General Information

Soundview, Bronx:

- Burdened by highways – cutting across west to east
- Population
  - Hip hop, hispanic, black, small asian population
  - Larger neighborhoods in NYC
  - Working class, 45.6K median income, 26% under 18
- Assets
  - Bronx River → flooding
  - Westchester Ave
  - NYCHA Community centers
  - Soundview Park helpful in reducing heat
- Subject to
  - Extreme heat
  - Air pollution
  - Flooding
- History of industrial use → contamination
- Using data
  - Food distributed
  - Immigration
  - Sampling bronx river
  - Contamination → supporting policy and infrastructure investment and design

Goals:

- Using existing temp increase to model creating new green spaces or parks
  - Making parks to address flooding
  - Tree canopy reduces local temperature
- Using air pollution data to model traffic reduction along expressways → advocating for traffic calming policies
- Use climate data and bus stop location to understand heat risk for commutes (walking to bus stops) and choose reroutes
- Utilizing existing communities, low budget, volunteers
- Can possible create digital communication tools
- Think about the lifecycle of our projects, what is the role of data in maintaining these public spaces?

Datasets:

- Can apply to NYC Open Data Week
- Flooding
  - Coastal Flooding – Both current and future projected sea level rise, storm surge, and tidal flooding

    - Inland Flooding: DEP stormwater flooding scenarios
    - Flood Vulnerability Index
- Heat
    - Temperature monitoring results
    - Heat Vulnerability Index
    - Extreme events projections
- Air Quality
    - New York City Community Air Quality Survey
    - Indoor Environmental Complaints
- Environmental Justice Mapping Tool
    - https://experience.arcgis.com/experience/6a3da7b920f248af961554bdf01d668b/page/Data-Explorer
    - 115+ data layers relevant to understanding EJ concerns
    - nyc.gov/ej
- City wide planning → existing flood protection plans
    - Coastal Surge + SLR – NPCC
        - Granular, projections based on probability and time interval
    - NYC DEP Stormwater Projections, Cloud Burst Hubs

Next Steps

1. Look at zoning in Soundview
2. Understand HVI, FVI, demographics
3. Overlaying them all
4. Final product: recommendations of how to utilize land parcels based on zoning codes
5. Data visualization of the zoning areas with all the data

Day 1:

1. Identify problem
2. Data sources

Brownfield Development

- Reece wants a tool that could recommend land use changes
- Has an inventory of properties they were considering
    - https://www.ympj.org/boa-report-page/
- The different options would be park land, 2-3 story development for community art space
    - Taking advantage of zoning or changing zoning
    - Looking at existing zoning first, otherwise he'll be looking for what he can do in other zones

    - Zoning change can be incredibly expensive or take a long time. Can find zoning information on NYC Zola
    - They look for ways to adhere to the existing zoning type, otherwise there
- Reece’s area of study is more on the Bronx River
- Housing redevelopment → sustainable building

Heat concerns from older residents
- Potential solutions: community gardens, green roofs, painting roofs white, planting more trees

Decrease walking distance to bus stops. In the Soundview Peninsula, you need to walk all the way to Westchester
- There was a bus re-design that increased the walking distance for neighbors
- Compare the network before and after
- East of the Bronx River is a special pilot area for e-mobility. West side is Citi Bikes. Can’t go from one side to the other. Wishes there was more
    - Citi-bike has reduced fare
- Expanding ferry network

Meeting with Reece:
- 12-12:15
- 3-3:30

Brainstorming Sheet

Dataset Ideas:

- HVI: https://data.cityofnewyork.us/Health/Heat-Vulnerability-Index-Rankings/4mhf-duep/about_data
- FVI: https://data.cityofnewyork.us/Environment/New-York-City-s-Flood-Vulnerability-Index/mrjc-v9pm/about_data
- Race map of NYC: https://bestneighborhood.org/race-in-new-york-ny/
- Primary Land Use Tax Lot Output (PLUTO, Single Building Resolution): https://data.cityofnewyork.us/City-Government/Primary-Land-Use-Tax-Lot-Output-PLUTO-/64uk-42ks/about_data
- Population over 60 census tract: https://data.census.gov/table/ACSST1Y2024.S0102?q=nyc+race

Shapefile for NYC median household income:
https://www.arcgis.com/home/item.html?id=42d3a15a6d294293855db01dcaf2a520

Dot Density for Race:
https://nyuds.maps.arcgis.com/apps/mapviewer/index.html?webmap=83b8925543994ffcaf4d2f95c93d10a5

NYC Trees (Single Tree Resolution):
https://tree-map.nycgovparks.org/tree-map/neighborhood/172

Land Cover Data (500 meter resolution):
https://modis.gsfc.nasa.gov/data/dataprod/mod12.php

Land Use Report Notes

Report Goals:

- Healthy, Livable Communities
  - Improve streetscape and open space to support active and safe living
    - Redesigning high-traffic intersections near public spaces by prioritizing safe, shaded, and accessible walking routes to transit, schools, and parks
    - Activate wide and underutilized sidewalks with tree plantings, benches, and community art
  - Increase access to health services through innovative community based models
    - Promote mobile health clinics and pop-up wellness events in partnership with local providers to reach underserved residents like seniors and youth
    - Encourage co-location of health services within new affordable housing or community centers to reduce barriers to access
  - Increase access to fresh and affordable food by reimagining underutilized land
    - Transform vacant lots and underused public spaces into hubs for healthy food access
    - Support permanent or seasonal greenmarkets and food cooperatives
    - Explore year-round structures or covered markets
  - Connect the community through improved transportation access and reliability
    - Expand the network of dedicated bus priority lanes along key corridors and improve pedestrian infrastructure connecting bus stops and subway stations
    - Explore wayfinding signage and lighting enhancements at transit hubs
  -

Objectives of report

The goals of the report are:

- Focus is on community and to make it healthy and more livable
- Plan to make underutilized spaces more livable
- The livable conditions are more of tree plantings, benches, and community art to create more welcoming and usable
- public space for all ages.
- 25% of the demographic is below 25yrs

Project Presentation

Problem Statement: How can we utilize Brownfield development sites in Soundview, Bronx to address heat vulnerability through green spaces?

Tools to use when building these sites

Summary/Inputs:

- Data we are using: EJNYC
    - Tree canopy cover
    - % impervious surface
    - % over 65
    - racial makeup
    - poverty rate
- Strategic Sites identified for redevelopment along banks of the Bronx River
- Current zoning

Methodology

- Arrange EJNYC and YMPJ data into excel / csv exportable file
- Model impact of greenscaping on heat / temperature data for Strategic Sites / EJNYC data

Gaps

- HVI data compared with the strategic sites

Outputs:

- Financial projection of the cost of solutions
- Stakeholders that would need to be convinced (ex land use owners, community board members)
- Maps of current heat and possible development project sites in context
- Projections of the effects of interventions like street trees and reflective surfaces
- An app that easily allows Reece and co. to understand the impact of different heat interventions at the strategic sites

Final Product Notes

Downscaling and Projecting Temperature

Overview:

We want to downscale the CMIP temperature data from its coarse resolution to the fine 30 meter NYC temperature resolution.

Input:

- CMIP SSP2-4.5

Nvidia temperature data from 3 kilometers to 30 meters within the confines of New York City. After we achieve an ML model that can do this downscaling, we will train a simple neural network to evolve the temperature forward by months or years in order to concretely get a difference in the air temperature with the intervention vs. after the intervention.

Workflow:

- Perform downscaling on the Nvidia dataset, going from 3 km to 30 meters via bilinear interpolation
- Learn a residual correction at 30 meters using the NYC air temperature
    - XGBoost/LightGBM
    - Small CNN/UNet
-

Workflow:

- We will implement a model similar to Nvidia's Earth 2 Model
    - Input data: 3 kilometer Nvidia OSN temperature data over NYC
        - Temperature
        - Latitude
        - Longitude
    - Output data: 30 meter temperature data over NYC
        - Temperature
        - Latitude
        - Longitude
    - Notes:
        - Will need to read the paper/Github
        - If this doesn't work, maybe we need to incorporate spatial data such as color band?
- We will now use a model to project what the temperature will be several years in advance
    - Input data: Current 30 meter NYC data

        - Temperature
        - Latitude
        - Longitude
    - Output data: Future 30 meter NYC data
        - Temperature
        - Latitude
        - Longitude
    - Notes:
        - Possible Models
            - Simple Neural Network
            - NeuralGCM
            - GoogleFGN
            - FourCastNet
            - PanguWeather
        - We will then subtract the average reduction in temperature for each of the interventions and then run that temperature plot forward in time
            - Trees
            - Reflective Surfaces
            - Community Garden

Questions:
- Did anything of note happen in Soundview between 2023 and 2025?
    - ChatGPT said no. Recreation center being built at Soundview Park and coastal habitat restoration and pedestrian pathway project at Bolton Point, but nothing created yet.
    - Maybe we can use the 2020 to 2022 data?
- Is the Nvidia dataset near-surface air temperature?
- What CMIP6 climate projections should I use?

Notes on Paper:
Overview:
- Two-step approach where a UNet predicts the mean and a corrector diffusion (CorrDiff) model predicts the residual
    - Shows good skill in bulk MAE and CRPS scores
    - Recover important power law relationships in the target data
- Case studies show that CorrDiff can help sharpen wind and temperature gradients
- Key contributions are
    - A physics-inspired, two-step approach (CorrDiff) to simultaneously learn mappings between low- and high-resolution weather data across multiple variables with high fidelity alongside new channel synthesis
    - For the case studies, CorrDiff adds physically realistic improvements to the representation of under-resolved coherent weather phenomena – frontal systems and typhoons
    - CorrDiff is sample-efficient, learning effectively from just 3 years of data

    - CorrDiff on a single GPU at least 22x faster and 1300x more energy efficient than the numerical model used to produce its high-resolution training data, which is run on 928 CPU cores

Introduction:

- Stochastic nature of atmospheric physics at km-scale makes downscaling a probabilistic task, making it natural to explore generative models at these scales
- GANs have been tested, but they pose practical challenges including mode collapse, training instabilities, and difficulties in capturing long tails of distributions
- Diffusion models offer training stability alongside demonstrable skill in probabilistically generating km-scales

Methods:

- Input is 12 x 36 x 36 (y)
- Output is 4 x 448 x 448 (x)
- Goal of probabilistic downscaling is to mimic p(x|y), which they learn using a diffusion model
    - Learns stochastic differential equations through the concept of score matching with a forward and backward processes working in tandem
    - In the forward pass, noise is gradually added to the target data until the signal becomes noise
    - The backward process then involves denoising the samples using a dedicated NN to eliminate the noise
        - The sequential denoising process iteratively refines the samples, bringing them closer to the target data distribution
- They hypothesize that the significant distribution shift between the input variables and challenging target variables necessitates high noise levels during the forward pass and numerous steps in the backward pass
- To sidestep this challenge, the first step predicts the conditional mean using UNet regression and the second step learns a correction using a diffusion model as follows:

$$\mathbf{x} = \underbrace{\mathbb{E}[\mathbf{x}|\mathbf{y}]}_{:=\boldsymbol{\mu}(\text{regression})} + \underbrace{(\mathbf{x} - \mathbb{E}[\mathbf{x}|\mathbf{y}])}_{:=\mathbf{r}(\text{generation})},$$

- The main idea of CorrDiff is that learning the p(r) distribution can be much easier than learning the distribution p(x)

Testing:

- The authors select a random set of 205 out-of-sample date and time combinations from 2021 for computing metrics and spectra and for intercomparing CorrDiff with the baseline models
- For CorrDiff ensemble predictions are examined using a 32-member ensemble, larger ensembles did not meaningfully modify key findings
- They compare CorrDiff to three baselines

- The first is a simple interpolation of ERA5
    - The second is a random forest model for each output variable (4 total)
    - The third is the UNet step of the CorrDiff
- The metrics they use to compare performance are
    - CRPS (probabilistic) for CorrDiff
    - MAE for UNet, RF, and ERA5 interpolation
- Power Spectrum is
    - $P(k) = |fhat(k)|^2$
    - So taking the Fourier transform, squaring the magnitude, and thus determining how much variance is at frequency k
- "Temperature downscaling is an easier task that is expected to be mostly driven by sub-grid variations in topography that can be learned deterministically from the static grid embeddings"

Discussion:

- CorrDiff consists of two steps, regression and generation
    - The regression step approximates the mean, while the generation step further corrects the mean but also generates the distribution, producing fine-scale details stochastically
    - Akin to the decomposition of physical variables into their mean and perturbations, common practice in fluid dynamics
- Can be improved with a larger training dataset that contains more diverse examples of rare coherent structures such as by pre-training on large libraries of typhoons generated by high-resolution physical simulators
- Another limitation is optimally calibrating CorrDiff's generated uncertainty to better match its error levels
    - Currently under-dispersed where the different ensemble members are too similar to each other, thus the model is too confident locally and still makes mistakes
    - Surprising because diffusion models are usually known to be over-dispersive by producing too much variance
- The authors propose three possible reasons:
    - Noise schedule in diffusion training. Diffusion models use a noise schedule or how much random noise is added at each step of training. Poorly chosen schedules result in reduced diversity in samples and making the model collapse toward similar solutions
    - The larger number of images (448 x 448) compared to typical image generation (64 x 64 or 256 x 256)
        - **Why would this result in lower variance?**
    - During training, CorrDiff balances multiple objectives and so the weighting in the loss function could result in this
    - **So figuring out why CorrDiff's uncertainty is not physically or statistically reliable at individual grid points is an open research problem!**
- Thoughts on the use of km-scale weather prediction:

    - Extensions of CorrDiff are encouraged to include temporal coherence (via video diffusion or learnt autoregressive km-scale dynamics) as with super-resolution, these must be formulated as stochastic ML tasks
    - There is no guarantee that CorrDiff's km-scale dynamics will be coherent in time
    - Additional integrations with km-scale data assimilation are also essential
- Proposed Extensions
    - Downscaling Coarse-Resolution Medium-Range Forecasts
    - Downscaling at Different Geographic Locations
    - Downscaling Future Climate Predictions
    - Synthesizing sub-km sensor observations

Methodology:
- They claim that the UNet-regression step can anticipate many of the physics of downscaling, some of which are deterministic
- "Stochastic phenomena such as convective storms that also change temperatures and winds are easier to model as deviations from the mean"
    - Cloud resolving models are explicitly formulated using deviations from a larger scale balanced state
- For the diffusion step, they use the Elucidated diffusion model or EDM, a continuous-time diffusion model that adheres to the principles of SDEs to design the diffusion process and architecture
    - It has an intuitive and physics-driven hyperparameter tuning, making it work across different domains
- Dataset contains:
    - 2-meter temperature
    - 10-meter wind vector
    - Total column water vapor
- The target data is provided in the NetCDF format, which is the output of the WRFDA assimilation process
    - A vertical interpolation from hybrid coordinates to pressure coordinates is applied
    - Separated into training and testing sets.
        - Three years from 2018 to 2020 are used for training
        - 2021 is used for testing
        - Some selected dates from 2022 and 2023 are used for case studies
- UNet Architecture
    - Increasing its size to include 6 encoder and 6 decoder layers
    - Base embedding size is 128 and is multiplied over channels according to the multipliers
    - Attention resolution is defined as 28
    - To represent timesteps in the diffusion process, they use the Fourier-based position embedding
    - In the regression network, the time embedding is disabled
- No data augmentation techniques are employed
- 80 million parameters

- They introduce 4 channels for sinusoidal positional embedding to improve spatial consistency
- Hyperparameters:
  - Adam optimizer with LR of 0.0002, b1 = 0.9 and b2 = 0.99
  - Exponential moving averages with a rate of n = 0.5 are applied
  - Dropout = 0.12

Google Earth Engine Javascript

```
// --------------------- NYC geometry ---------------------
var nyc_bounds = ee.Geometry.Polygon(
  [[[-74.28, 40.95],
    [-74.28, 40.47],
    [-73.65, 40.47],
    [-73.65, 40.95]]]
);

var nyc = ee.FeatureCollection('FAO/GAUL/2015/level2')
  .filter('ADM1_NAME == "New York"')
  .filter(ee.Filter.inList('ADM2_NAME', ['Kings', 'Richmond', 'New York', 'Queens', 'Bronx']))
  .geometry();

// --------------------- Mask function ---------------------
function prepL9(img) {
  var qaMask = img.select('QA_PIXEL')
    .bitwiseAnd(parseInt('11111', 2)).eq(0);
  var saturationMask = img.select('QA_RADSAT').eq(0);

  // Attach date string so we can group by day
  var dateStr = ee.Date(img.get('system:time_start')).format('YYYY-MM-dd');

  return img.updateMask(qaMask)
          .updateMask(saturationMask)
          .set('date', dateStr);
}

// --------------------- Choose ONE YEAR to export ---------------------
var year = 2000;
var startDate = ee.Date.fromYMD(year, 6, 1);
var endDate   = ee.Date.fromYMD(year, 9, 1);

// --------------------- Landsat 9 collection ---------------------
var l9 = ee.ImageCollection('LANDSAT/LC09/C02/T1_L2')
  .filterDate(startDate, endDate.advance(1, 'day'))
  .filterBounds(nyc)
  .map(prepL9);

// Keep only the band we care about early (reduces overhead)
l9 = l9.select(['ST_B10', 'QA_PIXEL', 'QA_RADSAT']); // QA bands kept for masking

print('L9 images in year:', l9.size());

// --------------------- Get distinct dates that actually exist ---------------------
```

```
var dates = ee.List(l9.aggregate_array('date')).distinct().sort();
print('Days with >=1 scene:', dates.length());

// ---------------------- Export controls ----------------------
// Start small to test, then increase.
var N_EXPORTS = 20;  // try 20 first, then 100, etc.

// Drive folder (TOP-LEVEL only)
var DRIVE_FOLDER = 'GEE_L9_LST_DAILY_' + year;

// ---------------------- Export loop (client-side) ----------------------
dates.slice(0, N_EXPORTS).evaluate(function(dateList) {
  dateList.forEach(function(dateStr) {
    // Make YYYYMMDD for filenames
    var yyyymmdd = dateStr.replace(/-/g, '');

    // Filter to this day’s images
    var dayImgs = l9.filter(ee.Filter.eq('date', dateStr)).select('ST_B10');

    // Mean + median for the day (per pixel)
    var meanImg = dayImgs.mean().rename('ST_B10_mean');
    var medImg  = dayImgs.median().rename('ST_B10_median');

    // Two-band output
    var out = meanImg.addBands(medImg);

    Export.image.toDrive({
      image: out,
      description: 'L9_STB10_daily_mean_median_' + yyyymmdd,
      folder: DRIVE_FOLDER,
      fileNamePrefix: 'L9_STB10_daily_mean_median_' + dateStr,
      region: nyc_bounds,
      scale: 30,
      fileFormat: 'GeoTIFF',
      maxPixels: 1e13
    });
  });
});
```

Intervention Strategies

We built a statistical model that predicts the average summer temperature on a hypothetical city block, based on the neighborhood factors we studied in the hyperlocal temperature study https://a816-dohbesp.nyc.gov/IndicatorPublic/data-stories/urban-heat-island/

US Green Building Council Reports, any kind of reporting Local All 97, American Planning Association

Surface to Air Temp Diff

- "On a hot, sunny summer day, the sun can heat dry, exposed **urban surfaces, such as roofs and pavement, to temperatures 50–90°F (27–50°C) hotter than the air**" Note here that roof ST are often significantly hotter than LSTs (land surface temperatures), GEE uses LST, rec use lower end
- https://19january2017snapshot.epa.gov/heat-islands/learn-about-heat-islands_.html
- The **relationship between LST and air temperature is much "looser" in the summer**. In unshaded **urban areas, surface temperatures were consistently higher than air temperatures, whereas shaded areas and grassy surfaces stayed much closer to the ambient air temperature**.
- https://ieeexplore.ieee.org/document/10642233
- **GUHIs (ground urban heat island) are warmer [than SUHIs (surface urban heat island)]** and show complex spatial contrasts with surface urban heat islands
- https://pmc.ncbi.nlm.nih.gov/articles/PMC11266779/
- Air Temp at central park (avg 74.7C) https://weatherspark.com/y/147190/Average-Weather-at-New-York-City-Central-Park;-New-York;-United-States-Year-Round
- Average GEE AugJul2025 Temp: 41.05230255 C (105.8941446 F)
- Average CESM AugJul2025 Temp: 24.09393 C (75.369074 F)
- Temp Increase CESM (Air Temp) to GEE (Land Surface Temp): 18.99637058 C (34.19346704 F)

Tree Canopy

- We find that tree canopy cover is the dominant cooling factor, explaining 67% of the spatial variation in Ta. Notably, a 10% increase in tree canopy reduces air temperature by 0.8 °C, while a **30% increase lowers it by as much as 1.5 °C**.
- https://tore.tuhh.de/entities/publication/c60e50c4-4902-446b-a033-9ee10a1cfe28
- NYC Street Design Manual https://www.urbanforestplan.nyc/#:~:text=PlaNYC%3A%20Getting%20Sustainability%20Done%2C%20New,years%20based%20on%20public%20input.
    - **Minimum 30% tree canopy cover goal for NYC**

Impervious Space

- **Air temperature increased linearly with increasing impervious cover** (Fig. 2). Effects were again larger when considering the surrounding landscape context at broader scales; increasing impervious cover from 0% to 100% within a 10-m radius corresponded to a mean increase of 0.5 °C (Fig. 2E) compared with 0.7 °C, 1.0 °C, and 1.3 °C when considering a surrounding area of radius of 30, 60, and 90 m, respectively

- https://www.pnas.org/doi/10.1073/pnas.1817561116#sec-1 (Fig 2, Row 2)
- An effective cooling of **0.4°F with 10% increase in canopy and 10% decrease in impervious cover** was determined applicable to use.
- https://cms5.revize.com/revize/chelseama/Document_Center/Departments/Housing%20&%20Community%20Development/Environment%20and%20Climate%20Resilience/volume_i_-_mill_creek_water_quality_improvement_project.pdf
- NYC Stormwater Manual (2022) pg 116 https://www.nyc.gov/assets/dep/downloads/pdf/water/stormwater/unified-stormwater-rule/uswr_nyc_stormwater_manual.pdf
    - **Minimum 25% reduction in imperviousness for redevelopment projects**

Reflective Roofs:

- if every roof in large cities around the world were painted white, raising their reflectivity — known to climate scientists as albedo — from a typical 32 percent today to 90 percent. He found that it would decrease the urban heat island effect by a third — enough to **reduce the maximum daytime temperatures by an average of 0.6 degrees C**, and more in hot sunny regions such as the Arabian Peninsula and Brazil.
- https://e360.yale.edu/features/urban-heat-can-white-roofs-help-cool-the-worlds-warming-cities
- In general, we find that **cool roofs are the more effective interventions to reduce the heat in the GLA boundaries with a 2-day average cooling of ~1.2°C** going up to ~2.0°C in certain locations
- https://discovery.ucl.ac.uk/id/eprint/10195643/1/Geophysical%20Research%20Letters%20-%202024%20-%20Brousse%20-%20Cool%20Roofs%20Could%20Be%20Most%20Effective%20at%20Reducing%20Outdoor%20Urban%20Temperatures.pdf
- They found that the three types of roofs reduced the near-surface temperature and AC consumption demand during daytime hours when air temperature is the highest. **Cool roofs reduced the near-surface temperature by 1.5 degrees Celsius**, followed by 1.2 degrees for green roofs and 0.6 degrees for solar panel roofs across the Chicago area.
- https://www.anl.gov/article/can-a-roofs-material-cool-the-outside-air-and-lower-energy-demand
- **NYC Local Law 92 and 94 (2019)** https://brooklynsolarworks.com/blog/nyc-local-law-92-and-94/
    - Any portion of the roof not covered by solar panels or a green (vegetated) roof must be a cool roof (highly reflective)

Green Roofs:

- They found that the three types of roofs reduced the near-surface temperature and AC consumption demand during daytime hours when air temperature is the highest. Cool roofs **reduced the near-surface temperature** by 1.5 degrees Celsius, **followed by 1.2 degrees for green roofs** and 0.6 degrees for solar panel roofs across the Chicago area.

- https://www.anl.gov/article/can-a-roofs-material-cool-the-outside-air-and-lower-energy-demand
- “As it concerns green roofs, existing simulation studies show that when applied on a city scale, they may reduce the average ambient temperature between 0.3 and 3 K.” (average 1.65)
- https://www.nyc.gov/html/ddc/downloads/pdf/cool_green_roof_man.pdf
- **NYC Local Law 92 and 94 (2019)** https://brooklynsolarworks.com/blog/nyc-local-law-92-and-94/
    - Any portion of the roof not covered by solar panels or a green (vegetated) roof must be a cool roof (highly reflective)

Green walls
- **Table 2** features median values for **temp decrease found in 11 different studies** (**averaged to 2.19C**) note this includes Csa study previously listed here: https://www.sciencedirect.com/science/article/pii/S1364032122000302
- **No definitive regulations/requirements yet** (sometimes used as bonus points to earn environmental certifications such as LEED)

Community Gardens:
- **Table 3** features air temperature values during the day on sunny and cloudy days in summer for Lawn, WT, and WM types (**6 values total, temp decrease averaged to 1.62C**)
- https://www.sciencedirect.com/science/article/pii/S0169204621000098?via%3Dihub
- **No definitive regulations/requirements yet for Public Spaces,** for Private Spaces some regulations exist (relevance?)

Strategic Site 1 Recommended Interventions
- Plans to use it for transit oriented affordable housing and rezone
- Green roofs, green walls, reflective roofs

Site 2.1
- Waterfront activation and community infrastructure
- Green roofs, green walls, reflective roofs

Site 2.2
- Waterfront activation and community infrastructure
- Green roofs, green walls, reflective roofs

Site 3
- Economic hub
- Green roofs, green walls, reflective roofs

Assumptions about density of tree canopy but need to be clear about the assumptions we are making in the calculations to reduce surface temperature?

- Tree density comparisons

Presentation Notes

Parameters

- Articulation of problem statement
    - How this grew from talking to community leaders/community prompts
- Innovative problem solving
    - How did we use data analysis and cs?
    - **Highlight our datasets**
- Integration of disciplines
    - Different knowledge areas within group
- Potential for future development
    - How could this be expanded on
    - “We got this far, but this is where it could go”
- Quality of presentation
    - Understandable

Data Transformation Notes

Columns:

- **CESM_[Model]_Avg_Temp_2025_K** = The projection for 2025
- **CESM_[Model]_Avg_Temp_2030_K** = The projection for 2030
- **CESM_[Model]_Avg_Temp_2035_K** = The projection for 2035

- **CESM_[Model]_Avg_Temp_2025_C** = CESM_Avg_Temp_2025_K - 273.15
- **CESM_[Model]_Avg_Temp_2030_C** = CESM_Avg_Temp_2030_K - 273.15
- **CESM_[Model]_Avg_Temp_2035_C** = CESM_Avg_Temp_2035_K - 273.15

- **CESM_[Model]_Avg_Temp_2025_2030_C** = **CESM_[Model]_Avg_Temp_2030_C - CESM_[Model]_Avg_Temp_2025_C**
- **CESM_[Model]_Avg_Temp_2025_2035_C** = **CESM_[Model]_Avg_Temp_2035_C - CESM_[Model]_Avg_Temp_2025_C**

- **CESM_[Model]_Projected_Temp_2030_C** = **CESM_[Model]_Avg_Temp_2025_C + CESM_[Model]_Avg_Temp_2025_2030_C**
- **CESM_[Model]_Projected_Temp_2035_C** = **CESM_[Model]_Avg_Temp_2025_C + CESM_[Model]_Avg_Temp_2025_2035_C**

- **CESM_[Model]_2030_25_Perc_Concrete_C = CESM_[Model]_Projected_Temp_2030_C** - 0.365
- **CESM_[Model]_2035_25_Perc_Concrete_C = CESM_[Model]_Projected_Temp_2035_C** - 0.365

- **CESM_[Model]_2030_30_Perc_Canopy_C = CESM_[Model]_Projected_Temp_2030_C** - 1.5
- **CESM_[Model]_2035_30_Perc_Canopy_C = CESM_[Model]_Projected_Temp_2035_C** - 1.5

- **CESM_[Model]_2030_Ref_Roof_C = CESM_[Model]_Projected_Temp_2030_C** - 1.65
- **CESM_[Model]_2035_Ref_Roof_C = CESM_[Model]_Projected_Temp_2035_C** - 1.65

- **CESM_[Model]_2030_Green_Roof_C = CESM_[Model]_Projected_Temp_2030_C** - 1.425
- **CESM_[Model]_2035_Green_Roof_C = CESM_[Model]_Projected_Temp_2035_C** - 1.425

- **CESM_[Model]_2030_Green_Walls_C = CESM_[Model]_Projected_Temp_2030_C** - 2.19

- **CESM_[Model]_2035_Green_Walls_C = CESM_[Model]_Projected_Temp_2035_C** - 2.19

- **CESM_[Model]_2030_Comm_Garden_C = CESM_[Model]_Projected_Temp_2030_C** - 1.62
- **CESM_[Model]_2035_Comm_Garden_C = CESM_[Model]_Projected_Temp_2035_C** - 1.62