greenspace_portfolio

February 3, 2026

1 Set-Up

1.0.1 This code is a workflow expanding on previous work with Chicago census tracts and NDVI data. I am focussed on implementing income data and evaluating/refining the performance of the model.

[1]:
```
### Import libraries

import pathlib                  # file paths
import os                       # file paths
import warnings                 # warnings

import pandas as pd             # dataframes
import geopandas as gpd         # geodataframes
import numpy as np              # arrays
import xarray as xr             # multi-dimensional arrays
import rioxarray as rxr         # rasters + xarray
import rioxarray.merge as rxrm  # raster merging
import shapely                  # geometric operations
import time                     # time operations

import geoviews as gv           # geospatial visualizations
import holoviews as hv          # interactive visualizations
import hvplot.pandas            # pandas visualizations
import hvplot.xarray            # xarray visualizations
from cartopy import crs as ccrs # coordinate reference systems

import matplotlib               # plotting
import matplotlib.pyplot as plt # plotting
import scipy.stats as stats     # statistical analysis

import pystac_client            # STAC catalog access
from sodapy import Socrata      # Socrata Open Data API
import requests                 # JSON Census API requests

from tqdm.notebook import tqdm      # progress bars
from scipy.ndimage import convolve  # image processing
from scipy.ndimage import label     # image processing
```

```
from bokeh.models import NumeralTickFormatter  # plot formatting

from sklearn.linear_model import LinearRegression          # linear regression␣
 ↪model
from sklearn.model_selection import train_test_split       # train-test split
from sklearn.model_selection import KFold                  # k-fold␣
 ↪cross-validation
from sklearn.metrics import mean_squared_error, r2_score    # model evaluation␣
 ↪metrics
```

[2]:
```
### Create reproducible file paths
dir = os.path.join(
    pathlib.Path.home(),

    'Data',
    'Earth Analytics',
    'greenspace-portfolio'

)

os.makedirs(dir, exist_ok=True)
```

[3]:
```
### Prevent GDAL from quitting due to momentary disruptions
os.environ["GDAL_HTTP_MAX_RETRY"] = "5"
os.environ["GDAL_HTTP_RETRY_DELAY"] = "1"
```

[4]:
```
### Set up the census tract path

tract_dir = os.path.join(dir, 'chicago-tract')
os.makedirs(tract_dir, exist_ok=True)
tract_path = os.path.join(tract_dir, 'chicago-tracts.shp')

### Download the census tracts (only once)
if not os.path.exists(tract_path):
    tract_url = ('https://data.cdc.gov/download/x7zy-2xmx/application%2Fzip')

    tract_gdf = gpd.read_file(tract_url)

    chi_tract_gdf = tract_gdf[tract_gdf.PlaceName == 'Chicago']

    chi_tract_gdf.to_file(tract_path, index = False)

### Load in census tract data

chi_tract_gdf = gpd.read_file(tract_path)
chi_tract_gdf
```

```
### Site plot -- Census tracts with satellite imagery in the background
(
    chi_tract_gdf

    .to_crs(ccrs.Mercator())

    .hvplot(
        line_color = 'blue', fill_color = None,
        crs = ccrs.Mercator(), tiles = 'EsriImagery',
        frame_width = 600,
        title = 'Chicago Census Tracts'
    )
)
```

[4]:
```
:Overlay
   .WMTS.I     :WMTS   [Longitude,Latitude]
   .Polygons.I :Polygons   [Longitude,Latitude]
```

[5]:
```
chi_tract_gdf
```

[5]:
```
     place2010    tract2010  ST PlaceName          plctract10  PlcTrPop10  \
0      1714000  17031010100  17   Chicago  1714000-17031010100        4854
1      1714000  17031010201  17   Chicago  1714000-17031010201        6450
2      1714000  17031010202  17   Chicago  1714000-17031010202        2818
3      1714000  17031010300  17   Chicago  1714000-17031010300        6236
4      1714000  17031010400  17   Chicago  1714000-17031010400        5042
..         …          …  ..       …                  …          …
804    1714000  17031835700  17   Chicago  1714000-17031835700           0
805    1714000  17031980000  17   Chicago  1714000-17031980000           0
806    1714000  17031980100  17   Chicago  1714000-17031980100           0
807    1714000  17043840000  17   Chicago  1714000-17043840000           0
808    1714000  17043840801  17   Chicago  1714000-17043840801           0

                                              geometry
0     POLYGON ((-9758835.381 5164429.383, -9758837.3…
1     POLYGON ((-9760143.496 5163888.741, -9760143.4…
2     POLYGON ((-9759754.212 5163883.196, -9759726.6…
3     POLYGON ((-9758695.229 5163870.91, -9758695.78…
4     POLYGON ((-9757724.634 5160715.939, -9757742.2…
..                                                 …
804   POLYGON ((-9754496.811 5132719.307, -9754491.8…
805   POLYGON ((-9788665.342 5161808.277, -9788667.6…
806   POLYGON ((-9766922.964 5128945.613, -9766938.5…
807   POLYGON ((-9787210.28 5154713.902, -9787240.67…
808   POLYGON ((-9787431.695 5154736.805, -9787441.0…

[809 rows x 7 columns]
```

[6]:
```python
### Set up a path for the asthma data
cdc_path = os.path.join(dir, 'asthma.csv')

### Download asthma data (only once)
if not os.path.exists(cdc_path):
    cdc_url = (
        'https://data.cdc.gov/resource/cwsq-ngmh.csv'
        "?year=2023"
        "&stateabbr=IL"
        "&countyname=Cook"
        "&measureid=CASTHMA"
        "&$limit=1500"
    )

    cdc_df = (
        pd.read_csv(cdc_url)

        .rename(columns = {
            'data_value': 'asthma',
            'low_confidence_limit': 'asthma_ci_low',
            'high_confidence_limit': 'asthma_ci_high',
            'locationname': 'tract'})

        [[
            'year','tract', 'asthma',
            'asthma_ci_low', 'asthma_ci_high', 'data_value_unit',
            'totalpopulation', 'totalpop18plus',
        ]]
    )

    cdc_df.to_csv(cdc_path, index = False)

### Load in asthma data
cdc_df = pd.read_csv(cdc_path)

### Preview asthma data
cdc_df
```

[6]:
```
      year        tract  asthma  asthma_ci_low  asthma_ci_high  \
0     2023  17031071700     9.1            8.1            10.1
1     2023  17031120300     8.8            7.8             9.8
2     2023  17031010501     9.9            8.9            11.0
3     2023  17031031000     8.9            7.9             9.9
4     2023  17031062400     9.2            8.2            10.3
…      …            …       …              …               …
1323  2023  17031840400     7.9            7.1             8.8
1324  2023  17031837300    13.7           12.3            15.0
```

```
1325  2023  17031840000     8.4            7.5             9.3
1326  2023  17031840700     8.3            7.3             9.2
1327  2023  17031838700    14.9           13.3            16.6

     data_value_unit  totalpopulation  totalpop18plus
0                  %             1660            1325
1                  %             6920            5212
2                  %             4206            3762
3                  %             3868            3439
4                  %             1673            1389
…                  …                …               …
1323               %             3369            2662
1324               %             2489            1835
1325               %             3001            2428
1326               %             3900            2885
1327               %             4132            2874

[1328 rows x 8 columns]
```

From what I can tell, it appears int64 and similar numerics will drop leading zeroes. Not an issue here, but something I wanted to try to avoid. I also found it much easier to convert the column types outside of the if statements downloading the data.

[7]:
```python
# Change tract identifier datatype for merging
cdc_df["tract"] = cdc_df["tract"].astype(str)
chi_tract_gdf["tract2010"] = chi_tract_gdf["tract2010"].astype(str)

# Merge census data with geometry
tract_cdc_gdf = (
    chi_tract_gdf.merge(
        cdc_df,
        left_on = 'tract2010',
        right_on = 'tract',
        how = 'inner'           # Only keep tracts with asthma data
    )
    [['tract2010', 'asthma', 'asthma_ci_low', 'asthma_ci_high', 'geometry',]]
)

tract_cdc_gdf
```

[7]:
```
       tract2010  asthma  asthma_ci_low  asthma_ci_high  \
0    17031010100    11.3           10.1            12.5
1    17031010201    11.2           10.0            12.4
2    17031010202    10.2            9.1            11.3
3    17031010300    10.2            9.1            11.3
4    17031010400    10.6            9.5            11.7
..           …       …              …               …
783  17031770700     9.7            8.6            10.8
```

```
784  17031770800     9.5            8.4            10.6
785  17031805600     9.1            8.1            10.1
786  17031807900     8.5            7.5             9.4
787  17031808100     9.2            8.1            10.3

                                              geometry
0    POLYGON ((-9758835.381 5164429.383, -9758837.3…
1    POLYGON ((-9760143.496 5163888.741, -9760143.4…
2    POLYGON ((-9759754.212 5163883.196, -9759726.6…
3    POLYGON ((-9758695.229 5163870.91, -9758695.78…
4    POLYGON ((-9757724.634 5160715.939, -9757742.2…
..                                                 …
783  POLYGON ((-9780753.304 5157066.079, -9780752.0…
784  POLYGON ((-9783235.84 5154620.343, -9783211.23…
785  POLYGON ((-9776210.02 5161605.738, -9776213.47…
786  POLYGON ((-9768609.902 5160576.634, -9768654.5…
787  MULTIPOLYGON (((-9774480.671 5161127.722, -977…

[788 rows x 5 columns]
```

[8]:
```python
### Plot asthma data as chloropleth
asthma_plot = (
    gv.tile_sources.EsriImagery
    *
    gv.Polygons(
        tract_cdc_gdf.to_crs(ccrs.Mercator()),
        vdims = ['asthma', 'tract2010'],
        crs = ccrs.Mercator()

    ).opts(color = 'asthma', colorbar = True, tools = ['hover'])
).opts(width = 600, height = 600, xaxis = None, yaxis = None)

asthma_plot
```

[8]:
```
:Overlay
   .WMTS.I     :WMTS    [Longitude,Latitude]
   .Polygons.I :Polygons    [Longitude,Latitude]   (asthma,tract2010)
```

1.1 Access income data and add to the GDF

[9]:
```python
# Census API Key
income_API_key = '87f7d00c90e94cc038e9714efd302a96d6d49803'

# Set up a path for the income data
income_path = os.path.join(dir, 'income.csv')

# Download income data (only once)
```

```python
if not os.path.exists(income_path):
    income_url = "https://api.census.gov/data/2023/acs/acs5" # Income only␣
 ↪tracked on ACS 5-Year Census data
    parameters = {
        "get": "B19013_001E,B19301_001E", # 'get' median household income and␣
 ↪per-capita income respectively
        "for": "tract:*",                  # one row per census tract
        "in": "state:17 county:031",        # 'in' Cook County, Illinois
        "key": income_API_key
    }

    # Make the API request
    response = requests.get(income_url, params = parameters)
    income_data = response.json()

    # Convert to DF
    income_df = pd.DataFrame(
        income_data[1:],
        columns = income_data[0]
    )

    # # Progress check
    # print(income_df.head())

    income_df = income_df.rename(columns={
    "B19013_001E": "median_household_income",
    "B19301_001E": "per_capita_income"
    })

    # Convert income columns to numeric
    income_df["median_household_income"] = pd.to_numeric(
    income_df["median_household_income"], errors="coerce")

    income_df["per_capita_income"] = pd.to_numeric(
    income_df["per_capita_income"], errors="coerce")

    # Create tractID column for merging
    income_df["tractID"] = income_df["state"] + income_df["county"] +␣
 ↪income_df["tract"]

    # # Progress check
    # print(income_df.head())

# Save to CSV
else:
    income_df = pd.read_csv(income_path)
```

```
income_df
```

[9]:
```
      median_household_income  per_capita_income  state  county   tract  \
0                       69460              45353     17      31   10100
1                       49639              31978     17      31   10201
2                       55119              33488     17      31   10202
3                       65871              42487     17      31   10300
4                       49017              33185     17      31   10400
…                         …                  …    …       …     …
1327                    56848              29766     17      31  844600
1328                    69583              27809     17      31  844700
1329               -666666666         -666666666     17      31  980000
1330               -666666666         -666666666     17      31  980100
1331               -666666666         -666666666     17      31  990000

          tractID
0     17031010100
1     17031010201
2     17031010202
3     17031010300
4     17031010400
…             …
1327  17031844600
1328  17031844700
1329  17031980000
1330  17031980100
1331  17031990000

[1332 rows x 6 columns]
```

[10]:
```
# Change tract identifier datatype for merging
income_df["tractID"] = income_df["tractID"].astype(str)


# Combine income data with existing tract + asthma data
inc_tract_df = (
    income_df.merge(
        tract_cdc_gdf,
        left_on = "tractID",
        right_on = "tract2010",
        how = "inner"  # Only keep tracts with full data
    )
    [['tractID', 'asthma', 'asthma_ci_low', 'asthma_ci_high',␣
 ↪'median_household_income', 'per_capita_income', 'geometry',]]

)
```

```
inc_tract_df
```

[10]:

```
        tractID  asthma  asthma_ci_low  asthma_ci_high  \
0    17031010100    11.3           10.1            12.5
1    17031010201    11.2           10.0            12.4
2    17031010202    10.2            9.1            11.3
3    17031010300    10.2            9.1            11.3
4    17031010400    10.6            9.5            11.7
..           …      …            …             …
783  17031843500     9.5            8.3            10.7
784  17031843600    12.5           11.2            14.0
785  17031843700     8.9            7.9             9.9
786  17031843800    10.9            9.7            12.0
787  17031843900    13.1           11.7            14.7

     median_household_income  per_capita_income  \
0                      69460              45353
1                      49639              31978
2                      55119              33488
3                      65871              42487
4                      49017              33185
..                       …                …
783                    55833               3546
784                    71359              38837
785                   134000             101400
786                    57885              27767
787                    47760              34298

                                              geometry
0    POLYGON ((-9758835.381 5164429.383, -9758837.3…
1    POLYGON ((-9760143.496 5163888.741, -9760143.4…
2    POLYGON ((-9759754.212 5163883.196, -9759726.6…
3    POLYGON ((-9758695.229 5163870.91, -9758695.78…
4    POLYGON ((-9757724.634 5160715.939, -9757742.2…
..                                                 …
783  POLYGON ((-9761322.813 5136241.389, -9761337.5…
784  POLYGON ((-9752318.844 5132492.145, -9752318.2…
785  POLYGON ((-9761412.872 5153004.52, -9761411.75…
786  POLYGON ((-9755524.513 5130243.96, -9755529.18…
787  POLYGON ((-9748410.585 5128192.165, -9748480.7…

[788 rows x 7 columns]
```

[11]:

```
# Convert to GeoDataFrame
inc_tract_gdf = gpd.GeoDataFrame(
    inc_tract_df,
    geometry='geometry',
```

```
    crs=chi_tract_gdf.crs  # use the original CRS from your tract GDF
)
```

[12]:
```
### Plot income data as chloropleth
pc_inc_plot = (
    gv.tile_sources.EsriImagery
    *
    gv.Polygons(
        inc_tract_gdf.to_crs(ccrs.Mercator()),
        vdims = ['per_capita_income', 'tractID'],
        crs = ccrs.Mercator()

    ).opts(color = 'per_capita_income', colorbar = True, tools = ['hover'],
           colorbar_opts = {'formatter': NumeralTickFormatter(format="$0,0")}) ␣
↪     # Format colorbar as currency
).opts(width = 600, height = 600, xaxis = None, yaxis = None)

pc_inc_plot
```

[12]:
```
:Overlay
   .WMTS.I     :WMTS   [Longitude,Latitude]
   .Polygons.I :Polygons   [Longitude,Latitude]   (per_capita_income,tractID)
```

[13]:
```
### Plot median income data as chloropleth
med_inc_plot = (
    gv.tile_sources.EsriImagery
    *
    gv.Polygons(
        inc_tract_gdf.to_crs(ccrs.Mercator()),
        vdims = ['median_household_income', 'tractID'],
        crs = ccrs.Mercator()

    ).opts(color = 'median_household_income', colorbar = True, tools =␣
↪['hover'],
           colorbar_opts = {'formatter': NumeralTickFormatter(format="$0,0")}) ␣
↪     # Format colorbar as currency
).opts(width = 600, height = 600, xaxis = None, yaxis = None)

med_inc_plot
```

[13]:
```
:Overlay
   .WMTS.I     :WMTS   [Longitude,Latitude]
   .Polygons.I :Polygons   [Longitude,Latitude]
(median_household_income,tractID)
```

[14]:
```
# Replace extreme negative outliers with NaN
```

```
inc_tract_gdf['median_household_income'] =␣
↪inc_tract_gdf['median_household_income'].replace({-666666666: np.nan})
inc_tract_gdf['per_capita_income'] = inc_tract_gdf['per_capita_income'].
↪replace({-666666666: np.nan})
```

[15]:
```
### Plot median income data as chloropleth
med_inc_plot = (
    gv.tile_sources.EsriImagery
    *
    gv.Polygons(
        inc_tract_gdf.to_crs(ccrs.Mercator()),
        vdims = ['median_household_income', 'tractID'],
        crs = ccrs.Mercator()

    ).opts(color = 'median_household_income', colorbar = True, tools =␣
↪['hover'],
           colorbar_opts = {'formatter': NumeralTickFormatter(format="$0,0")}) ␣
↪    # Format colorbar as currency
).opts(width = 600, height = 600, xaxis = None, yaxis = None)

med_inc_plot
```

[15]:
```
:Overlay
   .WMTS.I     :WMTS   [Longitude,Latitude]
   .Polygons.I :Polygons   [Longitude,Latitude]
(median_household_income,tractID)
```

1.2 NDVI Data

[16]:
```
### Connect to the planetary computer catalog
e84_catalog = pystac_client.Client.open(
    "https://planetarycomputer.microsoft.com/api/stac/v1"
)
```

[ ]:
```
# ONLY RUN ONCE TO DOWNLOAD DATA

### Convert geometry to lat/lon for STAC
tract_latlong_gdf = inc_tract_gdf.to_crs(epsg = 4326)

### Define a path to save NDVI stats
ndvi_stats_path = os.path.join(dir, 'chicago-ndvi-stats.csv')

### Check for existing data - do not access duplicate tracts
downloaded_tracts = []

if os.path.exists(ndvi_stats_path):
    ndvi_stats_df = pd.read_csv(ndvi_stats_path)
```

```
    downloaded_tracts = ndvi_stats_df.tract.values
else:
    print("No census tracts downloaded yet.")

### Loop through each census tract

scene_dfs = []


for i, tract_values in tqdm(tract_latlong_gdf.iterrows()):

    tract = tract_values.tractID

    ### Check if statistics are already downloaded for this tract
    if not (tract in downloaded_tracts):

        ### Repeat up to 5 times in case of a momentary disruption
        i = 0
        retry_limit = 5
        while i < retry_limit:

            ### Try accessing the STAC
            try:

                ### Search for tiles
                naip_search = e84_catalog.search(
                    collections = ['naip'],

                    intersects = shapely.to_geojson(tract_values.geometry),
                    datetime="2021"
                )

                ### Build dataframe with tracts and tile urls
                scene_dfs.append(pd.DataFrame(dict(

                    tract = tract,
                    date = [pd.to_datetime(scene.datetime).date()

                            for scene in naip_search.items()],

                    rgbir_href = [scene.assets['image'].href for scene in␣
 ↪naip_search.items()]
                )))
                break

            ### Try again in case of an APIError
```

```
            except pystac_client.exceptions.APIError:
                print(
                    f"Could not connect to STAC for tract {tract}. "
                    f"Retrying tract {tract}..."
                )
                time.sleep(2)
                i+=1
                continue

### Concatenate the url dataframes
if scene_dfs:
    scene_df = pd.concat(scene_dfs).reset_index(drop = True)
else:
    scene_df = None

### Preview the url dataframe
scene_df
```

[ ]:
```
# Save to csv, will only work when downloading data for the first time

scene_df.to_csv(ndvi_stats_path, index = False)
```

[18]:
```
# make csv for streaming ndvi data, has to be run each time to set the path

ndvi_stats_path_veg = os.path.join(dir, 'chicago-ndvi-veg-test.csv')
```

[ ]:
```
# ONLY RUN ONCE TO DOWNLOAD DATA

downloaded_tracts = []

if os.path.exists(ndvi_stats_path):
    ndvi_stats_df = pd.read_csv(ndvi_stats_path)
    downloaded_tracts = ndvi_stats_df.tract.values  # already processed tracts

# Filter scene_df to only tracts that haven't been processed
if scene_df is not None:
    scene_df_to_process = scene_df[~scene_df['tract'].isin(downloaded_tracts)]
else:
    scene_df_to_process = None


# Full loop for all tracts
if scene_df_to_process is not None and len(scene_df_to_process) > 0:

    ### Loop through the census tracts with URLs
    for tract, tract_date_gdf in tqdm(scene_df_to_process.groupby('tract')):
```

```
    ### Open all images for tract
    tile_das = []

    # loop through each scene for this tract
    for _, href_s in tract_date_gdf.iterrows():

        ### Open vsi connection to data
        tile_da = rxr.open_rasterio(

            # location of the raster image
            href_s.rgbir_href,

            # deal with no data, remove extra dimensions
            masked = True).squeeze()

        ### Clip data
        boundary = (
            inc_tract_gdf

            # deal with integer issues
            .assign(tractID = lambda df: df["tractID"].astype(str))

            # use tract ID as index
            .set_index('tractID')

            # select the geometry for this tract
            .loc[[str(tract)]]

            #reproject to match the tile CRS
            .to_crs(tile_da.rio.crs)

            #extract the geometry
            .geometry)

        ### Crop to bounding box
        crop_da = tile_da.rio.clip_box(
            *boundary.envelope.total_bounds,
            auto_expand = True)

        ### Clip data to the boundary of the census tract
        clip_da = crop_da.rio.clip(
            boundary,
            all_touched = True)

        ### Compute NDVI
        ndvi_da = (
            (clip_da.sel(band = 4) - clip_da.sel(band = 1)) /
```

```
            (clip_da.sel(band = 4) + clip_da.sel(band = 1))
        )

        ### Accumulate result
        tile_das.append(ndvi_da)

    ### Merge data
    scene_da = rxrm.merge_arrays(tile_das)

    ### Mask vegetation
    veg_mask = (scene_da > 0.3)

    ### Calculate statistics and save data to file

    # count all valid pixels
    total_pixels = scene_da.notnull().sum()

    # count all vegetated pixels
    veg_pixels = veg_mask.sum()

    ### identify vegetation patches
    labeled_patches, num_patches = label(veg_mask)

    # count patch pixels
    patch_sizes = np.bincount(labeled_patches.ravel())[1:]

    ### Calculate mean patch size
    mean_patch_size = patch_sizes.mean()

    ### Calculate edge density

    ### Make kernel to calculate edge density
    kernel = np.array([
        [1, 1, 1],
        [1, -8, 1],
        [1, 1, 1]])

    ### detect boundaries
    edges = convolve(veg_mask, kernel, mode='constant')

    # calculate edge density
    edge_density = np.sum(edges != 0) / veg_mask.size

    ### Add a row to the statistics file for this tract
    # create a dataframe for this tract
    pd.DataFrame(dict(
```

```
            #store tract ID
            tract = [tract],

            #store total pixels
            total_pixels = [int(total_pixels)],

            #store fraction of vegetated pixels
            fract_veg = [float(veg_pixels/total_pixels)],

            #store mean patch size
            mean_patch_size = [mean_patch_size],

            #store edge density
            edge_density = [edge_density]

        # write out as csv and save
        )).to_csv(
            ndvi_stats_path_veg,

            #append mode
            mode = 'a',

            # get rid of row numbers
            index = False,

            # write header only if file does not already exist
            header = (not os.path.exists(ndvi_stats_path_veg))
        )
```

[19]:
```
# check the file is loading correctly
# Save to CSV
ndvi_stats_df = pd.read_csv(ndvi_stats_path_veg)

ndvi_stats_df
```

[19]:

	tract	total_pixels	fract_veg	mean_patch_size	edge_density
0	17031010100	1059033	0.178657	55.225919	0.118612
1	17031010201	1531554	0.213859	57.543394	0.161668
2	17031010202	978546	0.186055	63.260250	0.123673
3	17031010300	1308392	0.191675	57.113642	0.126384
4	17031010400	1516964	0.198563	52.983817	0.079474
..	…	…	…	…	…
783	17031843500	5647650	0.075254	9.732779	0.104686
784	17031843600	1142916	0.054393	9.177296	0.101217
785	17031843700	6025768	0.027644	7.477533	0.047642
786	17031843800	3639014	0.093920	24.169295	0.105052
787	17031843900	4521964	0.199113	23.985215	0.124282

```
[788 rows x 5 columns]
```

[20]:

```python
# Change tract identifier datatype for merging
ndvi_stats_df["tract"] = ndvi_stats_df["tract"].astype(str)

# Add NDVI statistics to existing dataframe
ndvi_inc_gdf = (
    inc_tract_gdf.merge(
        ndvi_stats_df,
        left_on = 'tractID',
        right_on = 'tract',
        how = 'inner'           # Only keep tracts with NDVI data
    )
)

ndvi_inc_gdf.head()
```

[20]:

```
       tractID  asthma  asthma_ci_low  asthma_ci_high  \
0  17031010100    11.3           10.1            12.5
1  17031010201    11.2           10.0            12.4
2  17031010202    10.2            9.1            11.3
3  17031010300    10.2            9.1            11.3
4  17031010400    10.6            9.5            11.7

   median_household_income  per_capita_income  \
0                  69460.0              45353
1                  49639.0              31978
2                  55119.0              33488
3                  65871.0              42487
4                  49017.0              33185

                                            geometry        tract  \
0  POLYGON ((-9758835.381 5164429.383, -9758837.3...  17031010100
1  POLYGON ((-9760143.496 5163888.741, -9760143.4...  17031010201
2  POLYGON ((-9759754.212 5163883.196, -9759726.6...  17031010202
3  POLYGON ((-9758695.229 5163870.91, -9758695.78...  17031010300
4  POLYGON ((-9757724.634 5160715.939, -9757742.2...  17031010400

   total_pixels  fract_veg  mean_patch_size  edge_density
0       1059033   0.178657        55.225919      0.118612
1       1531554   0.213859        57.543394      0.161668
2        978546   0.186055        63.260250      0.123673
3       1308392   0.191675        57.113642      0.126384
4       1516964   0.198563        52.983817      0.079474
```

[21]:
```
fract_veg_plot = (
    gv.tile_sources.EsriImagery
    *
    gv.Polygons(
        ndvi_inc_gdf.to_crs(ccrs.Mercator()),
        vdims = ['fract_veg', 'tractID'],
        crs = ccrs.Mercator()

    ).opts(color = 'fract_veg', colorbar = True, tools = ['hover'])
).opts(width = 600, height = 600, xaxis = None, yaxis = None)

fract_veg_plot
```

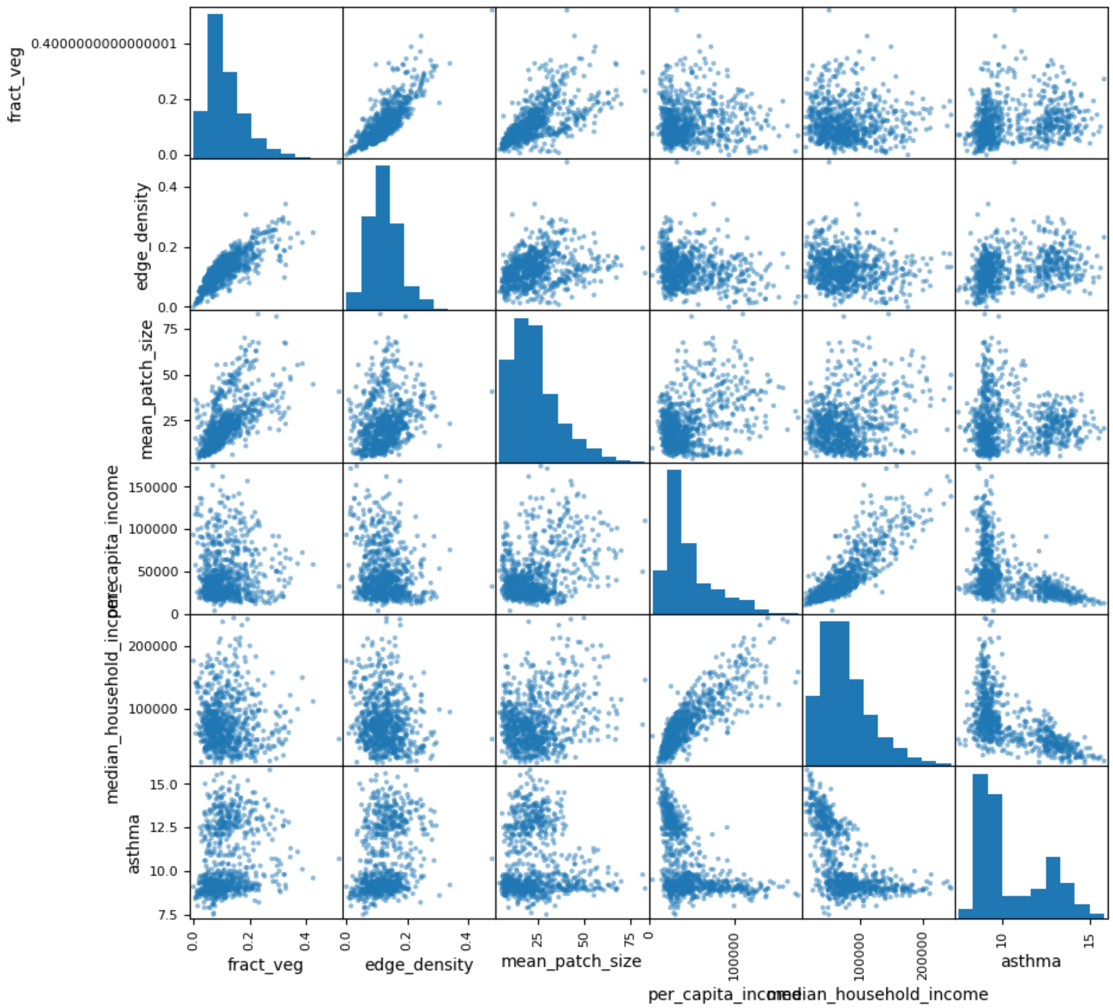
[21]:
```
:Overlay
   .WMTS.I     :WMTS   [Longitude,Latitude]
   .Polygons.I :Polygons   [Longitude,Latitude]   (fract_veg,tractID)
```

[22]:
```
mean_veg_plot = (
    gv.tile_sources.EsriImagery
    *
    gv.Polygons(
        ndvi_inc_gdf.to_crs(ccrs.Mercator()),
        vdims = ['mean_patch_size', 'tractID'],
        crs = ccrs.Mercator()

    ).opts(color = 'mean_patch_size', colorbar = True, tools = ['hover'])
).opts(width = 600, height = 600, xaxis = None, yaxis = None)

mean_veg_plot
```

[22]:
```
:Overlay
   .WMTS.I     :WMTS   [Longitude,Latitude]
   .Polygons.I :Polygons   [Longitude,Latitude]   (mean_patch_size,tractID)
```

[23]:
```
### Visualize distribution of data

# graph for variables
vars = ['fract_veg', 'edge_density', 'mean_patch_size',
        'per_capita_income','median_household_income','asthma']

# scatter plot matrix
pd.plotting.scatter_matrix(
    ndvi_inc_gdf[vars],
    figsize = (10, 10)
)
```

```
[23]: array([[<Axes: xlabel='fract_veg', ylabel='fract_veg'>,
         <Axes: xlabel='edge_density', ylabel='fract_veg'>,
         <Axes: xlabel='mean_patch_size', ylabel='fract_veg'>,
         <Axes: xlabel='per_capita_income', ylabel='fract_veg'>,
         <Axes: xlabel='median_household_income', ylabel='fract_veg'>,
         <Axes: xlabel='asthma', ylabel='fract_veg'>],
        [<Axes: xlabel='fract_veg', ylabel='edge_density'>,
         <Axes: xlabel='edge_density', ylabel='edge_density'>,
         <Axes: xlabel='mean_patch_size', ylabel='edge_density'>,
         <Axes: xlabel='per_capita_income', ylabel='edge_density'>,
         <Axes: xlabel='median_household_income', ylabel='edge_density'>,
         <Axes: xlabel='asthma', ylabel='edge_density'>],
        [<Axes: xlabel='fract_veg', ylabel='mean_patch_size'>,
         <Axes: xlabel='edge_density', ylabel='mean_patch_size'>,
         <Axes: xlabel='mean_patch_size', ylabel='mean_patch_size'>,
         <Axes: xlabel='per_capita_income', ylabel='mean_patch_size'>,
         <Axes: xlabel='median_household_income', ylabel='mean_patch_size'>,
         <Axes: xlabel='asthma', ylabel='mean_patch_size'>],
        [<Axes: xlabel='fract_veg', ylabel='per_capita_income'>,
         <Axes: xlabel='edge_density', ylabel='per_capita_income'>,
         <Axes: xlabel='mean_patch_size', ylabel='per_capita_income'>,
         <Axes: xlabel='per_capita_income', ylabel='per_capita_income'>,
         <Axes: xlabel='median_household_income', ylabel='per_capita_income'>,
         <Axes: xlabel='asthma', ylabel='per_capita_income'>],
        [<Axes: xlabel='fract_veg', ylabel='median_household_income'>,
         <Axes: xlabel='edge_density', ylabel='median_household_income'>,
         <Axes: xlabel='mean_patch_size', ylabel='median_household_income'>,
         <Axes: xlabel='per_capita_income', ylabel='median_household_income'>,
         <Axes: xlabel='median_household_income',
ylabel='median_household_income'>,
         <Axes: xlabel='asthma', ylabel='median_household_income'>],
        [<Axes: xlabel='fract_veg', ylabel='asthma'>,
         <Axes: xlabel='edge_density', ylabel='asthma'>,
         <Axes: xlabel='mean_patch_size', ylabel='asthma'>,
         <Axes: xlabel='per_capita_income', ylabel='asthma'>,
         <Axes: xlabel='median_household_income', ylabel='asthma'>,
         <Axes: xlabel='asthma', ylabel='asthma'>]], dtype=object)
```




```
[24]: # drop missing data

model_gdf = (
    ndvi_inc_gdf

    #make a copy to avoid modifying original data
    .copy()

    # subset to columns
    [['tractID','fract_veg', 'edge_density', 'mean_patch_size',
        'per_capita_income','median_household_income','asthma', 'geometry']]

    # drop NA
    .dropna()
)
```

```
model_gdf
```

[24]:

```
         tractID  fract_veg  edge_density  mean_patch_size  per_capita_income  \
0    17031010100   0.178657      0.118612        55.225919              45353
1    17031010201   0.213859      0.161668        57.543394              31978
2    17031010202   0.186055      0.123673        63.260250              33488
3    17031010300   0.191675      0.126384        57.113642              42487
4    17031010400   0.198563      0.079474        52.983817              33185
..           …          …           …              …                  …
783  17031843500   0.075254      0.104686         9.732779               3546
784  17031843600   0.054393      0.101217         9.177296              38837
785  17031843700   0.027644      0.047642         7.477533             101400
786  17031843800   0.093920      0.105052        24.169295              27767
787  17031843900   0.199113      0.124282        23.985215              34298

     median_household_income  asthma  \
0                    69460.0    11.3
1                    49639.0    11.2
2                    55119.0    10.2
3                    65871.0    10.2
4                    49017.0    10.6
..                       …       …
783                  55833.0     9.5
784                  71359.0    12.5
785                 134000.0     8.9
786                  57885.0    10.9
787                  47760.0    13.1

                                              geometry
0    POLYGON ((-9758835.381 5164429.383, -9758837.3…
1    POLYGON ((-9760143.496 5163888.741, -9760143.4…
2    POLYGON ((-9759754.212 5163883.196, -9759726.6…
3    POLYGON ((-9758695.229 5163870.91, -9758695.78…
4    POLYGON ((-9757724.634 5160715.939, -9757742.2…
..                                                 …
783  POLYGON ((-9761322.813 5136241.389, -9761337.5…
784  POLYGON ((-9752318.844 5132492.145, -9752318.2…
785  POLYGON ((-9761412.872 5153004.52, -9761411.75…
786  POLYGON ((-9755524.513 5130243.96, -9755529.18…
787  POLYGON ((-9748410.585 5128192.165, -9748480.7…

[777 rows x 8 columns]
```

[25]:

```
# Calculate logs
for col in ['fract_veg', 'edge_density', 'mean_patch_size',
            'per_capita_income','median_household_income','asthma']:
```

```python
    model_gdf[f'log_{col}'] = np.log(model_gdf[col])

model_gdf
```

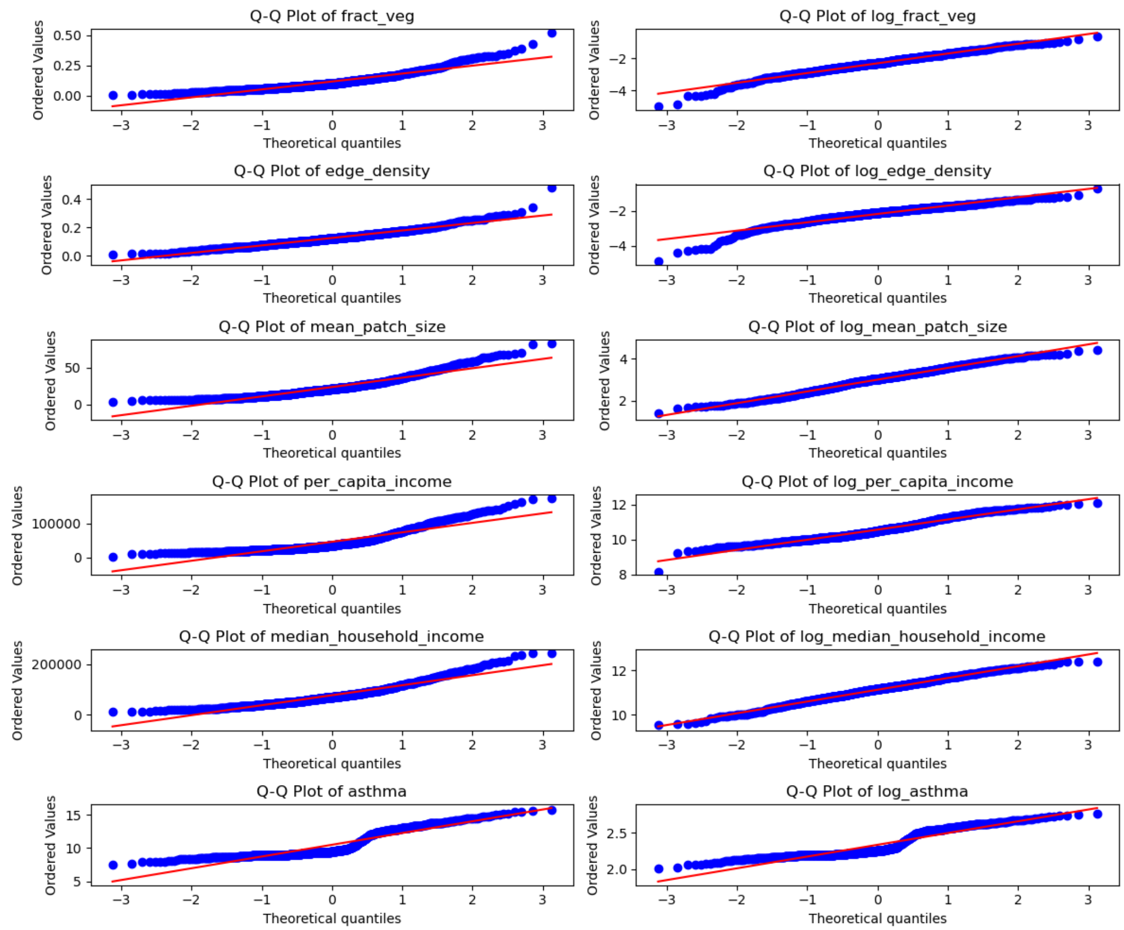
[25]:

```
         tractID  fract_veg  edge_density  mean_patch_size  per_capita_income  \
0    17031010100   0.178657      0.118612        55.225919              45353
1    17031010201   0.213859      0.161668        57.543394              31978
2    17031010202   0.186055      0.123673        63.260250              33488
3    17031010300   0.191675      0.126384        57.113642              42487
4    17031010400   0.198563      0.079474        52.983817              33185
..           …          …           …              …                  …
783  17031843500   0.075254      0.104686         9.732779               3546
784  17031843600   0.054393      0.101217         9.177296              38837
785  17031843700   0.027644      0.047642         7.477533             101400
786  17031843800   0.093920      0.105052        24.169295              27767
787  17031843900   0.199113      0.124282        23.985215              34298

     median_household_income  asthma  \
0                    69460.0    11.3
1                    49639.0    11.2
2                    55119.0    10.2
3                    65871.0    10.2
4                    49017.0    10.6
..                         …       …
783                  55833.0     9.5
784                  71359.0    12.5
785                 134000.0     8.9
786                  57885.0    10.9
787                  47760.0    13.1

                                              geometry  log_fract_veg  \
0    POLYGON ((-9758835.381 5164429.383, -9758837.3…      -1.722286
1    POLYGON ((-9760143.496 5163888.741, -9760143.4…      -1.542437
2    POLYGON ((-9759754.212 5163883.196, -9759726.6…      -1.681715
3    POLYGON ((-9758695.229 5163870.91, -9758695.78…      -1.651954
4    POLYGON ((-9757724.634 5160715.939, -9757742.2…      -1.616649
..                                                 …            …
783  POLYGON ((-9761322.813 5136241.389, -9761337.5…      -2.586880
784  POLYGON ((-9752318.844 5132492.145, -9752318.2…      -2.911514
785  POLYGON ((-9761412.872 5153004.52, -9761411.75…      -3.588343
786  POLYGON ((-9755524.513 5130243.96, -9755529.18…      -2.365307
787  POLYGON ((-9748410.585 5128192.165, -9748480.7…      -1.613884

     log_edge_density  log_mean_patch_size  log_per_capita_income  \
0           -2.131894             4.011432              10.722232
1           -1.822208             4.052539              10.372803
2           -2.090110             4.147257              10.418942
```

```
3          -2.068434           4.045043           10.656953
4          -2.532326           3.969987           10.409853
..               …                  …                  …
783        -2.256786           2.275499            8.173575
784        -2.290487           2.216733           10.567129
785        -3.044045           2.011903           11.526828
786        -2.253298           3.185083           10.231604
787        -2.085204           3.177438           10.442842

     log_median_household_income  log_asthma
0                      11.148506    2.424803
1                      10.812532    2.415914
2                      10.917250    2.322388
3                      11.095454    2.322388
4                      10.799922    2.360854
..                           …          …
783                    10.930120    2.251292
784                    11.175479    2.525729
785                    11.805595    2.186051
786                    10.966214    2.388763
787                    10.773944    2.572612

[777 rows x 14 columns]
```

[26]:
```python
# q-q plots

# set variables for q-q plots
var_qq = [
    'fract_veg', 'log_fract_veg', 'edge_density', 'log_edge_density',␣
 ↪'mean_patch_size', 'log_mean_patch_size',
   ␣
 ↪'per_capita_income','log_per_capita_income','median_household_income','log_median_household
]

# make plot for each variable
plt.figure(figsize = (12,10))
for i, var in enumerate(var_qq, 1):

    # 2x2 facet
    plt.subplot(6, 2, i)

    # norm distribution q-q plot
    stats.probplot(model_gdf[var], dist="norm", plot=plt)

    # add title
    plt.title(f'Q-Q Plot of {var}')
```

```
plt.tight_layout()
plt.show()
```



From what I can tell from the histograms and q-q plots, fract_veg and edge_density as well as median_household_income and per_capita_income are correlated most closely to each other so I will pick one (or the log version) from each pair. Log_fract_veg seems to perform best of the top four options from non-exhaustive prior testing, and log_median_household_income looks most normally distributed of that grouping. I will now build a model with log_fract_veg, log_median_household_income, and log_mean_patch_size as x variables and asthma as our y variable.

1.3 Run Regression

[29]:
```
# Set predictor and response variables for modeling
X = model_gdf[['log_fract_veg', 'log_mean_patch_size',␣
 ↪'log_median_household_income']]
Y = model_gdf[['log_asthma']]
```

```
# Split data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(
    X, Y, test_size=0.33, random_state=42
)

# Fit linear regression model
reg = LinearRegression()
reg.fit(X_train, Y_train)

# Make predictions on the test set
Y_test['pred_asthma'] = np.exp(reg.predict(X_test))

# use the trained model to predict asthma for all tracts
model_gdf['pred_asthma'] = np.exp(reg.predict(X))

Y_test['measured_asthma'] = np.exp(Y_test['log_asthma'])

Y_test
```

[29]:

	log_asthma	pred_asthma	measured_asthma
574	2.332144	11.898119	10.3
535	2.091864	10.189445	8.1
616	2.602690	11.847563	13.5
109	2.240710	10.113142	9.4
592	2.493205	12.858251	12.1
..	…	…	…
18	2.151762	9.718228	8.6
576	2.219203	11.059941	9.2
141	2.186051	7.897718	8.9
337	2.617396	11.558575	13.7
260	2.174752	8.782103	8.8

[257 rows x 3 columns]

[30]:

```
# vmin = Y_test[cols].min().min()
# vmax = Y_test[cols].max().max()

p_est = (Y_test
    .hvplot.scatter(x='measured_asthma', y='pred_asthma',
                    xlabel = 'Measured Asthma Prevalence',
                    ylabel = 'Predicted Asthma Prevalence',
                    title = 'Regression Model Distribution')
    .opts(aspect='equal',
        #   xlim=(xylim), ylim=(xylim),
          width=600, height=600)
) * hv.Slope(slope=1, y_intercept=0).opts(color='black')
```

```
p_est
```

[30]:
```
:Overlay
   .Scatter.I     :Scatter    [measured_asthma]    (pred_asthma)
   .Annotation.I :Slope    [x,y]
```

[31]:
```python
model_gdf = gpd.GeoDataFrame(
    model_gdf,
    geometry='geometry',
    crs=ndvi_inc_gdf.crs  # use the original CRS
)
```

[32]:
```python
model_gdf
```

[32]:
```
         tractID  fract_veg  edge_density  mean_patch_size  per_capita_income  \
0    17031010100   0.178657      0.118612        55.225919              45353
1    17031010201   0.213859      0.161668        57.543394              31978
2    17031010202   0.186055      0.123673        63.260250              33488
3    17031010300   0.191675      0.126384        57.113642              42487
4    17031010400   0.198563      0.079474        52.983817              33185
..           …          …           …              …                 …
783  17031843500   0.075254      0.104686         9.732779               3546
784  17031843600   0.054393      0.101217         9.177296              38837
785  17031843700   0.027644      0.047642         7.477533             101400
786  17031843800   0.093920      0.105052        24.169295              27767
787  17031843900   0.199113      0.124282        23.985215              34298

     median_household_income  asthma  \
0                    69460.0    11.3
1                    49639.0    11.2
2                    55119.0    10.2
3                    65871.0    10.2
4                    49017.0    10.6
..                       …       …
783                  55833.0     9.5
784                  71359.0    12.5
785                 134000.0     8.9
786                  57885.0    10.9
787                  47760.0    13.1

                                              geometry  log_fract_veg  \
0    POLYGON ((-9758835.381 5164429.383, -9758837.3…      -1.722286
1    POLYGON ((-9760143.496 5163888.741, -9760143.4…      -1.542437
2    POLYGON ((-9759754.212 5163883.196, -9759726.6…      -1.681715
3    POLYGON ((-9758695.229 5163870.91, -9758695.78…      -1.651954
4    POLYGON ((-9757724.634 5160715.939, -9757742.2…      -1.616649
..                                                 …            …
```

```
783  POLYGON ((-9761322.813 5136241.389, -9761337.5…      -2.586880
784  POLYGON ((-9752318.844 5132492.145, -9752318.2…      -2.911514
785  POLYGON ((-9761412.872 5153004.52, -9761411.75…      -3.588343
786  POLYGON ((-9755524.513 5130243.96, -9755529.18…      -2.365307
787  POLYGON ((-9748410.585 5128192.165, -9748480.7…      -1.613884

     log_edge_density  log_mean_patch_size  log_per_capita_income  \
0           -2.131894             4.011432              10.722232
1           -1.822208             4.052539              10.372803
2           -2.090110             4.147257              10.418942
3           -2.068434             4.045043              10.656953
4           -2.532326             3.969987              10.409853
..                …                    …                     …
783         -2.256786             2.275499               8.173575
784         -2.290487             2.216733              10.567129
785         -3.044045             2.011903              11.526828
786         -2.253298             3.185083              10.231604
787         -2.085204             3.177438              10.442842

     log_median_household_income  log_asthma  pred_asthma
0                      11.148506    2.424803    10.519589
1                      10.812532    2.415914    11.441303
2                      10.917250    2.322388    11.061450
3                      11.095454    2.322388    10.686823
4                      10.799922    2.360854    11.427801
..                           …          …           …
783                    10.930120    2.251292    10.668535
784                    11.175479    2.525729     9.903013
785                    11.805595    2.186051     8.277265
786                    10.966214    2.388763    10.595762
787                    10.773944    2.572612    11.641832

[777 rows x 15 columns]
```

[46]:
```python
# Calculate error
model_gdf['error_asthma'] = model_gdf['pred_asthma'] - model_gdf['asthma']

# Set limit
abs_max = model_gdf['error_asthma'].abs().max()
clim = (-abs_max, abs_max)


# Plot error
model_plot = (
    gv.tile_sources.EsriImagery
    *
    gv.Polygons(
```

```
        model_gdf.to_crs(ccrs.Mercator()),
        vdims=['error_asthma', 'pred_asthma', 'asthma', 'tractID'],
        crs = ccrs.Mercator()
    ).opts(color = 'error_asthma', colorbar = True, tools = ['hover'],
           clim = clim, cmap = 'RdBu'  # Diverging color map)
).opts(width = 600, height = 600, xaxis = None, yaxis = None, title = 'Asthma␣
↪Prediction Error for Chicago, IL Census Tracts',
       clabel = 'Lower values indicate under-prediction, higher values indicate␣
↪over-prediction')
)
model_plot
```

[46]:
```
:Overlay
   .WMTS.I      :WMTS   [Longitude,Latitude]
   .Polygons.I :Polygons   [Longitude,Latitude]
(error_asthma,pred_asthma,asthma,tractID)
```

1.4 R2 Calculation

[34]:
```
y_true = model_gdf['asthma'].values       # observed
y_pred = model_gdf['pred_asthma'].values  # predicted
```

[36]:
```
# Example if you know which rows were training/testing
train_mask = model_gdf.index.isin(X_train.index)
test_mask  = model_gdf.index.isin(X_test.index)

r2_train = r2_score(y_true[train_mask], y_pred[train_mask])
r2_test  = r2_score(y_true[test_mask], y_pred[test_mask])

print(f"Training R²: {r2_train:.3f}")
print(f"Test R²: {r2_test:.3f}")
```

```
Training R²: 0.522
Test R²: 0.584
```

[39]:
```
# Calculate R² for all data
r2 = r2_score(y_true, y_pred)
print(f"R² (all): {r2:.3f}")
```

```
R² (all): 0.546
```

[38]:
```
# Calculate R² for training and test sets
train_mask = model_gdf.index.isin(X_train.index)
test_mask  = model_gdf.index.isin(X_test.index)

r2_train = r2_score(y_true[train_mask], y_pred[train_mask])
r2_test  = r2_score(y_true[test_mask], y_pred[test_mask])
```

```python
print(f"Training R²: {r2_train:.3f}")
print(f"Test R²: {r2_test:.3f}")
```

```
Training R²: 0.522
Test R²: 0.584
```

[48]:
```python
descriptor_text = (
    f"Model performance summary:\n"
    f"Using log_fract_veg, log_mean_patch_size, and log_mean_household_income,␣
 ↪\n"
    f"this model estimates log_asthma with R² = {r2:.3f}."
)

text_panel = hv.Text(
    0.5, 0.5, descriptor_text
).opts(
    width=600,
    height=120,
    xaxis=None,
    yaxis=None,
    text_align='center',
    text_baseline='middle',
    text_font_size='10pt'
)
```

[49]:
```python
final_plot = (model_plot + text_panel).cols(1)
final_plot
```

[49]:
```
:Layout
   .Overlay.I  :Overlay
      .WMTS.I     :WMTS    [Longitude,Latitude]
      .Polygons.I :Polygons    [Longitude,Latitude]
(error_asthma,pred_asthma,asthma,tractID)
   .Text.I     :Text    [x,y]
```

[50]:
```python
# save final plot
hv.save(final_plot, 'descrip_asthma_error_map.html', fmt='html')
```