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Monitoring canopy quality and improving equitable outcomes of urban tree planting using LiDAR and machine learning

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ABSTRACT

Urban tree canopies are fundamental to mitigating the impacts of climate change within cities as well as providing a range of other important ecosystem, health, and amenity benefits. However, urban tree planting initiatives do not typically utilize data about both the horizontal and vertical dimensions of the tree canopy, despite height being a critical determinant of the quality and value of urban canopy cover. We present a novel pipeline that uses airborne LiDAR data to train a multi-task machine learning model to generate estimates of both canopy cover and height in urban areas. We apply this to multi-source multi-spectral imagery for the case study of Chicago, USA. Our results indicate that a multi-task UNet convolutional neural network can be used to generate reliable estimates of canopy cover and height from aerial and satellite imagery. We then use these canopy estimates to allocate 75,000 trees from Chicago's recent green initiative under four scenarios, minimizing the urban heat island effect and then optimizing for an equitable canopy distribution, comparing results when only canopy cover is used, and when both canopy cover and height are considered. Through the introduction of this novel pipeline, we show that including canopy height within decision-making processes allows the distribution of new trees to be optimised to further reduce the urban heat island effect in localities where trees have the highest cooling potential and allows trees to be more equitably distributed to communities with lower quality canopies.

1. Introduction

Cities across the world such as London, Singapore, and Nairobi have set forth tree planting initiatives as part of larger efforts to mitigate climate change, improve quality of life, and promote environmental equity (Mayor of London, 2022; Tress 2023; Nyamasege, 2022). Within these initiatives, policymakers face hurdles when deciding how to allocate tree planting resources because there is little consensus surrounding distribution strategies (Young, 2011). Additionally, there is a general lack of information about the quality of urban canopies as initiatives tend to focus on increasing the quantity of canopy cover (Eisenman et al. 2021). By itself, canopy cover overlooks critical differences in canopy structures throughout urban areas. Two areas with similar canopy cover can provide varying benefits for communities if one is comprised of low stature vegetation, shrubs, or newly planted saplings, and the other is filled with mature stands of trees (Le Roux et al., 2015; Stephenson et al., 2014).

Many factors influence the impact trees have on the urban environment. Using canopy cover alone to make policy decisions is problematic because the height of trees (Poulsen et al., 2020), species of trees (Franceschi et al., 2022), leaf area index (Rahman et al., 2015), and local environmental conditions (Wang et al., 2022), all influence how much benefit is gained from investments in additional urban greenery. Indeed, quantifying the structure of canopies is crucial to understanding the benefits of trees in urban environments (McPherson et al., 1997). For example, the height of trees effects how much shade, and therefore temperature reductions, are provided by an area with a given canopy cover (Lindberg and Grimmond 2011a; Lindberg and Grimmond 2011b). By including the height of trees into the decision-making pipeline, we aim to show that resources can be allocated more effectively and comprehensively than by using canopy cover alone. We argue that tree metrics such as height can help to distinguish the value of canopy cover, which when used together can help ensure that the environmental and equity impacts from tree planting initiatives are better reaching the communities most in need.

This paper proposes a novel pipeline utilising machine learning (ML)

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to generate estimates of urban canopy quality i.e., moving beyond canopy cover, by combining both canopy cover and height using a combination of aerial and satellite imagery. Estimated data are then used to show how tree planting policies can benefit from the inclusion of multiple canopy metrics for decision making. This study is not intended to provide the most thorough demonstration of how best to allocate trees, but rather how the inclusion of tree height can provide important information regarding canopy quality not currently utilized by tree planting policies. Previous research has used ML approaches to estimate forest canopy height (Li et al., 2020) but these techniques have not been leveraged to create detailed estimates of urban canopy cover and height; we address that gap here. To explore how the addition of canopy height can improve policy decisions we utilize the case study of Chicago, USA due to the availability of open data and recent policy goals against which progress can be judged.

As part of a larger environmental investment in response to the climate crisis, the mayor of Chicago plans to spend 46 million dollars planting and maintaining 75,000 trees between 2022 and 2026 (Office of the Mayor, 2021). Chicago's mayor aims to take an "equity-centered and data-driven approach" to distribute the benefits of this investment to "historically marginalized and underserved communities" (ibid.). Here historically marginalized communities refer to communities on the south and west sides of Chicago which are and have been disproportionately "Black, low income, and often denied access to economic opportunity" (Chicago Metropolitan Agency for Planning, 2020). While the mayor's office is working with various stakeholders to determine where new trees should be planted, a critical (and open) question is how Chicago, and similar urban centres, should leverage canopy metrics to make decisions about where to plant trees to meet their climate and environmental equity goals.

We begin by examining the ways trees provide benefits to cities, before exploring the methods that have previously been used to determine where cities should plant trees. To determine where trees should be planted in Chicago, we propose a novel pipeline, utilising a deep learning model called UNet, for generating estimates of both canopy cover and height which can be updated regularly using aerial and satellite imagery. Previous work has utilized the UNet architecture (Ronneberger et al., 2015) for various image segmentation tasks, but studies have yet to leverage this technique to create estimates of canopy cover and height in an urban environment. Additionally, we explore how canopy height, in addition to using canopy cover, can provide nuance to policy decisions around how to allocate tree planting resources.

1.1. Why Invest in the Urban Canopy?

The mayor of Chicago committed to investing in trees because of the urban canopy's direct impact on metrics linked to the climate crisis, specifically rising temperatures (CMAP 2020). Wang et al. (2022) showed that while the urban canopy can be an effective way to reduce elevated temperatures caused by the urban heat island (UHI) effect, the cooling efficiency of the tree canopy can vary substantially within cities due to local conditions. This relationship between trees and their cooling efficiency has been well explored, particularly in relation to the amount of impervious surface that exists within communities (Ziter et al., 2019), the species of tree (Rahman et al., 2020), the level of social vulnerability within communities (Zhou et al., 2021), and the height of the tree canopy (Chen et al., 2020; Shahidan et al., 2012). Research has confirmed that prioritizing locations with higher cooling efficiencies can lead to greater reductions in UHI per tree planted. While we focus on the UHI effect, it is important to note that trees provide numerous environmental benefits, such as reducing levels of sulphur dioxide, ozone, and nitrogen dioxide (Nowak et al. 2018), mitigating stormwater runoff (Berland et al., 2017), carbon sequestering and storage (Nowak and Crane, 2002), and enhancing urban biodiversity (Zhang and Jim, 2014).

Alongside the climate benefits provided by the urban canopy, trees also have numerous non-ecological 'amenity' benefits (Price, 2003). In a national survey of the United States, urban residents reported that some of the most important reasons to have trees in urban areas were the trees' aesthetic benefits such as "to help people feel calmer" (Lohr et al., 2004, p.33). Tree's aesthetic benefits can impact people's reported quality of life (Hipp et al., 2015) and change how they interact with their outdoor environment (Kuo, 2003), affecting livelihoods above and beyond measurable climate indicators. Theories such as Biophyllia hypothesis (Kellert and Wilson, 1993) and Attention Restoration Theory (Kaplan, 1995) have been proposed to explain these intangible health and wellbeing benefit of vegetations. Moreover, research has shown that the positive perceptions people have of urban trees are substantiated by higher property values (Donovan and Butry, 2011). Where a city chooses to invest in the placement of public trees can therefore have long lasting additive effects on the economic prospects of communities.

In an effort to address inequities caused by historical investment practices, Chicago's tree planting initiative contains a dedicated focus on environmental equity. This echoes recent works which have called on tree planting initiatives to address environmental justice by targeting disadvantaged communities (Nyelele and Kroll, 2020; Foster et al., 2022). Environmental amenities such as public parks and the urban canopy have long been inequitably distributed in urban areas throughout the United States. In a study of 37 metropolitan areas in the United States, findings indicate that historically marginalized communities on average contain half the canopy cover of more affluent neighbourhoods (Locke et al., 2021). Nowak et al. (2022) show that these communities are often also associated with higher amounts of impervious surface, areas such as roads and concrete which present barriers to where trees can be planted. The numerous benefits provided by trees demonstrates the scope of impacts that tree-planting investments can have on communities, and therefore how contentious the decision of where to place trees can be, especially given the discriminatory history of resource allocation in many American cities (Locke et al. 2021).

1.2. Deciding where to plant trees

Deciding where to plant trees requires some knowledge of the urban canopy. Surveying techniques have been used, for example, by Morton Arboretum in Chicago to produce a tree census based on counting trees in selected plots (The Morton Arboretum, 2021). An alternative to surveying techniques is airborne Light Detection and Ranging (LiDAR), which utilizes light beams to create a cloud of millions of points that can be accurate within a few centimetres (Kim et al., 2020). Numerous algorithms exist for detecting and measuring trees from LiDAR point clouds which can be used to generate three-dimensional representations of the urban canopy. LiDAR collection is often unavailable on a regular basis, so ML techniques offer an alternative method to generate urban canopy estimates from imagery when and where LiDAR data is unavailable. For example, image segmentation has been used to identify individual trees using natural RGB (red, green, and blue) images (Weinstein et al., 2019, Amati et al., 2023), while multi-spectral (MS) imagery has been used to predict forest canopy height (Li et al., 2020).

Once urban canopy estimates are identified, the complicated decision of where specifically to plant trees arises. To tackle this challenge, Bodnaruk et al. (2017) focused on the mitigation of environmental stressors such as air pollution and the UHI effect when developing optimization algorithms for determining new tree locations. In Boston, Danford et al. (2014) used the Gini Index, a measure of the degree of inequality in a variable's distribution, to evaluate scenarios in which tree placements are estimated based on the availability of space. Wu et al. (2008) locate planting sites in Los Angeles using spatial analysis to rule out sites that are too small or too close to other urban infrastructure. Additionally, past work in Chicago used a multi criteria decision analysis to identify priority areas where trees should be planted based on criteria including income, English proficiency, air pollution, low canopy cover, urban flooding, and high temperatures (Chicago Region Trees Initiative, 2018), while a study in New York (Nyelele and Kroll, 2021) utilized a multi-objective decision support framework to balance improvements in environmental metrics and inequality of the canopy cover between more and less advantaged areas.

The diverse methodologies put forward in previous studies, alongside tools such as i-Tree, demonstrate that there is no agreed upon method for determining where trees should be planted in urban areas. Furthermore, other works have focused primarily on canopy cover without accounting for more holistic measures of canopy quality, as done in this study. Taken together, prior work has provided limited research that fuses high and low resolution natural and MS imagery to predict tree height and cover simultaneously from LiDAR data in an urban setting. Additionally, there is limited work showing how tree height and cover can be used simultaneously within an urban planning setting to reduce the UHI effect, accounting for local environmental conditions, and improve environmental equity. Through our novel pipeline, we demonstrate the use of a deep learning model to monitor tree canopy and the potential of including one measure of canopy quality, height, to supplement canopy cover when allocating urban trees.

2. Material and methods

2.1. Study Area

This study has been carried out on the case study of Chicago, the third most populous city in the US with a land area of about 600 km^2. Chicago is located right alongside Lake Michigan and remains heavily segregated alongside economic as well as racial and ethnic lines with a roughly one third split of residents between each of Latino, Black, and White residents (United States Census Bureau, 2019). The right side of Fig. 4 shows where these populations cluster. Many of the majority Black communities reside on the south and west sides, the bulk of majority White communities occupy large portions of the north and north-east, and many of the majority Latino communities can be found on the north-west and south-west sections of the city.

To determine how the tree canopy is related to the UHI effect in different parts of the city, 46,149 census blocks in Chicago are used as the level of analysis. Census blocks are the smallest statistical area used by the United States Census Bureau (United States Census Bureau, 2021). To examine post-hoc equity of tree placements in Chicago, census block-group data was pulled from the 2019 American Community Survey (ACS) 5-year estimates (United States Census Bureau, 2019). Estimates for the percent of households with income below the poverty level (categorized into quartiles), as well as the percent of White, Black, Latino, and Asian residents were extrapolated to the census blocks from the block-group data.[1]

2.2. Materials

LiDAR point cloud data from 2017 were retrieved from the Illinois Height Modernization Program (2017). This data consisted of 1131 762 × 762 m tiles with a derived nominal pulse spacing of one point every 0.35 m. Additional MS imagery was gathered from the National Agriculture Imagery Program (NAIP) and the Sentinel-2 satellite program. Four-band NAIP RBG and near infrared (NIR) data was collected for 2017 and 2021. NAIP data is at 1 m resolution and consists of roughly 30 tiles in each year. Sentinel-2 data from 2017 and 2021 were also used, with four bands at 10 m resolution, and six bands at 20 m resolution.

To measure the UHI effect, Landsat-8 satellite data was used to calculate the land surface temperature (LST) at 30 m spatial resolution. Chakraborty et al. (2020) note the difference between surface UHI, which uses LST, and canopy UHI which utilizes air temperature measurements. While these measurements are not identical (Chakraborty et al., 2017, Hu et al., 2019), LST is derived from satellite observations which allows for a consistent data collection measure and has been shown to capture intra-urban UHI differences in a large-scale study of the United States (Chakraborty et al. 2020). While recent research has been able to examine the effect of trees on both air and surface urban heat using handheld measurements (Sharmin et al., 2023), this was not practical for a study of this size. When we reference UHI in the following pages of this paper, we are referring to surface UHI measured via satellite imagery. More information about the image data used in this paper can be found in Supplemental Table 1.

2.3. Environmental and equity metrics

LST was calculated using formulas derived from Weng et al. (2004) at three timepoints in 2021[2] for the extent of Chicago, shown on the left side of Fig. 4. LST raster values were first aggregated to US census blocks. The three timepoints were then averaged together and standardized to limit bias. The average LST during this period was 23.4 °C with a standard deviation of 1.4 °C. More formally;

$$LST = \frac{T_b}{1 + \left(\frac{\lambda_Q T_b}{p}\right) \ln \epsilon}$$

where $\lambda$is the top of atmosphere spectral radiance, T_b is the brightness temperature, ϵ is the emissivity, p is a physical constant, and Q is the Botlzmann constant.

Similar to Danford et al. (2014), and recent research looking at the equity of urban green space (Chen et al., 2023), we used the Gini coefficient as a measure of urban canopy inequality. While the Gini coefficient was developed to study poverty (Farris, 2010), it has also been used within astronomy (Abraham et al., 2003), genetics (Gianola, et al., 2003), and to measure the inequality environmental benefits across socio-economic groups (Nyelele and Kroll, 2020). Ranging from 0 to 1, a Gini value of 0 indicates perfect equality, where each census block has the same percent canopy cover, while a value of 1 implies that all the canopy cover is concentrated in a single block. Although the Gini coefficient allows for a measure of canopy cover equality across the city, it says nothing about historical inequities in investment that have led to the current canopy distribution. To help evaluate the equity of tree placements in this paper beyond the equality measure provided by the Gini coefficient, Chicago's blocks are examined post-allocation based on their majority racial/ethnic group (or are identified as having 'no racial majority' if the block does not contain >50% of a single racial/ethnic group) and the percent of households with income below the poverty line, shown on the right side of Fig. 4. This was done to see if the addition of tree height alongside canopy cover might actually help increase tree

Table 1
Tree Allocation Scenarios.

	Tree Metric (s) Used	Variable Minimized
UHI Scenario 1 (c)	Canopy cover	LST
UHI Scenario 2 (d)	Canopy cover and height	LST
Environmental Equality 1 (e)	Canopy cover	Gini Coefficient
Environmental Equality 2 (f)	Canopy cover and height	Gini Coefficient

[1] Block-group data is the most detailed level of demographic data captured for these types of measures by the ACS. Block-groups exist as an area larger than a block, but smaller than a census tract. Block-groups are made up of a set of contiguous blocks (mean=21; sd=14), which given their spatial proximity and the generally segregated nature of Chicago's population, should give reliable estimates of the block-level population.

[2] May 17, 2021; September 10, 2021; September 26,2021

canopy equity for the most segregated and income disadvantaged groups while the distribution policy is optimized by the Gini coefficient.

2.4. Methodological pipeline

Fig. 1 shows the methodological pipeline employed for this analysis. First, we derive canopy estimates from airborne LiDAR data in 2017. We then train a deep learning model with this baseline data from 2017 to predict canopy cover and height in 2021 when LiDAR data is unavailable. Next, we use a geographically weighted regression (GWR) analysis to identify the relationship between canopy cover, canopy height and the UHI effect in different localities throughout Chicago. Finally, we use an optimization algorithm to assess four different canopy distribution scenarios to minimize the UHI effect and inequitable canopy distribution, comparing results when only canopy cover is used, and when both canopy cover and height are considered.

2.5. Data preparation

Baseline tree metrics were derived from the 2017 LiDAR data. The raw LiDAR point cloud was first processed in R using the lidR package (v. 4.0.2) with a method similar to Roussel et al. (2020). First, a vegetation mask was created using the NIR and red bands of the NAIP images, creating a normalized difference vegetation index (NDVI) raster layer as calculated in Zhao et al. (2019). For the tree mask, the point cloud was then masked to remove non-vegetation points which prevents buildings and non-biological objects from being classified as trees.

Next, a digital terrain model normalization was run using a k-nearest neighbour approach with inverse distance weighting to align the height of all points relative to ground level. For the tree mask, points below 2 m and above 25 m were filtered out to ignore small shrubbery and any incidental non-vegetation points (e.g., birds), while for the pixel height layer, heights were capped at 200 m to allow for better downstream modelling of tree heights. A canopy height model (CHM) was then generated using a pitfree algorithm which allowed for individual tree detection using a local maximum filter. Finally, the CHM and the individual tree detection results were used for tree segmentation based on the Dalponte and Coomes (2016) algorithm.

Fig. 2 shows examples of the two baseline raster layers which were generated from this process, one with binary values if a pixel was identified as being part of a tree, while the other raster layer contained the average max height of each pixel. These raster layers were then mosaiced together and stacked on top of the Sentinel-2 and NAIP data which were all projected to the extent and resolution of the NAIP 1 m data. These raster stacks were then cut into 9535 240 × 240 pixel patches, where each pixel represents one square metre, to be used as the input for the ML model.

2.6. Deep learning model for tree canopy prediction

To predict canopy cover and height in 2021 from only the combination of aerial and satellite imagery, we train a deep learning model using 2017 LiDAR-derived canopy cover and height estimates. As noted previously, LiDAR data provides a highly accurate data source from which to estimate features of the urban canopy; however, Chicago's most recent collection of LiDAR data occurred six years ago. Alternatively, aerial and satellite imagery from public and commercial sources are collected on a more regular basis and are therefore well suited to generate up-to-date maps for monitoring and evaluating urban tree policies. A recent Chicago tree census estimated that from 2010 to 2020 the city lost about 3% of its canopy coverage, largely due to an invasive pest (The Morton Arboretum, 2021). This equates to differences in tens of thousands of trees across the city per year, which would be difficult to forecast using only years-old LiDAR data but can be easily observed through regularly acquired imagery.

For this study, we adopted a multi-task (MT) learning approach for

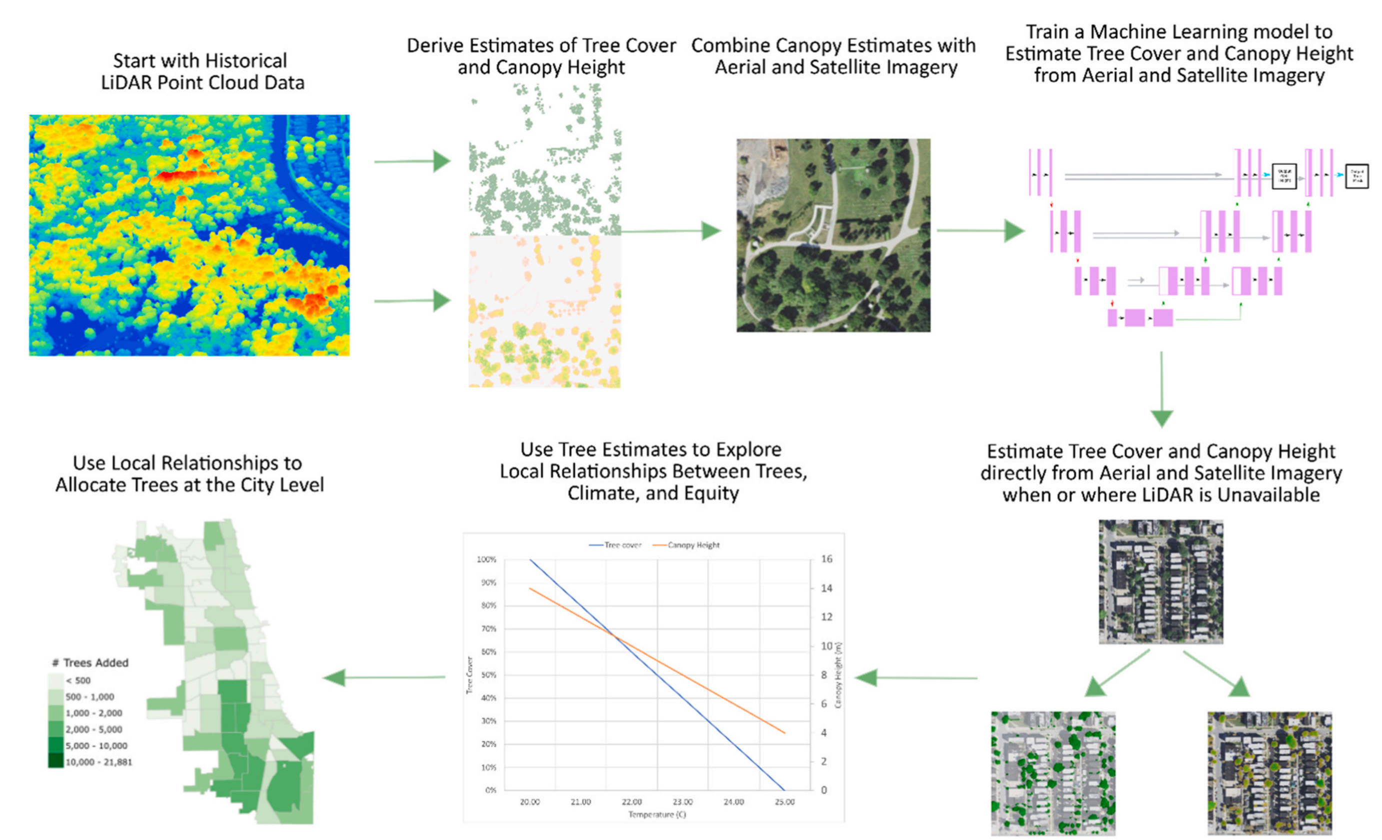

Fig. 1. Methodological Pipeline.

Fig. 2. LiDAR-derived Canopy cover and Height Estimates. The top row contains RGB images of example ML-input patches (240 m x 240 m), while the middle row is the associated LiDAR derived height estimates, and the bottom row is the associated LiDAR derived canopy cover estimates.

tree canopy prediction, utilizing a fully convolutional UNet architecture, that has demonstrated good performances on various pixel-level prediction tasks (Singh and Nongmeikapam, 2022; McGlinchy et al., 2019; Andersson et al., 2021; Alsabhan and Alotaiby, 2022). This approach involved combining two tasks, detecting whether a pixel belongs to a tree (tree mask) and estimating the height of a pixel (pixel height), into a single model. We hypothesized that this combined approach would enable better generalisations on the individual tasks, similar to recent research which tried to predict relative building and vegetation height and semantic segmentation masks simultaneously (Lu et al., 2022; Karatsiolis et al., 2021).

The UNet architecture, shown in Fig. 3, consists of a contracting encoding path that performs a series of convolutions to reduce the spatial dimension of the input image followed by an expanding decoding path that performs de-convolutions back to the size of the input image with shared representations between paths to increase the resolution of the output (Ronneberger et al., 2015). The output of the encoding path is fed into two separate decoding pathways, one culminating in a linear activation function (pixel height task) and one with a sigmoid activation function (tree mask task). Retrieving tree canopy height involves masking the predicted tree mask over the predicted pixel height which ensures only the height of pixels classified as trees are retained for later analyses.

We trained a UNet that maps the input MS data to pixel heights and a binary tree canopy mask, minimising the mean squared loss over all n pixels, L_{height} as follows;

$$L_{height} = \frac{1}{n}\sum_{i}^{n}(H_i - \widehat{H}_i)^2$$

where H_i is the LiDAR-derived pixel height and $\widehat{H}_i$ is the predicted pixel height and the binary cross entropy loss function;

$$L_{mask} = -\frac{1}{n}\sum_{i}^{n}(M_i \log \widehat{M}_i + (1 - M_i)\log(1 - \widehat{M}_i)))^2$$

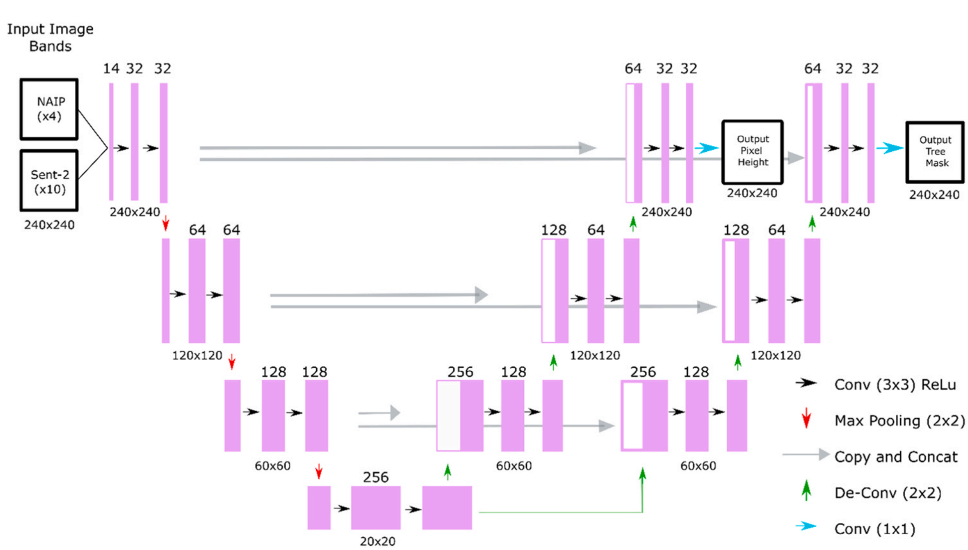

Fig. 3. The fully convolutional UNet Architecture. Each pink rectangle corresponds to a multi-channel feature map. The number of z-dimension channels (filters) is denoted on top of the rectangle. The x-y dimensions of each feature map are provided at the bottom of the rectangles. White boxes represent copied feature maps.

where M_i is the LiDAR-derived tree mask and $\widehat{M}_i$ is the predicted tree mask from the UNet model.

The final loss function is a simple weighted additive loss that incorporates two hyper-parameters λ, γ. During training, the model used the Adam optimizer algorithm (Kingma and Ba, 2014) with a learning rate of 0.001 for 50 epochs using early stopping if the model does not improve after ten epochs.

$$L_{total} = \lambda \quad L_{height} + \gamma L_{mask}$$

The weighting of the individual losses can have a significant impact on the model results. As a result, we compared two MT methods: first, a naïve approach that involved systemically tuning the weights through a grid search on a small validation subset (N = 500) randomly chosen from the training data; and second, an automatic weighting function outlined in Kendall et al. (2018) which attempts to learn a relative task weighting that accounts for the homoscedastic uncertainty of each task.

In total, 9535 240 × 240 images from 2017 were used to train the model, with 20% of these images randomly held out as a testing set. The input images for the model consisted of the 14 spectral bands from the NAIP and Sentinel 2 images. Despite their lower resolution, Sentinel 2 image bands were included because they are regularly available and provided minor improvements at little cost to training, shown in Supplemental Table 2. In addition to the primary model shown in Fig. 3, single-task models for each output were trained, alongside a model where both the encoding and decoding features were shared by the two tasks. Separate multi-task models for the automatic and manual weighting functions were run for a total of six models. These models were trained and evaluated solely using data from 2017. The best performing model was then used to predict canopy cover and height for 2021 when LiDAR data does not exist (N = 12,972 240 ×240 pixel images). To evaluate model performance, Intersection over Union (IoU);.

$$IoU = \frac{\text{True Positives}}{\text{True Positives+False Positives+False Negatives}}$$

is used for the tree mask as the dataset is highly unbalanced which would naturally inflate accuracy metrics, while Mean Absolute Error (MAE) is used for pixel height.

2.7. Relationship between the urban canopy and the UHI effect

To quantify how census blocks are related to the UHI effect, we employed GWR (Fotheringham et al. 2003; Comber et al., 2023), which is a local regression approach, with the SPGWR R package (Bivand et al., 2022). Initial tests on the residuals of a global ordinary least squares (OLS) regression model revealed, as expected, a significant level of spatial autocorrelation (Moran's I =.956, $p < 0.001$) in this dataset, thereby contradicting the assumptions for OLS and requiring a more spatially explicit model. GWR has been extensively applied to address this type of spatial non-stationarity (Brunsdon et al., 1996) where the relationship between the dependent variable and predictors varies across geographical locations (Foody, 2003; Su et al., 2012; Zhang et al., 2004) Fig. 4.

A GWR model calculates a unique local regression equation for each polygon (census block) and only considers a certain number of bordering polygons (the bandwidth) when calculating these coefficients, weighted by their distances to the centre of the kernel (Comber et al., 2023). An adaptive bandwidth was implemented which resulted in roughly 250 nearest neighbour polygons (census blocks) being included in each of our 46,149 regression equations, measured from the centroid of each block. Through this local regression technique, we aim to account for some of the neighbourhood effects not modelled explicitly but captured implicitly by each blocks' neighbours. The equations below (a, b) show the formulas used to analyse these spatial relationships, first just for canopy cover (a) and then for canopy cover and height (b).

(a) $y_i = \beta_{i0} + \beta_{i1}x_{i1} + \varepsilon_i$
(b) $y_i = \beta_{i0} + \beta_{i1}x_{i1} + \beta_{i2}x_{i2} + \beta_{i3}x_{i1}x_{i2} + \varepsilon_i$

Where:
i = census block x_{i1}= percent canopy cover at block i.
y_i = outcome (LST) at block i x_{i2}= avg. canopy height at block i.
β_{i0} = intercept at block i β_{i1} = coefficient 1 at block i β_{i2} = coefficient 2 at block i β_{i3} = coefficient 3 at block i ε = random error at block i.

2.8. Determining where to plant trees

Simulating where to place Chicago's 75,000 trees was done through a set of four scenarios described in Table 1. For the two UHI scenarios, LST predictions were minimized using the Sequential Least SQuares Programming (SLSQP) (Kraft, 1988) optimisation algorithm and the marginal effects generated by the GWR equations (c, d). Limits based on the initial observed climate values are placed on predictions to avoid predicting unobserved values. For the two environmental equality scenarios, the Gini coefficient was also minimized using SLSQP and the tree metrics (e, f). For the UHI scenarios block-level average canopy height was held constant; for the environmental equality scenarios a height factor was included. Looking at the 2017 LiDAR data, there is a positive correlation (0.603) between canopy cover and height in census blocks. Using this correlation, average canopy height was therefore estimated to increase by 0.084 m for each percentage increase in canopy cover to allow for height to be considered in the environmental equality scenarios.

(c) $y_i = \beta_{i0} + \beta_{i1}(x_{i1} + z_i * T)$
(d) $y_i = \beta_{i0} + \beta_{i1}(x_{i1} + z_i * T) + \beta_{i2}x_{i2} + \beta_{i3}(x_{i1} + z_i * T)x_{i2}$
Given: $z_i <$ available space in block i & Sum(z_i) = 75,000;
Minimize: Mean($y_1, y_2 \ldots y_n$)
Where:
i = census block x_{i1}= percent canopy cover at block i
y_i = predicted LST at block i x_{i2}= avg. canopy height at block i
β_{i0} = GWR intercept at block i β_{i1} = GWR canopy cover effect at block i β_{i2} = GWR canopy height effect at block i β_{i3} = GWR interaction effect at block i z_i = # of trees added at block i
T = constant canopy cover added by one tree
(e) $y_{i1} = x_{i1} + (z_i * T)$
(f) $y_{i1} = x_{i1} + (z_i * T)$ & $y_{i2} = x_{i2} + H(\frac{z_i * T}{A_i})$

Given: $z_i <$ available space in block i & Sum(z_i) = 75,000.
Minimize: (f) Gini($y_{a1}, y_{a2} \ldots y_{an}$);.
(g) Sum(Gini($y_{11}, y_{21} \ldots y_{n1}$), Gini($y_{12}, y_{22} \ldots y_{n2}$)).
Where:
i = census block x_{i1}= percent canopy cover at block i.
y_{i1} = new canopy cover at block i y_{i2}= new canopy height at block i x_{i2}= avg. canopy height at block $i$$z_i$ = # of trees added at block i T = constant canopy cover added by one tree H = constant height added

Table 2
UHI GWR results.

	Local R^2 (Range)	Mean Canopy cover Effect (Range)	Mean Average Canopy Height Effect (Range)	Mean Interaction Effect (Range)
Equation B (LST predicted by canopy cover)	0.325 (−0.032 to 0.726)	-0.392 (−2.25 to 2.19)	X	X
Equation C (LST predicted by canopy cover and average canopy height)	0.346 (0.021–0.725)	-0.336 (−2.36 to 2.06)	0.029 (−0.225 to 0.424)	-0.225 (−2.05 to 0.984)

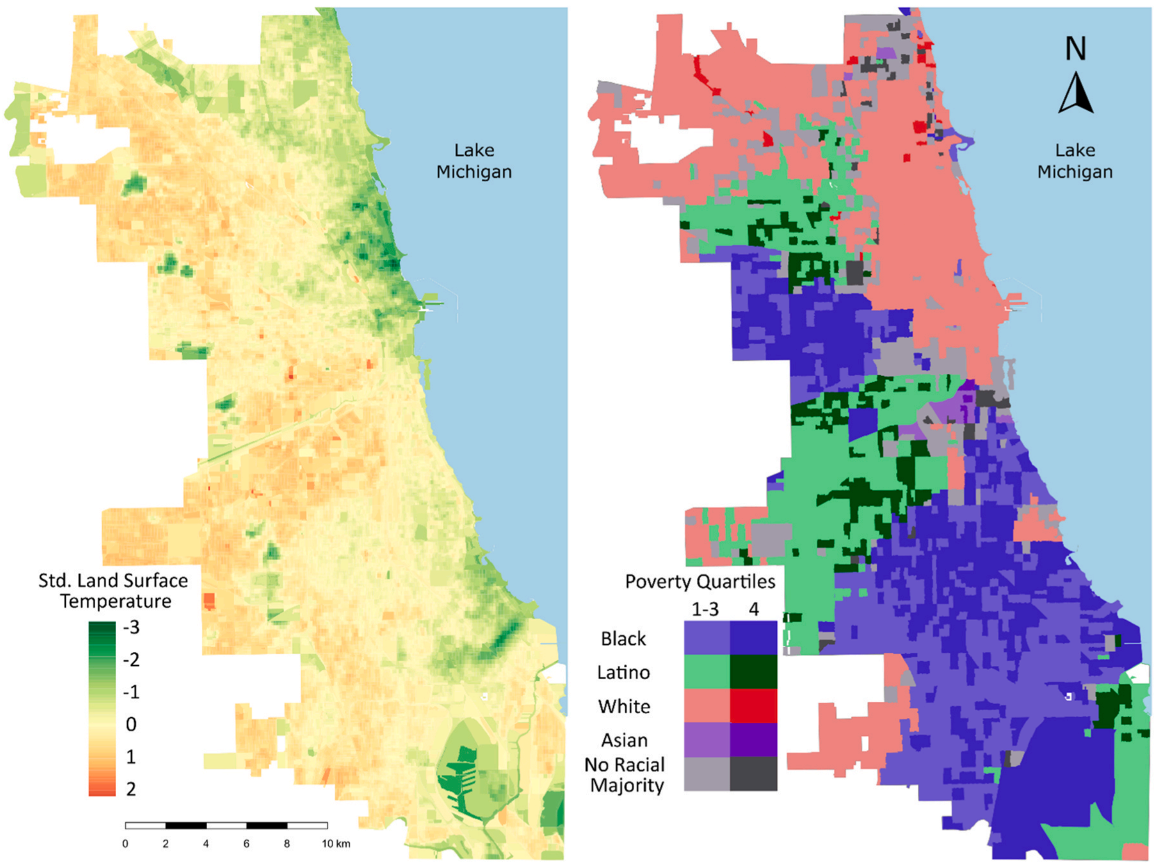

Fig. 4. Left: Land Surface Temperature map. **Right:** Census-derived Race/Ethnicity and Poverty bivariate map. Land Surface Temperature was standardized across three time points in 2021. For race/ethnicity, blocks were categorized if they contained 50% or more of a single group. Poverty is measured as the % of households with income below the poverty line. Quartile 4 represents blocks with the highest % of households with income below the poverty line.

by % increase in cover A_i = area of block *i*.

The number of trees that could be allocated to each block was bounded by the amount of available space, determined using the 2021 NAIP data as the estimated pervious surface (NDVI >.15) not already covered by trees. This method is similar to (Codemo et al., 2022), who estimate pervious surface using an NVDI value of.1 and note the need for careful consideration of the threshold value in urban environments to capture barely vegetated areas without including impervious surfaces. Previous work has used the National Land Cover Data (NLCD) to determine plantable areas (Nowak and Greenfield, 2009) similar to methods included within i-Tree Landscape, while more recent work has utilized alternative historic land cover datasets (Nyelele and Kroll, 2021). Similar to Merry et al., (2013), we believe plantable land is best assessed in rapidly changing urban environments using the most current available imagery. Additionally, the use of NAIP data allows for a measure of available space at the same resolution as our tree metrics, while restricting our analysis to pervious space allows for a simulation of tree placements that would not require additional changes to or investments into the urban environment. To determine how much space should be allotted for new trees, we follow Nowak and Crane (2002) who showed the average canopy of a city tree in Boston to be roughly 27 square metres. The number of trees each block can hold was therefore the available estimated pervious space not already occupied by trees divided by the estimated space for a tree.

Based on these four scenarios, the 75,000 new trees were allocated to one of Chicago's 46,149 census blocks. Final allocations are shown at the scale of Chicago's 77 community areas which have been in continual use since the early 1920 s for city-level statistics and policymaking (Zangs, 2014). These community areas align with the census blocks perfectly by design.

3. Results

3.1. Canopy cover and height estimates

In total, six UNet models were trained to determine which method was best able to locate trees and determine their height. The out of sample results of these models are shown in Supplemental Table 2. The model that was best able to locate trees (IoU = 0.665) and determine their height (MAE = 0.0033) was the MT model with manual weights in which only the encoder layers of the UNet were shared between tasks. This equates to an average error of about 0.644 m for tree height and an average overlap of 66.5% between the predicted and the LiDAR derived canopy cover. Notably, the automatic weighting function did not lead to any improvements. We also visually inspected the results to ascertain where predicted estimates proved most effective, and what circumstances caused the model to struggle in its estimates of the urban canopy. Consistently, the prediction accuracy is enhanced from the incorporation of multi-source MS imagery as opposed to a single source (NAIP only) imagery model (see Supplemental Fig. 1 for further results).

Fig. 5 shows five hand-picked test images from the 2017 image data, alongside the tree pixel height and canopy cover predictions generated by the best performing model and the LiDAR derived estimates. From the variety of areas displayed in Fig. 5 we can see that canopy cover appears to be estimated best on trees with larger crowns and in areas with higher numbers of trees. Canopy cover estimates struggled when faced with lots of smaller shrubbery and in some industrial areas. For canopy height at the pixel level, estimates are most precise in open areas and with shorter trees. As expected, areas with large numbers of buildings make canopy height predictions more error-prone, however the model is still able to consistently infer the shape of tree crowns.

Fig. 5. Visual Inspection of selected samples comparing the baseline LiDAR derived estimates and the 2017 ML Predictions. Higher IoU scores indicate better canopy cover predictions, while lower MAE scores indicate better canopy height estimates.

Using the best model trained from 2017 data, we next inferred the 2021 canopy cover and height metrics for all of Chicago at a 1 m resolution. We estimated a total city-wide cover of 19.7% and an average canopy height of 7.9 m. This indicates a slight increase in canopy cover from the 2017 LiDAR derived baseline data which estimated the city-wide cover to be about 17.9% and the average canopy height to be about 8.2 m. Our canopy cover estimates are larger than recent work in Chicago which used different methodologies. Chicago's 2020 tree census estimated the canopy cover to be nearly 16% when including shrubs (The Morton Arboretum, 2021), while researchers at the University of Chicago estimated canopy cover to be closer to 19% when using a 2010 LiDAR—based land cover layer (Healthy Regions and Policies Lab, 2021).

Fig. 6 shows the UNet predictions after each of the 12,974 image tiles from 2021 were extracted to the census blocks. Fig. 6 indicates that the areas of highest canopy cover are concentrated primarily in the northern part of the city, as well as within the many parks that line Chicago's eastern coast along Lake Michigan. A further concentration of areas with higher canopy cover can be seen on Chicago's south-west side. Areas with the highest average canopy heights are found along the north-western and south-western sections of the city, while the west and central portions of the city have some of the lowest average canopy heights. Large lines of low canopy heights throughout the city primarily follow the path of the Chicago River as well as the major highways that run through the city, while the large area of low canopy height in the south of the city corresponds to marsh land. Interestingly, even though there is relatively high canopy cover in many spots along Lake Michigan, the average canopy height remains relatively low in most of these areas. With these estimated tree metrics in hand, analysis turned to how the trees are related to the UHI effect.

3.2. Spatial regression results

Coefficient statistics from the two sets of GWR models are shown in Table 2. GWR generates a different set of coefficients for each census block, maps of which can be found in Supplemental Fig. 2. Not all blocks demonstrate a clear negative relationship between trees and LST, and some blocks predict increased LST as canopy cover or average canopy height increases. This reflects the heterogeneity of Chicago's census blocks whereby depending on the local environmental conditions, simply adding more trees in some locations may not result in reduced LSTs. The inclusion of canopy height leads to an improvement in goodness of fit, demonstrating its added effectiveness in modelling LST.

3.3. Tree allocation scenarios

Fig. 7 explores how the four scenarios would allocate trees to Chicago's 77 community areas. For the UHI scenarios, a larger average number of trees ($N \approx 28$ and $N \approx 29$) are allocated to a smaller number of blocks ($N = 2658$ and $N = 2631$), while in the environmental equality

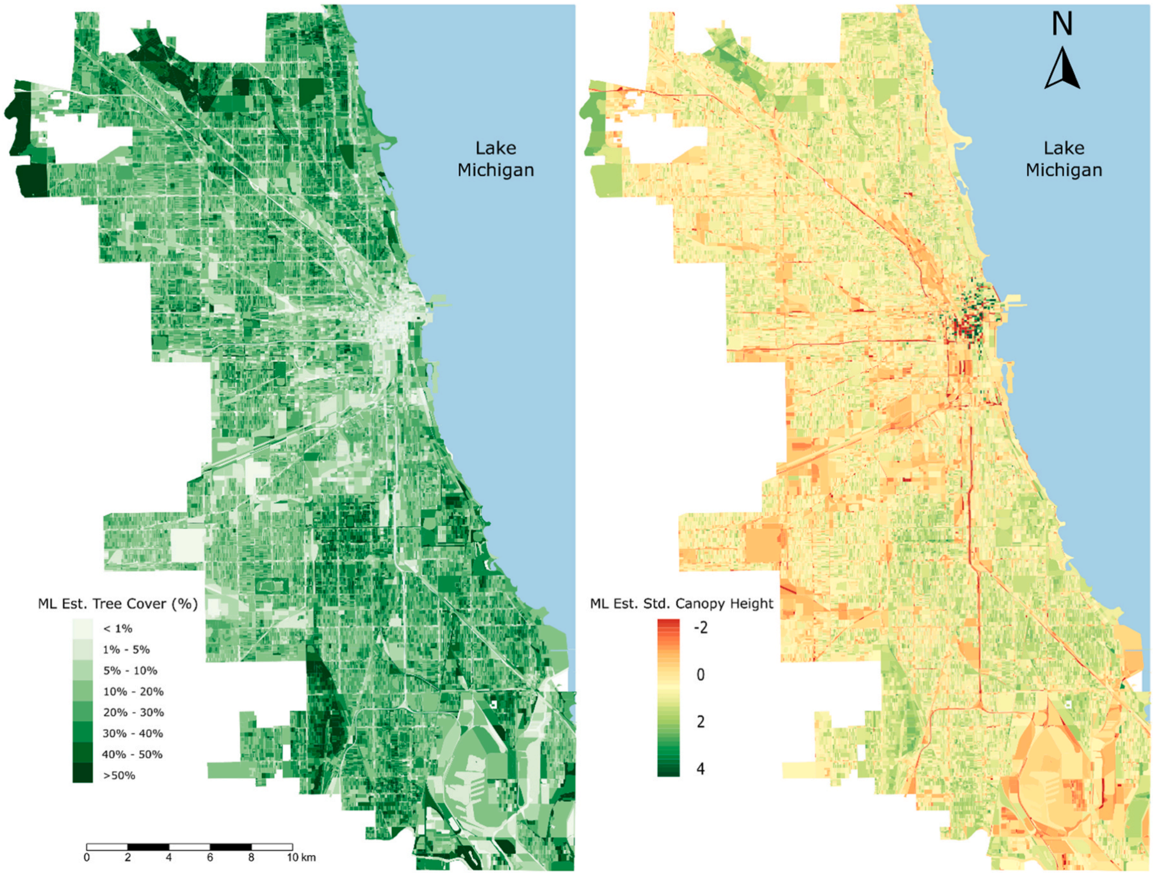

Fig. 6. 2021 Predicted Canopy cover and Average Standardized Canopy Height. While tree canopy metrics were estimated for each square metre of Chicago, here estimates are mapped to each of the 46,149 census blocks included in this work for visual clarity.

scenarios a smaller average number of trees ($N \approx 21$ & $N \approx 25$) are allocated to a larger number of blocks ($N = 3549$ & $N = 2960$). Communities on the far south and north sides of Chicago are the primary beneficiaries of tree allocations aimed at reducing the UHI effect in Chicago. For the environmental equality maps, communities on the western side of Chicago receive most tree allocations. In both the UHI scenario and the environmental equity scenario, adding height resulted in a slightly higher centralization of tree allocations. For the UHI scenario the addition of height resulted in more trees allocated to the northern and southern extremes of the city, and in the environmental equality scenario many trees were redistributed from southern communities into the western and central sections of the city. Next, we examine how these tree placements align with the city's equity goals.

Table 3 explores the equity of Chicago's urban tree canopy using the 2021 canopy estimates as well as the equity of this study's four allocation scenarios. In contrast with some previous work (Chicago Region Trees Initiative, 2018; Iverson and Cook, 2000), this study found that blocks with the highest percentage of household income below the poverty line and Majority Black census blocks in Chicago had some of the city's highest canopy cover and average canopy heights. For Chicago, Majority Latino and Majority Asian blocks had the lowest estimated canopy cover and average canopy heights in 2021, while having the hottest observed LSTs. Despite this, relatively few trees are allocated to Majority Latino and Majority Asian blocks across our four scenarios, as shown in the right side of Table 3. One reason for this, is the large discrepancies in the amount of available pervious space for new trees in the blocks of different racial/ethnic majorities. We found that Majority Latino blocks have room for 75 fewer trees on average than Majority Black blocks,.

For the UHI scenarios which only considered tree's impact on LST, the addition of height as a variable saw an increase in tree allocations to Majority White census blocks. This is likely due to blocks on the far south-west side of the city where trees were found to be particularly effective at lowering the LST. Examining how the addition of height in the UHI scenario effects predicted temperatures, we find that city-wide temperatures decrease by about .04 C (decreasing by as much as 1.4 C depending on local conditions) for each metre of average canopy height increase across the city if canopy cover is held constant. For the environmental equality scenarios which only considered the equality of canopy coverage using the Gini coefficient, the addition of height as a variable led to more trees allocated to Majority Asian, Latino, White and no racial majority census blocks than when only canopy cover was used. The addition of height also led to 2% more trees allocated to blocks with the highest percentage of household income below the poverty line.

4. Discussion

We present a new pipeline for estimating canopy cover and height in urban areas using a deep learning approach with MS imagery and airborne LiDAR. Combining canopy cover with measures of canopy quality, such as height, allows better quantification of the impact of trees in urban areas, particularly on temperature. This in turn should allow better decisions to be made about where to plant new trees in cities to maximize climate benefits as well as improving equity. Urban tree canopies are constantly evolving, as are city plans more generally, therefore policymakers and urban planners need to use the most relevant and up-to-date data. LiDAR remains the most informative data for estimating structural measures of the urban canopy, as exemplified by recent research in New York (Ma et al., 2023). However, LiDAR data are not always available, or are infrequently updated, making them less

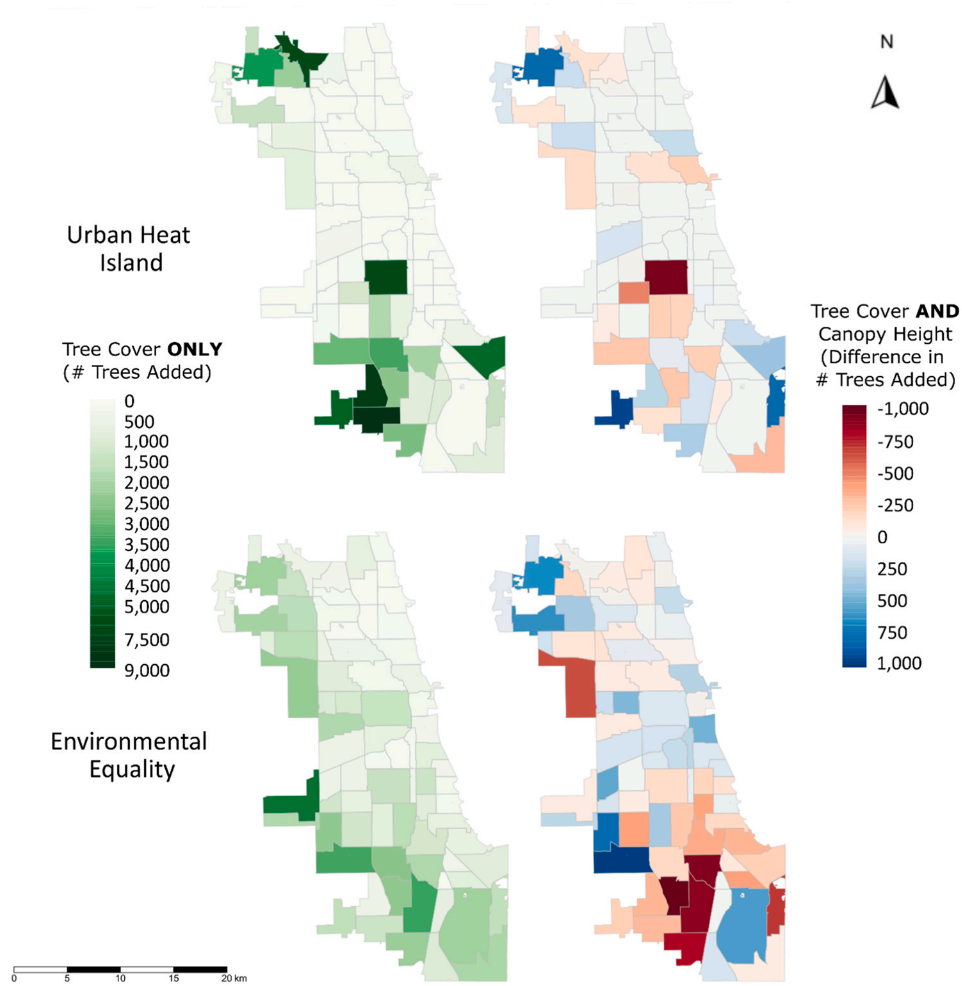

Fig. 7. **Top row:** Tree Allocations minimizing the UHI effect. **Bottom row:** Tree Allocations optimizing for Environmental Equality. The left-side maps use canopy cover alone while the right-side maps show the allocation differences when including canopy height. A key for the community area names can be found in Supplemental Fig. 1.

reliable for regular monitoring and evaluation of urban canopies. In locations where LiDAR data are unavailable, ML methods which have been trained on LiDAR data elsewhere provide a promising alternative for researchers and governments to fill in gaps.

We explore how factors beyond canopy cover alone influence the impact trees have on the environment. By including canopy height and the varying localised effect of trees into the decision-making pipeline, resources can be allocated more effectively. In our case study, the inclusion of height led to thousands more trees allocated to low income and Majority Asian, Latino, White and no racial/ethnic majority census blocks when the Gini coefficient was used to maximize tree canopy equality. By including height into the tree allocation strategy, fewer trees were allocated to blocks with higher quality pre-existing canopies and were instead redistributed to blocks with relatively lower quality tree canopies. When the UHI effect was minimized, the inclusion of height led to trees being primarily allocated to Majority White and Majority Black blocks where trees were most effective at reducing land surface temperature. More work utilizing strategies which incorporate multiple environmental, health and equity conditions (Nyelele and Kroll, 2021; Chicago Region Trees Initiative, 2018) are necessary in combination with additional canopy quality metrics to ensure that equity of urban canopies is being achieved while investments in urban greenery are allocated to areas where they have the strongest impacts.

The tree allocation scenarios presented here provide a top-down approach to distributing trees, which may be necessary to ensure equitable outcomes. Prior research has shown that many tree planting initiatives rely on residents and community groups for tree requests, and residents of historically marginalized communities are less likely to engage with the institutions required to make these requests (Pincetl, 2010). For this work, the largest barrier to addressing tree equity that we identified was a lack of available pervious space for trees in some communities, particular among Chicago's Majority Latino blocks. Previous studies have noted that even when a focus is placed on planting trees in historically marginalized communities, lack of space will be a barrier (Danford et al., 2014).

At a local level, alternative strategies exist for cities hoping to invest in greening these communities. Strategies such as green roofs and bioswales can provide small pockets of nature where tree planting is normally impossible, while more extensive measures can be taken to restructure the urban landscape in communities that are largely covered by impervious surfaces, such as the central business district of cities which are normally hotter than other areas of cities. Additionally, broadening the scope of tree initiatives to include urban nature investments beyond a specific number of newly planted trees is also valuable, particularly in densely developed cities (Danford et al., 2014). Investments that prioritize the maintenance and expansion of existing mature canopy cover is crucial, especially in communities with limited space for new trees. However, even when optimal canopy cover equity is unobtainable, smaller clusters of added trees can still provide important local benefits (Strohbach et al., 2013).

Table 3
Equity of Chicago's urban tree canopy and the four allocation scenarios.

Demographic Areas (% of total blocks)	Avg. Predicted 2021 Canopy cover %	Avg. Predicted 2021 Avg. Canopy Height (m)	Avg. # of trees given available pervious space	Avg. 2021 Scaled LST	Allocation Scenarios # (%) of 75,000 Trees Allocated[3]			
					Urban Heat Island (Cover Alone)	Urban Heat Island (Cover and Height)	Environmental Equality (Cover Alone)	Environmental Equality (Cover and Height)
Poverty Quartiles 1–3 (75%)	20.7%	7.1	101	.0732	62,400 (83.2%)	63,200 (84.3%)	55,700 (74.3%)	54,700 (72.9%)
Poverty Quartile 4[1] (25%)	21.6%	7.1	126	.0439	12,600 (16.8%)	11,800 (15.7%)	19,300 (25.7%)	20,300 (27.1%)
Majority[2] Asian (1.0%)	11.8%	5.2	54.5	0.285	0 (0%)	0 (0%)	290 (0.4%)	740 (1.0%)
Majority Black (37.9%)	22.7%	7.3	143	-0.002	31,600 (42.1%)	31,200 (41.6%)	36,700 (48.9%)	30,800 (41.1%)
Majority Latino (22.1%)	17.3%	6.8	67.7	0.491	9230 (12.3%)	9020 (12.0%)	18,500 (24.7%)	20,700 (27.6%)
Majority White (28.4%)	21.8%	7.1	106	-0.160	30,400 (40.5%)	31,200 (41.6%)	14,500 (19.3%)	16,300 (21.7%)
No Racial/Ethnic Majority (10.7%)	20.6%	6.9	79.9	0.000	3770 (5.0%)	3520 (4.7%)	4980 (6.6%)	6410 (8.5%)

Notes: 1- Blocks in Poverty Quartile 4 represent blocks with the highest percentage of households that have income below the poverty line. 2- Majority racial/ethnic blocks are those with at least 50% of a single group as estimated by the ACS. 3- While SLSQP allows for a precise allocation of trees, the numbers in this table have been rounded (and may not add to 75,000) to reflect the uncertainty contained within this pipeline.

We have not discussed which types/species of trees should be planted in Chicago, or how different tree species may provide varying benefits. This is beyond the scope of the current work. Darling et al. (2017, p.125) assessed the positive benefits of species diversity in planting in Chicago. They also note that it is vital that sustained resources are provided to help marginalized communities retain trees and expand their local ecosystems. Simply expending resources to plant trees is not enough. Continued investment in the management of urban trees is necessary to ensure that trees reach maturity, are properly integrated into the local ecosystem, and that environmental justice is achieved through the sustainability of urban forestry efforts (Sousa-Silva et al., 2023).

We identify several limitations in our current study. There may be some spatial bias in the UNet predictions because publicly available thermal data are only available at a lower spatial resolution than the optical and LiDAR data. Additionally, while Sentinel 2 data are global and free, the aerial imagery and airborne LiDAR used in this work are not universally available. However, the acquisition and availability of these data is growing very rapidly, due to their utility for urban planning and environmental applications (Wellmann et al., 2020).

For assessing where trees could/should be allocated, available space to plant trees was based on estimates of pervious surface using NDVI. However, there are various other options for tree planting on impervious surfaces, such as installing boxes for street trees or re-configuring urban areas to create new spaces for trees. Furthermore, more precise estimates of useful pervious surfaces are possible by considering surrounding context and size (Wu et al. 2008). Finally, other factors that contribute to LST in cities such as building height, land use or land cover could be included in the GWR as controls to improve fit estimates.

5. Conclusion

We demonstrate an application of ML to leverage aerial and satellite data for generating estimates of urban canopy cover and canopy height over Chicago. We show that the relationship between these urban canopy metrics and climate outcomes can be predicted spatially and that these impacts vary substantially across city blocks. This implies that certain types of localities may be a more effective tree planting location for reducing UHI effects than other locations. Lastly, we show that the inclusion of average canopy height provides important additional information about the quality of urban canopy cover that can help determine where planting future trees may be most effective. This approach can help inform decisions around how urban planners should allocate resources to meet equity and climate goals.

Not all canopy cover is equal, and in general larger trees tend to have a greater environmental effect than smaller trees, with numerous smaller trees often unable to match the effects of a single large tree (Le Roux et al., 2015; Stephenson et al., 2014). Using both horizontal and vertical measures of the urban canopy, the method laid out in this paper allows for a more complete assessment of the relation between the urban canopy and the wider urban environment. Our approach also provides a simple framework to include additional tree metrics in building a more holistic view of the urban canopy. While we showed how this method could be used in two discrete scenarios, we view this pipeline to be method agnostic and believe this framework in whole or in part could easily be integrated into other workflows and prioritization strategies leveraging the code provided in the associated project GitHub.

The approach we have developed has the potential to be more widely applicable to urban areas. More advanced ML models could be integrated into this pipeline, along with higher resolution remotely-sensed data and multiple health and environmental objectives for tree planting. There is a need to test model generalizability, incorporating global LiDAR datasets (e.g., GEDI) as well as including additional ML tasks (e.g., species type, above ground carbon estimates). More effective use of new datasets on the quality of canopy cover will be key to better decision-making around the value of and access to urban canopies.

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CRediT authorship contribution statement

John Francis: Conceptualization, Methodology, Software, Writing – original draft. **Mathias Disney:** Conceptualization, Writing – review & editing. **Stephen Law:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

All of the data sources used throughout this paper are publicly available and can be found as referenced in the text. The code used for this work can be found at: https://github.com/johnfrancis13/where_to_plant_trees.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ufug.2023.128115.

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