ASSESSMENT OF URBAN EXPANSION AND ITS IMPLICATIONS ON THERMAL RISK USING MACHINE LEARNING IN THE GOOGLE EARTH ENGINE PLATFORM

Stergiadis Stergios[1,2], Philippopoulos Kostas[1], Cartalis Constantinos[1], Agathangelidis Ilias[1]

1: National and Kapodistrian University of Athens, Greece 2: Contact info: stergios.stergiadis@gmail.com

Abstract

Urban expansion is identified as a pivotal factor in the dynamics of the urban thermal environment. This study presents a novel machine learning application, using the Google Earth Engine (GEE) framework to assess urban expansion and its subsequent impact on thermal risk in two major cities: Beijing, China, and Athens, Greece. Utilizing Earth Observation data, the research identifies urban growth patterns. Neural networks are selected for their proven efficacy in classification tasks in complex environmental datasets. Urban expansion introduces significant thermal risks, including heat islands and altered local climates, which necessitate robust adaptation and mitigation strategies. The findings illustrate the relationship between urbanization and its thermal consequences, underscoring the urgency of sustainable urban planning practices to combat these challenges. For this purpose, a methodology to accurately correlate urban expansion and heat risk was employed, as well as a deep neural network to identify urban expansion patterns. The research highlights the replication potential of the methodology on a global scale across various urban settings to better understand and mitigate the thermal risks associated with urban expansion and contributes to more informed decision-making processes in urban planning .

Introduction

Urban expansion significantly impacts the urban thermal environment, primarily through the creation of urban heat islands (UHIs), which lead to higher temperatures, increased energy consumption, and health risks. Understanding and mitigating these thermal risks is crucial as cities continue to grow. Advancements in remote sensing and Earth Observation (EO) data, facilitated by platforms like Google Earth Engine (GEE), offer new opportunities for monitoring urban expansion.

Objective and Study Areas

The objectives of this research is to inform sustainable urban planning and environmental management strategies by correlating urban expansion with thermal risk. This is achieved through the use land surface temperature (LST) images and impervious surface change maps in the context of trend identification and urban expansion prediction. The methodology can be applied globally to enhance the understanding of urbanization's thermal effects and support the development of resilient cities. The study areas we focus on are the greater Beijing, China, and Athens, Greece, (Figures 1,2) which offer a diverse perspective on the dynamic interplay between climate, urbanization, and environmental sustainability.

Figure 1. Greater Athens Area , Greece

Figure 2. Greater Beijing Area, China

Methodology

The images and maps required for the study were accessed, filtered and preprocessed using the google earth engine python-API. First the image collections where filtered for the images with the least cloud cover and missing data. Then, the image with the highest mean LST was chosen for each year. To obtain evidence correlating urban expansion with the urban thermal environment, the mean LST of locations where urban expansion occurred was monitored over the historic period. The Mann-Kendall test was then used on the extracted time-series to identify any statistically significant trend. The intensity of the trend was then calculated by Sen's slope.A Convolutional Long Short-Term Memory Neural Network (Conv-LSTM) integrates CNN's spatial processing with LSTM's temporal modelling, ideal for tasks needing robust spatiotemporal pattern recognition. It retains spatial information across time frames, enhancing tasks like video analysis and prediction. This fusion makes it efficient for processing large-scale data while capturing intricate relationships over sequences. For these reasons it was chosen as an architecture, in order to capture the highly intermittent urban growth patterns, using a sequence of years as input in order to predict the following year. The urban expansion data for both Athens and Beijing was first resampled to a resolution of 256 x 256 to be computationally manageable and vectorized to binary values, with pixels of value 1 representing urban expansion and pixels of value 0 corresponding to no urban expansion. It was then split into sequences containing 5 consecutive years of images as input data, with the next image in the sequence serving as the label. Data augmentation was performed by rotating the images by integer multiples of 90 degrees, and the original dataset was randomly mixed to improve robustness. A partition of 90% training data and 10% validation data was used. A custom weighted binary cross-entropy function was utilised for loss, with weights computed by class frequency in the data. The neural network produces outputs between 0 and 1, representing the probability (confidence) that a pixel belongs to a class. To refine these probabilities, a threshold was applied. This threshold pushes extreme values—those beyond two standard deviations from the mean—towards each class. The predictions are processed by convolving them with a kernel whose values diminish exponentially from the centre to de-cluster the outputs and then the threshold is applied. The Methodology described is summarised in Chart 1

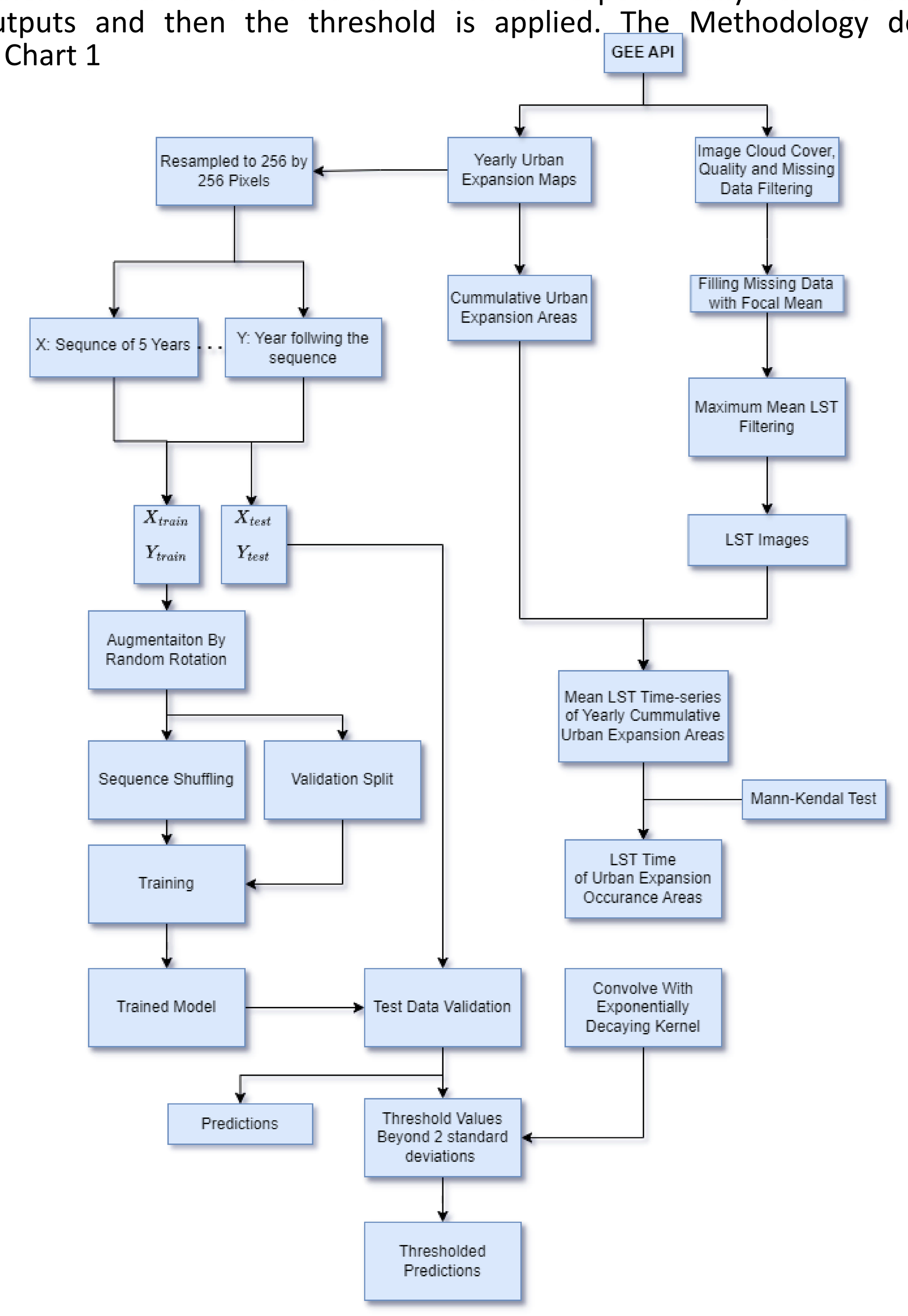

Chart 1. Methodology Flow chart

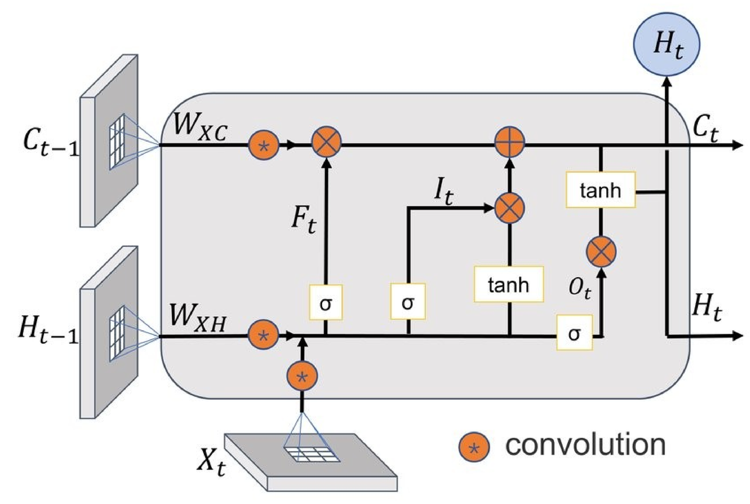

Figure 3. Conventional Long Sort Memory Neural Network architecture

Results

The time series of mean LST of areas with cumulative urban expansion of both Athens and Beijing present statistically significant trends, rising by approximately 12 and 8 degrees Celsius respectively (Figures 1,2). The predictions of the trained neural network do not precisely match the label data, however it achieved 82% accuracy on unseen data using the Area Under the Curve (AUC) metric. The AUC measures the model's ability to distinguish between classes, with a higher AUC indicating better performance.

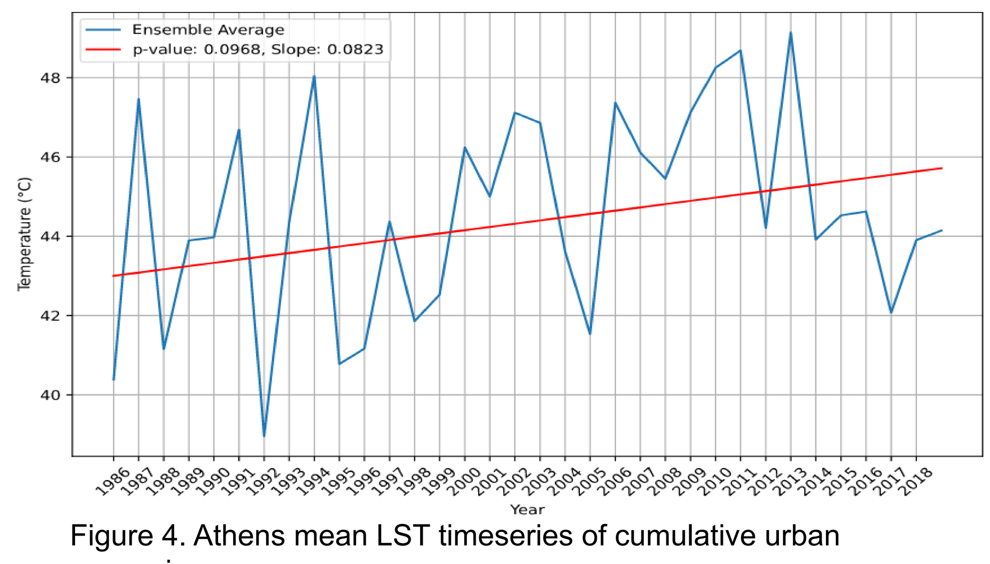

Figure 4. Athens mean LST timeseries of cumulative urban expansion areas

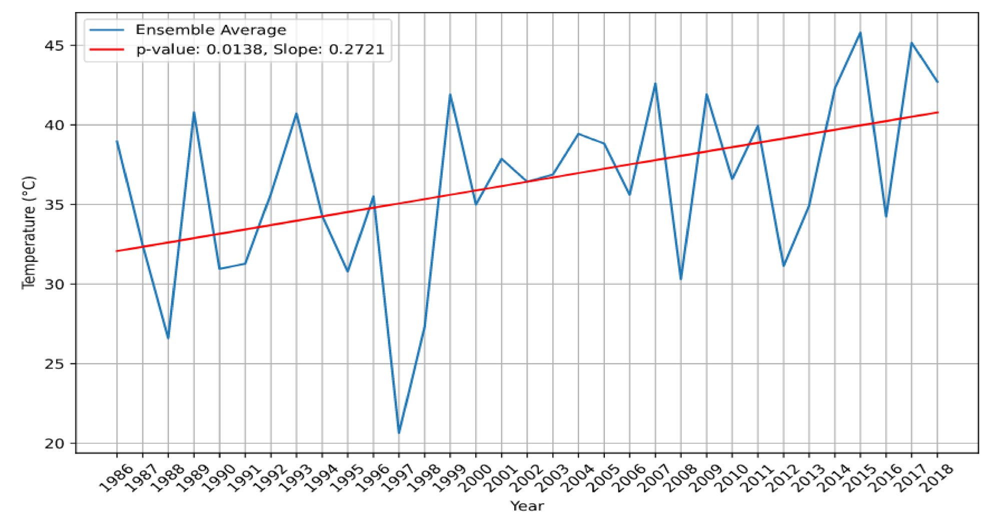

Figure 5. Beijing mean LST timeseries of cumulative urban expansion areas

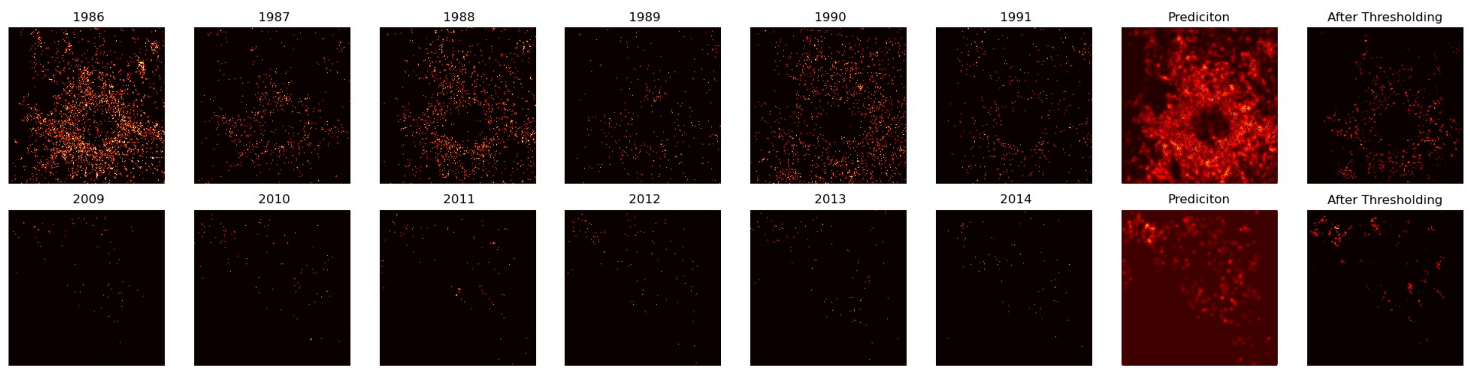

Figure 6. First row: Beijing, Second row: Athens. The first 5 columns correspond to the sequence that was used as input by the neural network. The 6th column presents the label data. The last two columns show case the original predictions of the network and the post processed predictions which resemble the actual label data visually.

Discussion

The results of the time series analysis contradict expectations. The images used for the analysis, taken from various Landsat collections, were captured around 10:00 AM local time. This timing would suggest that thermally inertial materials in buildings haven't been heated significantly due to limited solar exposure. Literature documents reverse urban heat islands during morning hours [2]. Thus, an increase in urban areas should theoretically show a negative trend in Land Surface Temperature (LST). However, the opposite trend was observed in both cities. A possible explanation for this could be that the replacement of natural vegetation with impervious surfaces, which retain heat, changes the ratio of land cover types and therefore shifts the mean of the distribution of LST to higher values. The result, though unexpected, justifies the second objective of the study to provide foresight with regards to urban expansion. Improved forecasting can equip policy makers and urban planners with the necessary tools for effective adaption and mitigation plans. Assessment of neural network outputs can often be ambiguous and challenging. In this case there is slight visual resemblance between the label data and the predictions. This does not suggest a failure of the model, since its outputs are probabilistic, capturing effectively non-developed areas, but struggling to pinpoint exact locations of future urban expansion. The thresholding performed boosts the interpretability of predictions and bridges the gap between label data and predictions. The high accuracy achieved is impressive, given the limited and sparse data, but there is substantial room for improvement by utilizing newer architectures, extracting additional features, and optimizing hyperparameters, which could further enhance the model's accuracy (and even absorb the post-processing altogether) at the cost of training time and computational capacity.

Conclusions

The methodology is highly scaleable and can be applied to a global dataset that would be more appropriate for the training of such a neural network. The results could inspire monitoring and decision making tools to support the development of resilient cities. By studying urban growth and thermal impacts in Beijing, China, and Athens, Greece, unique insights into the dynamic interplay between climate, urbanization, and environmental sustainability were gained.

Major References

1. Gong, P., Li, X., Wang, J., Bai, Y., Chen, B., Hu, T., ... & Zhou, Y. (2020). Annual maps of global artificial impervious area (GAIA) between 1985 and 2018. Remote Sensing of Environment, 236, 111510.

2. Zhou, B., Rybski, D., & Kropp, J. P. (2013). "On the statistics of urban heat island intensity." Geophysical Research Letters, 40(20), 5486-5491. doi:10.1002/2013GL057081)

3. Shi, Changjiang & Zhang, Zhijie & Zhang, Wanchang & Zhang, Chuanrong & Xu, Qiang. (2022) Learning Multiscale Temporal–Spatial–Spectral Features via a Multipath Convolutional LSTM Neural Network for Change Detection With Hyperspectral Images. IEEE Transactions on Geoscience and Remote Sensing. 10.1109/TGRS.2022.3176642.