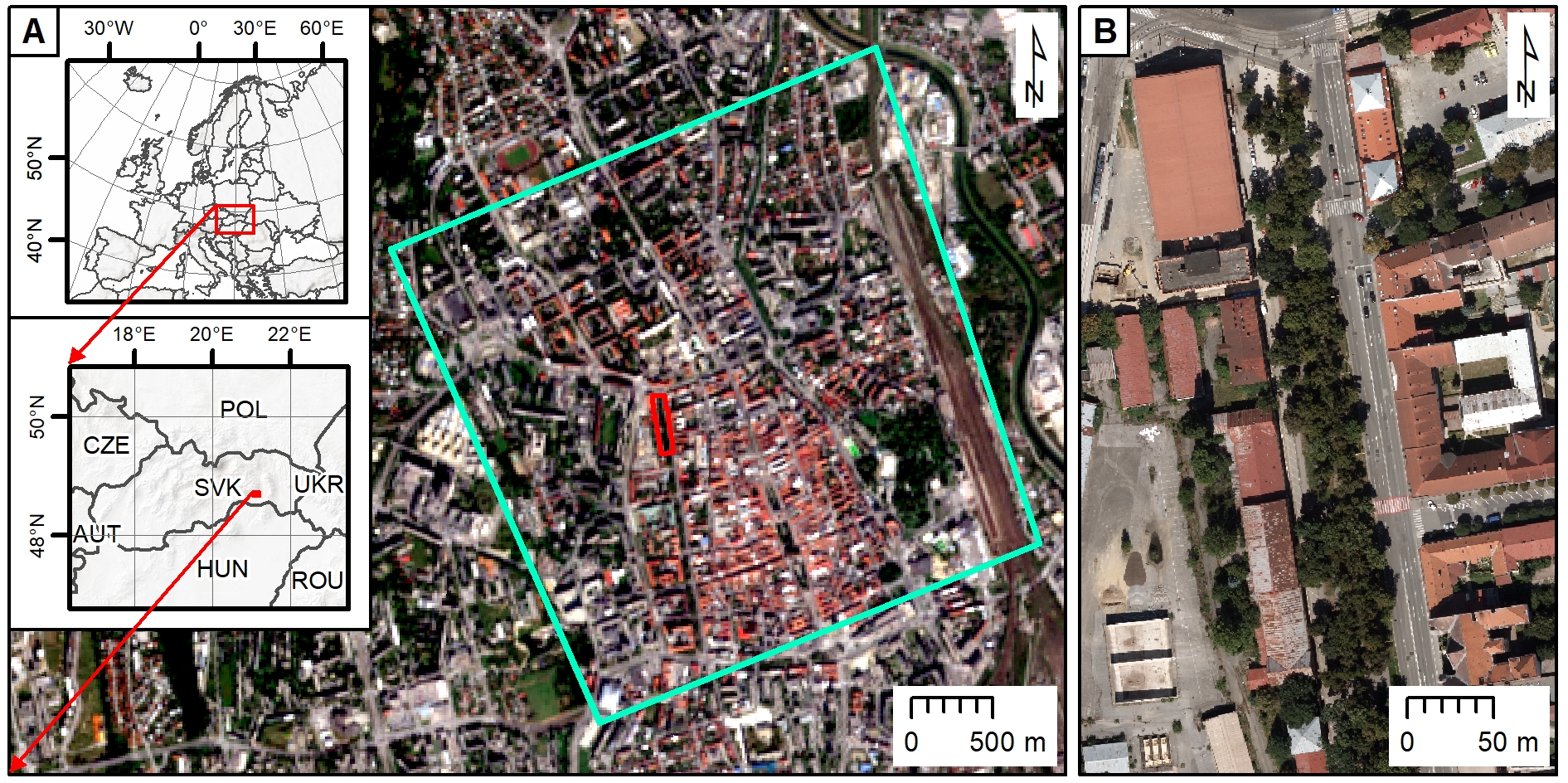


Figure 1. Location of the study area in the Košice City, Slovakia. The cyan line outlines the area subject to airborne lidar and photogrammetric mapping. The red outline delineates a site (Moyzesova street) selected for a detailed view on the right with aerial orthoimage as natural color composite. The background maps are   
© Copernicus, Sentinel 2A image acquired on 29 June 2016.

In this study, we have used various data sources. The airborne laser scanning (ALS) and photogrammetry data were used to build a 3D city model and derive digital surface models and land cover maps, spaceborne multispectral imagery of Sentinel 2A satellite was used to derive input parameters such as albedo for the LST model. Landsat-8 data were used to compare Landsat-derived LST with results of our modeling.

The airborne laser scanning (ALS) and photogrammetry data were acquired in leaf-on conditions during late summer of 2016 to build 3D city model consisting of buildings and terrain with a level of detail (LoD) 2 (Fig. 2, 3). Leica ALS70 laser scanner was used for ALS resulting in 365 million of points covering the whole area (point cloud density 91/15 all/ground points per m2, respectively). The points were processed in LAStools to classify them in ground, vegetation, buildings and other returns. Ground returns were used to derive a gridded digital terrain model (DTM), vegetation and buildings returns were also used to derive digital surface models (DSMs) of 0.5 m cell size (Fig. 3).

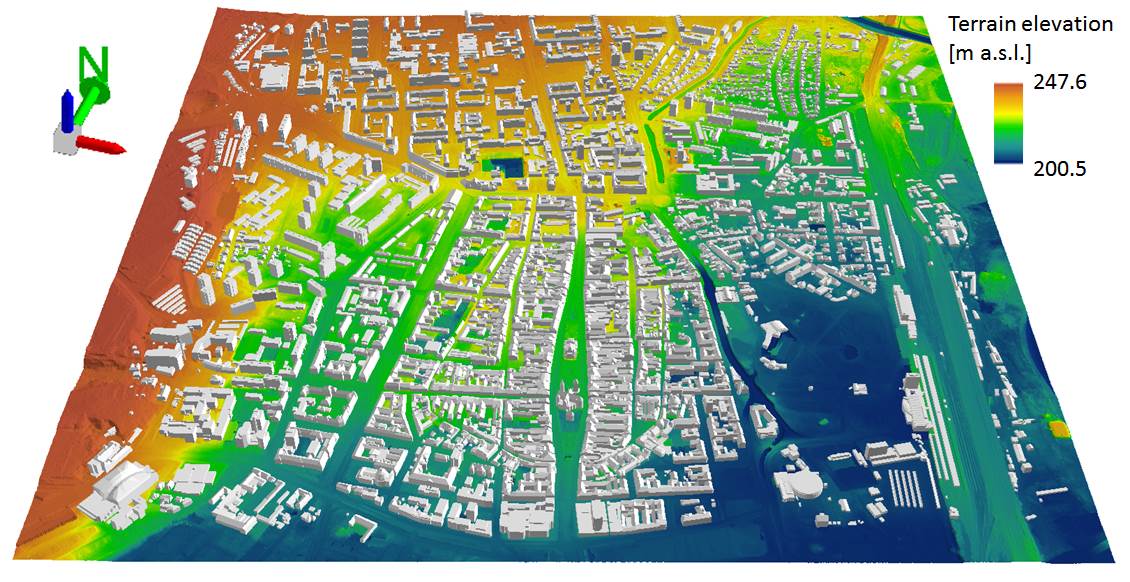


Figure 2. Perspective 3D view of the entire study area (cyan outline in Fig. 1) for which the 3D city model was generated. 3D buildings are dispalyed on a digital terrain model in the ArcScene software by ESRI.

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Figure 3. A detailed view of 3D city model (left) and lidar based digital surface models (DSM) for the smaller site (Moyzesova street) including buildings (middle) and vegetation (right). The area size is 200 m by 400 m. DSM cell size is 0.50 m.

The aerial orthoimagery was used to map land cover categories found in the study area. We have identified 21 categories completely covering the study area. The areas of categories were visually identified and delineated in a vector data format in ArcGIS (Fig. 4). The land cover categories were used to assess spatial differentiation of convective heat transfer coefficient *hc* within the city. Table 1 and Figure 4 summarize how we assigned different land cover categories with the values of *hc* which was based on expert judgment supported by the values reported by Mirsadeghi et al. (2013), Liu et al. (2015), Vollaro et al., (2015) and Amir et al. (2018). The values are estimated for typical hot summer atmospheric conditions with clear sky and moderate wind. The resulting data layers were derived at 0.50 m spatial resolution. The data represent ground cover thermal properties, however, they do not account for urban greenery effects.

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Figure 4. Land cover in 21 categories representing the material of the ground below the trees and shrub for the entire study area and smaller site (Moyzesova street).

Table 1. Convective heat transfer coefficients assigned to land cover categories in the Košice city

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| --- | --- |
| Land cover category | Convective heat transfer  coefficient [W.m-2.K-1] |
| roofs | 20 |
| red bricks, concrete, concrete paver blocks, concrete paver blocks with tram rails, crushed stone pavement, dark stone blocks pavement, loose pebbles pavement, gravel stones, red clay courts, railway, stone graves with grass, concrete channel with water, dark grey and dark pink asphalt roads and pavements | 40 |
| bare soil, grass, lawn | 50 |
| low shrubs | 60 |
| water surface | 80 |

In this study, we have used spaceborne multispectral imagery of Sentinel 2A satellite to derive land surface albedo and specific vegetation metrics. The study area is covered by two Sentinel 2A data granules 34 UEU, 34 UEV which were downloaded for the year of 2016 via Copernicus Open Access Hub (<https://scihub.copernicus.eu/dhus/>). The time period corresponded with the acquisition of the other datasets. The data were distributed as level 1C products meaning the pixel values (10 m spatial resolution) represent the top-of-atmosphere spectral reflectances projected in a cartographic system (UTM/WGS84).

The albedo was derived as the broadband surface albedo by the approach used in Vanino et al. (2018). The albedo was calculated as the integration of at-surface reflectance across the shortwave spectrum (D'Urso and Calera, 2006), as shown in equation (2).

 (2)



where  is albedo, is surface reflectance for a given band obtained using the ESA's Sen2Cor algorithm (Version 2.3.1) implemented in the SNAP (2018) software utility,  is the weighting coefficient representing the solar radiation fraction derived from the solar irradiance spectrum (Thuillier et al., 2003) within the spectral range (spectral response curves) for bands *bi*. In particular, the bands 2-8 and bands 11-12 were used with the following weights: = 0.1324, = 0.1269, = 0.1051, = 0.0971, *=* 0.089, *=* 0.089, = 0.0722, = 0.0167, = 0.0002. The resulting albedo raster layer was resampled from 10 m to 0.5 m resolution by bicubic interpolation and mapped into individual polygon objects of land cover categories as zonal mean per object. Two versions of albedo were generated to show the colling effect of urban greenery (Fig. 5). Figure 5a shows the albedo of the land cover including the surface of trees while Figure 5b displays the albedo per object of the land cover below the trees (ground cover).

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| (a) | (b) |

Figure 5. Broad-band albedo derived from atmospherically corrected Sentinel 2A data for (a) land cover classes including trees and (b) ground cover (without trees). The land cover classes were derived by manual interpretation of aerial orthoimagery and field survey.

The solar light attenuation (solar transmittance *τ*v) of tree canopy in the entire study area was estimated as a rescaled value of *LAIe* which was calculated by a linear regression model:

*LAIe* = 11.23\* *S2NDVI* - 1.80 (3)

where *LAIe* is the effective leaf area index, and *S2NDVI* is the calculated normalized difference vegetation index from Sentinel 2 spectral bands (as sensed on 29 June 2016) using the Eq. 6. Thislinear model was defined with *LAIeTLS* derived from terrestrial laser scanning (TLS) data acquired on 4 smaller sites within the city including our smaller site in Moyzesova street (29 June 2016) as described in Hofierka et al. (2017). For this purpose, *LAIeTLS* was calculated by the modified approach of Klingberg et al. (2016) based on Beer-Lambert law:

*LAIeTLS* = - *β* . ln(*Rground* / *Rtota*l) (4)

where *Rground* is the number of ground returns (including all return types), *Rtotal* is the number of ground and canopy returns and *β* is a constant which can be expected to take a value around 2 (Richardson et al., 2009; Klingberg et al. 2016). We calculated the *LAIeTLS* for grid cells of 10 by 10 metres to match the resolution of Sentinel 2 imagery. *τ*v was then calculated as:

τv = (LAIe – LAIe,min)/(LAIe,max - LAIe,min) (5)

where *LAIe,min*and *LAIe,max* are the lowest and the highest value of *LAIe* in the study area within the tree canopy mask, respectively.

To assess the effects of trees and shrub vegetation on LST we have used LAI derived from Sentinel 2A data to increase the value of *hc* proportionaly to the LAI values (hc2 = hc1 \* (1+LAI)). This increase in hc effectively results in lower LST values in areas with trees and shrubs (Fig. 6). In fact, this effectively account for moisture and evapotranspiration effects of urban greenery leading to lower LST as documented by xxx (cit).

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Figure 6. Spatially distributed convective heat transfer coefficient *hc* (W.m-2.K-1) for the entire study area and smaller site (Moyzesova street) based on land cover of the ground (upper row) (Table 1) and increased for the tree and shrub vegetation based on leaf area index and expert judgement (bottom row).

2.4 Land surface temperature derived from Landsat 8 data

There are a number of spaceborne multispectral sensors to date providing multispectral data in visible and thermal infrared spectrum simultaneously. Such data allow for comparing the modelled LST with the brightness temperature recorded by the satellite sensors which can be converted to LST. For our purpose, we opted for the Landsat 8 data which provide the highest possible spatial resolution of thermal band among the deployed missions on the Earth’s orbit. Also there was a favourable temporal coincidence with Sentinel 2 acquisition used in our approach. We used Landsat-8 data L1T product (path 186, row 26, 30 June 2016, scene centre time 9:20:19 GMT) containing data recorded by two instruments - the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) with a spatial resolution of 30 meters for visible, near infrared and short-wavelength infrared bands (bands 1-7, band 9), 15 meters for panchromatic band 8, and 100 by 30 meters for thermal bands 10 and 11. The data of thermal bands is resampled to 30 by 30 meter pixels in the L1T product which was downloaded from <https://earthexplorer.usgs.gov/>. Specific wavelengths of the bands are reported for example in Loveland et al. (2016). We used a single channel approach (Li et al. 2013) of Sobrino et al. (2004, 2008) for deriving LST from the TIRS band 10 as the data of band 11 is significantly more contaminated by thermal energy from outside the normal field of view (stray light) than band 10 (Barsi et al., 2014). Sobrino et al. (2004, 2008) developed the approach for Landsat 5 Thematic Mapper thermal band 6 having approximately the same spectral range as the TIRS band 10. A number of subsequent studies have been built on this approach, e.g. Amiri et al. (2009), Chatterjee et al. (2016), Deng et al. (2018).

*TsL8* was calculated in several steps performed as map algebra operations. First, 16-bit digital numbers (DN) of band 10 were converted to at-sensor spectral radiance *Lλ* (W·m−2·sr−1·µm−1) using the radiance scaling factors provided in the metadata file associated with the downloaded satellite scene according to USGS (2018, p. 54). The recorded *Lλ* could be converted to brightness temperature at the top of atmosphere but its values do not accurately express the real land surface skin temperature. The relation of *Lλ* with surface *Ts* can be expressed by:

*Lλ =*[*ε*\**B*(*Ts*) *+* (*1－ε*) \* *Ld*] \**τ + Lu,.* (6)

where *ε* is the land surface emissivity, *B*(*Ts*) is the radiance of a blackbody (W·m−2·sr−1·µm−1) having the real LST *Ts* (K), *τ* is the atmospheric transmittance for the thermal infrared radiation recorded by band 10 and *Ld* and *Lu* is the atmospheric downward and upward radiance (W·m−2·sr−1·µm−1), respectively. Assuming a Lambertian surface, the thermal radiation of a blackbody with the temperature equivalent to the real surface temperature *B*(*Ts*), can be obtained according to the radiative transfer equation by revising the Eq. (6).

*B*(*Ts*) = [*Lλ － Lu*－ τ\*(1*－ε*) \**Ld*] / *(τ*\**ε)*, (7)

The three atmospheric correction parameters can be calculated through the online service of NASA (<http://atmcorr.gsfc.nasa.gov>) developed by Barsi et al. (2005). The following input parameters were entered in our case: latitude = 48.719°, longitude = 21.259°, GMT time = 9:20, altitude = 230 m a.s.l., temperature = 26.7°C, air pressure = 989.6 hPa (mbar), relative humidity = 46.22%. The weather parameters were extracted from the database of the OGIMET service developed by Guillermo Ballester Valor of the Spanish Meteorological Institute ([www.ogimet.com](http://www.ogimet.com)) for 30 June 2016 at 9:00 GMT for Košice. The resulting values for the atmospheric correction were interpolated to the set location as follows: *τ* = 0.76, *Lu* = 1.98 W·m−2·sr−1·µm−1, *Ld* = 3.24 W·m−2·sr−1·µm−1.

Surface emissivity *ε* was calculated using the threshold method proposed by Sobrino et al. (2004) based on the normalized difference vegetation index (NDVI) and vegetation coverage *Pv*. The method considered the following three cases. For NDVI < 0.2, the entire land was considered bare soil, and its surface emissivity was the bare land typical emissivity of 0.973. When NDVI 0.2 ≤ NDVI ≤ 0.5, the pixel was regarded as mixed pixels composed of vegetation and bare soil, and its surface emissivity was calculated by the formula expressed in Eq. (8).

*ε* = 0.004\**Pv* + 0.986. (8)

For NDVI > 0.5, vegetation was considered to be covering the ground completely and its surface emissivity ratio was 0.99. NDVI was calculated from atmospherically corrected surface reflectance derived from the Landsat 8 OLI band 4 (*ρred*) and band 5 (*ρnir*) using the formula:

NDVI = (*ρred* – *ρnir*) / (*ρred* + *ρnir*) (9)

The correction is recommended by Sobrino et al. (2004). It was performed by the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH®) algorithm in ENVI software by Harris Geospatial Solutions. The method incorporates the MODTRAN® radiation transfer model and corrects wavelengths in the visible through near-infrared and shortwave infrared regions, up to 3 µm.

Subsequently, *Pv* was calculated by the formula expressed in Eq. (10).

Pv = [( *NDVI－* *NDVIs*) / (*NDVIv－* *NDVIs*)], (10)

where *NDVIv* = 0.5 for vegetation and *NDVIs* = 0.2 for bare soil. After estimating *B*(*Ts*) the LST was obtained according to the inverse function of Planck’s law with formula:

*Ts=K2* / ln[*K1/B*(*Ts*) + 1], (8)

where K1 = 774.8853 W·m−2·sr−1·µm−1 and K2 = 1,321.0789 K as stated in the metadata file of the downloaded scene.

# 3. Results and discussion

To document the versatility of the presented methodology, we have applied it to 3 different scenarios representing different situations and/or available data. For example, urban planners may want to analyze the effects of growing or cutting trees in a local neighborhood or effects of building renovations with higher albedo coatings or even green roofs. All the scenarios were calculated for June 30, 10:20 zonal time (9:20 GMT) with available Sentinel 2 and Landsat 8 data. In scenario 1 we were interested in exploring the LST for the city with no trees or shrub vegetation. Buildings and other urban surfaces are represented by DSM that includes building structures. Ground surface albedo is derived from land cover classes and mean areal values of albedo are derived from Sentinel 2 for 29 June 2016 (day of year 181, 10:40 zonal time). Grass, lawns and small shrubs were considered as land cover of the ground surface. Scenario 2 includes DSM with buildings, trees and shrub vegetation taller than 1.5 m. Albedo of urban surfaces including trees and shrub vegetation were derived using Sentinel 2 data and averaged for land cover zones, the cooling effects of urban greenery are expressed via heat transfer coefficient as a single parameter. In scenario 3 we were interested in the assessment of LST below the trees, so we assumed a partial transmittance of solar rays through trees and shrub vegetation effectively attenuating the beam solar irradiance on ground surfaces. Mean areal values of albedo for ground surfaces represented by land cover areas were derived from Sentinel 2 for 29 June 2016 (day of year 181, 10:40 zonal time).

The selected day and time corresponds with the availability of cloudless scenes of Landsat 8 for this moment and Sentinel 2 for previous day of June 29, 2016. The key component of LST model, the global solar irradiance *I* (eq. 1) was calculated using the the *r.sun* module in GRASS GIS (GRASS, 2018; Šúri and Hofierka, 2004). The input parameters for the *r.sun* module included elevations of the DSM and Sentinel-derived albedo values. The calculation was performed for clear-sky conditions with Linke's turbidity coefficient set to the typical city atmospheric conditions in June (i.e., 4.3) suggested by the *r.sun* manual page and using a shadowing option, i.e., the global irradiance was reduced by a beam component in shadows cast by buildings and trees (Figure 7). The calculated global solar irradiance on horizontal surfaces such as roads (orange color of global irradiance in Fig. 7) corresponds well with the measured global irradiance at the Košice airport weather station on (887.15 W.m-2) on June 30, 2016 at 10:00 zonal time with weather conditions close to a clear-sky situation.

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| Digital surface model [m.a.s.l.] with buildings and no trees-vymenit obrazok | Global clear-sky irradiance [W.m -2] |
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| Digital surface model [m.a.s.l.] with buildings and trees | Global clear-sky irradiance [W.m -2] |
|  |  |
| Digital surface model [m.a.s.l.] with buildings and trees | Global clear-sky irradiance [W.m -2] |

Figure 7. Global solar irradiance (W.m -2) calculated by the *r.sun* model for June 30 at 10:20 zonal time for the smaller site and a) scenario 1, b) scenario 2, c) scenario 3.

The suggested algorithm (lst.stefan-boltzman.sh) implemented as a shellscript in GRASS GIS was used to calculate a LST for the three scenarios mentioned above. In all scenarios, we used the following single parameters of the script describing the initial conditions: the initial estimation of the land surface temperature 300 K, the effective radiant sky temperature *Tsky* = 280 K, the air temperature *Ta* = 300 K. The air temperature was taken from the Košice airport weather station. The convection heat transfer coefficient was spatially distributed according to land caver classes (Table 1) and modified for scenario 3 as described above. We have used 10 iterations of the algorithm to get sufficiently accuarate results of the LST values. Figure 8 shows the resulting land surface temperature for the three scenarios for the entire study area as well as zoom-in area in site 1. The modelled temperatures are strongly associated with global irradiance, heat transfer coefficient and albedo values. Shadows cast by buildings or trees strongly decrease LST. Low values of heat transfer coefficient increases LST. In our examples roofs have the lowest values of *hc* effectivelly increasing LST for these land cover areas. As expected, higher albedo decreases LST. The scenario 1 has generally higher values of LST with temperatures in the range of xx K. The scenario 2 takes into account urban greenery thus also its cooling effects resulting in generally lower temperatures in these areas (xx K) and a larger range of values across the entire area. Areas with lower values of LST are associated with compact areas of urban greenery such as city parks and trees in residential areas. The scenario 3 represents LST below the trees and shrubs and exhibits the lowest temperatures close to the ambient air temperature.

To validate modelled values of LST, we compared the LST calculated for scenario 2 with the LST sensed by Landsat 8 TIRS Band 10 at 30 m spatial resolution. Due to the fact that we have modelled the LST values at 0.5 m spatial resolution we re-interpolated the modelled LST raster values to a lower spatial resolution of 30 m using *v.surf.rst* spatial interpolation module in GRASS GIS (GRASS, 2018) using tension=10, smoothing parameter=30 and minimum distance between input points 25 metres to preserve general trends in the data. Figure 9 compares the modelled LSTs with Landsat 8 LSTs. The differences in absolute values (lower left picture) shows that modelled values are in a good agreement with L8 data with a range of differences within a few degrees of K. The Pearsons coefficient of correlation r=0.867 showing a strong correlation of both datasets. It should be noted that resampling from 0.5m to 30 m results in a substantial information loss and therefore a spatial pattern of the modelled LST in Fig. 9 is strongly dependent on the resampling technique, in this case re-interpolation parameters.

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Figure 8. Modelled land surface temperature for the entire study area and smaller site and a) scenario 1, b) scenario 2, c) scenario 3.

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Figure 9. Modelled temperature of land cover surface (left) derived for 30 June 2016 at 9:20 AM of GMT 10:20 zonal time and land surface temperature at the bottom of the atmosphere (right) as sensed at the same time by Landsat 8 TIRS, band 11. The spatial resolution (raster cell size) is 30 m, the units of temperature are degrees Kelvin.

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Figure 10. Differences between the Landsat8 observed and modelled temperature in degrees Kelvin (left), and s Scatterplot of modelled temperature and temperature sensed by Landsat 8 TIRS Band 11 at 30 m spatial resolution (right).

Discussion and comparison with other works.

# 4. Conclusions

Land surface temperature modeling is a key component of the UHIs analysis using 3D city models. The interaction of incoming solar radiation with urban surfaces is the main source of urban heat islands within the city. Spatial distribution of solar radiation income can be modelled based on physical and geometric principles in a relatively straightforward and accurate way. We used the *r.sun* module implemented in the GRASS GIS open-source software as a base for calculating the solar radiation income and we developed an algorithm based on the Stefan-Boltzmann Law, which describes the power radiated from a black body in terms of its temperature. The key inputs of the LST calculation comprise spatially distributed global solar irradiation of a DSM, convective heat transfer coefficient of the surface material, albedo of the surface and the emissivity of the material. While solar radiation income can be calculated with a high degree of reliability, the latter three parameters are difficult to be measured directly by remote sensing instruments in such a fine resolution as the solar irradiation can be computed. We assumed ideal atmospheric conditions for deriving LST in various scenarios with and without urban greenery.

The results of our LST modelling in the city of Košice showed great spatial variations that cannot be captured by current satellite sensors. However, we have demonstrated that it can be modelled by proper software tools and input data such as LiDAR and satellite imagery (e.g., Sentinel 2A). The proposed algorithm is a novel contribution to modelling the land surface temperature in a GIS environment where tools for calculating temperature of surface have not been implemented to our knowledge to date. Despite the input variables, such as convective heat transfer coefficient and surface emissivity, are difficult to ascertain with high degree of certainty and the transfer of heat in the environment being a complex phenomenon, the proposed approach provides means for assessing various scenarios of land cover in urban planning. Importantly, it enables to model surface temperature on a much finer scale than contemporary thermal sensors such as TIRS of Landsat 8 or SLSTR of Sentinel 3 sense it. We have demonstrated that Sentinel 2 data can be used in the algorithm for estimating the broad-band albedo, emissivity of surface material and transmittance of urban trees. It should be emphasized, that the resulting temperature values require validation in respect to more reliable data sets or methods.

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# Table captions

Table 1. Convective heat transfer coefficients assigned to land cover categories in the Košice city.

# Figure captions

Fig. 1. Location of the study area in the Košice City, Slovakia. The cyan line outlines the area subject to airborne lidar and photogrammetric mapping. The red outline delineates a site (Moyzesova street) selected for a detailed view on the right with aerial orthoimage as natural color composite. The background maps are © Copernicus, Sentinel 2A image acquired on 29 June 2016.

Fig. 2. Perspective 3D view of the entire study area (cyan outline in Fig. 1) for which the 3D city model was generated. 3D buildings are dispalyed on a digital terrain model in the ArcScene software by ESRI.

Fig. 3. A detailed view of 3D city model (left) and lidar based digital surface models (DSM) for the smaller site (Moyzesova street) including buildings (middle) and vegetation (right). The area size is 200 m by 400 m. DSM cell size is 0.50 m.

Fig. 4. Land cover in 21 categories representing the material of the ground below the trees and shrub for the entire study area and smaller site (Moyzesova street).

Fig. 5. Broad-band albedo derived from atmospherically corrected Sentinel 2A data for (a) land cover classes including trees and (b) ground cover (without trees). The land cover classes were derived by manual interpretation of aerial orthoimagery and field survey.

Fig. 6. Spatially distributed convective heat transfer coefficient hc (W.m-2.K-1) for the entire study area and smaller site (Moyzesova street) based on land cover of the ground (upper row) (Table 1) and increased for the tree and shrub vegetation based on leaf area index and expert judgement (bottom row).

Fig. 7. Global solar irradiance (W.m -2) calculated by the r.sun model for June 30 at 10:20 zonal time for the smaller site and a) scenario 1, b) scenario 2, c) scenario 3.

Fig. 8. Modelled land surface temperature for the entire study area and smaller site and a) scenario 1, b) scenario 2, c) scenario 3.

Fig.9. Modelled temperature of land cover surface (left) derived for 30 June 2016 at 9:20 AM of GMT 10:20 zonal time and land surface temperature at the bottom of the atmosphere (right) as sensed at the same time by Landsat 8 TIRS, band 11. The spatial resolution (raster cell size) is 30 m, the units of temperature are degrees Kelvin.