

For this assignment, you will chose to run one of the OTHER InVEST models that we haven't yet run in class. You can use the InVEST sample data as your input. You will turn in a PDF/WordDoc that documents:

1. What model you ran and the general concept of why this ecosystem service is valuable to humans?

Ans: I ran the Urban InVest Cooling model which is a process-based model using causal relationships from previous studies to model ecosystem service valuation of urban cooling.

Urban heat island (UHI) effect, i.e. increase in temperature in urban environment as compared to surrounding environment, has major health and well-being consequences on rising urban population. Vegetation (ecosystem) plays a vital role in reducing UHI by evapotranspiration, providing shade and albedo. Such effects have been proven to reduce mortality, increase productivity and reduce the use of A/C. Ecosystem infrastructure thus play a vital role in reducing the health and economic impacts of UHI. Quantification and valuation of these cooling effects can prove out to be vital in planning urban development and formulating polices. Urban InVest Cooling model provides critical input for this by estimating the cooling effect of vegetation based on readily available datasets.

2. A brief description of the key calculations to be done:

Ans: Urban InVest Cooling model calculates a heat mitigation index based on the above mentioned three mechanism of cooling which is used to estimate temperature reduction by vegetation. A brief description of the key calculation that undergoes during this is mentioned below:

- a) Cooling Capacity index (CC): Based on local shade, evapotranspiration (ETI) and albedo the model first calculates the CC index for each pixel (i).

$$CC_i = 0.6 * \text{shade} + 0.2 * \text{albedo} + 0.2 * \text{ETI},$$

where (0.6, 0.2, 0.2) is recommended weights by the user index.

Alternatively, given that we have building intensity factor for each land use class we can calculate CC based on following equation:

$$CC_i = 1 - \text{building_intensity}$$

- b) Urban Heat Mitigation (UHM) index: HM index accounts the cooling effect of large green spaces (> 2 ha), which is equal to CC index if the individual pixels are unaffected by large green spaces but otherwise are equal to distance-weighted average of CC values.

To do this, the model first computes two metrics: area of green space around each pixel (GA_i), and CC provided by each park (CC_{parki}). Based on this HM is estimated as:

$$HM_i = \begin{cases} CC_i & \text{if } CC_i \geq CC_{parki}, \text{ or } GA_i < 2ha \\ CC_{parki} & \text{otherwise} \end{cases}$$

- c) Air temperature estimates: For each area of interest, the model also calculates average temperature and temperature anomaly.
- d) Valuation of heat reduction: The monetary valuation of heat reduction services is provided as estimates of energy savings from reduced A/C use, and work productivity increase for outside workers.

3. A briefer description of each data input

- a) Land use/land cover – which is simply the LULC map for area of interest.
- b) Evapotranspiration - which is map of ETI values.
- c) Biophysical table - a table that has biophysical data for each LULC class. The table has following parameters of interest are: lucode, kc (crop coefficient for LULC class), green_area (dummy to indicate green area), shade (proportion of area covered by at least 2m high tree canopy), albedo (proportion of reflected solar radiation), and bilding_intensity (ration of building floor area to footprint area).
- d) Reference Air temperature (°C) – area temperature in rural reference area.
- e) UHI effect (°C)- magnitude of urban heat island effect.
- f) Air bending distance (m) – radius over which air temperature is averaged to account for air mixing.
- g) Maximum cooling distance (m)- distance over which green areas larger than 2 ha have cooling effect.
- h) Cooling capacity calculation method – air temperature predictor method to use.

4. Image(s) of your result. Refer to the InVEST users' guide to see which output layers are actually the interesting outputs and how you should interpret them.

Ans: Three output layers are derived from running the model:

- a) hm_tif: which gives us the calculated heat mitigation index (HMI). Using QGIS, we can look at the HMI for each pixel or sum them up using gdal in python. The values range from 0 to 1, with higher index in green areas which shows more cooling effect in area of vegetation.
- b) uhi_results.shp
- c) building_with__stats

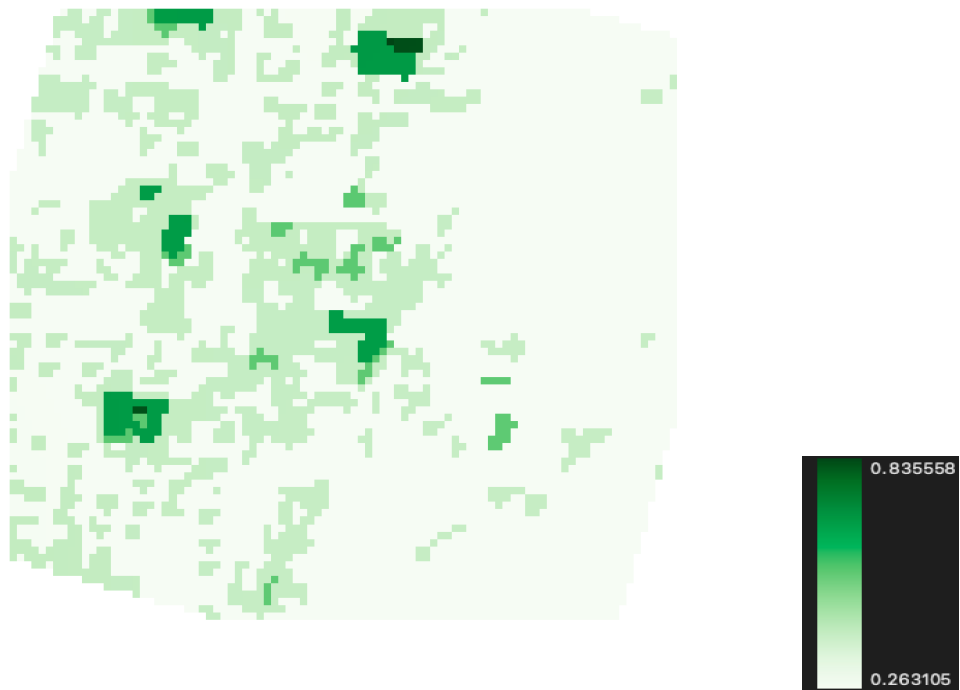


Fig 1: Calculated HMI for sample data (with bands)

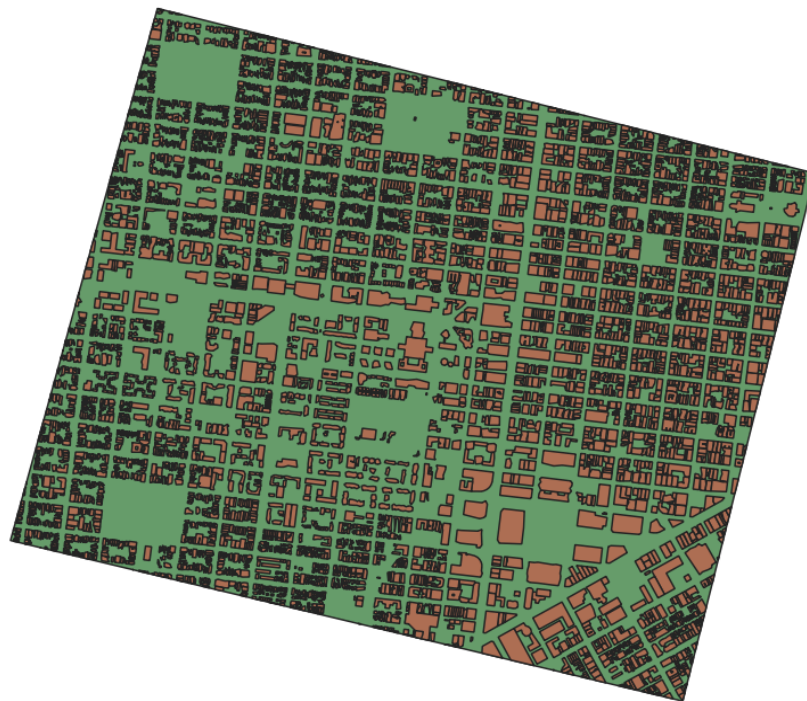


Fig 1: building footprints plotted over area of interest.

5. A sensitivity analysis of at least 1 variable (of your choosing) where you will iteratively run in Python (include your script as an appendix) InVEST for at least 10 values of the variable. Create a graph of how the output(s) for your ES change over the range of parameters.

Ans: For this question, I choose sensitivity analysis of altering the shade value for cultivated area (lulc code 6) in the biophysical table input. The input for shade parameter lies between 0 to 1, so I choose to have 10 increments starting from 0 to 0.9. The plotted graph depicts the relationship between change in HMI (output) over the range of lulc code 6 (shade from cultivated land).

The script is attached at the end as an appendix.

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Model: Urban Cooling

```
import logging
import sys

import natcap.invest.urban_cooling_model
import natcap.invest.utils

from osgeo import gdal
import numpy as np
import os, random
import matplotlib.pyplot as plt

def load_array(input_raster_path):
    """Load a raster into a numpy array"""
    raster = gdal.Open(input_raster_path)
    band = raster.GetRasterBand(1)
    array = band.ReadAsArray()
    return array

LOGGER = logging.getLogger(__name__)
root_logger = logging.getLogger()

handler = logging.StreamHandler(sys.stdout)
formatter = logging.Formatter(
```

```

    fmt=natcap.invest.utils.LOG_FMT,
    datefmt='%m/%d/%Y %H:%M:%S ')
handler.setFormatter(formatter)
logging.basicConfig(level=logging.INFO, handlers=[handler])

args = {
    'aoi_vector_path': '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/aoi_vector.shp',
    'avg_rel_humidity': '80',
    'biophysical_table_path': '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/biophysical_table.csv',
    'building_vector_path': '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/building_vector.shp',
    'cc_method': 'factors',
    'cc_weight_albedo': '0.2',
    'cc_weight_eti': '0.6',
    'cc_weight_shade': '0.2',
    'do_energy_valuation': True,
    'do_productivity_valuation': True,
    'energy_consumption_table_path': '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/energy_consumption_table.csv',
    'green_area_cooling_distance': '450',
    'lulc_raster_path': '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/lulc_raster.tif',
    'ref_eto_raster_path': '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/ref_eto_raster.tif',
    'results_suffix': '',
    't_air_average_radius': '500',
    't_ref': '30',
    'uhi_max': '3.5',
    'workspace_dir': '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData'
}

#for sensitivity analysis, I change the shade value of lulc code 6 (cultivated land)
#10 times (from 0 to 1) at an increment of 0.1 which are represented in the
#10 different biophysical csv files

if __name__ == '__main__':
    list_of_csv_path = [
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/0.0.csv',
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/0.1.csv',
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/0.2.csv',
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/0.3.csv',
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/0.4.csv',
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/0.5.csv',
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/0.6.csv',
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/0.7.csv',
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/0.8.csv',
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/0.9.csv',
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/BiophysicalData/1.0.csv'
    ]

```

```

'/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/Biophysical
'/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/Biophysical
hm = []

for path in list_of_csv_path:
    args["biophysical_table_path"] = path
    natcap.invest.urban_cooling_model.execute(args)
    hm_path = os.path.join(
        '/Users/prayashpathak/Files/base_data/invest_sample_data/UrbanCoolingModel/output'
    )
    hm_array = load_array(hm_path)
    hm_sum= np.sum(hm_array)
    hm.append(hm_sum)

#plotting the graph
lucode_6_values = np.linspace(0, 1, 10)
plt.plot(lucode_6_values, hm, marker='o')
plt.xlabel('Shade')
plt.ylabel('Heat Mitigation Index')
plt.title('Sensitivity Analysis')
plt.show()

```