Recommending Strategies for Urban Heat Island Mitigation Using Remote Sensing and Optimization

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Abstract

The urban heat island effect causes urbanized areas to experience significantly warmer temperatures than their rural counterparts, especially during summer. Cities have a wide array of heat island mitigation strategies to choose from, but selecting the most efficient and cost-effective set of strategies is vital. Previous work on heat island mitigation strategy selection has tended to involve the use of expensive or resource intensive simulation software, or produced results with too low of granularity to be policy-relevant. This paper proposes a framework for mitigation strategy selection using remote sensing and linear optimization that is cost-effective and feasible for local or municipal governments.

Introduction

The urban heat island effect causes urbanized areas to experience significantly warmer temperatures than surrounding areas (National Geographic Society, n.d.). As global temperatures continue to increase due to climate change, urban heat islands have become more intense, and it is expected that this trend will continue (US EPA, 2014). For example, according to the Environmental Protection Agency, even under low-emissions scenarios, summer conditions in Chicago, Illinois, could become comparable to those currently observed in Atlanta, Georgia by the end of the century (US EPA, 2015). More than 1,300 Americans are estimated to die from heat-related causes each year, and the rate of heat-related deaths has risen since the last century to 2.9 per million (US EPA n.d.). Furthermore, these impacts are not evenly or equitably distributed; those older than 65 and Black populations experience the highest health risks, while Black and Hispanic communities live in hotter neighborhoods than their white counterparts (US EPA n.d.). Cities must develop cooling strategies to mitigate urban heat islands in order to protect vulnerable populations and improve livability. Local governments play an essential role in mitigating urban heat island and little work has been done to provide a feasible toolkit for governments to take actions. Our approach will allow local governments to use their own satellite imagery to visualize the optimal heat mitigation strategies according to fundings approved. That way, local governments are not limited by the computational resources required to run intensive simulation and the visualization and the quantification of cooling effect would help local governments to take a more proactive approach on combating urban heat island.

Related Work

Previous work on using machine learning to address the urban heat island (UHI) effect has centered on highly detailed, data-intensive simulations of urban microclimates paired with optimization algorithms to select the optimal set of mitigation strategies. Qi, Ding and Lim (2022) proposed a three-part framework for automating and optimizing UHI mitigation: 1) develop ontological representation of the relationships among UHI strategies and how they interact with the specific features of the city under consideration; 2) perform sensitivity analyses on urban climate simulations the identify the range of impacts for each potential mitigation strategy, and 3) use a genetic algorithm to select the optimal combination of mitigation strategies based on the simulation and sensitivity analysis results. The team then applied this methodology to a test case in Leppington, Australia, to demonstrate its feasibility and produced a city-wide plan expected to reduce average ambient temperatures by 0.8°C, though they do not specify how much it would cost to achieve this plan (Qi, Ding and Lim 2020). This framework appears thorough and robust, but it comes at a cost in terms of the intensive data collection required. The simulation software used by the team, ENVI-met, is the industry standard and relies on detailed inputs about the shape and size of buildings and green spaces, including the types of materials and plants used. While cities with robust geospatial analytics teams may have the capacity to create these detailed simulations, many U.S. cities and towns do not have the capacity or data required for such analysis.

In a different vein, Zhang et al. (2021) used Landsat 8 satellite and infrared imagery with 30m x 30m cells to impute the land use classification for each cell as the basis for optimization. After classifying each cell, the team implemented a modified multi-ant colony optimization (MACO) to identify hotspots in the urban landscape and recommend which cells should have their land use converted in order to maximize cooling effects, while subject to a constraint set to minimize the total number of cells to be converted. Using this strategy, the team estimated the recommendations would lead to a cooling effect between 0.43-0.85°C while converting only 4.7-4.8% of cells, though again a cost estimate for converting these cells was not provided.

In this paper, we draw on these previous bodies of work to inform a new model that can provide recommendations at a granular spatial resolution without requiring intensive data gathering and simulation. Using 3-inch pixel satellite imagery of Pittsburgh, Pennsylvania, the team used a U-net model to classify each pixel according to land use categories relevant to UHI mitigation initiatives, such as roofs and roads (which contribute greatly to absorbing and re-emitting heat in urban areas). Using the classification results alongside literature on the effects of different cooling strategies, the team then implemented a linear optimization to maximize the average expected cooling effect that could be achieved under different budget scenarios.

Urban Heat Island Domain and Data

Strategies for Addressing the Urban Heat Island Effect

Multiple technologies and techniques have been developed to lower the amount of heat energy absorbed and re-emitted by urban environments. These strategies fall roughly into two categories: increasing albedo or increasing vegetation, where albedo is a measure of the amount of energy reflected off of a surface (rather than absorbed) (US EPA 2015). In the first category are included cool roofs and cool pavement, two of the most commonly discussed solutions to the UHI effect. Where traditional asphalt and roof shingles in the U.S. tend to be dark shades of grey, brown and black that readily absorb heat into the urban environment, substituting these with lighter colors or incorporating reflectivity into the materials would reduce the amount of energy absorbed and increase the amount that instead reflects off these surfaces and back into the atmosphere (Cool Roofs 2008, Cool Pavements 2008). The second category of mitigation strategies involves planting vegetation in a variety of forms, such as green roofs, green walls, and tree planting. These strategies work by reducing the amount of heat stored in the air and soil through evapotranspiration, and in the case of trees and tall shrubs, plants can additionally provide cooling shade to the people, animals and ecosystems below (Trees and Vegetation 2008).

For the purposes of this analysis, the team focused on cool roofs, cool pavements, and planting trees specifically. These represent some of the most commonly discussed strategies given that they are the most readily implemented and feasible, as well as some of the most effective. The team additionally considered green roofs, but these require very specific styles of roof construction that introduce a much higher level of modeling complexity while applying to only a small number of roofs. Similarly, while green walls are a possibility, they have not been widely implemented in the U.S. and provide a relatively smaller cooling effect.

Data on the expected cooling effects of tree planting and cool roofs and pavements were sourced from reports by the U.S. Environmental Protection Agency (EPA). Research cited by the EPA indicated that neighborhoods with trees were 2-3°C cooler than comparable neighborhoods without trees (Trees and Vegetation 2008). Another study found that the air temperature in a park fell by 1.9°C after 4,500 sq m of cool pavement was installed along paths and roadways (Santamouris et al. 2012). Lastly, a simulation study investigating the impacts of installing cool roofs in New York City estimated that the cooling effect could range between 0.4-0.8°C with an adoption rate of 50% (Cool Roofs 2008); while a similar study in Kansas City found that the cooling effect varied according to the density of roofs there were treated, i.e. the urban intensity (Gilbert et al. 2019). Each of these estimates were based on daytime temperatures and reflected the impact of a particular amount of each technology being installed (i.e. trees throughout an entire neighborhood, 4,500 sq m of cool pavement, or 50% of roofs in an area). Accordingly, the methodology that follows was not intended to recommend individual roofs to retrofit or exact locations for planting trees, but rather it focuses on identifying the regions that are best suited to installing a given mitigation measure while highlighting potential installation sites within that region.

Datasets

The dataset used for training is the LoveDA dataset for remote sensing (Wang et al., 2021). This dataset (n=5,987) includes satellite imagery of Nanjing, Changzhou, and Wuhan, China, annotated with labels for Background, Building, Road, Water, Barren, and Forest. The ArcGIS deep learning model is trained on imagery of Los Angeles, California, with labels for Tree Canopy, Grass/Shrubs, Bare Soil, Water, Buildings, Roads/Railroads, Other Paved, and Tree Shrubs. These sets were chosen because the labels are useful for identifying land cover categories that are relevant to identifying candidate sites for urban heat island mitigation strategies.

The remote sensing models were deployed on imagery of Pittsburgh, Pennsylvania, from Pennsylvania Satellite Imagery Access (PASDA, n.d.). The initial deployment is on 16 tiled images of the Oakland neighborhood, each of which is approximately ⅓ mile on each side. This area was chosen because it has a broad mix of land uses, including a university campus, riverfront, and commercial and residential areas.

Cooling Strategy	Approximate Cooling Effect (°C)	Source
Cool pavements	1.9	Santamouris et al., 2012
Tree planting	2-3	US EPA, 2008
Cool roofs, High Density	0.8	US EPA, 2008 Gilbert et al., 2019
Cool roofs, Medium Density	0.6	US EPA, 2008 Gilbert et al., 2019
Cool roofs, Low Density	0.4	US EPA, 2008 Gilbert et al., 2019

Table 1: Estimated cooling effects of installing different UHI mitigation strategies

Remote Sensing

Semantic segmentation is used in order to identify land use of a specific region as an input to the optimization model. The optimization model will identify the optimal heat mitigation strategies based on the labels identified by the semantic segmentation techniques on each pixel of the Pittsburgh Satellite Imagery. Three different semantic segmentation models were trained on 5000 iterations on the LoveDA dataset. The three different backbones chosen have achieved state-of-the-art accuracy on the cityscape semantic segmentation task benchmark.

The first model uses High-Resolution Network (HRNet) as the backbone, which has two key characteristics: 1) Connects high-to-low resolution convolution streams in parallel; 2) Repeatedly exchanges information across resolutions. The major benefit of using this backbone is the resulting representation is semantically richer and spatially more precise (Wang et al., 2020). HRNet set a new state-of-the-art performance in the cityscapes dataset in 2020, with 84.5% mIoU test performance (Wang et al., 2020). Therefore, HRNet is a strong backbone in semantic segmentation tasks.

The second model uses Deeplabv3plus as the backbone, which was built upon the Deeplabv3 architecture by adding a decoder module to recover detailed object boundaries. The Deeplabv3 backbone has an encoder-decoder structure and a spatial pyramid pooling module (Chen et al., 2018). Deeplabv3plus set a new state-of-the-art test performance on PASCAL VOC 2012 and cityscapes datasets with 89.0% and 82.1% mIoU without any post-processing in 2018 (Chen et al., 2018).

The third model uses Pyramid Scene Parsing Net (PSPNet) as the backbone, which uses a pyramid parsing module to harvest sub-region representations, followed by upsampling and concatenation layers to form the final feature representation, which is then used to form the final pixel-level prediction. The strength of this architecture is it aggregates global context with the local context through the pyramid pooling layer, where the global prior representation is effective to produce good quality results in scene parsing tasks. PSPNet set a SOTA record at 80.2% mIoU on the cityscapes dataset in 2017 (Zhao et al., 2017).

The ArcGIS deep learning model uses U-net as the backbone, which deploys a contracting path for downsampling and an expansive path for upsampling. The contracting path increases input feature resolution and decreases image resolution and the expansive path decreases feature resolution and increases image resolution. The whole architecture consists of 23 fully connected convolutional layers. U-net combines features from different spatial regions of the image and allows it to localize more precisely regions of interest (Ronneberger, Fischer, Brox, 2015) . Since U-net is designed for biomedical use originally, there is no accuracy record on the cityscapes dataset.

HRNet, Deeplabv3plus, and PSPNet were run in Python 3.9. The U-net model was run in Esri's ArcGIS Pro 3.0.2. All models were run on standard commercial laptops.

Linear Optimization

The optimization for city-wide cooling built on the classification predictions produced by the U-net semantic segmentation model (SSM). The classification labels of interest for this project were "Buildings", "Roads/Railroads", "Grass/Shrubs" and "Bare Soil"; all other labels were ignored for the purposes of optimization. Because the satellite imagery was taken from directly above rather than at an angle to the buildings in the images, the "Buildings" label represents rooftops where "cool roof" technology could be applied. The "Roads/Railroads" label represented streets where cool pavement could be applied; there may be a small amount of railroad track in the analysis area as well that could not be distinguished from roads (see Future Work under Discussion section). Last, the "Grass/Shrubs" and "Bare Soil" labels were combined to represent areas where trees could be planted. As noted above, each of these proposed cooling measures requires a minimum installation quantity in order to be effective; for example, installing a single cool roof is not likely to have a measurable effect on ambient temperatures. Therefore, within each geographic unit of analysis, if any of the three labeled categories did not reach a certain threshold amount of surface area, it was converted to a zero in the optimization inputs, as the area would not be suitable to support effective cooling. In the end, each satellite image tile's classification mask was converted into a 1D array of five values representing the amount of surface area in square feet covered by the land use type associated with each of the five UHI mitigation measures: cool roofs (which is subdivided into areas with a high density of roofs, medium density, and low density, each of which would produce a different cooling effect), cool pavements, and tree planting. An additional "allowed-to-install" array of zeroes and ones was created for each tile to indicate whether or not it could support a given mitigation strategy.

The linear optimization model assigned whether or not to install each of the five UHI mitigation strategies in a given region defined by a satellite image tile using binary decision variables. The objective function maximized the mean expected cooling effect across the entire neighborhood of Oakland by averaging the sumproduct of the cooling effects and "allowed-to-install" array within each tile. The only model constraint was budget. The optimization formulation is outlined below.

For *j* in [*Cool Roof - High Density, Cool Roof - Medium Density, Cool Roof - Low Density, Cool Pavement, Tree Planting*]

For *n* in 1, …, N (*where N = number of satellite image tiles*)

Inputs:

- $CoolingEffect_j$: Cooling effect of installing intervention *j* in one tile
- $AllowedToInstall_{jn}$: Whether intervention *j* can be installed in tile *n* in a sufficient quantity to produce cooling effects (binary)
- $Cost_j$: Estimated cost to install intervention *j* in one tile
- Budget : Amount allocated to UHI Project (USD)

Decision variables:

- $Intervention_{jn}$: Whether or not to install intervention *j* in tile *n* (binary)

Objective Function:

$$Max \frac{1}{N} \sum_n \sum_j Intervention_{jn} * CoolingEffect_j * AllowedToInstall_{jn}$$

Constraints:

Budget Constraint

$$\sum_n \sum_j Intervention_{jn} * Cost_j \leq Budget$$

$Intervention_{jn}$ and $AllowedToInstall_{jn}$ are binary

Results

Remote Sensing

The validation accuracy of the HRNet, Deeplabv3plus, and PSPNet models after 5,000 iterations of training on the LoveDA dataset are shown in Table 2. Metrics for the labels of interest for this project - Building, Road, Barren, and Forest - are marked in bold.

Accuracy (%)	**HRNet**	**Deeplabv3 plus**	**PSPNet**
Background	67.69	91.1	91.57
Building	**56.18**	**77.64**	**72.95**
Road	**38.44**	**32.94**	**30.44**
Water	91.98	38.46	48.16
Barren	**16.01**	**17.93**	**21.71**
Forest	24.85	28.17	35.84
Agriculture	70.99	56.15	46.34

Table 2: Validation accuracy of fine-tuned models after 5,000 iterations of training.

After 5,000 iterations, the Deeplabv3plus model performs best at identifying buildings, the HRNet model performs best at identifying roads, and the PSPNet model performs best at identifying forest and barren land. None of the three models converged within 5,000 iterations; due to lack of computing resources it was not possible to train for any longer.

The reported validation F1 score of the pretrained U-Net model is shown in Table 1 with metrics for labels of interest for this project marked in bold.

F1 Score	U-Net
Tree Canopy	82.47
Grass/Shrubs	**67.04**
Bare Soil	**90.12**
Water	98.41
Buildings	**93.34**
Roads/Railroads	**86.62**
Other Paved	81.17
Tall Shrubs	67.12

Table 3: Reported validation F1 scores for ArcGIS U-Net model (Esri, 2022).

Because the fine-tuned models were clearly not able to outperform this baseline model with so few iterations of training, the pretrained U-net model was chosen for segmenting the deployment images in order to recommend mitigation strategies.

The PASDA satellite imagery of the area initially chosen for deployment is shown in Figure 1. The segmented imagery is shown in Figure 2. Visually, the model appears to be mostly successful at identifying roofs, paved roadways, grassy area, and trees in this particular image. However, it may be misclassifying some of the campus building roofs as paved area or soil, perhaps because they are more made of concrete and thus more grey or brown in color than the roofs of typical single-family homes.

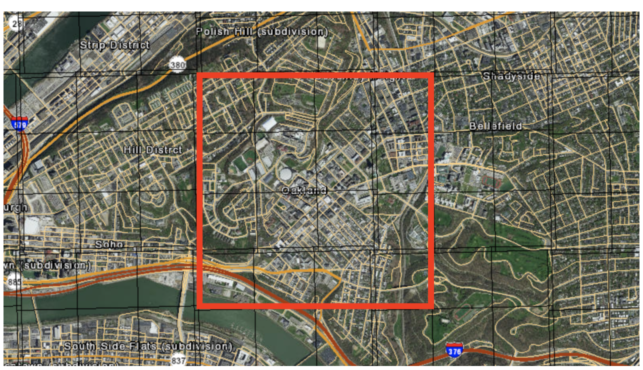

Figure 1: PASDA imagery tiles with selected tiles marked in red square.

Figure 2: Selected PASDA tiles with pixels segmented by ArcGIS U-Net model. Red indicates “Roof”, black indicates “Roads/Railroads”, and light green indicates “Grass/Shrubs”.

Optimization

The linear optimization model was used to optimize for the maximum expected cooling effect over all of the tiles in the segmented imagery. Because the budget for a UHI mitigation project is uncertain, budgets ranging from $1,000,000 to $25,000,000 were tested. The resulting efficient frontier is shown in Figure 3. The expected cooling effect that can be achieved begins to plateau at a budget of around $17,000,000. A budget of $1,500,000 was chosen for carrying out the optimization.

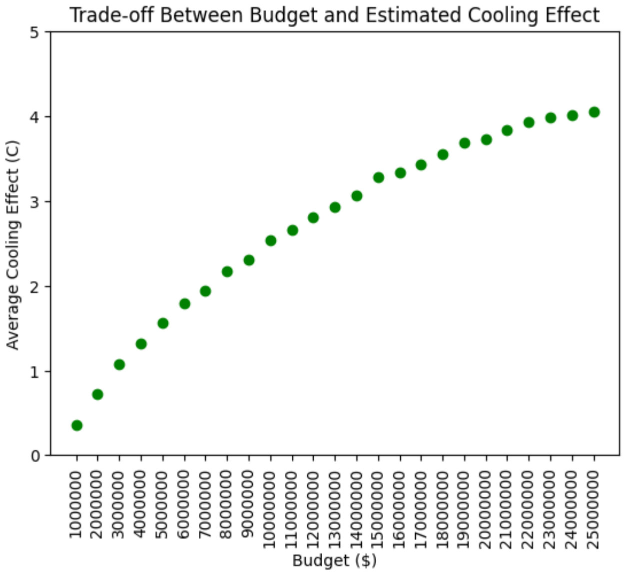

Figure 3: Efficient frontier showing trade-off between project budget and cooling effect under optimal solution.

There is also uncertainty about the specific installation costs associated with each type of intervention. low, medium, and high installation cost scenarios for each intervention were specified. These are shown in Table 4. The efficient frontier associated with varying between low, medium, and high installation costs is shown in Figure 4.

Range	Low	Medium	High
Cool Roof - High Density	$0.60 / sq ft	$1.33 / sq ft	$2.05 / sq ft
Cool Roof - Medium Density	$0.60 / sq ft	$1.33 / sq ft	$2.05 / sq ft
Cool Roof - Low Density	$0.60 / sq ft	$1.33 / sq ft	$2.05 / sq ft
Cool Pavement	$0.35 / sq ft	$0.50 / sq ft	$0.65 / sq ft
Trees	$2,059 / tree	$3,048 / tree	$3,936 / tree

Table 4: Installation costs under low, medium, and high cost scenarios.

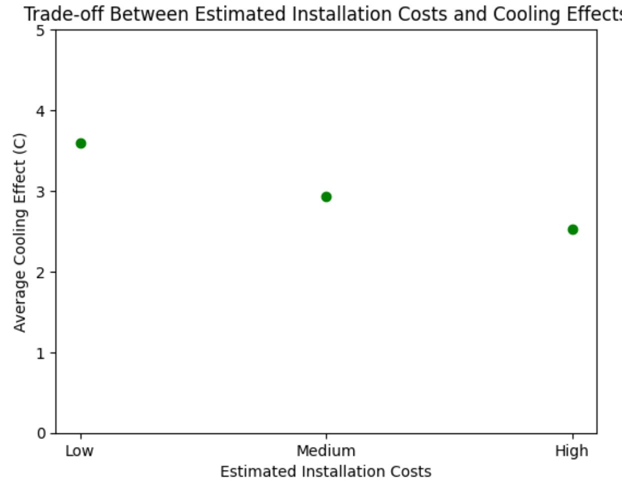

Figure 4: Efficient frontier showing cooling effect under optimal solution given low, medium, and high installation cost scenarios.

The recommended strategies after optimizing for maximum expected cooling effect over the tiles in the Oakland area with budgets ranging from $1,000,000 to $5,000,000 are displayed in Table 5.

Budget	Tiles with Tree Planting	Tiles with Cool Pavement Installation	Tiles with Cool Roof Installation	Cooling Effect (°C)
$1 mil	0	3	0	0.36
$2 mil	1	5	0	0.72
$3 mil	0	9	0	1.07
$4 mil	2	9	0	1.32
$5 mil	2	11	0	1.56

Table 5: Optimal strategies and expected cooling effect under budgets ranging from $1,000,000 to $5,000,000 under medium installation cost scenario.

As an example, the recommended strategy with a budget of $2,000,000 and medium installation costs is displayed in Figure 5. Under this particular scenario, it is recommended to install cool pavement in 5 tiles, plant trees in 1 tiles, and install cool roofs in none of the tiles.

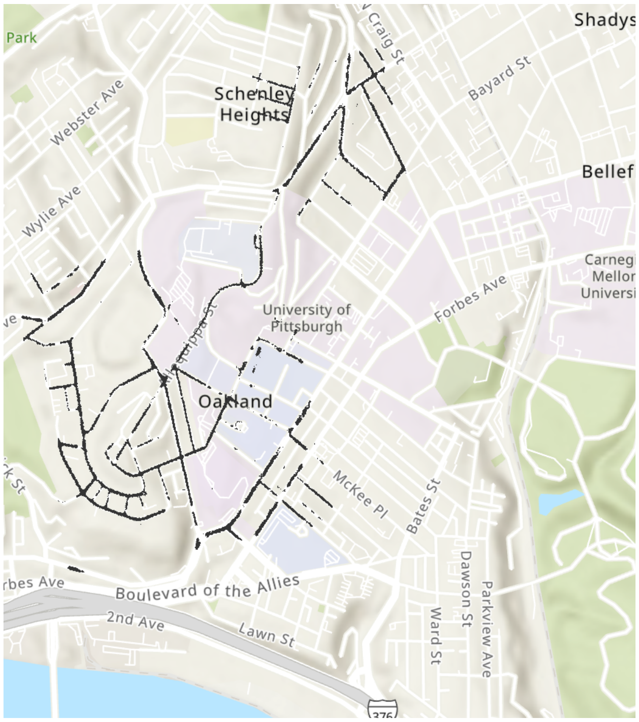

Figure 5: Recommended roads for installing cool pavements in Oakland are shown in black for a $2 million budget.

Discussion

Remote Sensing Results

Since the accuracy by the pretrained U-Net model in ArcGIS outperformed all of the other three models, the semantic segmentation results that were fed to the optimization model were from the U-net architecture. It is uncertain whether the other three models can outperform the U-net architecture with significantly more training iterations. However, due to limitations in computation resources, we are unable to train more than 5,000 iterations. The accuracy of the U-net architecture achieves 83.29% mIoU, which is comparable to the current SOTA benchmark of 86.50% in the cityscapes dataset (Cityscapes Dataset, n.d.).

Optimization Results

The optimization model is sensitive to the budget constraints and recommends different combinations of cooling strategies under different budget constraints. We chose $2,000,000 as our example budget because there are several policy initiatives that support different heat mitigation strategies including tree planting and cool roof replacement. However, it would fall to local government officials to decide on how much funding to approve to support the urban heat island project. The following examples from different local governments show the wide range of budgets for similar projects.

For projects focused on tree planting, the Biden-Harris administration approved a federal budget of $50,000,000 on the Urban & Community Forestry Inflation Reduction Act Grants. The minimum budget for each project from this grant is $10,000 (USDA, 2023). For projects focused on cool roof replacement, there are multiple government programs in the form of rebates and loans and public-private partnership programs. For example, the Louisville, Kentucky government has a cool roof replacement incentive program which subsidizes home owners $1 per square foot of cool roof installed (Louisville-Jefferson County Metro Government, n.d.). In Baltimore, the city requested energy companies to set aside $112 million for consumer programs and the city used some of the funding for cool roof replacement projects (Capital News Service, 2019). In Pittsburgh, the city council created the Housing Opportunity Fund to address the city's affordable housing problem. The ordinance requires the city to set aside $10 million each year for the fund. Roof replacement is one of the major areas that the fund is supporting (URA, n.d.). Some local governments including Philadelphia, New York City, and Los Angeles passed mandatory cool roof ordinance and offer rebate programs for existing homeowners to switch to cool roofs (LADWP, 2022) (NYC Mayor's office of Climate and Environmental Justice) (PEA, 2010).

Since the cost and budgets of heat mitigation strategies depend heavily on the policy of local government, there are uncertainties in monetary terms that cannot be determined. Our results show how the heat mitigation strategies vary with different budgets. Pittsburgh local government can decide to adopt different policies to reach the goal of lowering temperature with the budgets they can acquire. The optimization model is robust to the average cooling effects, which shows a diminishing return on cooling effects with increase in budget. Our results show that with a budget of $2,000,000, a reduction in 0.9 °C can be achieved.

Future Work

The optimization model does not take spatial contiguity constraints into account. To combat this shortcoming, while minimizing the manual efforts required, additional constraints can be added in the ArcGIS model before passing on to the optimization model. ArcGIS allows users to edit the classification results from the semantic segmentation model through adjustments on land size and land use. For example, a user could set a constraint such as requiring the program to identify land parcels that are made up of grass and soil and that are larger than 4,225 sq ft (size needed for a mature tree). By setting up spatial constraints for each heat mitigation strategy, the optimization output would be closely aligned to spatial constraints in reality. Another benefit of setting up spatial constraints is to reduce the misclassification on smaller fragments that are noise to our input in the optimization model.

Heat mitigation strategies produced by our model only show the optimal solution without ownership constraints. Local governments cannot replace cool roofs in private housing without homeowners consent or mandatory policy on cool roof replacement. To reflect the ownership constraints, local governments could additionally restrict the ArcGIS output to only include properties that are publicly owned, as many city planning departments would already have an ArcGIS shapefile of where their properties are located.

Lastly, the relationship among cooling effects produced by multiple UHI mitigation strategies may not be a linear combination of each strategy's individual cooling effect, as modeled in the linear optimization. Further research on the effects of installing multiple cooling strategies in one area could help to quantify the nonlinearities in this relationship and improve the optimization model accuracy. Results from our proposed workflow could additionally be benchmarked against results form a simulation software such as ENVI-met to evaluate performance and further refine the methodology.

Conclusion

As climate change continues to push temperatures higher around the world, mitigating the worst impacts of heat will become increasingly crucial to protect human health and save lives during heat waves. Cities are home to more than half of the world's population, yet they consistently measure up to 7°F warmer than their surroundings (*Learn About Heat Islands* 2014). While strategies to change the environmental conditions contributing to the urban heat island effect are well-known, deciding where to implement these strategies in a cost-effective manner is not straightforward. Where some methodologies have required intensive data collection and simulation that may be out of reach for small or medium-sized cities with limited capacity, other methodologies operate at a low resolution and provide vague recommendations; these approaches would still require collecting further data as a follow up in order to inform real policy strategies. Our proposed methodology strikes a balance between the two by using readily available data sources such as satellite imagery together with Esri ArcGIS software, which is common in most U.S. city planning departments, and an approachable optimization algorithm to model the urban environment with sufficient detail to inform policy decisions. While the current model relies on multiple simplifications and assumptions, it offers a test case for a workflow that can be readily adopted in city planning departments and is highly modifiable for future improvements and refinement. Given the urgency of the climate crisis for cities experiencing elevated temperatures, developing a feasible, readily-packaged modeling solution meets a critical social good need for urban residents nationwide.

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