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Research paper

SPATIAL DOWNSCALING OF LAND SURFACE TEMPERATURE MAPS – A CASE STUDY FOR THE CITY MUNICIPALITY MEDIJANA, THE CITY OF NIŠ, SERBIA

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Abstract

Urban heat islands are becoming an increasingly important challenge in the 21st century. Land surface temperature is a key factor in the urban heat island risk assessment. Its monitoring is possible through satellite land surface temperature (LST) detection. However, satellite images with insufficient spatial resolution are available to monitor temperature changes in urban areas, which arise due to the technical limitations of satellite thermal infrared sensors. Numerous algorithms have been proposed to solve the problem of the coarse spatial resolution of LST. This study explores the application of a machine learning algorithm based on a Random Forest (RF) regression model between LST and predictor variables such as aspect, digital elevation model (DEM), hillshade, normalized difference vegetation index (NDVI), building heights, digital height model (DHM), and land cover. The study focuses on the municipality of Medijana, located in the City of Niš in the Republic of Serbia. The spatial resolution of MODIS LST was improved from 1 km to 250 m. The results indicate that the applied machine learning method can predict potential temperatures at a finer scale with high accuracy, with NDVI indicating a significant local influence on LST. The results indicated that the RF approach demonstrated a robust and high-performance methodology. The Mean Square Error (MSE) values ranged from 0.730 °C² to 1.028 °C², while the Root Mean Square Error (RMSE) values varied from 0.854 °C to 1.100 °C across the 84 models generated.

Key words: *Random Forest Regression, Land Surface Temperature, Spatial Downscaling, Urban Area*

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1. INTRODUCTION

Urban Heat Islands (UHIs) are the regions within urban areas that are considerably hotter than the surrounding rural or urban environment [1]. The UHI phenomenon arises from the uncontrolled growth of urban areas largely from anthropogenic reasons – the modification of natural landscape due to urban expansion by replacing forests, wetlands, and grasslands with structures, roads, and other construction interventions in general [2]. UHI poses a risk because it intensifies heat exposure in cities, leading to increased health problems, energy demand, and reduced liveability, especially during extreme heat events. Therefore, UHI topic has recently attracted many researchers.

Land surface temperature (LST) is widely used in UHI research [3, 4], as it enables the quantification of temperature differences between urban and rural areas, as well as spatial variations within cities, thereby enhancing the understanding of hazard component of UHI risk. Obtaining LST data over extensive areas via ground measurement is impractical, but the improvement of satellite-based thermal infrared (TIR) sensors addresses this issue [5]. A single sensor cannot provide LST data that combines both high frequency and precise spatial resolution due to the limits of TIR technology. Spatial downscaling of LST products with poor resolution but high frequency, together with additional auxiliary data, is an efficient way to overcome this difficulty [6]. Terra/MODIS sensors can observe surface temperature twice a day in the same study area, but their spatial resolution of 1 km is low [6]. Thus, MODIS sensors provide high temporal and poor spatial resolution. Some sensors, such as the Advanced Spaceborne Thermal Emission Reflection Radiometer (ASTER), have a high spatial resolution of 300 m but a temporal resolution of 15 days. This indicates the importance of developing and using appropriate methods for scaling satellite LST data. Spatial downscaling of LST is a widely adopted approach to enhance the spatial resolution of LST products [6, 7].

There are currently two primary types of downscaling techniques for LST: models based on physical mechanisms and models based on statistics [8]. Based on the concepts of thermal radiation, physical mechanism-based models aim to establish a significant, empirically supported relationship between thermal radiance (or LST) and auxiliary data, including land cover maps. Although these models offer insightful scientific information, their complexity may restrict their usefulness [9].

The statistical correlations between LST and different land surface parameters are the foundation of statistics-based models. These relationships are usually obtained from supplementary data with relatively high spatial resolutions. The addition of adequate predictor variables and the creation of reliable regression models are the two main phases through which statistics-based LST downscaling techniques have largely developed to improve the accuracy of downscaled LST [10]. Digital elevation models (DEM), land cover maps, and the normalized difference vegetation index (NDVI) are some of the frequently used elements in these models [6]. Statistics-based models are becoming increasingly common because they are simpler to develop than models based on physical mechanisms [11].

Although one-factor models are typically simple, utilizing a single indicator is often insufficient to capture LST fluctuations. As a result, multifactor models are used in practice more frequently. Tang et al. [12], for instance, combine several variables, including topography characteristics like DEM, slope, and aspect, remote sensing spectral indices, and land surface reflectance data from the Red, Blue, Green, and NIR bands. The non-stationary relationship between LST, NDVI, and DEM was also investigated by Duan and Li [13]. To create a correlation with LST, Bechtel et al. Also used DEM in conjunction with the normalized difference built-up index [14].

The most common algorithms used for downscaling by statistics are linear regression models. Linear regression formulas, however, sometimes cannot account for nonlinear relationships between LST and remote sensing indices. To deal with this deficiency, various models have been presented to explain linear and nonlinear relationships between LST and driving variables.

This study aims to apply the Random Forest (RF) regression model to produce detailed maps of LST in the municipality of Medijana, located in the city of Niš in the Republic of Serbia. This model was applied in many works dealing with the same issue [6, 12]. The enhanced maps of LST are useful in delivering vital information on the spatial patterns of temperature anomalies, supporting the creation of enhanced UHI mitigation strategies and urban resilience planning. With this case study, we intend to show potential applications of using spatial downscaling as a method of overcoming the gap between coarse satellite data and the need for detailed UHI mapping. The spatial resolution of MODIS LST in this research was enhanced from 1 km to 250 m by incorporating various predictor variables, including Aspect, DEM, hillshade, NDVI, building heights, the digital height model (DHM), and Land Cover. The results indicate that NDVI plays a crucial role in influencing local LST.

The paper is organized as follows. The methodology framework, the study region, datasets, downscaling approach, model development, and model validation are briefly introduced in the Methodology. Results with the discussion of the developed models and their parameters are shown in the Results and Discussion, followed by the Conclusions section.

2. METHODOLOGY

The methodology in this research comprises the following steps:

Study Area Definition - Defining the geographical boundaries of the study area.

Data Collection – Collection of remote sensing data, MODIS LST at a 1 km spatial resolution, and predictor variables.

Data Preprocessing – This part involves transforming the data to the same coordinate reference system (EPSG:3857 -WGS 84 / Pseudo Mercator), and determining the DHM.

Spatial Downscaling – Applying spatial downscaling techniques to reduce MODIS LST data from 1 km to 250 m resolution, using the collected predictor variables.

Model Development – Development of the RF regression model as the analytical tool for predicting LST.

Model Validation – Model validation is performed on out-of-bag (OOB) samples using metrics such as mean square error (MSE) and root mean square error (RMSE).

Heat Map Generation – Creation of LST map with 250 m spatial resolution, utilizing the validated RF model to predict LST across the study area.

2.1. Study Area

The City of Niš is situated nearby the confluence of the Nišava and Južna Morava rivers, and surrounded by hills in the Niš valley. It has a diverse population of approximately 250,000 residents. This study focuses on the central city municipality of Medijana of close to 90,000 inhabitants, covering 10 km² [15] (Figure 1). The City has a temperate continental climate, with an average annual temperature of 12.4 °C and 614 mm precipitation in 1991-2020. The warmest months are July and August with an average temperature of 23.1 °C, and the coldest is January with an average temperature of +0.9 °C [16].

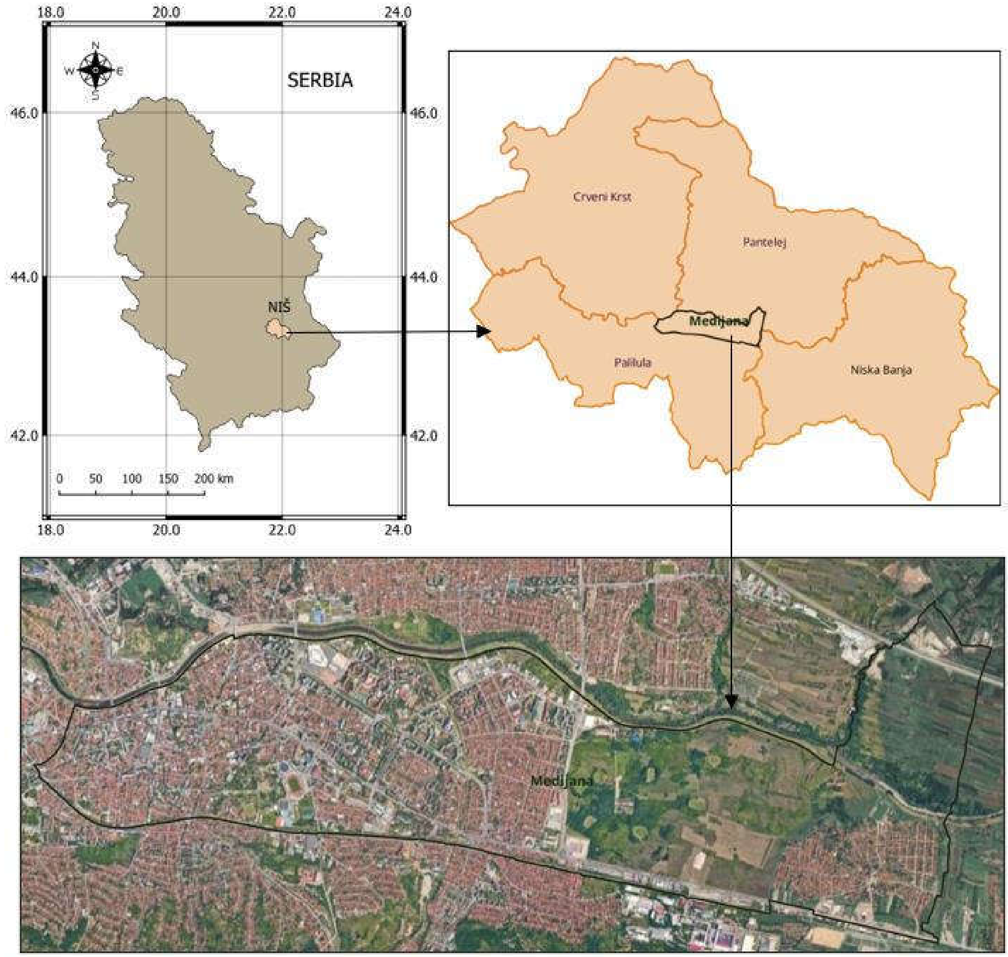

Figure 1. The location of the city of Niš in Serbia, its City Municipalities, and the study area – the Municipality of Medijana boundaries shown on a satellite map.

2.2. Data collection and preprocessing

The data collection and preprocessing stages dealt with laying a foundation for the RF regression model. Table 1 provides information regarding the data used in this research. As mentioned earlier, the MODIS LST product, with a spatial resolution of 1 km and a temporal resolution of 1 day, was used for the study area. The period of analysis in this research is from 04/08/2024 to 11/08/2024, during which exceptionally high LST were recorded, ranging from 37.7 to 41.8 °C in the study area. To enhance the resolution of the available LST product, relationships were established with the following predictors: aspect, DEM, hillshade, NDVI, building heights, DHM, and Land cover. DHM is the difference between digital surface model (DSM) and DTM [17].

DHM accounts for the volume effectively utilized for residential use [17]. In general, DHM represents building height, with a higher resolution of 30m.

Table 1. The dataset information

Dataset	Source	Spatial Resolution	Usage	Reference
MODIS/Terra Land Surface Temperature/Emissivity Daily L3 Global 1km SIN Grid V061 (MOD11A1) v 6.1	Earth Data https://search.earthdata.nasa.gov/search	1 km	Downscaling	[18]
Copernicus GLO-30 Digital Elevation Model	Open Topography https://opentopography.org/	30 m	Predictor	[19]
Aspect from Copernicus GLO-30 Digital Elevation Model			Predictor	
Hillshade from Copernicus GLO-30 Digital Elevation Model			Predictor	
ALOS Global Digital Surface Model (AW3D30)			To obtain DHM	[20]
MODIS/Terra Vegetation Indices 16-Day L3 Global 250 m SIN Grid (MOD13Q1 v006) - NDVI	Earth Data https://search.earthdata.nasa.gov/search	250 m	Predictor	[21]
GHS-BUILT-S R2023A	Copernicus https://human-settlement.emergency.copernicus.eu/download.php?ds=builtH	100 m	Predictor	[22]
CORINE Land Cover 2018 (vector/raster 100 m), Europe, 6-yearly	Copernicus https://land.copernicus.eu/en/products/corine-land-cover/clc2018	100 m	Predictor	[23]

In the context of the RF regression model applied to LST mapping, predictor variables play a crucial role in determining the accuracy and reliability of the model's outputs. Predictor variables serve as inputs that help the model understand the relationships between different factors and how they influence LST. Figure 2 shows the maps for each of the predictors used across the study area.

2.3. Spatial Downscaling

Statistics-based models are developed by identifying statistical relationships between LST and various land surface parameters obtained from auxiliary data with comparatively high spatial resolution. If the relationships between LST and its predictors remain consistent across spatial resolutions, high-resolution LST can be estimated using these predictors. To develop the connections required to improve the LST resolution with this approach, it is necessary to adapt the predictors to the coarse resolution of the LST (Re-sampling process). The predictive model was formed using the XLStat software [24]. The software allows building a predictive model for a quantitative response variable based on explanatory quantitative and/or qualitative variables.

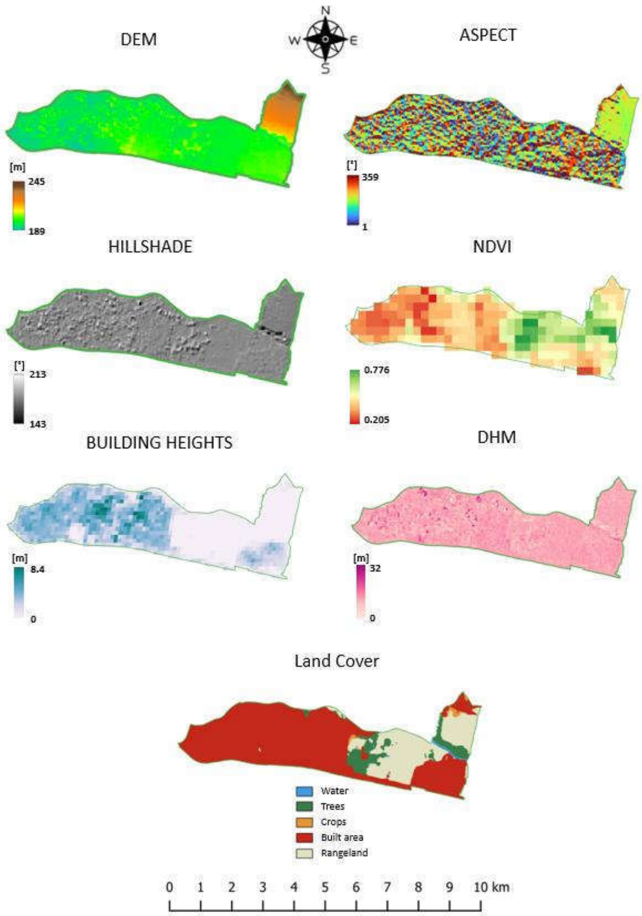

Figure 2. Thematic maps of predictors

The resolution of 250 meters is chosen because it is the lowest resolution among the predictors used. As indicated in Table 1, this 250-meter resolution corresponds to the NDVI. To work with an even finer resolution, it is necessary to utilize predictors that also have high resolutions. However, this increased level of detail demands more data, time, and memory for processing.

Furthermore, to obtain the final LST map with high resolution, a residual correction must be performed between the initial LST map (1 km) and the LST map obtained from the model (250 m), on which disaggregation is now performed to a resolution of 1 km. Figure 3 shows a schematic of the LST downscaling procedure.

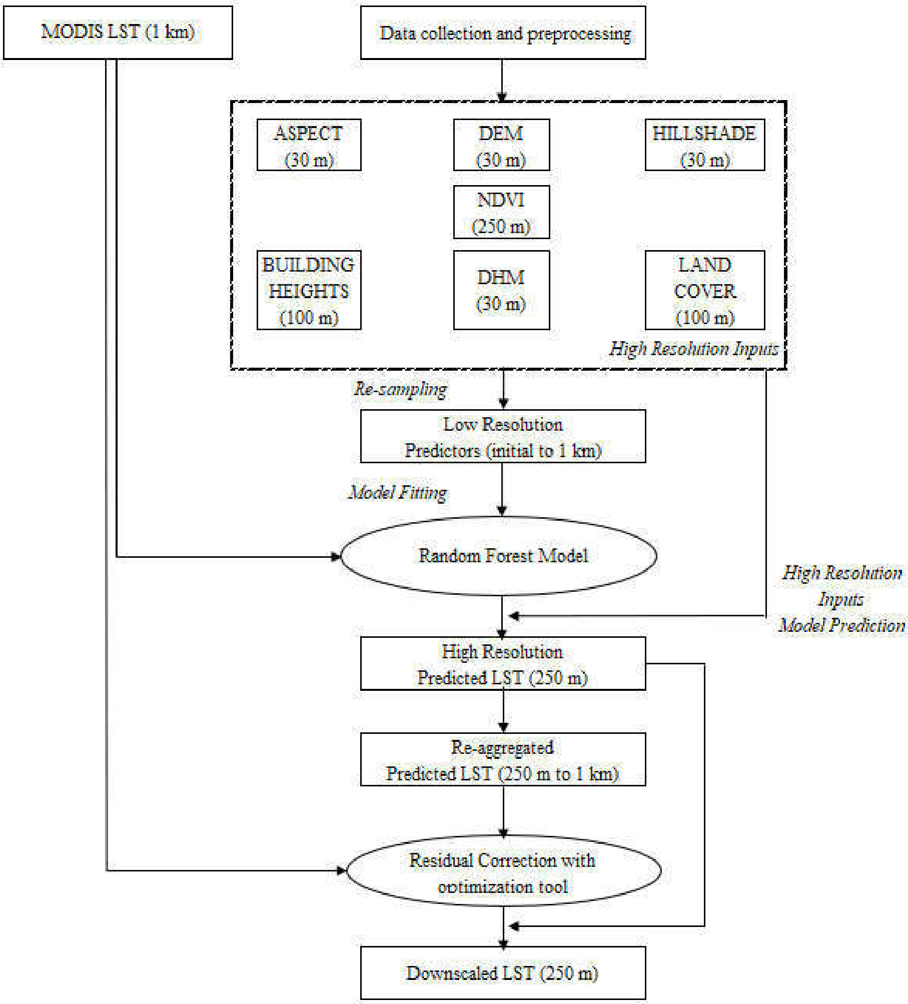

Figure 3. Land surface temperature (LST) downscaling procedure scheme

2.4. Model Development

MODIS LST products are known for their coarse spatial resolution. Regression models have been developed to enhance LST resolution by incorporating auxiliary environmental predictors. RF are ensembles of decision trees that can be used to solve classification and regression problems [25]. RF regression is a powerful ensemble learning technique used for predictive modeling. Built upon decision trees, it combines multiple individual trees to enhance accuracy and reduce overfitting. The development process involves data preprocessing, parameter selection, model training, and performance evaluation. For model development, we use the Random Input variant, an essential modification of the bagging XLstat [26]. Its objective is to increase the independence between the models (trees) to obtain a final model with better performance. XLstat requires the entry number of trees, mtry, and tree parameter values, such as minimum node size, minimum son size, and maximum depth. More trees enhance stability but increase computation time. Maximum depth restricts tree complexity to prevent overfitting. Mtry refers to the number of features randomly selected at each split when building individual decision trees. It controls the level of randomness in feature selection, ensuring that different trees in the ensemble consider different subsets of features. To assess the predictive ability of RF regression, we use evaluation metrics Mean Squared Error (MSE) and Root Mean Squared Error (RMSE):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2} \tag{2}$$

where n is the number of sample data; Y_i is the observed surface temperature in °C, and $\hat{Y}_i$ is the predicted surface temperature in °C.

The following RF parameter values were used:

- Forest parameters: Sampling (Random with replacement); Method (Random Input); Sample size (40); Number of trees (100, 200, 500, and 1000),
- Stop conditions: Construction time (300); Convergence (50),
- Tree parameters: minimum node size (2); minimum son size (1); maximum depth (10, 20, and 30); mtry (1, 2, 3, 4, 5, 6, and 7); CP (0,0001).

The sensitivity of model parameters was tested by varying model parameters such as maximum depth, number of trees, and mtry.

2.5. Model Validation

When training a RF model, each tree is constructed using a bootstrap sample of the data. This means that some data points are randomly selected (with replacement) to build the tree, while those not included in this sample are referred to as OOB samples. These OOB samples serve as a means to evaluate the model predictions, offering an internal validation method that eliminates the need for separate test data. This technique is especially advantageous as it allows for the evaluation of the model during training, thus conserving both time and computational resources [27]. Also, OOB samples can be used in the model parameter tuning process, in order to choose the optimal model for LST prediction. We use OOB samples for parameter optimization and model validation.

3. RESULTS AND DISCUSSIONS

3.1. Predictor Significance and Parameter Sensitivity

To adapt the RF machine learning model to various problem domains, it is required to calibrate the model parameters accordingly. The selection of the optimal parameter configuration is crucial, as it significantly influences the overall performance and predictive accuracy of the model. Ensuring that these parameters are finely tuned can lead to more effective and reliable outcomes in a range of applications. One of RF valuable features is the ability to measure the importance of each variable (or feature) in making predictions. Mean Decrease in Impurity (MDI) – also known as Gini Importance, measures the extent to which each feature contributes to reducing uncertainty (impurity) when making splits in decision trees. Features that create significant splits receive higher importance scores. High importance values indicate features that strongly influence predictions. Features with low importance may contribute little and could be considered for removal in optimization processes. Because in recent studies of size reduction techniques, many authors have shown that introducing a large number of predictors improves model performance [9, 28], our preliminary model concept included a variety of explanatory variables. We also included some predictors that we have not seen used in similar studies, such as building heights and DHM. However, our analysis indicated that increasing the number of predictors does not significantly affect the accuracy of the model, which was also pointed out by Bartkowiak, P. et al. [29]. This is illustrated in Figure 4, which highlights the significance of the seven variables employed to predict surface temperatures, represented by the mean increase error (MIE). MIE values indicate that DEM, NDVI, and Building Heights have a more significant role in the LST prediction process. We assumed that DHM would have a more significant influence in predicting LST, however, it did not come to this, most likely due to insufficiently good fitting of DSM and DEM.

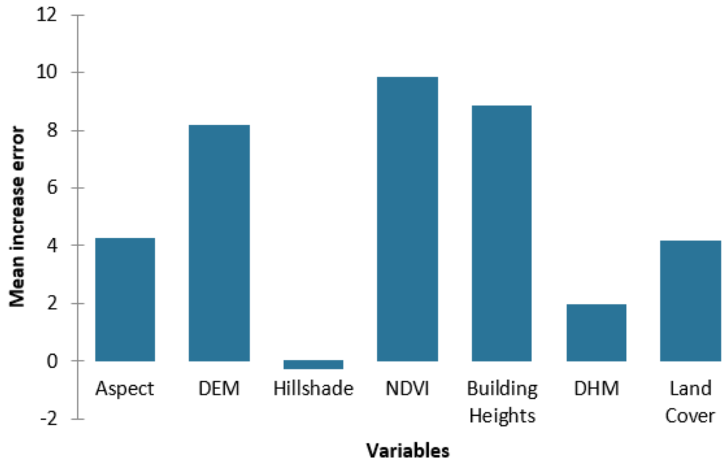

Figure 4. Variable significance in the prediction of LST

Figure 5 demonstrates the sensitivity of the developed models to varying parameters: maximum depth (3 cases) and mtry (from 1 to 7) for the fixed number of trees (4 cases), which yields a total of 84 models (3x7x4=84).

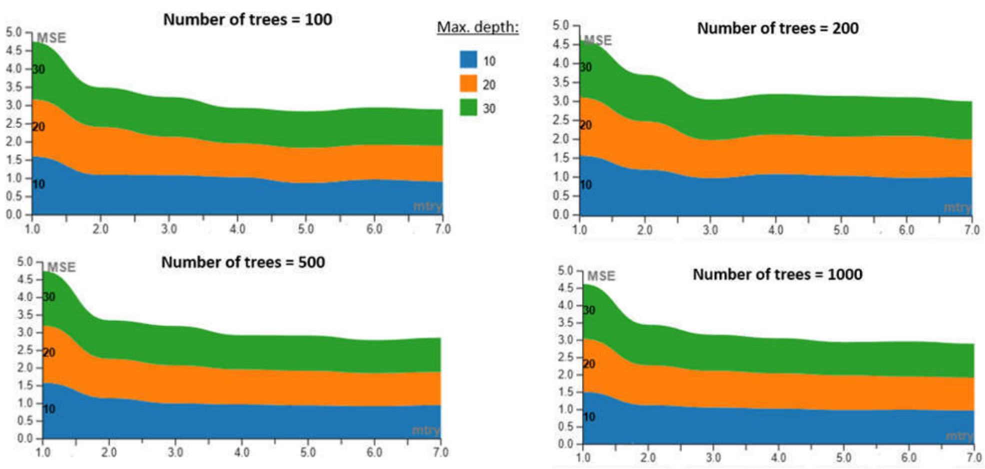

Figure 5. Sensitivity of the model to changes in the number of trees, maximum depth, and mtry (x-axis) through MSE

The highest variability, shown by the highest MSE, corresponds to the value mtry = 1. A number of trees and max depth did not cause a significant variation in model performance.

3.2. Results of Model Validation

Out-of-bag (OOB) error is a key indicator in RF models. OOB error is computed during training. It provides an internal estimate of the model's performance without the need for a separate validation set or cross-validation. For each data point, predictions are made using only the trees that did not include that point in their training set. The OOB error (MSE), is then calculated as the average error across all these predictions. The errors varied from 0.730 °C² to 1.028 °C² across the 84 models generated. Figure 6 illustrates the evolution of OOB error as the number of trees changes. The left diagram depicts the model with the smallest error, while the right diagram illustrates the model with the largest developed error.

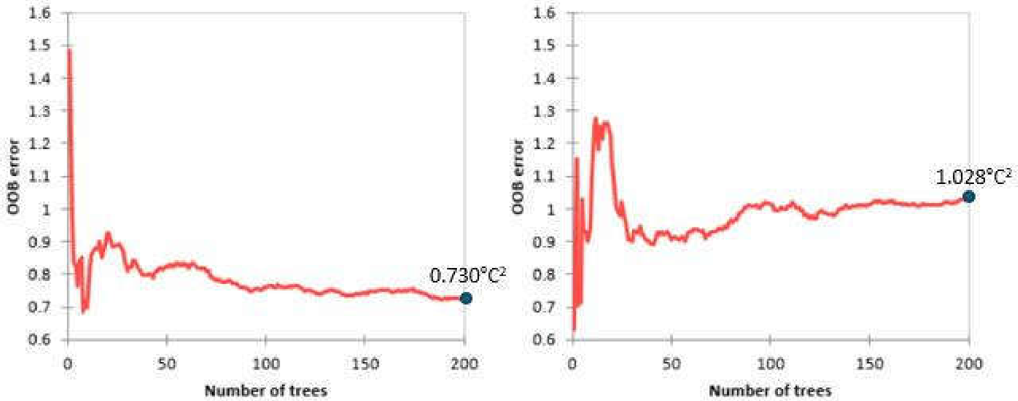

Figure 6. OOB error evolution. Left: the best performing model, Right: the worst performing model

The model selected for LST downscaling has the following parameter values: mtry = 6; number of trees = 200; max. depth = 30.

The selected model has RMSE of 0.854 °C, while in the work that also used the RF approach, RMSE of 2.2 K was obtained [29]. Hutengs & Vohland [28] applied random forest regression to MODIS LST data with RMSEs ranging from 1.41 K to 1.92 K. Similarly, good results were obtained by Maeda [30]. The mentioned RMSE values depend on the location and are greatly influenced by the topographical complexity, as well as the heterogeneity of the vegetation in the study area. Our RMSE value indicates that we have established a highly accurate model for LST prediction.

3.3. Results of Downscaling – Identifying UHI Hotspots

Spatial downscaling of LST data allows us to identify localized areas of temperature peaks, i.e., UHI hotspots. Figure 7 illustrates the temperature distribution across the municipality of Mediana at its original resolution of 1 km. It can be seen that the western part of the municipality, which is the most built-up area, is also the warmest. However, areas of 1 km^2 require considerable investments to mitigate the effects of UHI, which may not be justified because it is not likely that the whole area suffers from overheating. To determine if a high investment is justified or if it needs to be reduced to a smaller area, it is rational to work on improving the resolution of the LST map. Figure 8 shows the results of spatial downscaling of LST, which is produced by the model formed using a RF.

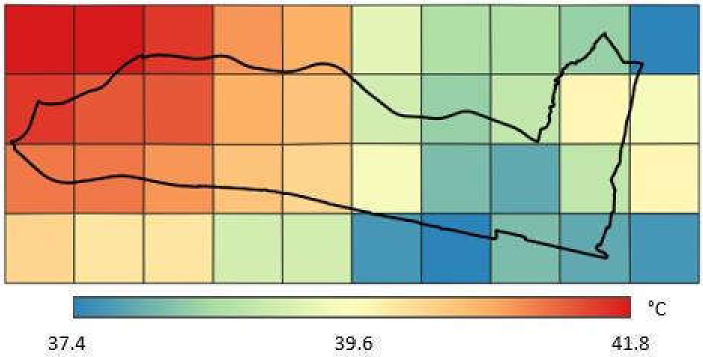

Figure 1. Original MODIS 1 km LST map over the municipality of Medijana

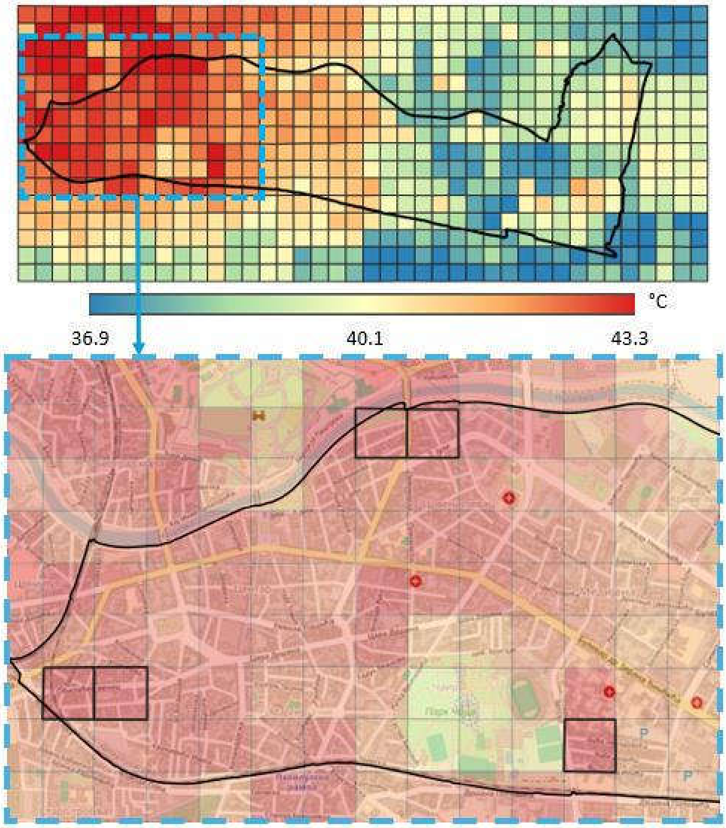

Figure 2 . Downscaled MODIS map with 250 m resolution, with zoom on the hottest part of the study area and five identified UHI hotspots (black boxes)

In the lower part of Figure 8, we highlighted five fields with a resolution of 250 m, where the highest LST values are predicted, ranging from 41.6 °C to 43.1 °C. These areas include Obilićev venac neighborhood, the street of 7. Juli (Šećer mala neighborhood) and the area around the Medical Secondary School.

4. CONCLUSION

The hazard component of UHI risk involves the assessment of LST data. In urban areas, more precise identification of UHI hotspots enables the application of targeted mitigation measures. In this research, we applied a machine learning - RF downscaling method to enhance the spatial resolution of LST data (from 1 km to 250 m), using MODIS/Terra Land Surface imagery for the central City Municipality of Niš, Serbia, during a heat wave event recorded in 2024. The following can be concluded:

1. Among the seven predictors considered in the LST prediction models, the most significant were NDVI, Building Height, and DEM; Aspect and Land Use were moderately significant, while DHM and Hillshade had the least impact.
2. The established models demonstrated robust and consistent performance, with MSE values remaining rather stable for mtry values greater than 2, regardless of the examined number of trees and the maximum depth.
3. The achieved accuracy (RMSE = 0.854 °C) of the downscaled LST model - using mtry = 6, 200 trees, and a maximum depth of 30 - outperforms similar studies that applied the RF approach.
4. Five UHI hotspots were identified in the City Municipality of Medijana, providing insights for urban planning and UHI effect mitigation. The enhanced-resolution LST dataset can support stakeholders in identifying heat stress-prone areas and implementing targeted adaptation interventions, such as green, blue and white measures.

In future research, we aim to incorporate additional predictors into the RF downscaling model, such as the Tropical Night Index, which is not only an indicator of UHI presence but is also available in future climate projections. Because climate models offer long-term simulations of this parameter until the end of the 21st century, it will be possible to assess potential shifts in UHI locations under various urban development scenarios.

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