# Urban Heat Island Detection and Causal Inference Using Convolutional Neural Networks

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## Abstract

Compared to rural areas, urban areas experience higher temperatures for longer periods of time because of the urban heat island (UHI) effect. This increased heat stress leads to greater mortality, increased energy demand, regional changes to precipitation patterns, and increased air pollution. Urban developers can minimize the UHI effect by incorporating features that promote air flow and heat dispersion (e.g., increasing green space). However, understanding which urban features to implement is complex, as local meteorology strongly dictates how the environment responds to changes in urban form. In this proposal we describe a methodology for estimating the causal relationship between changes in urban form and changes in the UHI effect. Changes in urban form and temperature changes are measured using convolutional neural networks, and a causal inference matching approach is proposed to estimate causal relationships. The success of this methodology will enable urban developers to implement city-specific interventions to mitigate the warming planet's impact on cities.

## 1 Motivation

Heat waves are becoming more frequent, more intense, and lasting longer each year as a result of climate change [1]. This heat is even more extreme in cities, where the urban heat island (UHI) effect can cause temperatures to be up to 9°C higher than surrounding rural areas [2]. Briefly, the UHI effect is the temperature difference between urban and rural regions attributed to human activity and urban form [3]. For example, buildings that use air conditioning push heat outside to keep the inside cool, and asphalt absorbs more solar radiation than grass, resulting in higher land surface temperatures. Heat islands also trap heat, prolonging high temperatures throughout the night [4]. The consequence of this added heat stress is severe: extreme temperatures can increase mortality by up to 12% [5]. Furthermore, the UHI effect increases energy demand, changes precipitation patterns, and impacts local air quality [3].

Knowledge of how the urban environment causes the UHI effect allows developers to implement mitigation strategies (e.g., trees can be planted to add shade, or buildings can be designed to promote air flow). To implement such interventions, we need a better understanding of how individual cities are experiencing the UHI effect at the urban canopy layer, the layer of air between the land surface and the tops of buildings. Previous research instead focuses on land surface temperature [6, 7, 8, 9].

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While land surface temperature is a closely linked covariate to urban canopy temperatures, local meteorological conditions can cause substantial discrepancies between the temperature of the land surface and of the air just above (e.g., the wind can carry air above a warm surface) [9]. This discrepancy matters, because humans live above the land surface. We also need to understand causality and confounding variables, as one-size-fits-all heat reduction solutions can backfire. A tree planted to provide shade, placed in the wrong spot, might unintentionally prevent air flow, thus causing heat to linger through the night [10].

Due to this need to find city-specific solutions, we propose a machine-learning powered methodology to understand causal relationships between a city's land use and the corresponding UHI impact. This methodology uses machine learning to analyze satellite imagery and temperature records to link changes in urban form to subsequent changes in the UHI effect. By incorporating a causal inference approach, researchers can estimate the causal impact of urban changes on the UHI effect. Subsequently, local communities can use these results to make informed policy decisions that mitigate the societal impact of increasing global temperatures.

## 2 Outline of Proposed Approach

We propose a four-step procedure to estimate the causal impact of potential interventions on the UHI effect, as visualized in Figure 1, consisting of the following: first, create a model to detect changes in urban form using satellite imagery; second, label changes and train a model to classify changes into meaningful categories; third, create a model to combine satellite imagery with ground-level temperature measurements; fourth, model the impact that changes in urban form have on changes in urban heat islands. In brief, this fourth step uses the first two models to match two similar locations, one of which is stable and the other has a change in the built environment, and then estimates the difference in the UHI effect at these two matched locations. This estimates a causal inference estimate of the intervention based on a matching approach.

The first model will apply a change detection method to satellite imagery to capture changes in urban form over time. Change detection methods require a series of images over time, with the goal of uncovering which parts of the image change during each time step. In recent years, convolutional neural networks have proven to be a highly accurate approach to perform this task [11, 12, 13]. With this first model implemented, we will capture what parts of the city have changed over time.

Next, we want to classify how different types of change impact temperature, so we will categorize the changes. We can do this by applying a land cover classification model to the satellite images and change map. Land cover classification is a semantic segmentation task that consists of mapping pixels in a satellite image to a set of classes (e.g., agriculture, grass field, high-rise buildings, parking lot, et cetera). This task is well studied in the field of remote sensing [14]. We can apply the obtained binary masks from model to understand land use changes over time.

Our third model will measure urban heat islands over time, so that we can monitor the associated impacts on temperature. Recent efforts have shown the ability to capture precise environmental quantities from high-resolution satellite imagery, such as air quality [15], and this satellite imagery goes back for over 5 years for much of the world. As previous methods using land surface temperature fail to capture the UHI effect, we will instead use a strategy that combines *in situ* temperature measurements with satellite images. Highly accurate, frequently sampled temperature data will be supplemented with satellite images to get temperature maps of high spatiotemporal resolution. To do this, a convolutional neural network will use the satellite images as the input, and the *in situ* measurements as the labels. Such data is increasingly available due to the sampling efforts of the NOAA Heat Island Project. We will additionally incorporate local meteorology into our model.

The final model will seek to estimate the causal relationship between changes in land use and changes in temperature over time. To do so, we will apply a matching technique to pair each land use change (the treatment) with a control area, so that subsequent temperature changes can be compared. Matching is useful for causal analysis in the absence of randomized controlled trials, as it allows for the comparison of a treatment and control unit [16]. In our case, we want to match a tile containing a land use change to a similar tile that did not experience a land use change. These pairs will be used to estimate the impact that specific land use changes have.

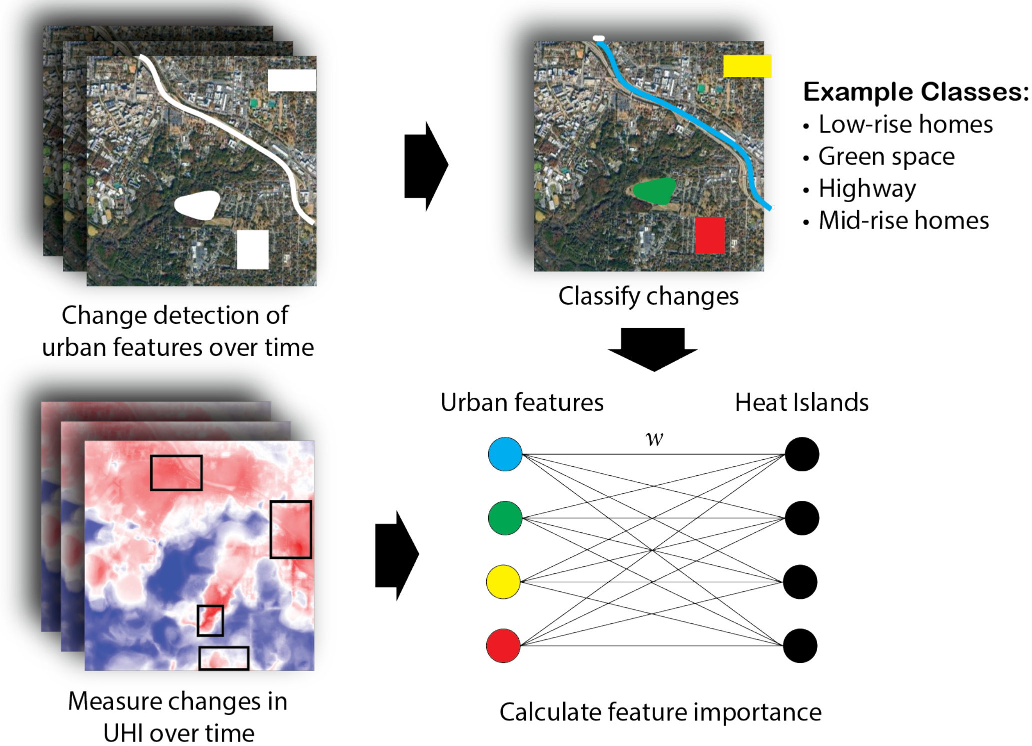


Figure 1: Conceptual visualization of the proposed multi-step methodology.

The pipeline suggested here could be further extended to large geographic areas, including most of the world, by studying the ability of this model to generalize to new locations. In this context, we want to build a model for measuring heat island effects and land use changes that is easily applied to new cities.

## 3 Pathway to Climate Impact

Machine learning is anticipated to play a key role in helping humans to adapt to and mitigate climate change [17], and our proposed solution to measure causal impacts of urban form on urban heat islands demonstrates just one way how. First, armed with a greater understanding of urban micro-climates, we hope urban planners and engineers will design neighborhoods and buildings to prevent the worst of UHI effects. By paying attention to the impact of urban form on micro-climates, designers can decrease energy consumption, promote cleaner air through increased vertical mixing, and stabilize temperatures during heat waves. Second, we expect that improved identification of UHI locations will promote greater awareness of risks during heat waves, so that communities can better prepare by putting into place temperature reduction measures.

Our proposal consists of a machine learning pipeline that we hope to deploy across multiple cities so that we can understand city-specific UHI causes and prevention mechanisms. Previous research on urban heat island effects is numerous, yet inconsistent in its approach, which means a methodology such as ours is needed to solidify conclusions and empower urban developers [9]. Our methodology incorporates best practices in both urban climate research and causal inference. Namely, we present a methodology that focuses on temperature at the urban canopy layer, and we apply a statistical matching approach that seeks to directly measure the impact of urban changes on the UHI effect. Lastly, this methodology focuses on application at the local level, which is the level of insight needed by urban planners if they are to effectively mitigate the heat island effect.

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