Impact of urban sprawl on land surface temperature in Mashhad City, Iran: A deep learning and cloud-based remote sensing analysis Postprint

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Abstract

Abstract

The evolution of land use patterns and the temporal manifestation of urban heat island (UHI) effects represent critical challenges in urban development strategies. This study develops a model to characterize the relationship between land use change and land surface temperature (LST) in Mashhad, northeastern Iran. Leveraging the Google Earth Engine (GEE) platform, we calculated LST and extracted land use maps spanning from 1985 to 2020. A convolutional neural network (CNN) approach was employed to deeply investigate the relationship between LST and land use, with results compared against standard machine learning methods including Support Vector Machine (SVM), Random Forest (RF), and linear regression.

The findings reveal that LST across all land use categories increased by 1.00°C–2.00°C. Variations in temperature increases among different land use types demonstrate that land use change exerts a strong influence on temperature rise, beyond the effects of global warming and climate change alone. Built-up areas in Mashhad exhibited an estimated LST increase of 1.75°C, while forest land showed the minimal increase at 1.19°C.

The developed CNN achieved an overall prediction accuracy of 91.60%, significantly surpassing linear regression and standard machine learning methods through its capacity to extract higher-level features. Additionally, deep neural network (DNN) modeling projects that urban land—comprising 69.57% and 71.34% of the study area in 2025 and 2030, respectively—will experience extreme temperatures exceeding 41.00°C and 42.00°C in those years.

In summary, the LST prediction framework integrating the GEE platform with CNN methodology provides an effective tool for urban planning and UHI impact mitigation.

Full Text

Preamble

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Impact of Urban Sprawl on Land Surface Temperature in Mashhad City, Iran: A Deep Learning and Cloud-Based Remote Sensing Analysis

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Abstract: The evolution of land use patterns and the emergence of urban heat islands (UHI) over time are critical issues in urban development strategies. This study aims to establish a model that maps the correlation between changes in land use and land surface temperature (LST) in Mashhad City, northeastern Iran. Employing the Google Earth Engine (GEE) platform, we calculated LST and extracted land use maps from 1985 to 2020. The convolutional neural network (CNN) approach was utilized to deeply explore the relationship between LST and land use. The obtained results were compared with standard machine learning (ML) methods such as support vector machine (SVM), random forest (RF), and linear regression. The results revealed a 1.00°C–2.00°C increase in LST across various land use categories. This variation in temperature increases across different land use types suggested that, in addition to global warming and climatic changes, temperature rise was strongly influenced by land use changes. The LST surge in built-up lands in Mashhad City was estimated to be 1.75°C, while forest lands experienced the smallest increase of 1.19°C. The developed CNN demonstrated an overall prediction accuracy of 91.60%, significantly outperforming linear regression and standard ML methods due to its ability to extract higher-level features. Furthermore, the deep neural network (DNN) modeling indicated that urban lands, comprising 69.57% and

71.34% of the studied area, were projected to experience extreme temperatures above 41.00°C and 42.00°C in the years 2025 and 2030, respectively. In conclusion, the LST prediction framework, combining the GEE platform and CNN method, provided an effective approach to inform urban planning and mitigate the impacts of UHI.

Keywords: convolutional neural network; machine learning; Google Earth Engine; land use change; random forest

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1 Introduction

Land use and land cover (LULC) changes have various consequences on the environment, ecosystem, and human society. These changes play a crucial role in influencing land surface temperature (LST), making it a key element in global warming research and an indicator of climate change acceleration. Anthropogenic activities such as deforestation and urbanization have significantly altered the land surface over the past half-century (Jibitha et al., 2024). Rapid transitions in land utilization raise concerns as a significant ecological issue, leading to challenges such as the dwindling of vegetated areas and the emergence of urban heat island (UHI) effects (Amiri et al., 2009). These changes exert multiple impacts on surface temperatures at both local and global scales (Liu et al., 2022). It is imperative to recognize the upsurge of LST as a critical concern and explore the correlation between land use and LST using a precise approach that considers all relevant factors. This exploration can guide urban planners in developing sustainable urban spaces (Alavipanah et al., 2022).

Comprehensive research has been directed toward recognizing the underlying factors affecting the relationship between LULC changes and LST (Nega and Balew, 2022; Khan et al., 2023; Patel et al., 2023; Jibitha et al., 2024). A nonlinear correlation between LST and LULC changes has been extensively explored in prior studies, emphasizing the complexity of their interactions (Tran et al., 2017; Wang et al., 2018; Wang et al., 2019b). Tran et al. (2017) highlighted that

LST is influenced non-linearly by LULC types. Their methodology, which utilized non-parametric regression and simulated LULC scenarios, demonstrated that UHI patterns are shaped by urban landscape characteristics and development types. However, their approach, although effective in forecasting LST patterns, relied heavily on hotspot and regression analyses, which might oversimplify dynamic processes. Similarly, Wang et al. (2018) investigated LULC impacts on LST in Yangon, Myanmar, showing that agricultural practices significantly affect atmospheric and climatic systems. They identified temporal and seasonal variations in LST associated with different land cover types, particularly water bodies and built-up lands; however, their study primarily focused on correlation analysis, leaving room for integrating more advanced methods with non-linear interactions. Wang et al. (2019b) examined spatio-temporal LULC changes in the Pearl River Delta, China, using local climate zone (LCZ) classifications. Their findings revealed that urban densification and vertical expansion of low-rise areas contribute significantly to LST increases, but the study relied on LCZ classifications without exploring deeper non-linear relationships. Collectively, these studies underscore the limitation of traditional methods, such as linear regression and correlation analysis, in addressing the intricate and dynamic relationships between LULC changes and LST. This limitation highlights the need for advanced methodologies like deep learning to capture complex, non-linear, and spatially heterogeneous interactions more effectively.

Moreover, many environmental factors can affect the relationship between LULC changes and LST. Feng et al. (2019) examined the impacts of three primary factors—the normalized difference vegetation index (NDVI), the normalized difference built-up index (NDBI), and the normalized difference water index (NDWI)—on LST variation. Their findings indicated a significant influence of these indices on LST variation. Similarly, He et al. (2019) utilized Landsat satellite images to explore the effect of land characteristics on LST in Chinese mountainous terrains. They found a negative correlation between altitude and LST and noted that LST fluctuations were more pronounced in southern exposures, with vegetation cover being a predominant influencing factor. Patel et al. (2023) analyzed the impact of different land use types on LST using Landsat imagery. They found that vegetation indices such as NDVI, along with indices related to soil moisture and proximity to water bodies, were crucial in regulating LST. The study emphasized that areas with high vegetation cover exhibited significantly lower LST, while barren lands and urban lands showed elevated temperatures. Komeh et al. (2023) monitored and compared the spatial autocorrelation of LST with land use in two districts with dissimilar climates. Results showed that most urban lands with temperate climate in coastal areas of the Caspian Sea have high LST; however, rangelands have low LST. Zhan et al. (2015) investigated the relationships between LST and land cover ratio and building volume density. Results discovered a strong association between LST and land cover; however, the correlation between LST and building volume density was not significant.

In most studies, classical methods such as linear regression have been used to investigate the relationship between land use change and LST. Nowadays, non-linear procedures and artificial intelligence like deep neural networks (DNN) are widely utilized (Ma et al., 2019; Mazzia et al., 2019; Boulze et al., 2020). Recent studies in remote sensing have primarily applied deep learning techniques to generate land use maps. However, these studies often rely on traditional methods, such as linear regression, to analyze the connection between land use changes and LST, rather than using deep learning for this purpose. Therefore, this study applies DNN to capture the complex spatial and non-linear interactions between land use changes and LST. This approach represents a novel application of deep learning in this context, aiming to offer a more precise understanding of these relationships.

DNN types include convolutional neural networks (CNN), auto-encoders, recursive neural networks, and recurrent neural networks. Selecting the right model and optimizing its parameters is crucial and challenging, significantly impacting the final accuracy. According to research on remote sensing data analysis, CNNs are highly regarded in image-related applications, with demonstrated effectiveness in many studies (Zhang et al., 2016; Ma et al., 2019; Li et al., 2024). CNNs have demonstrated strong learning capabilities, particularly when combined with data augmentation techniques like rotation, random noise, and cropping, which prevent overfitting (Gharbia et al., 2020; Naushad et al., 2021). Kussul et al. (2017) applied both one-dimensional (1-D) and two-dimensional (2-D) CNNs to analyze large-scale areas (28$×10^{3}$ km^{2}) using high-resolution free data from Landsat 8 and Sentinel-2 satellites, enabling the discrimination of 11 complex land cover types. The rise of open recognition competitions, such as the large-scale visual recognition challenge, has further accelerated the development of CNNs, with architectures like Visual Geometry Group (VGG), Residual Neural Network (ResNet), and Fully Convolutional Networks (FCN) being adapted for remote sensing applications (Qin et al., 2020; Hao et al., 2023; Li et al., 2024).

This study investigates the patterns of LST in relation to land use changes in Mashhad City, Iran, from 1985 to 2020. The DNN was developed to model the relationship between LST and land use changes. Using projections of future land use changes, the CNN model was employed to forecast LST in 2025 and 2030, owing to its capability to solve multifaceted and non-linear problems.

2.1 Study Area

The study area is located in Mashhad City, Khorasan Razavi Province, Iran (36°10 42 -36°24 12 N, 59°26 05 -59°43 36 E; Fig. 1 [Figure 1: see original paper]). The city is nestled between the Hezar Masjed and Binaloud mountains, with elevation ranging from 950 to 1150 m above sea level. Mashhad City has a cold semi-arid climate with hot, dry summers and cool, somewhat damp winters, receiving around 250 mm of annual precipitation. Temperatures can soar up to 43.00°C in summer, while dropping to as low as -23.00°C in winter.

2.2 Data Source

The Google Earth Engine (GEE) platform was used to process all steps related to image pre-processing and preparation of input features. GEE is a web-based remote sensing platform capable of performing spatial and temporal analyses on multiple satellite image datasets, allowing users to conduct their analysis on geo-big data without requiring a personal processing system (Kumar and Mutanga, 2018; Sidhu et al., 2018). This capability addresses the challenges associated with data loading, storage, and processing encountered when working with big land surface data (Kumar and Mutanga, 2018; Ravanelli et al., 2018). We utilized a collection of Landsat satellite images chosen for their suitable spectral, spatial, and temporal resolutions, as well as their comprehensive archival record within the period under assessment. To avoid the impact of seasonal variations, we utilized images from May, June, and July with cloud cover under 5.00% to derive land use maps. Consequently, the average summer temperatures for these three months were computed from the images.

2.3 Methods

Figure 2 [Figure 2: see original paper] shows a flowchart of three computational steps for data processing and LST modeling. Step 1 involves all necessary cloud computations in the GEE platform; Step 2 entails the application of the Land Change Modeler (LCM) toolbox for simulating land use maps; and Step 3 comprises the use of deep learning to model the relationship between land use and LST.

2.3.1 Land Use Classification

Land use mapping was facilitated by the object-oriented classification approach, which has proven to yield significantly superior precision compared with common pixel-based techniques (Li et al., 2016; Zeraatkar et al., 2021; Wang et al., 2022). Utilizing the support vector machine (SVM) algorithm, we delineated five distinct land use types: built-up lands, forest lands, agricultural lands, barren lands, and rangelands. Typically, this technique involves a two-step process: segmentation followed by classification (Yan, 2003; Memarian et al., 2013). During segmentation, pixels are grouped to separate image objects using spatial and spectral metrics set by user-defined spectral and geometric properties (Agarwal et al., 2013). Following this, the SVM algorithm is applied for classification purposes. The SVM algorithm is widely recognized for its high classification accuracy and effectiveness in object-oriented classification, specifically in complex environments (Tzotsos and Argialas, 2008; Puissant et al., 2014).

The object-oriented approach through the SVM algorithm was applied to the selected area across eight temporal intervals. Image classification involved three key stages: initial pre-processing, which encompassed radiometric and atmospheric adjustments as well as contrast enhancement; selection of an appropriate classification technique, determined by quantitative evaluation of its accuracy; and subsequent post-processing that included the application of majority/minority filters.

2.3.2 LST Retrieval

Thermal infrared radiation and physical models have been effectively proven for assessing temperature over large-scale areas (Wang et al., 2019a). Various techniques have been introduced for analyzing thermal data from different sensors, yet the accuracy of these methods continues to be a subject of ongoing scrutiny. This research utilized the mono-window algorithm to derive and ascertain LST and explore its correlation with land use types. The mono-window algorithm necessitates the calculation of average atmospheric temperature, alongside brightness temperature, emissivity, and Planck' s equation, to determine LST accurately (Rongali et al., 2018). Incorporating average atmospheric temperature into this formula has been shown to enhance LST results (Wang et al., 2015; Wang et al., 2019a). The computational steps for extracting LST are described in detail in Komeh et al. (2023).

2.3.3 Land Use Change Simulation

In this study, LCM was used to project land use changes in 2025 and 2030. LCM provides a tool for land cover change assessment and planning. This model demonstrates good efficiency in simulating complex land change processes by combining the capabilities of the cellular automata (CA)-Markov chain model with the multi-layer perceptron (MLP) neural network through error backpropagation training (Eastman, 2009; Tajbakhsh et al., 2018). The LCM model is an integrated method able to simulate changes in several land use types simultaneously (Eastman, 2009). In LCM, the transition probability matrix and the area of changes are calculated using the Markov chain model. This matrix shows the probability of changing a specific land use to other types during the calibration time interval. Based on the major changes that occurred in the study area, we defined sub-models of land use transitions. The variables include digital elevation model (DEM), slope, aspect, proximity to residential area, proximity to agricultural land, proximity to forest land, and proximity to road (Christensen and Jokar Arsanjani, 2020), which are static variables. The distances to residential area, road, and agricultural land were considered dynamic variables and recalculated in several steps.

According to the selected independent variables, we modeled the transition potential of each land use type through CNN after choosing the sub-models. Because each pixel of the image has the potential to change from one land use type to another, a multi-layer perceptron neural network was used to model the nonlinear relationships between land use change and employed static/dynamic variables. Operationally, the MLP in LCM produces a random sample set of cells that have changed and a set of samples that have remained constant. Based on the utilized spatial variables, the number of neurons in the input layer (n) equals the number of variables, and the number of neurons in the output layer equals the number of changed and consistent land use types. The number of hidden layer neurons equals n+1. After obtaining the highest accuracy and lowest root mean square error (RMSE) and ensuring grid adjustment, we prepared the transition potential map. Finally, projected land use maps were produced for the years 2025 and 2030.

2.3.4 Land Cover Indices

Four main urban elements can affect a city' s microclimate: buildings, vegetation, barren land, and water bodies (Rosenzweig et al., 2008). The intensity of LST is directly related to the degree of urbanization, land use pattern, and building density (Xiong et al., 2012). Therefore, land cover indicators that are used in many studies to correlate with LST were employed as auxiliary features in this study (Chen et al., 2006; Liu and Zhang, 2011; Essa et al., 2012; Kafy et al., 2021a). These indices have a linear correlation with LST with a high coefficient of determination (Kafy et al., 2021a). NDVI is a measure of vegetation quantity on the land surface, which is connected with vegetation vigor due to greater energy reflectance of healthy vegetation compared to unhealthy and sparse vegetation. NDVI values range between 1 and -1, with higher values indicating dense, healthy vegetation and lower values designating poorer vegetation (Taloor et al., 2021). Areas with water bodies and rivers show higher NDWI values compared with areas without water bodies. NDBI is a spectral metric to obtain a trustworthy relationship between LST and built-up lands in a city (Guha et al., 2020). The application of these indices has been proven effective in many studies investigating LST (Malik et al., 2019; Shahfahad Kumari et al., 2020; Taloor et al., 2021; Alademomi et al., 2022; Alavipanah et al., 2022). LULC indicators including NDVI, NDBI, and NDWI were calculated using red spectral bands, shortwave infrared, and near-infrared spectral bands (Abutaleb et al., 2015; Yengoh et al., 2015; Gascon et al., 2016; Arekhi et al., 2019).

In this work, three widely recognized land use indices—NDVI, NDBI, and NDWI—were utilized. These indices were selected as they effectively represent vegetation cover, urban development, and water bodies, which are critical components influencing LST variations. This approach ensured a more detailed and robust investigation of the relationship between land use changes and LST, offering insights that traditional methods might not capture. All these indicators for the studied intervals were extracted through the GEE platform and used as supporting features in the CNN.

2.3.5 Modeling Relationship Between Land Use and LST

In this study, we utilized ML algorithms to analyze data, learn, and make informed decisions based on what they have learned. Deep learning procedures were used to extract features from input data and add supplementary information from investigated variables to achieve higher accuracy. Deep learning, as a subset of artificial intelligence, facilitates hierarchical representational learning of data. The concept of deep learning originates from CNNs, which are multi-layered structures of perceptrons with several hidden layers (Hinton and Salakhutdinov, 2006; Günen, 2022). In DNNs, it is possible to incorporate more complex relationships to achieve improved results.

Based on studies conducted for remote sensing data analysis, CNN is one of the most famous neural networks for image-related applications, with proven performance in various research (Adam et al., 2014; Maxwell et al., 2018; Wang et al., 2022). Typically, a CNN is structured into three primary layers: convolution layer, pooling layer, and fully connected layer, each with distinct functions (Shin et al., 2016). The training process involves two main phases: the feed-forward phase and the back-propagation phase. During the feed-forward phase, the input image undergoes a series of point multiplications with neuron parameters, followed by convolution operations across each layer, culminating in computation of the network' s output. Subsequently, the network' s parameters are fine-tuned by utilizing output values to determine the network' s error margin through comparison with the correct answer via an error function. Following error computation, the back-propagation process determines the gradient for each parameter using the chain rule. Adjustments are then made to all parameters based on their contribution to the network' s error. Once parameters are adjusted, the feed-forward process initiates again. This cycle repeats until the network achieves the required precision, at which point training is considered complete.

Essentially, a CNN is a layered neural network where convolutional layers alternate with pooling layers, leading up to several fully connected layers. Within the convolutional layer, the CNN employs various kernels to process the input image and map intermediate features, creating a range of feature maps. Typically, a pooling layer follows a convolutional layer to diminish the dimensions of feature maps and reduce network parameters. Pooling layers maintain stability in the face of positional changes due to their processing of adjacent pixel values. The most prevalent forms of pooling are max pooling and average pooling. Subsequently, fully connected layers convert the two-dimensional feature map into a one-dimensional feature vector, facilitating continuation of the feature representation process (Wang et al., 2019c; Fang et al., 2020). The theoretical underpinnings and formulas of deep convolutional neural networks are extensively documented in several studies (Rezaee et al., 2018; Mazzia et al., 2019; Boulze et al., 2020).

The overall structure and architecture of the designed network is shown in Step 3 (Fig. 2). The network comprised two general parts. In the first part, a total of three layers were used. The initial layer was responsible for mining low-level features, and the final layer extracted higher-level features. All three layers were composed of a convolution layer, batch normalization layer, and activation function, respectively. Convolutional layers employed three-dimensional (3D) kernels for feature extraction, enabling the network to simultaneously present spatial and temporal characteristics of each image pixel and utilize them in the final decision (Li et al., 2017). To deepen network learning by increasing the number of convolutional layers, the output dimensions of each convolution layer were maintained similar to its input dimensions through layering technique. The number of filters employed in the three layers was determined to be 128, 256, and 512, respectively, using a trial-and-error approach to achieve the highest accuracy. The output of the convolutional layer was normalized by the batch normalization layer to facilitate training, prevent overfitting, and generalize the network as much as possible (Ioffe and Szegedy, 2015; Zhao et al., 2019). The output of the batch normalization layer was prepared for entry into the next layer by the rectified linear unit (ReLU) nonlinear function to empower the network in modeling nonlinear relationships. In addition to high speed in the error back-propagation process, the ReLU function is the most common activation function used in convolutional networks.

In addition to the above layers, a 2$×2×$2 max pooling layer was used, with input from the ReLU activation function. These dimensions were chosen as the most widely used for max pooling layers in various studies (Krizhevsky et al., 2012; Zhao et al., 2019). Besides reducing calculation volume and maintaining extracted main features, the max pooling layer facilitates network training by decreasing the number of network connections and reducing trainable parameters (Guidici and Clark, 2017).

All stages of designing, implementing, training, and evaluating the network were completed within the Keras deep learning library in Python. To train the network, we used cross-entropy as the chief cost function in classification applications (Mazzia et al., 2019; Boulze et al., 2020). The network was trained in 1000 iterations to find the minimum value of the cost function via gradient descent optimization. The optimal learning rate was chosen among values of 0.10000, 0.0100, 0.0010, and 0.0001 through network search to obtain the highest final accuracy on the validation dataset (Carranza-García et al., 2019).

2.4 Accuracy Assessment

The accuracy evaluation of the proposed method and comparison of its performance with other procedures was performed using the confusion matrix and overall accuracy measure. Performance evaluation was accomplished in two stages. In the first stage, the classification accuracy of predicted maps was evaluated. In the second stage, the proposed method was compared with two other standard ML approaches: random forest (RF) and support vector machine (SVM).

2.4.1 RF

RF consists of multiple decision trees to achieve a goal and is used for classification and regression prediction (Breiman, 2001; Lausch et al., 2017). The bootstrap sampling method was applied to conduct random sampling with replacement of samples. Each sampling result was used to construct a regression tree, and multiple decision trees were combined to form the RF model. Variables were screened and classified utilizing the model to predict unknown parameters. The RF model does not require assumptions about prior probability distribution, providing good flexibility, stability, high computation speed, and accuracy (Naidoo et al., 2019).

2.4.2 SVM

No assumption is required in the SVM model regarding underlying data distribution and dimensions of the input space. SVM provides a group of classified data samples (Vaglio Laurin et al., 2016). Additionally, SVM is applied to regression, known as support-vector regression (SVR). Numerous studies have applied SVR to remote sensing quantitative estimations (Camps-Valls et al., 2006; Du et al., 2018).

The RF and SVM methods have their own input parameters. Network search technique was employed to explore parameters including number of trees (100, 200, 300, 400), depth (4, 6, 8, 10, 12), kernel type (radial or linear), and cost coefficient (0.1, 1.0, 10.0, 100.0) to find optimum values. According to investigations, changing other parameters has very minor impact on final results; therefore, the study focused only on parameters with significant influence (Axelsson et al., 2013).

The employed methods were evaluated with 1000 repetitions due to usage of training data and various evaluations in each implementation. Training and validation analysis with different datasets in each execution enables fairer assessment of the presented model and provides more accurate performance comparison. Ground data collected through field survey was randomly divided into validation (30.00%) and training (70.00%) groups for each implementation to prevent possible network overfitting.

3.1 LULC Changes

Land use patterns in Mashhad City are depicted in Figure 3 [Figure 3: see original paper]. Accuracy assessment of classified land use maps with 300 ground points was completed using GPS and the GEE platform. Validation results are given in Table 1 , with diagrams shown in Figure 4 [Figure 4: see original paper]. Producer accuracy and user accuracy are displayed for each class, providing clear comparison between the model' s ability to classify samples correctly and the reliability of those classifications. Results from Table 1 and Figure 4 collectively demonstrate strong performance of the classification methodology across all studied time periods. While minor fluctuations exist in certain land use types, overall accuracy metrics and class-wise trends indicate that generated land use maps were reliable and suitable for further analysis. These results confirm the effectiveness of the approach in capturing land use change dynamics over time.

Figure 5 [Figure 5: see original paper] shows area changes for each land use type across different years. In 1985, agricultural land occupied the largest area; however, by 2020, built-up land covered the largest area. In other words, rangeland, agricultural land, and barren land areas were reduced by 14.50%, 13.00%, and 10.00%, respectively.

3.2 Land Use Change Simulation

The extent of changes for each land use type was extracted using the proposed Markovian model and the LCM toolbox within TerrSet software. Projected land use maps for 2025 and 2030 were acquired (Fig. 6 [Figure 6: see original paper]). For this purpose, the ANN-based CA-Markov model was first used to simulate land use in 2020, then results were validated by comparing observed and predicted maps. Simulated results indicated that if current built-up land growth persists without rational planning, these areas will expand further in 2025 and 2030, accounting for 69.57% and 71.34% of the total area, respectively. This trend will result in reduction of agricultural land and rangeland with urban expansion.

3.3 LST Changes

The process of identifying changes in various land use types and subsequently calculating LST for specific times was performed within the GEE platform. LST results are depicted in Figure 7 [Figure 7: see original paper]. In 1985, the highest recorded temperature was 43.21°C, which increased to 44.73°C in 2020. Similarly, the lowest temperature of 24.90°C recorded in 1985 increased significantly to 27.34°C in 2020. According to results, Mashhad City experienced an average temperature increase of 1.75°C (Fig. 8 [Figure 8: see original paper]). Additionally, by correlating average LST with land use dynamics throughout the study period, temperature rise varied among different land use types. In urbanized districts, the temperature increase was calculated to be approximately 1.75°C. Consequently, mean summer temperature in urbanized areas of Mashhad City escalated from 34.50°C in 1985 to 36.25°C in 2020. In contrast, rangeland also experienced a temperature rise of 1.75°C, while the smallest increment was observed in forest land, registering a rise of 1.19°C (Fig. 8).

3.4 Modelling Process of Temperature

After modeling the relationship between LULC and LST using CNN, predicted LULC maps for 2025 and 2030 were utilized to generate corresponding LST maps. Figure 9 [Figure 9: see original paper] shows predicted LST maps for 2025 and 2030. Based on obtained results, the majority of the study area will have temperatures above 41.00°C and 42.00°C for 2025 and 2030, respectively. Moreover, simulated average LST for residential areas will be 40.00°C and 43.00°C, respectively.

3.5 Accuracy of Simulated LST Map

Validity of simulated LST maps was analyzed using coefficient of determination (R^2) and mean squared error (MSE) through comparison between predicted and observed LST for 2020. The deep learning method established a good fit according to R^2 and MSE values of 0.914 and 0.31°C, respectively (Fig. 10 [Figure 10: see original paper]). Additionally, to compare the proposed method, these parameters were calculated for RF and SVM methods. The optimal performance of RF was achieved with 300 trees and maximum depth of 10. Furthermore, optimum performance for SVM was obtained through a radial kernel with a cost coefficient of 10.0.

The CNN method, with an average accuracy of 91.60%, performed better than other methods. In Figure 10, CNN showed the closest alignment, with most points clustered near the trend line, particularly in the 32.00°C–40.00°C range, suggesting highest accuracy. Among investigated methods, linear regression ranked lowest with average accuracy of 73.73% and greatest scattering, indicating weaker correlation. The designed DNN method achieved better accuracy than the two known ML methods (RF and SVM) due to its ability to extract higher-level features. RF and SVM were ranked second and third, respectively, with average accuracies of 86.23% and 85.80% (Fig. 10). These results highlight significant variability in predictive power among employed methods.

4 Discussion

Based on results from land use change detection analysis in Mashhad City, reduction in agricultural land area and increase in built-up land area clearly indicated urban sprawl and conversion to other land uses (Tajbakhsh et al., 2016; Komeh et al., 2023). Several factors, including uncontrolled migration, unplanned expansion to accommodate urban population growth, and indiscriminate infrastructure development, may all play significant roles in this urban sprawl. The underlying hypothesis suggests that substantial urban growth is driven by strategic and economic factors that lead to insufficient increases in land cover such as green spaces and water bodies (Fu and Weng, 2018; Kafy et al., 2021a).

Decreased vegetation cover and intensified urbanization may affect the city' s ecosystem services, urban health, and thermal properties. If unplanned urban growth continues, UHI effects will likely intensify, resulting in economic, environmental, and health problems (Kafy et al., 2021b). Appropriate land use planning, protection of water bodies, afforestation, and growth of urban green spaces can help make Mashhad more sustainable by reducing UHI impacts. Results also confirmed that the increasing LST trend from 1985–2020 was consistent with increased construction. Furthermore, this trend of expanding urban areas and reducing vegetation cover in Mashhad intensified UHI impacts. Temperature increases were most pronounced in areas where vegetation was diminished or eradicated, specifically in transitions from forest lands and agricultural lands to urban and barren lands. Conversely, in areas where forest and agricultural lands expanded, temperature rise was mitigated to the lowest levels, as illustrated in Figure 8. Higher LST occurred in rangelands surrounding the city compared with urban lands because barren lands in hot, dry climates heat up quickly during the day, resulting in higher temperatures (Lazzarini et al., 2013; Rasul et al., 2015). Research by Alavipanah et al. (2014) also found that reduction of vegetation cover was the most important factor in heat island expansion in Mashhad City. Despite urbanization issues, other possible causes such as increased greenhouse gas emissions and surface Earth warming can also result in temperature increase (Alavipanah et al., 2022). These results are consistent with other remote sensing studies confirming that deep learning is a powerful modeling technique for nonlinear and complex datasets (Schmidhuber, 2015). Projected LST showed consequences of temperature increase at current trends, including effects of higher UHI expansion. Further increases in greenhouse gas emissions harm human well-being, degrade urban health quality, and reduce environmental sustainability (Kafy et al., 2021b). Moreover, increasing temperature, especially minimum temperature, can affect evapotranspiration rates and future snowfall in the area. These hydro-climatic changes will certainly affect watershed biodiversity (Rahimpour et al., 2021).

Use of NDVI, NDBI, and NDWI as auxiliary variables in the CNN model played a significant role in capturing spatial heterogeneity of land use patterns and their impacts on LST variations. Through comparing CNN with other machine learning approaches, we found that the CNN model had superior accuracy in exploring intricate spatial patterns and establishing relationships between LST and LULC. This improvement is attributed to CNN' s layered architecture, which allows automatic learning of spatial features, making it more capable of handling spatial dependencies and variations (Feng et al., 2019).

It is necessary to mention that greenhouse effects and global warming in surface features are also main reasons affecting LST increase even in areas without significant urbanization (Aslan and Koc-San, 2023; Munawar et al., 2023). As confirmed by the IPCC (Intergovernmental Panel on Climate Change, 2014), Asian regions face temperature rise higher than the global average. The heat capacity of LULC is affected by LST increase, leading to UHI formation. The UHI phenomenon poses significant environmental challenges that negatively affect human health and broader ecosystem biodiversity, as highlighted by Grimmond (2007). UHI and global warming impacts can be significantly reduced by planting urban vegetation around building blocks and forming green rooftops (Pérez et al., 2017).

While this study primarily focused on NDVI, NDBI, and NDWI as key environmental factors in LST modeling, findings demonstrate feasibility of extending this framework to include additional climatic and environmental variables such as humidity, precipitation, and soil moisture in future research. Incorporating these variables can provide more comprehensive understanding of multifaceted interactions influencing LST. This approach not only validates CNN application in modeling complex relationships but also highlights potential for addressing diverse environmental challenges through improved spatial analysis and predictive capabilities.

Despite promising findings, this study has limitations. First, although analysis primarily focused on NDVI, NDBI, and NDWI as auxiliary variables, incorporating additional factors such as latitude and other climatic/environmental variables could potentially yield even more accurate and comprehensive results. Second, while the CNN model demonstrated superior performance, its computational intensity and longer processing time remain challenges for applying this framework to larger areas or datasets with higher temporal resolution. Future research should address these aspects to enhance methodology robustness and scalability.

5 Conclusions

This study examined LST variations and their association with land use type conversions in Mashhad City, Iran, from 1985 to 2020. Over the last 35 years, Mashhad City has experienced significant urban growth, leading to substantial changes in land use types. The observed temperature rise, ranging from 1.00°C to 2.00°C, corresponded with land use alterations. Moreover, built-up land expansion continued, mainly associated with decreases in rangelands, agricultural lands, and barren lands, with LST in built-up lands observed at its highest level. According to simulation results, built-up lands will expand further in 2025 and 2030.

To model the relationship between land use and LST, we found that CNN application achieved higher accuracy compared with other methods. Urban land areas will have temperatures above 41.00°C and 42.00°C for 2025 and 2030, respectively, according to CNN simulation results. Future research should investigate application of the proposed method in diverse climatic areas, incorporating a wider range of environmental factors to enhance validation and adaptability. Moreover, development of new architectures based on alternative neural networks, such as recurrent neural networks, could provide valuable insights and further improvements for future studies.

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Note: Figure translations are in progress. See original paper for figures.