BTP - 1 [2025]

SMART
POWER GRID

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GEOSPATIAL SOLUTIONS FOR SMART (POWER) GRID IMPLEMENTATIONS

Access to real-time and historical **power grid data** is often **restricted** due to privacy and security concerns, making it unavailable for civilian research and development. This limitation poses **a challenge for developing and testing innovative solutions** in the power grid domain. To address this, we propose to explore alternative publicly accessible data sources that can serve as substitutes for actual grid data. The project aims to evaluate the effectiveness, accessibility, and predictive capability of the chosen method. Furthermore, the goal is to use **this method to build a prototype capable of forecasting future grid scenarios and generating actionable suggestions for power grid management**

OUR SOLUTION

To overcome the lack of access to real-world power grid data, we utilize **night-time satellite imagery,** specifically night lights data, as a proxy for estimating power consumption patterns. Night lights serve as a valuable alternative, as their intensity is generally correlated with electricity usage in a given area. We assume that higher night light intensity indicates higher power consumption, making it a suitable indicator for our analysis.

Moreover, night lights data show a meaningful correlation with Land Use Land Cover (LULC) classifications, allowing for a more comprehensive understanding of energy usage in different types of regions (e.g., urban, rural, industrial). This data is publicly accessible and relatively easy to obtain, which makes it a practical resource for large-scale studies.

OUR SOLUTION

However, the dataset comes with limitations, including low spatial resolution and limited temporal coverage. Despite these drawbacks, its broad coverage enables the monitoring of large geographical areas, making it especially useful for regional or national-level analyses.

Using night lights data, we conducted further analysis to extract insights, predict future scenarios, and suggest improvements for power grid planning. The results and methodology of this prototype will be presented next.

HOW DID WE GET DATA ?

VIIRS Nighttime Day/Night Band Composites Version 1

Dataset Availability
2012-04-01T00:00:00Z–2025-03-01T00:00:00Z

Dataset Provider
Earth Observation Group, Payne Institute for Public Policy, Colorado School of Mines

Earth Engine Snippet
`ee.ImageCollection("NOAA/VIIRS/DNB/MONTHLY_V1/VCMCFG")`

Cadence
1 Month

Tags
dnb eog lights monthly nighttime noaa population viirs visible

Description | Bands | Terms of Use

Pixel Size
463.83 meters

Bands

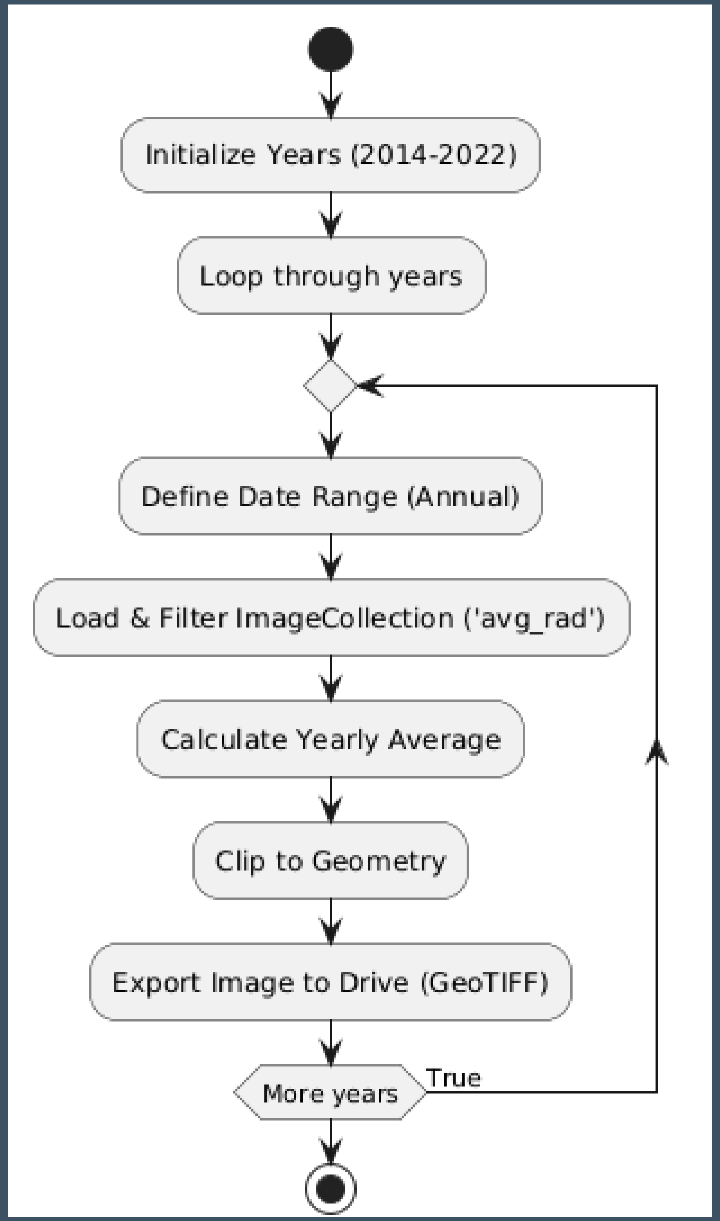
Name	Units	Min	Max	Description
avg_rad	nanoWatts/sr/cm^2	-1.5*	340573*	Average DNB radiance values.

HOW DID WE GET DATA ?

we collected the data each year from **2014 to 2022** for the following regions

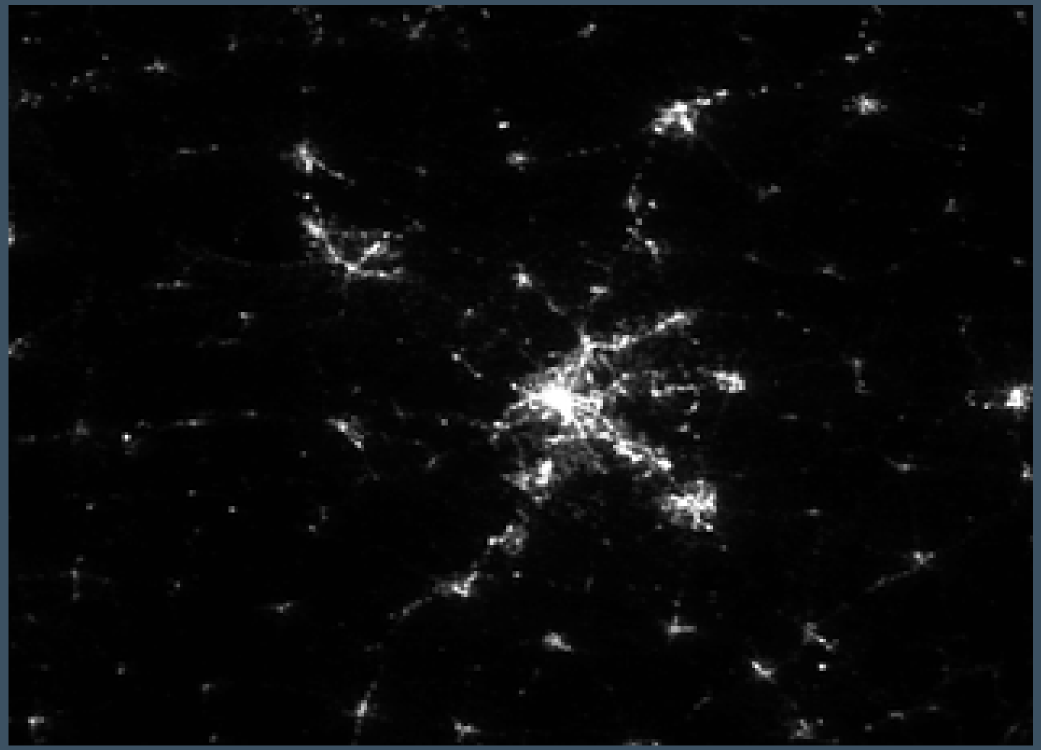
1. Washington DC
2. Nashvillie
3. Delhi

```
var startYear = 2014;
var endYear = 2022;

for (var year = startYear; year <= endYear; year++) {
  var startDate = ee.Date.fromYMD(year, 1, 1);
  var endDate = ee.Date.fromYMD(year + 1, 1, 1);

  var dataset = ee.ImageCollection('NOAA/VIIRS/DNB/MONTHLY_V1/VCMCFG')
                .filterDate(startDate, endDate)
                .select('avg_rad');

  var yearlyAvg = dataset.mean().clip(geometry);

  Export.image.toDrive({
    image: yearlyAvg,
    description: 'NTL_' + year,
    folder: 'NTL_01_Washington',
    fileNamePrefix: 'NTL_' + year,
    region: geometry,
    scale: 500,
    maxPixels: 1e13,
    fileFormat: 'GeoTIFF'
  });
}
```

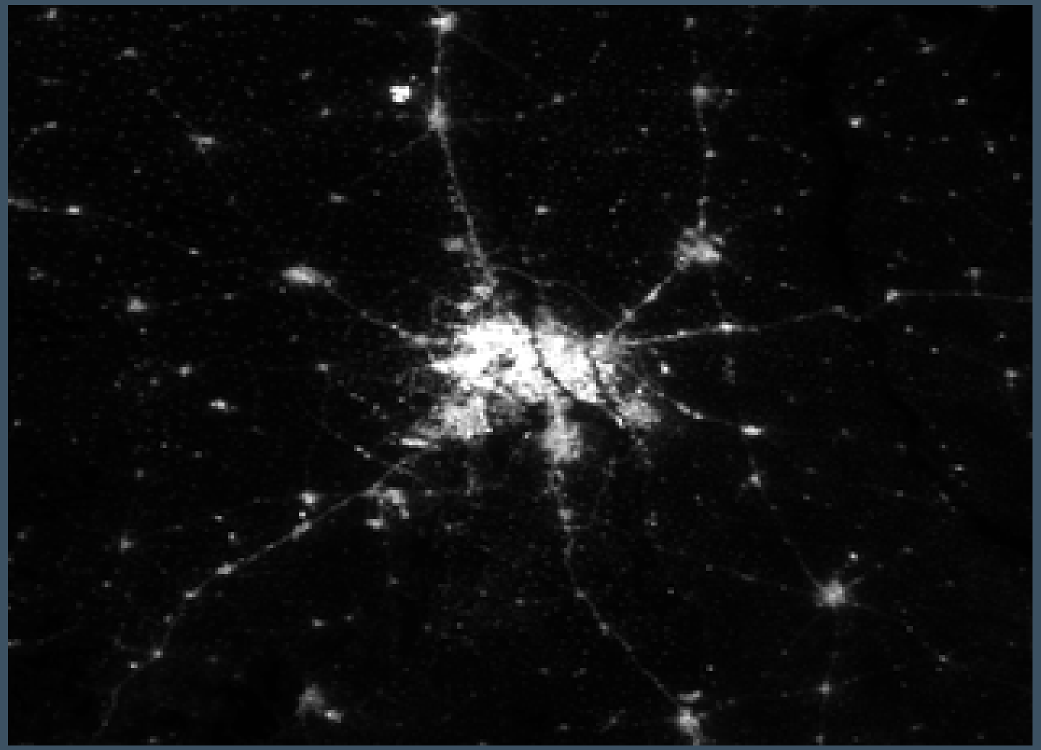


NIGHT LIGHTS DATA

WASHINGTON



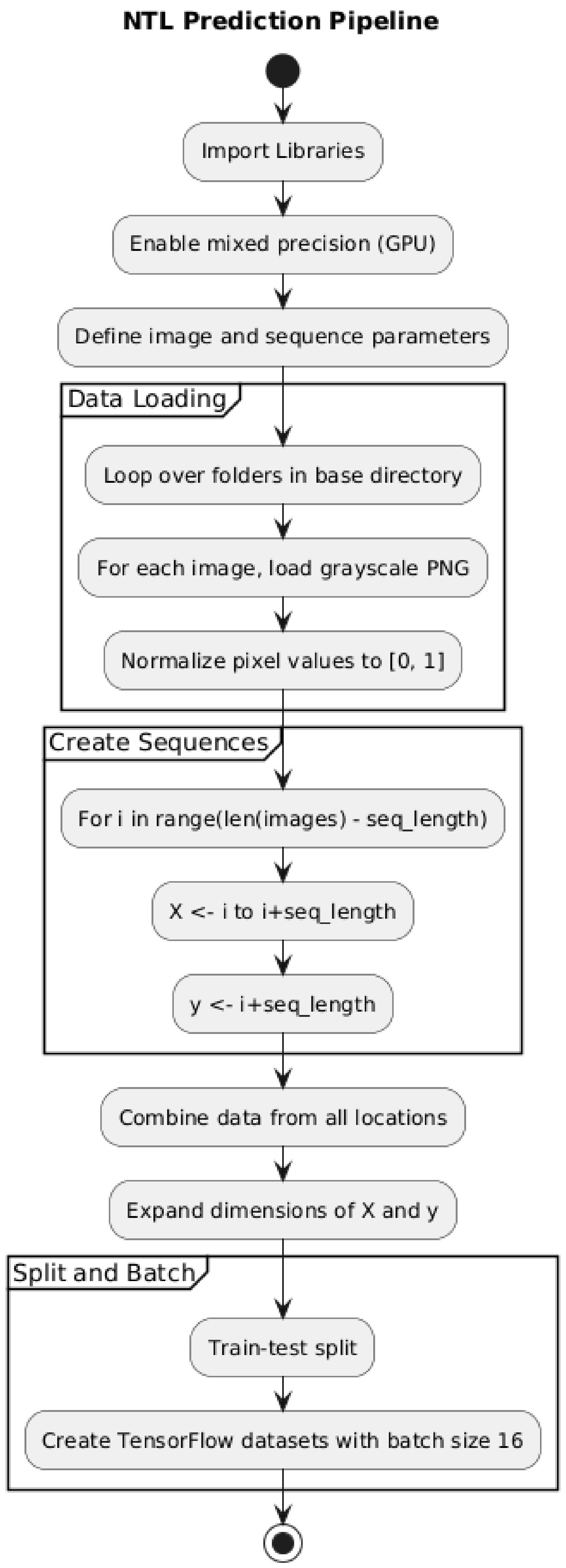
NASHVILLIE



DELHI

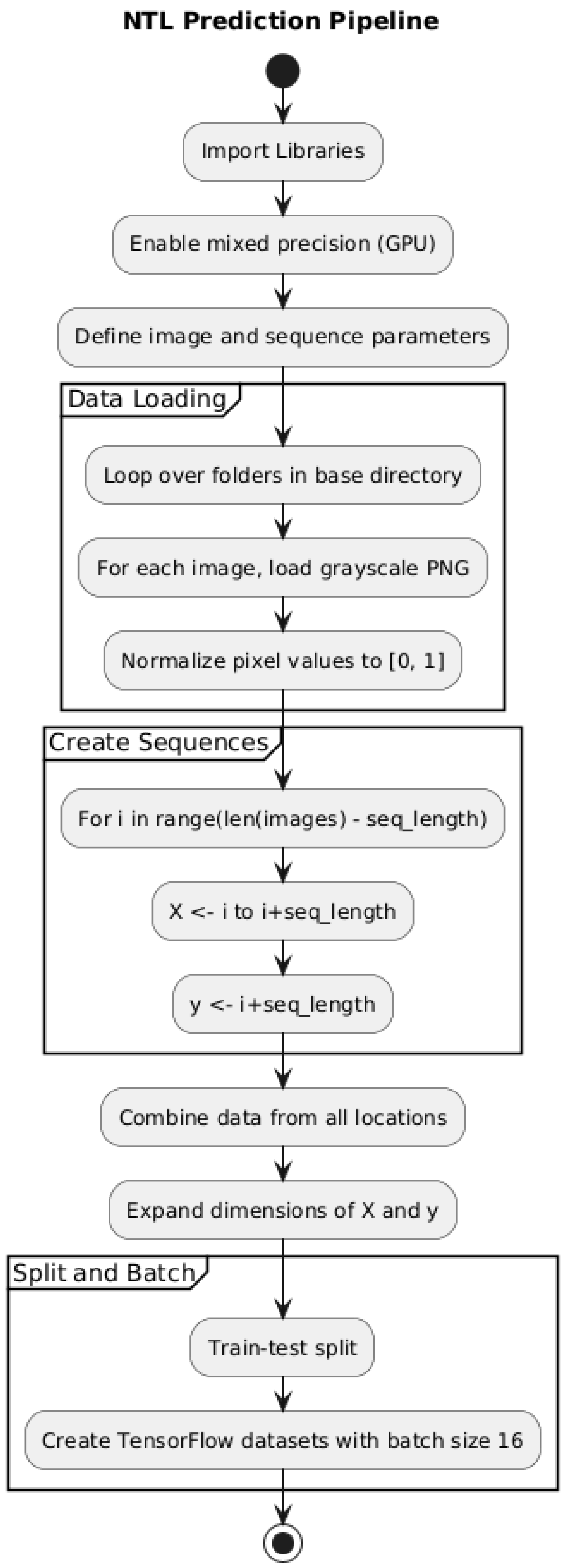
NTL PREDICTION

- Input: Sequences of past grayscale images.
  - Each input sequence contains SEQUENCE_LENGTH images.
  - Example: Using Images from Year 1, 2, 3 to predict Year 4.
- Output: The single grayscale image that follows the input sequence.
- Preprocessing:
  - Convert images to grayscale.
  - Normalize pixel values (0-1).
  - Organize data into input sequences (X) and target images (y).
  - Split into Training and Testing sets.



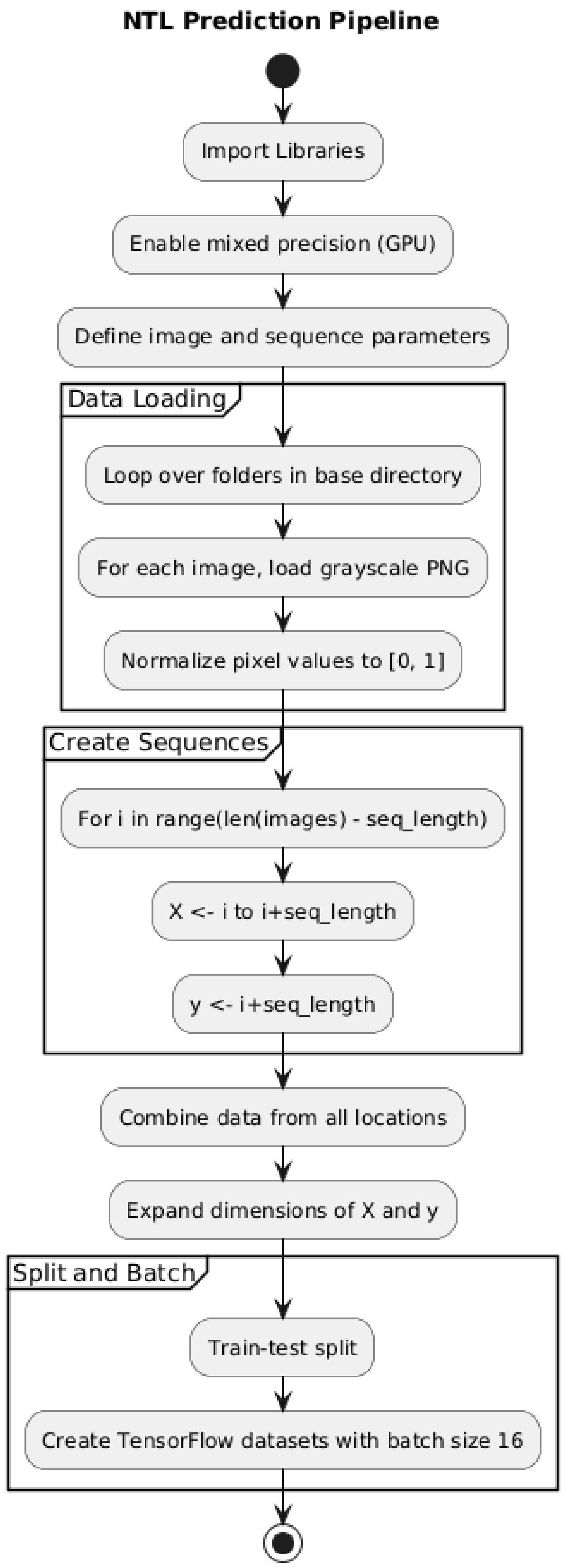
ML APPROACH

- Problem Type:
  - Spatio-temporal sequence forecasting.
- Method:
  - Uses a Deep Neural Network model.
  - The model learns patterns in both:
    - Space: Features within each image.
    - Time: How images change over the sequence.



MODEL DETAILS

- Uses a ConvLSTM2D model.
  - ConvLSTM2D is ideal for image sequences because it combines:
  - Convolution: Extracts spatial features from images.
- LSTM:
  - Handles sequential data and learns temporal dependencies.
- Model Structure:
  - ConvLSTM2D layer followed by Conv2D layers.
- The final layer outputs the predicted grayscale image.
- Model Accuracy :
  - loss: 3.6193e-04 | mae: 0.0070 | val_loss: 3.1812e-04 | val_mae: 0.0065



INFERENCING

- Once trained, the model can forecast future images.
- Single-Step Prediction:
  - Predicts the immediate next image using the last available real sequence of images as input.
- Multi-Step Prediction (Recursive):
  - Predicts the next image.
  - Then, uses the predicted image (along with recent images) as part of the input sequence to predict the step after that.
  - This process is repeated to forecast multiple steps (e.g., 10 years) into the future.

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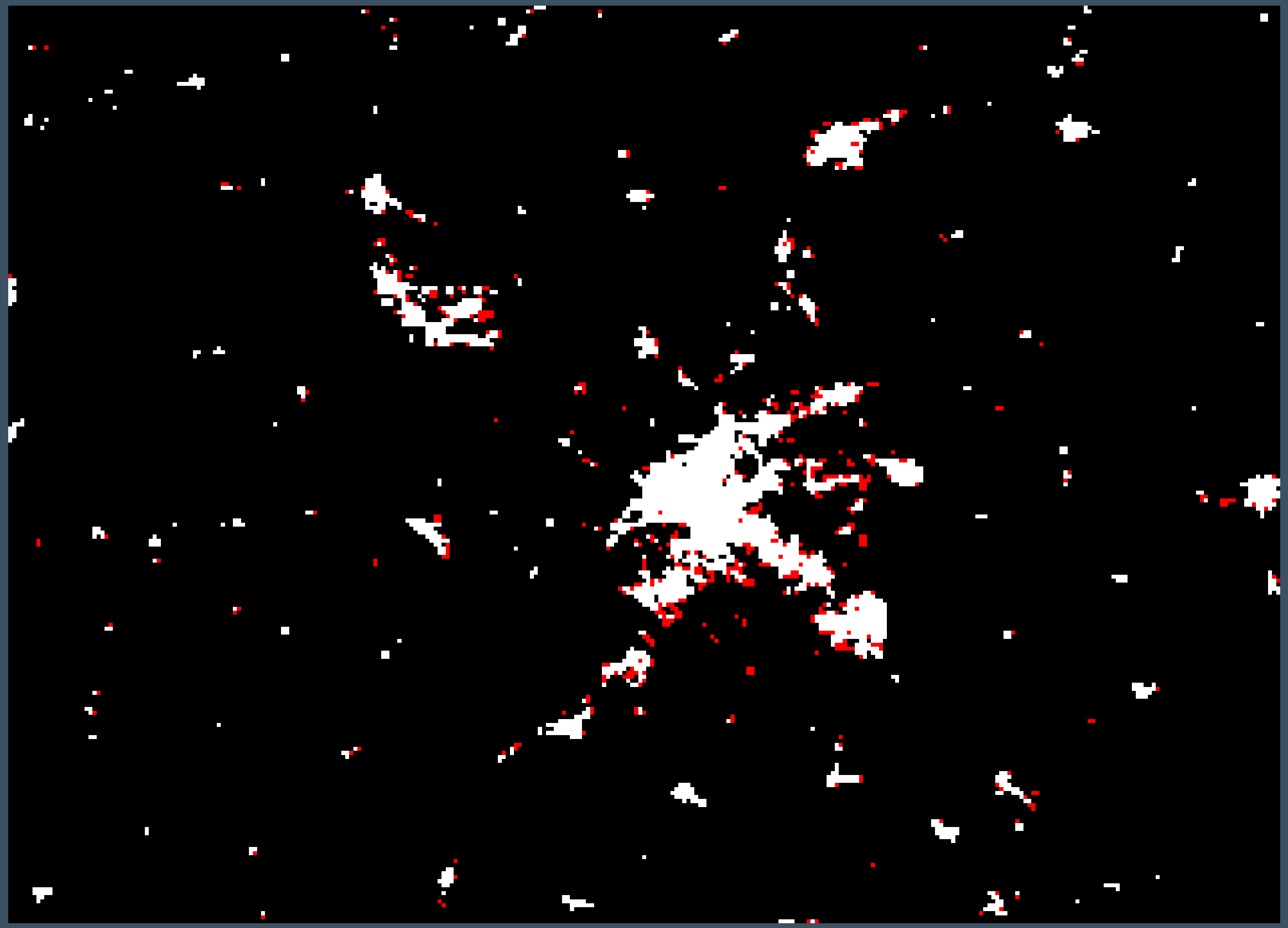
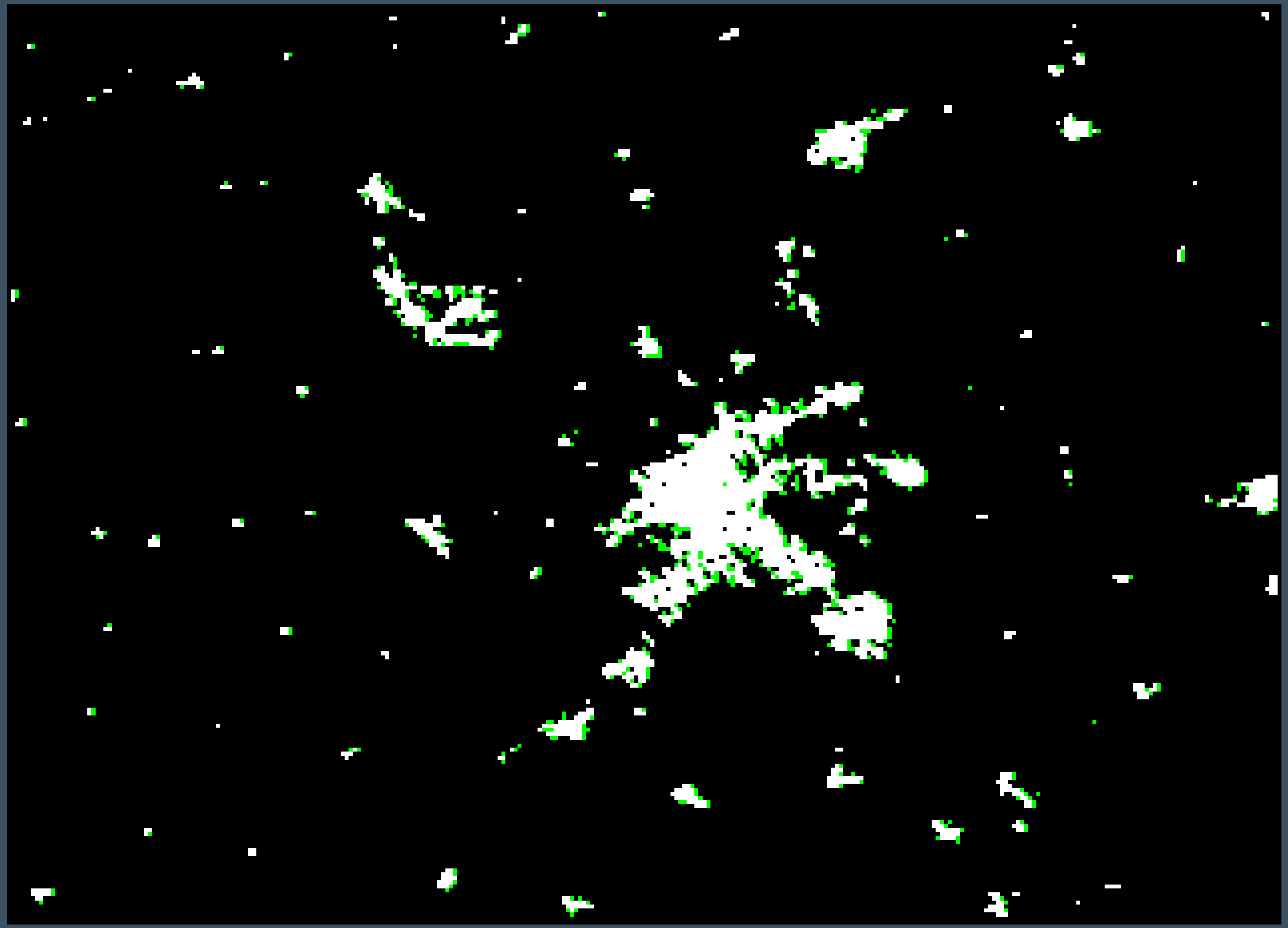
OUTPUTS



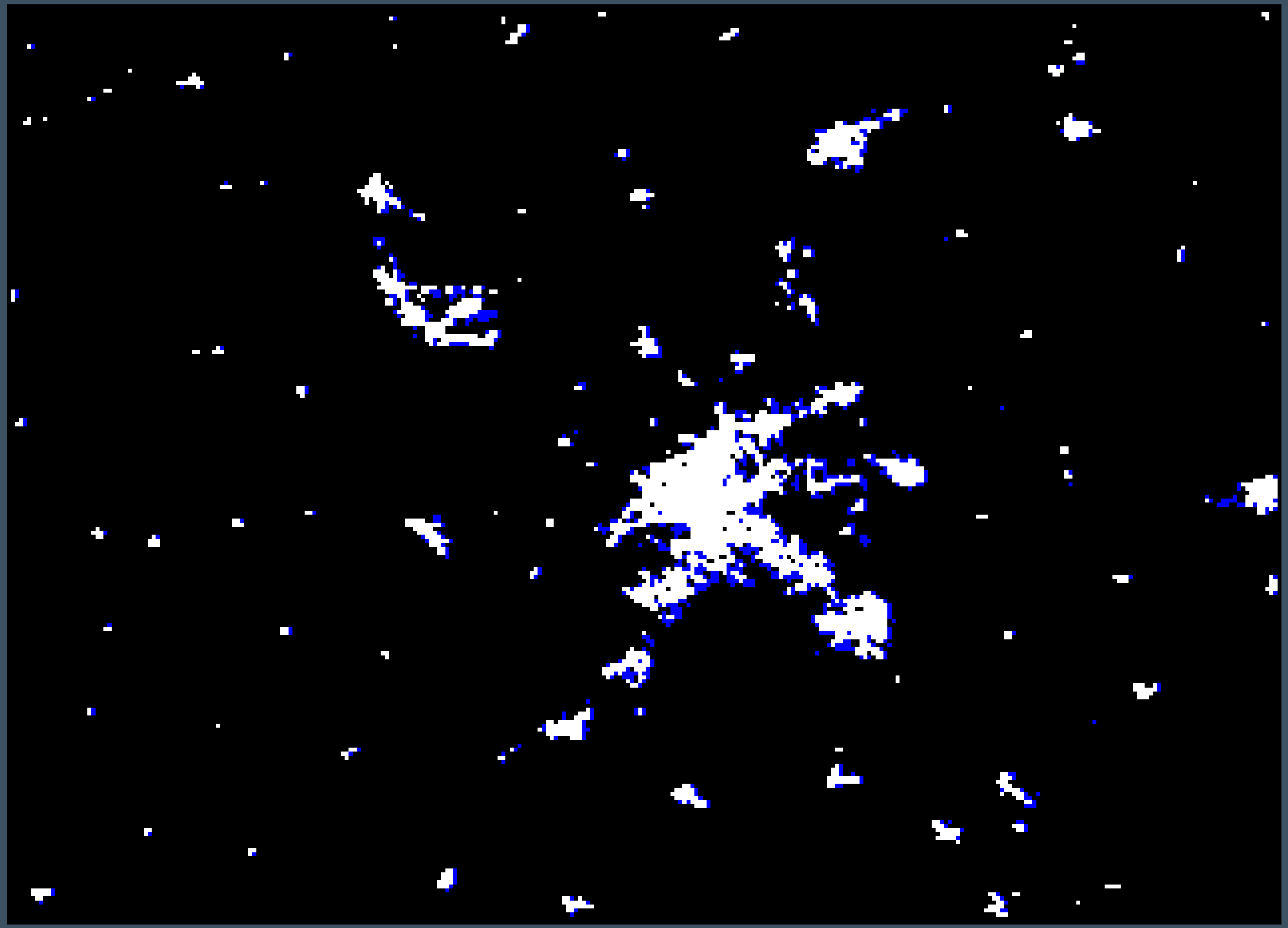
Nashvillie 2014 to 2022

OUTPUTS



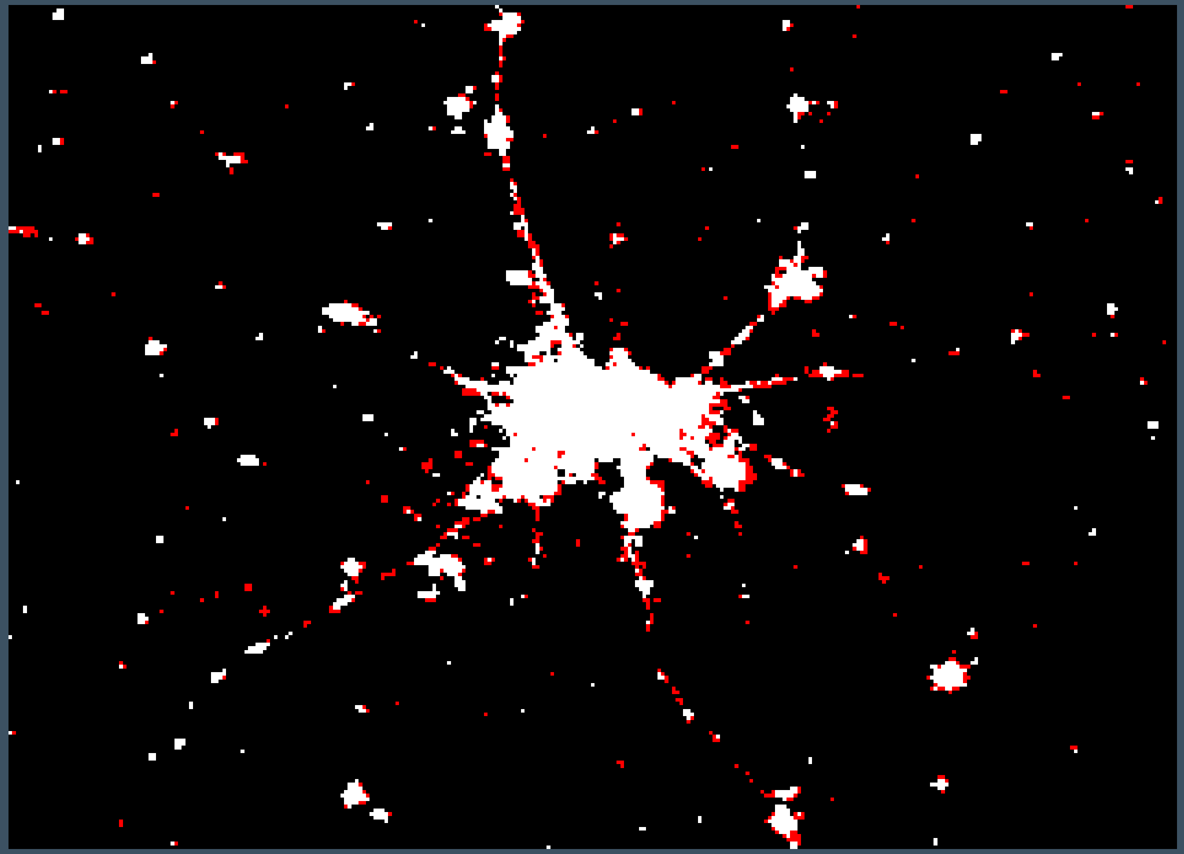
Nashvillie 2023 - 2032

OUTPUTS

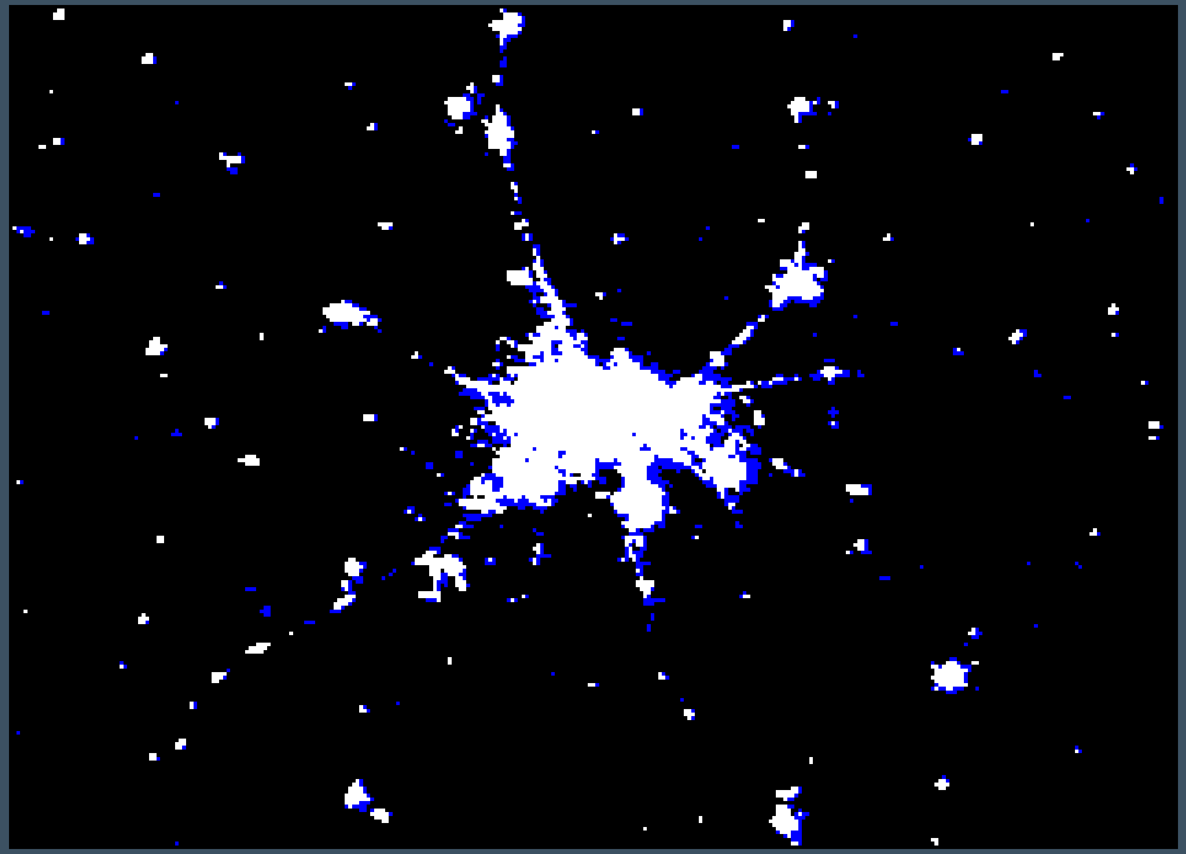


Nashvillie 2014 to 2032

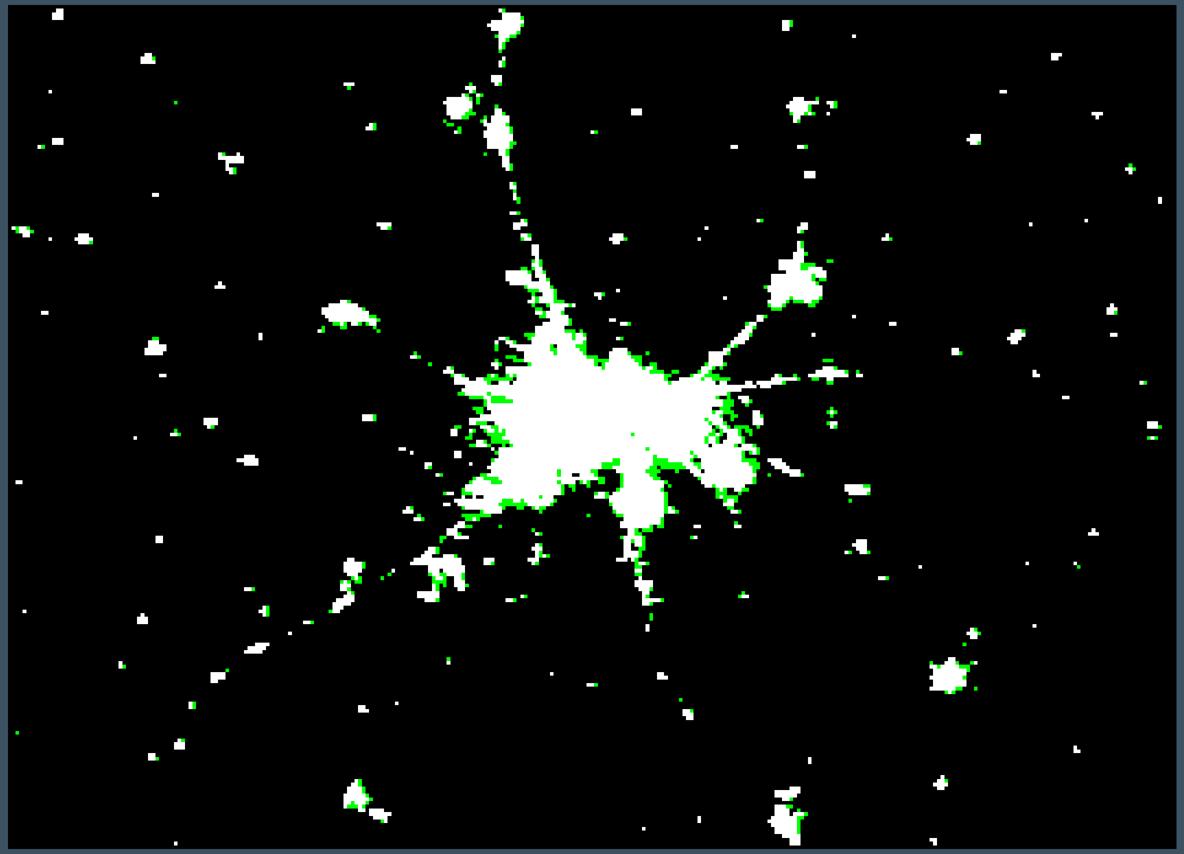
OUTPUTS



Delhi 2014 to 2022

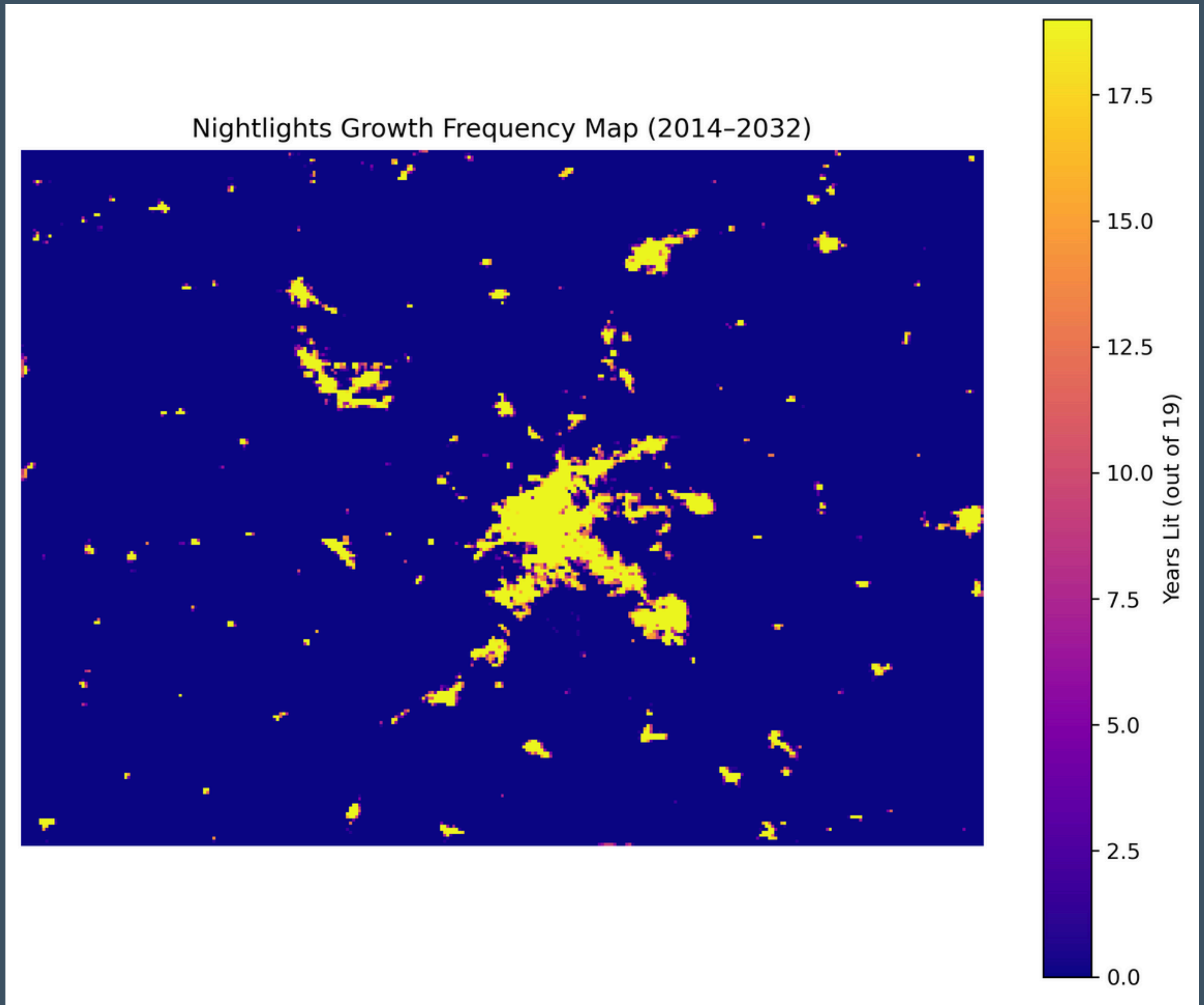


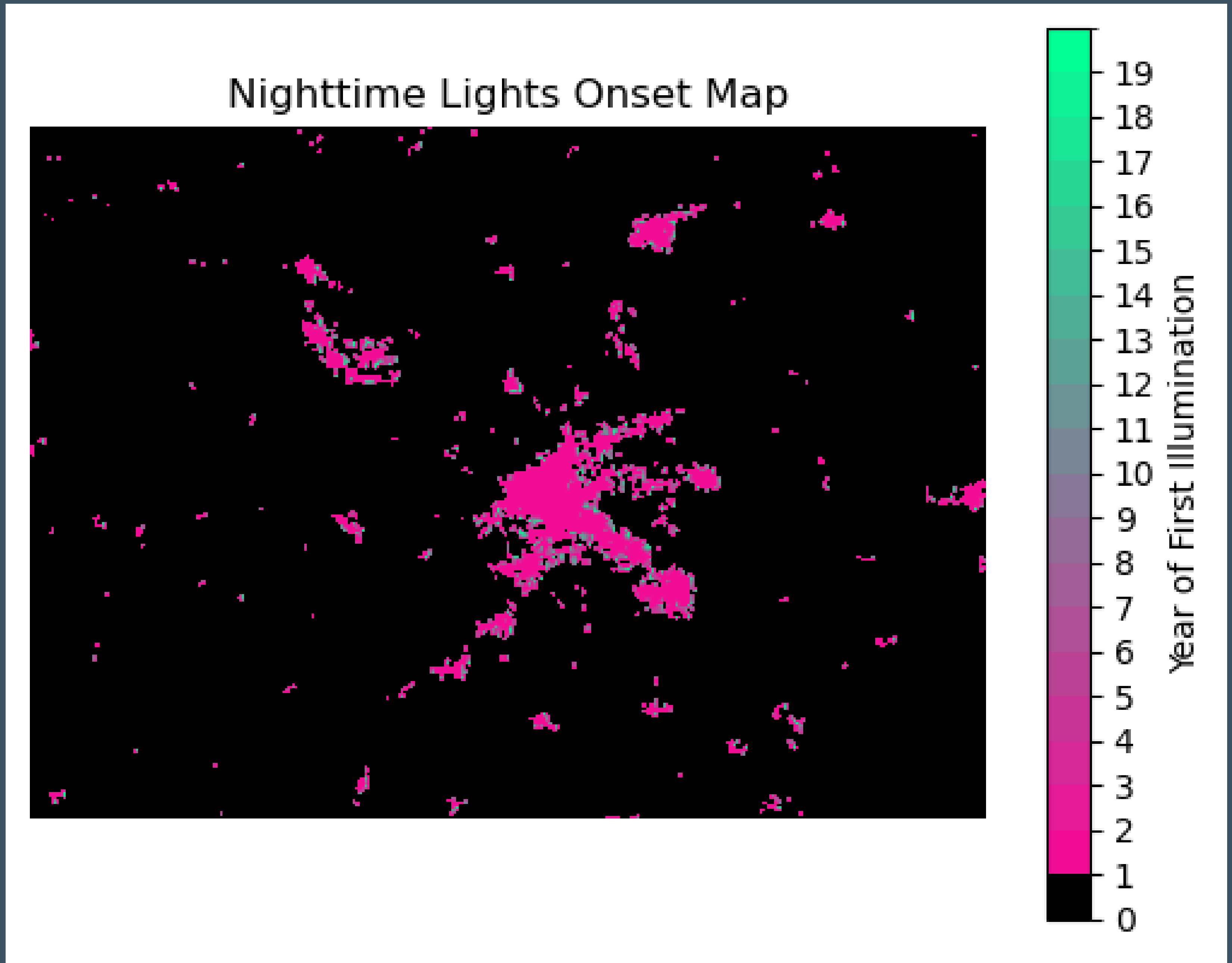
Delhi 2014 to 2032



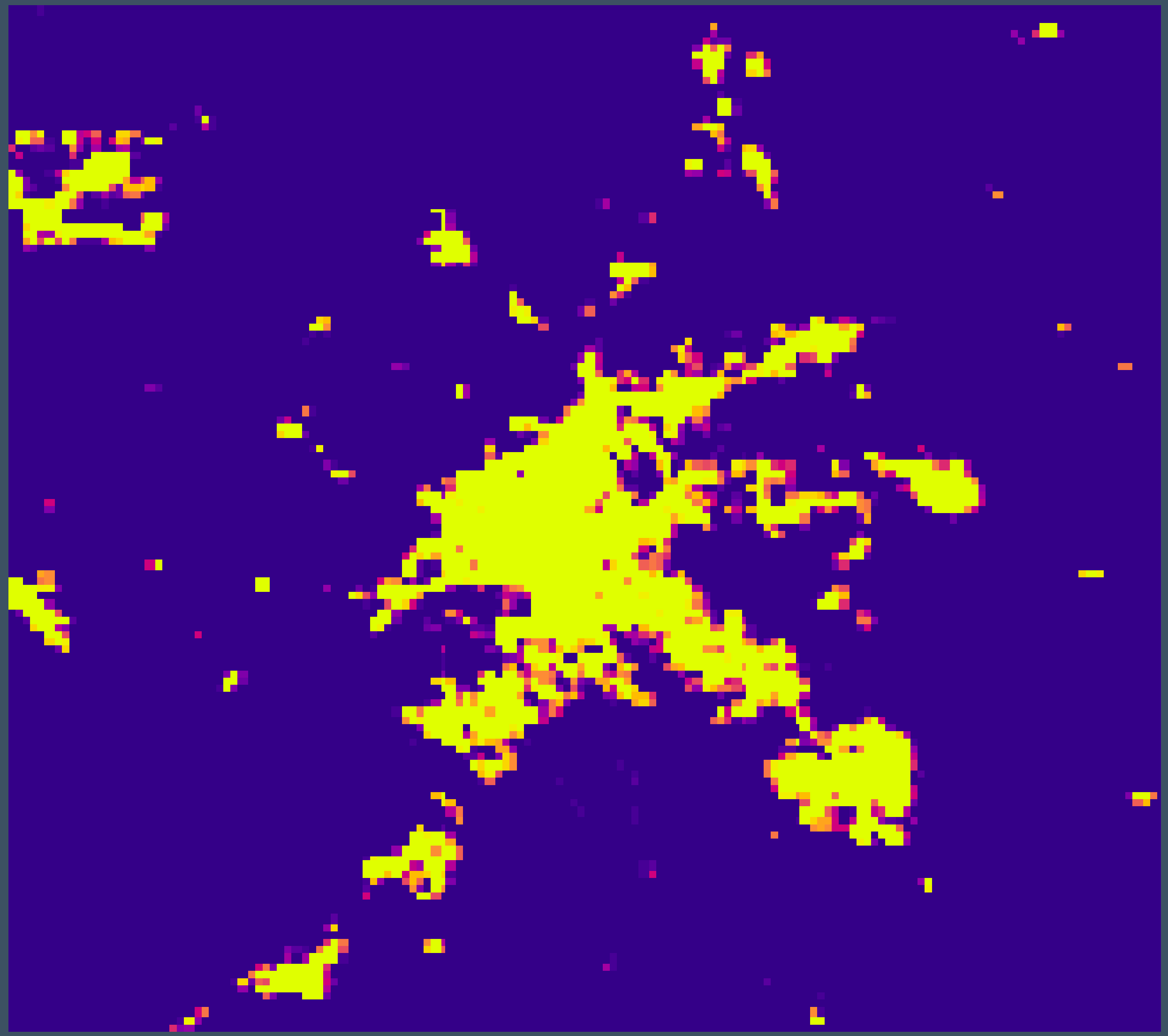
Delhi 2023 - 2032

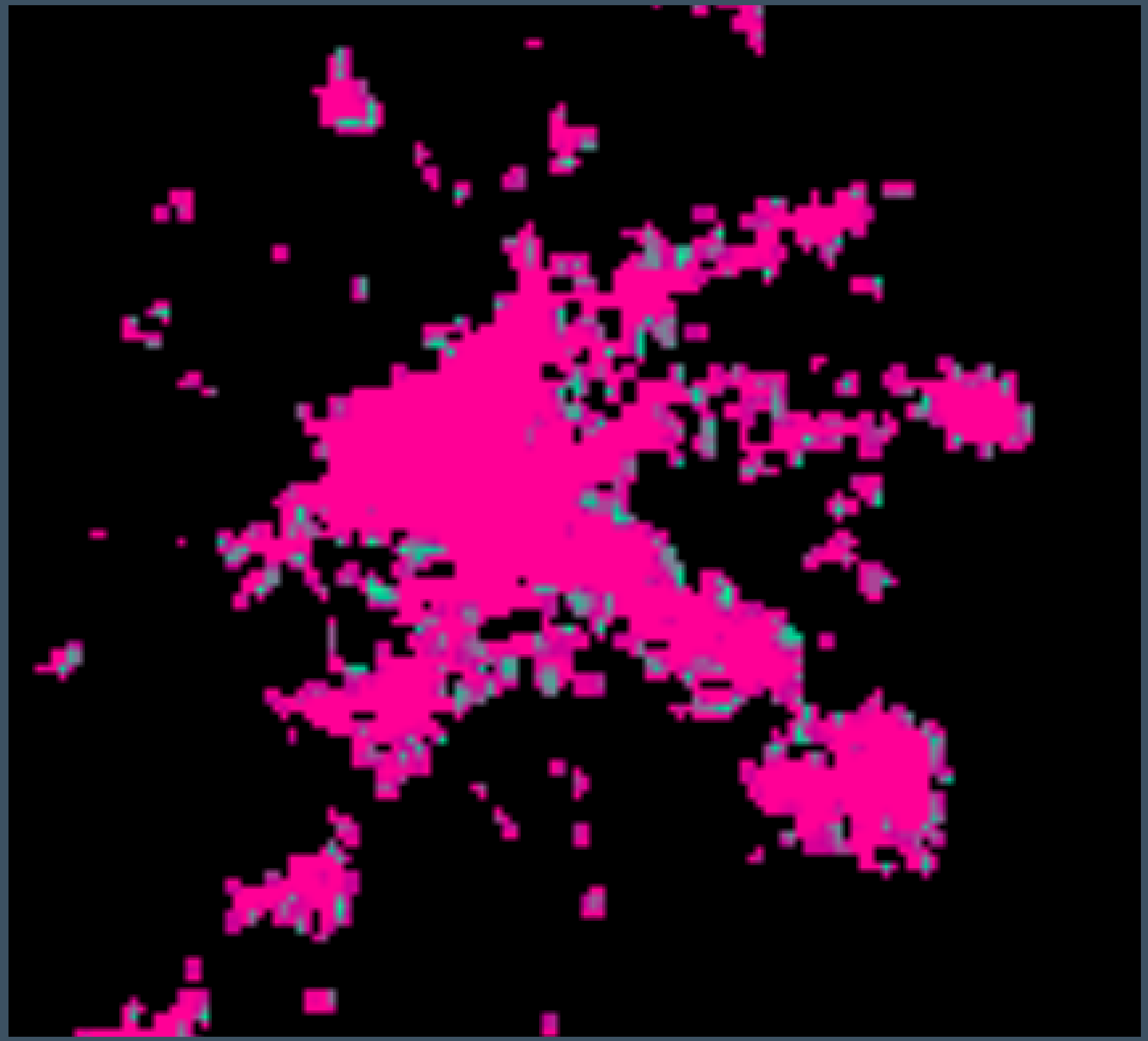
OUTPUTS


Nightlights Growth Frequency Map (2014–2032)
Years Lit (out of 19)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

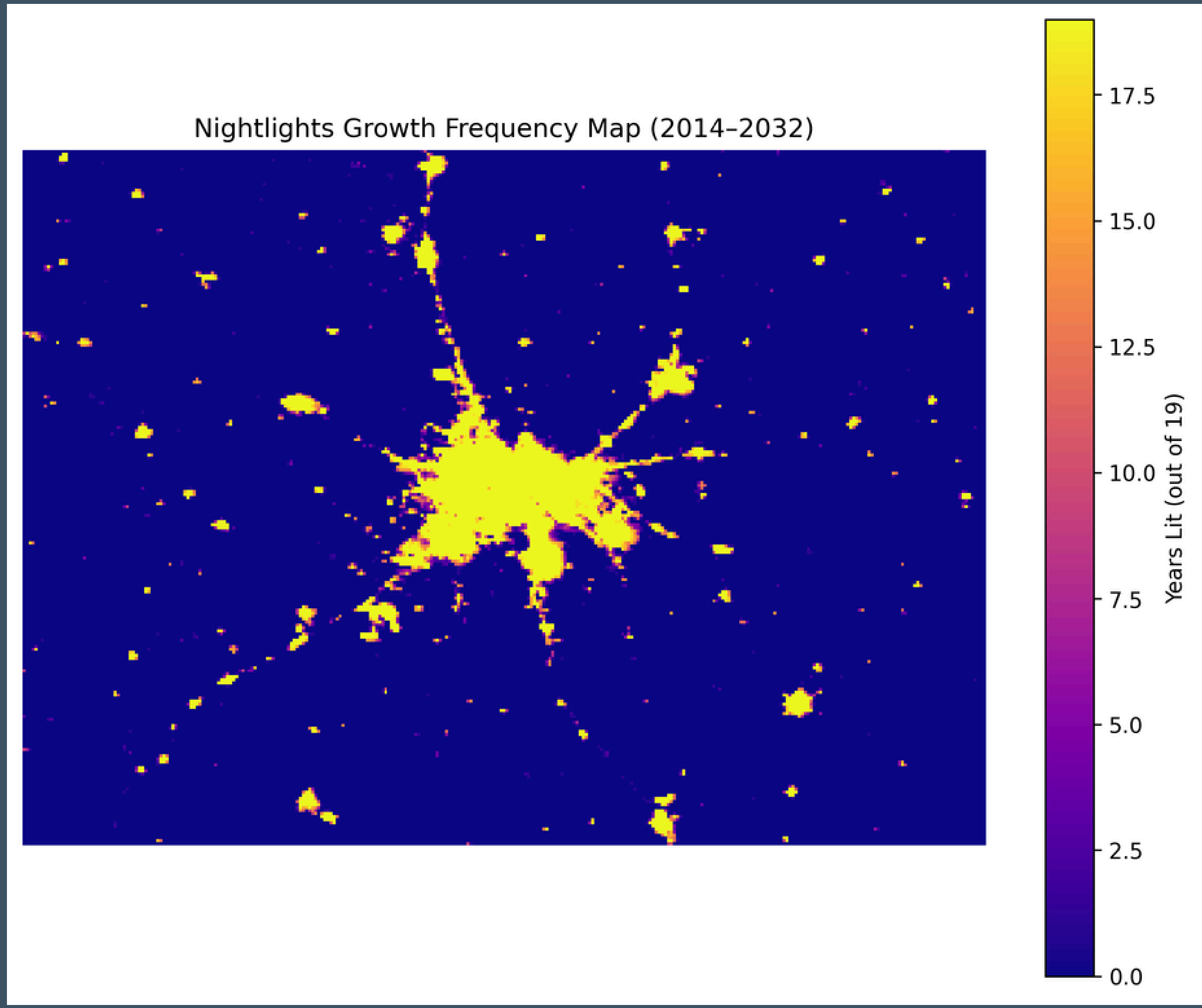

Nighttime Lights Onset Map
Year of First Illumination
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19

OUTPUTS





OUTPUTS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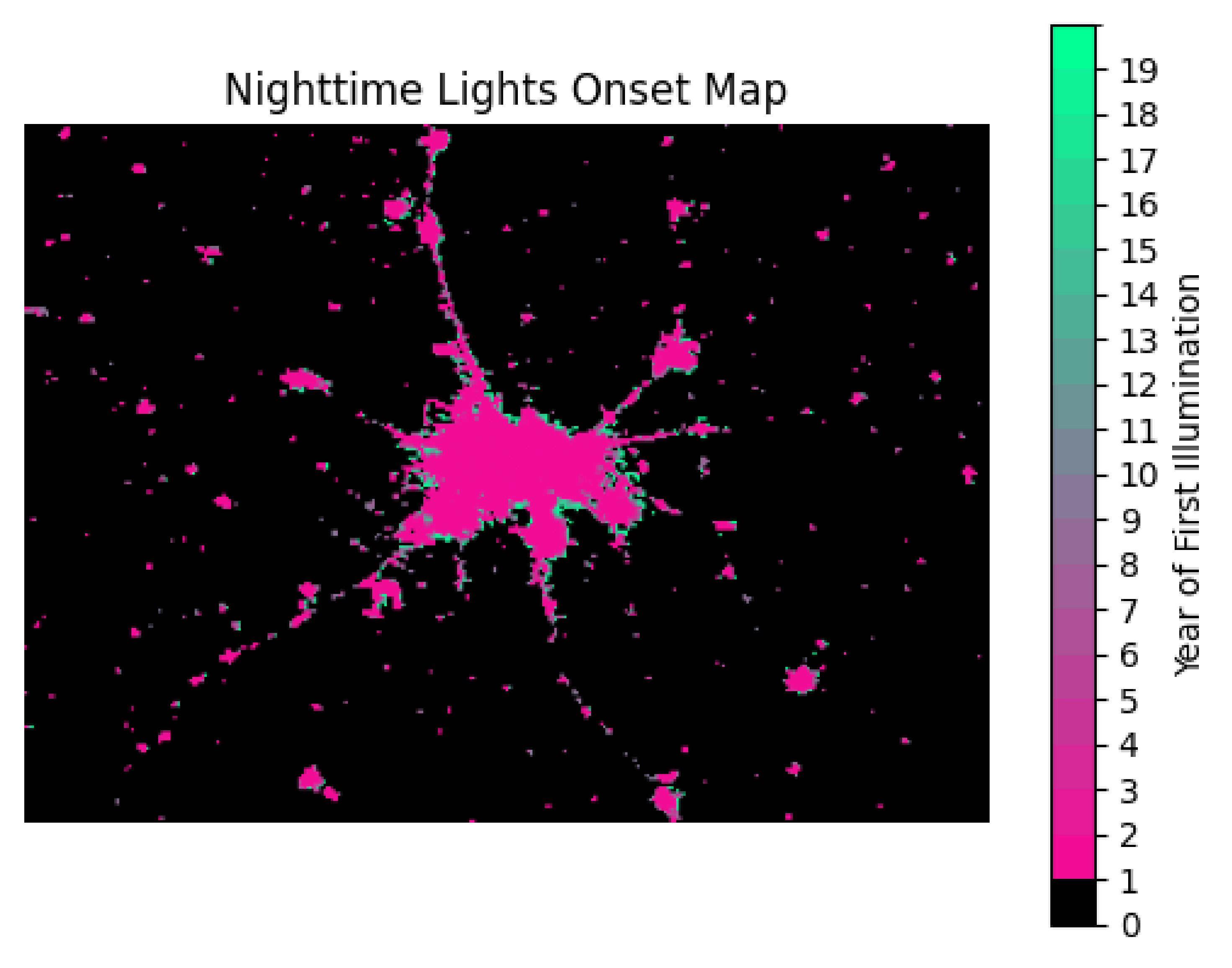
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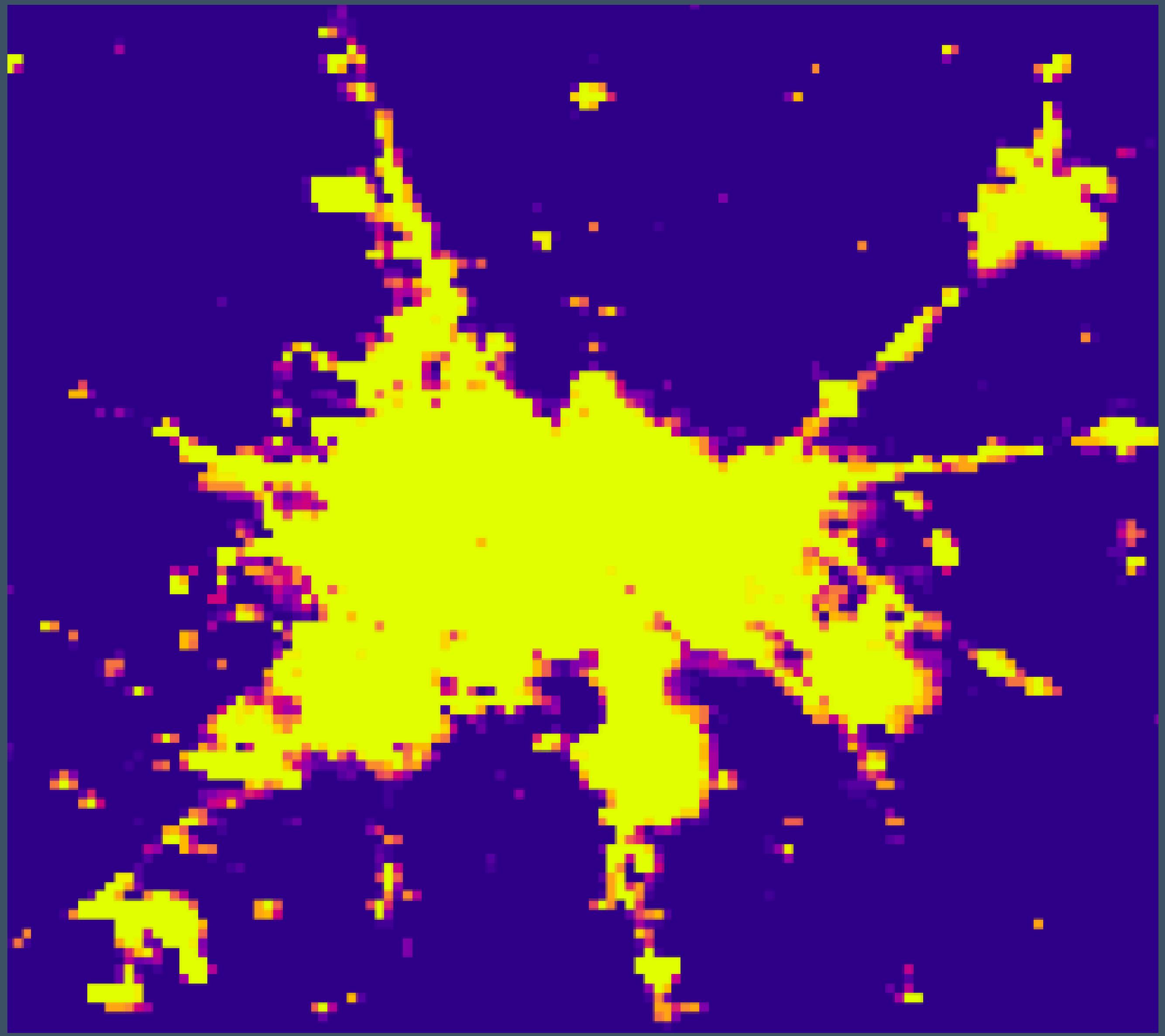
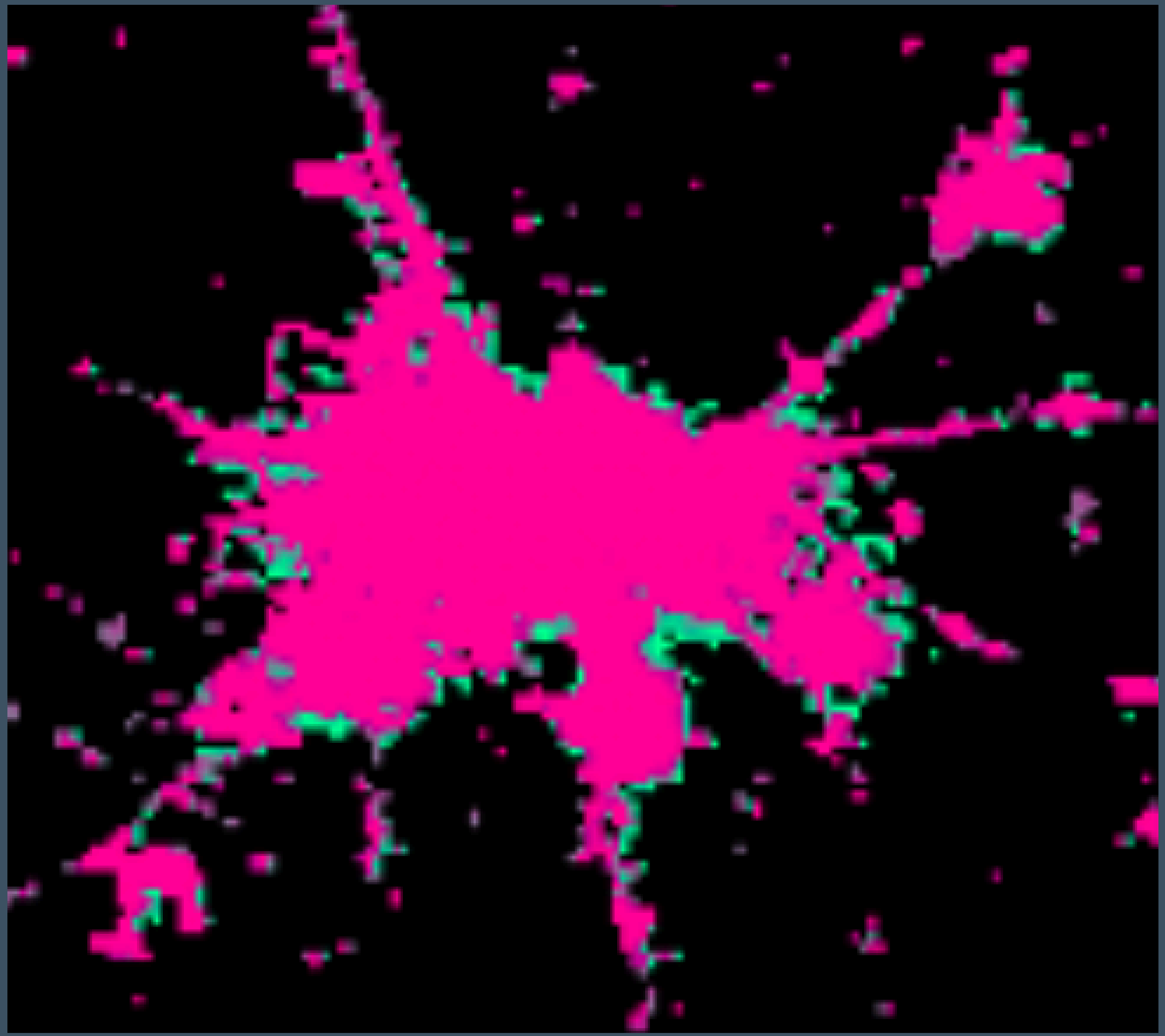
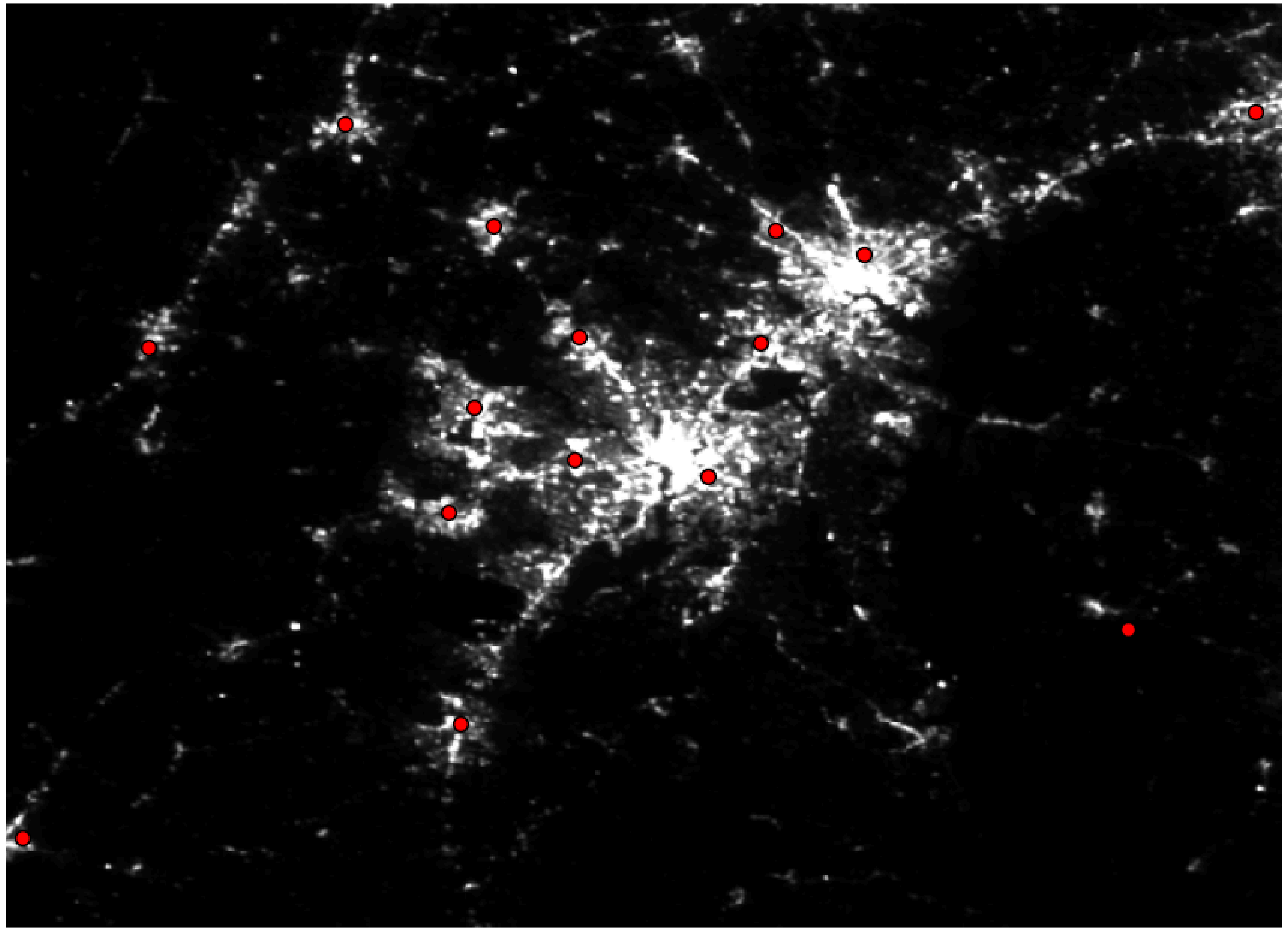
OUTPUTS





IDEAL LOCATIONS

Suggested Power Grid Locations



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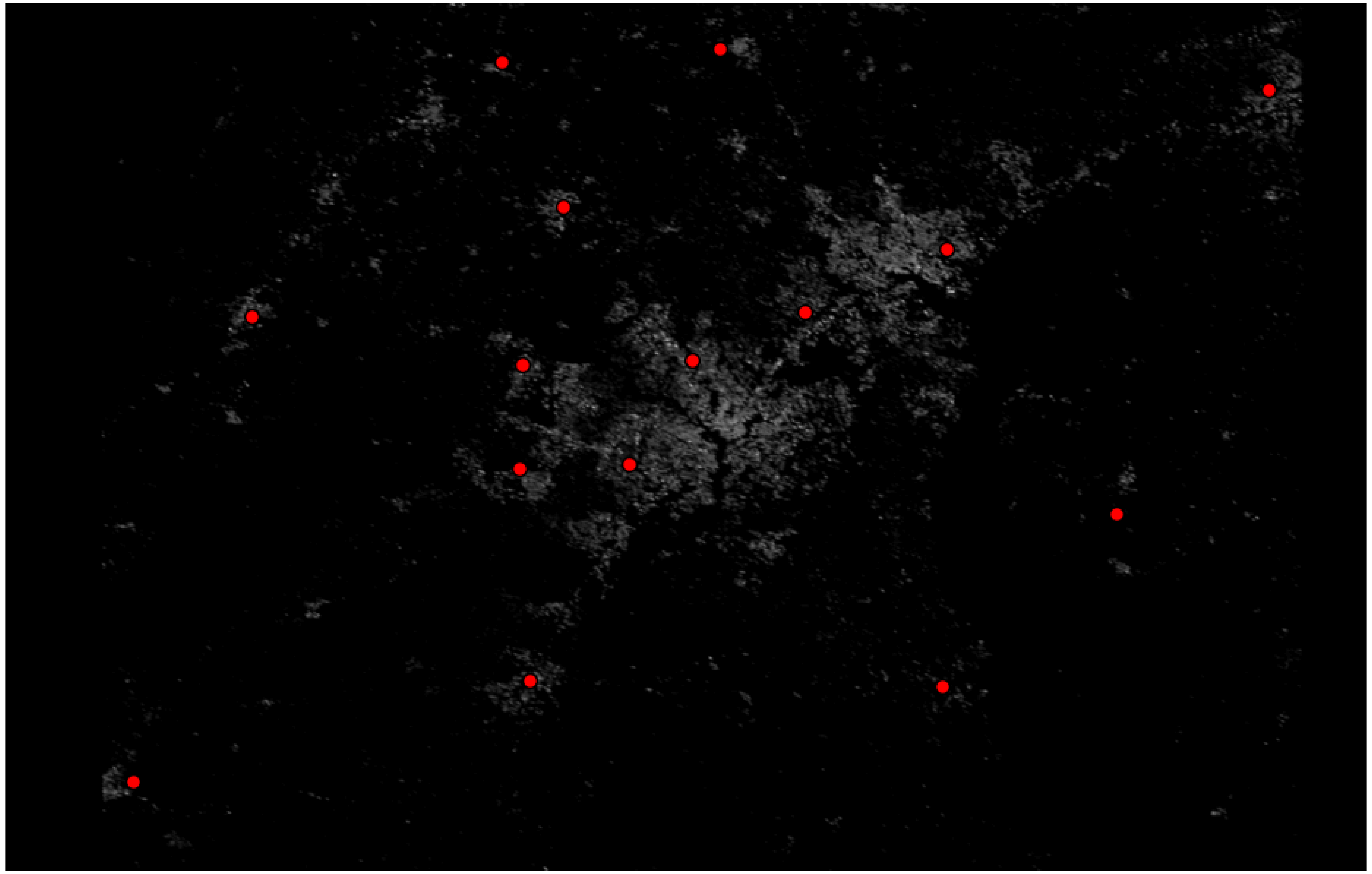
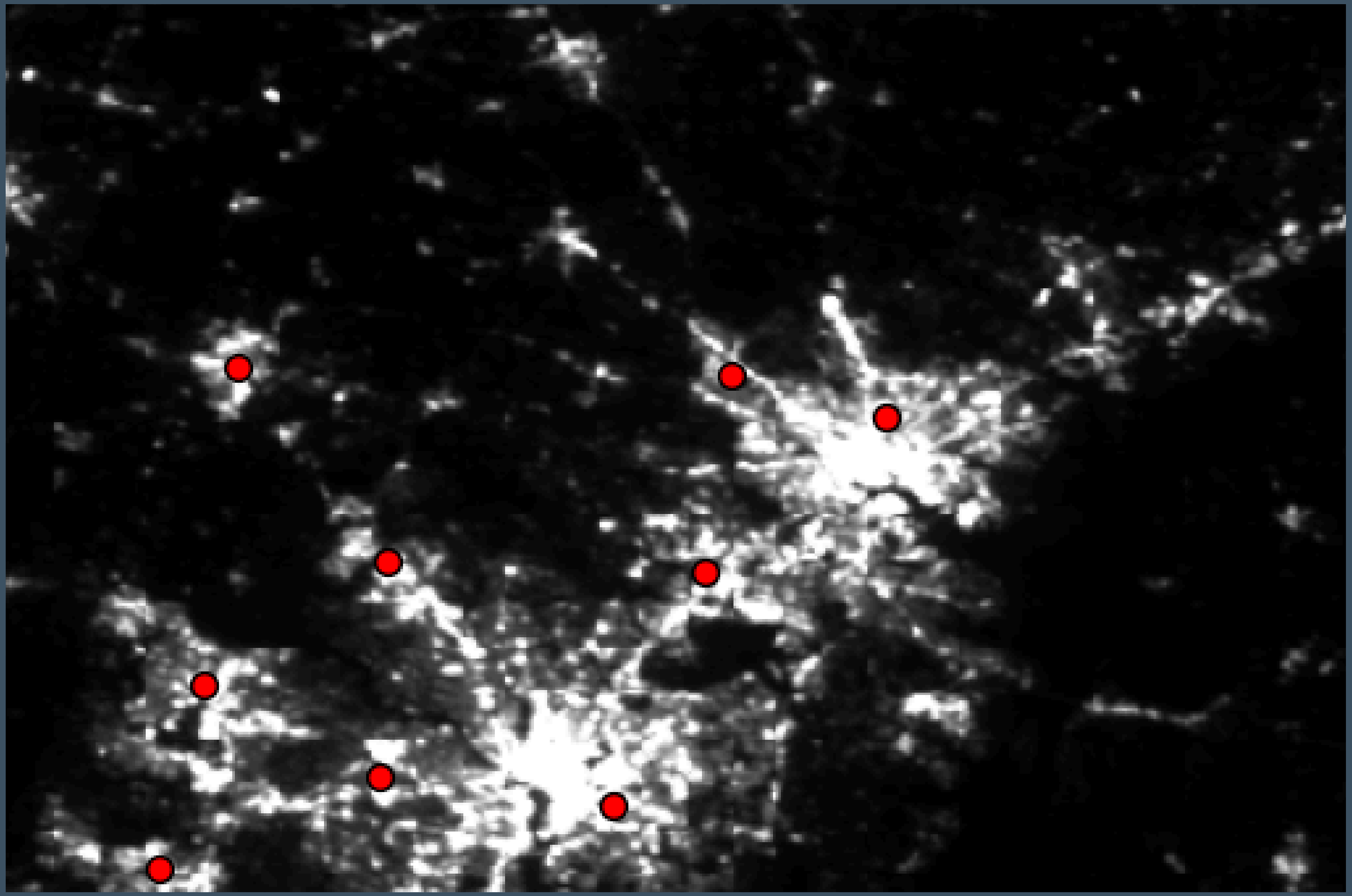
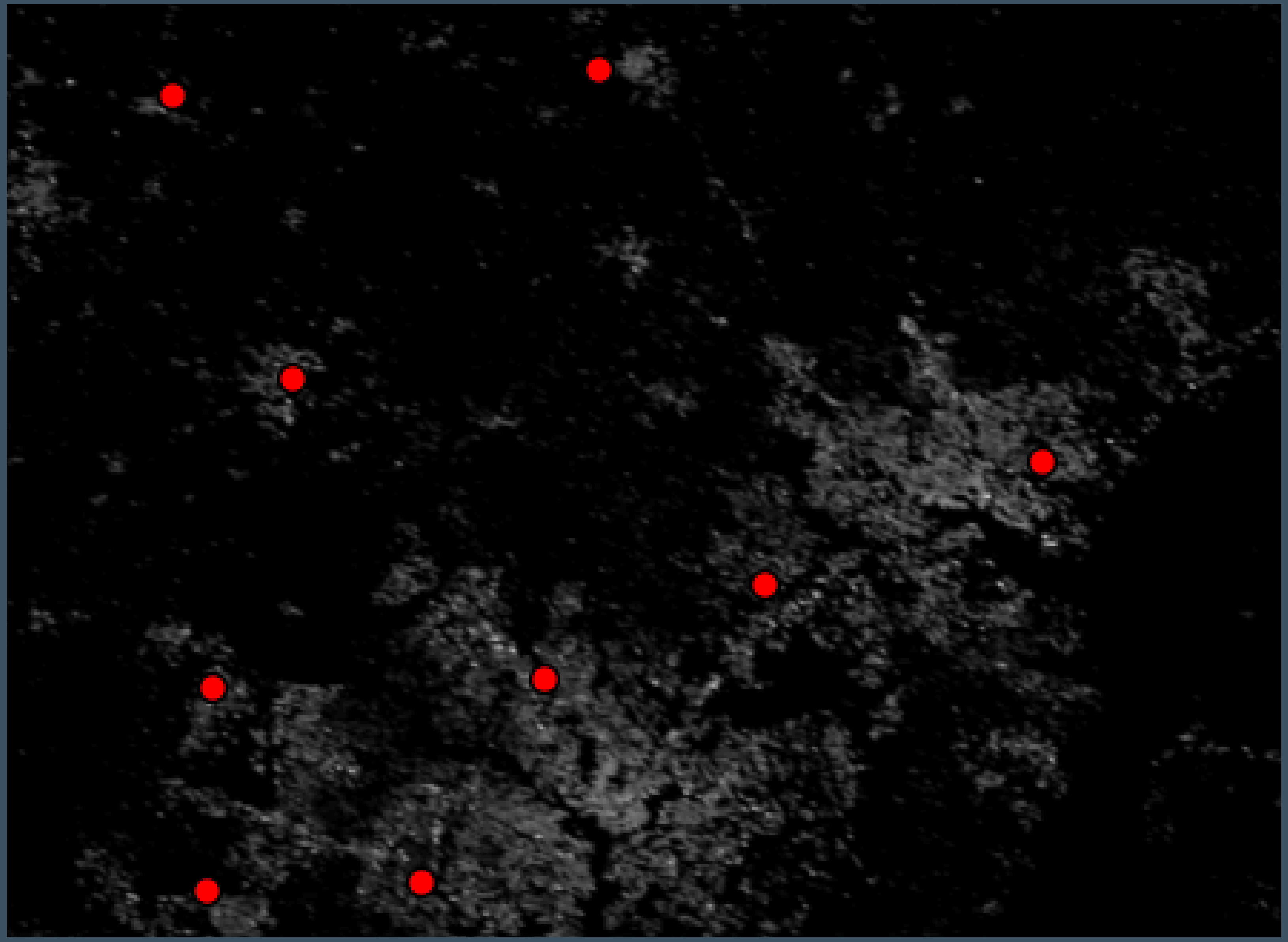


IDEAL LOCATIONS





WHY DIFFERENT ?

- Night lights reflect usage (active regions), whereas GHSL reflects existence (built-up areas).
- High building density may not emit strong light (e.g., slums, abandoned areas), and bright areas may have low permanent structures (e.g., markets, temporary stalls).

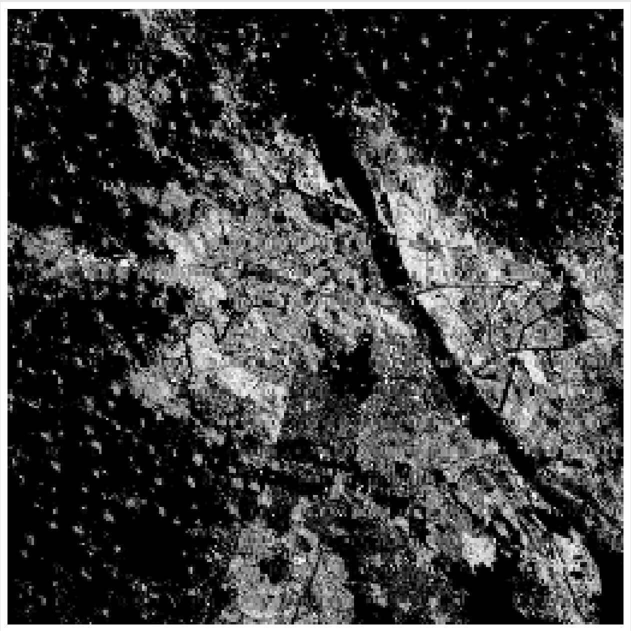
Factor	Night Lights (NTL)	GHSL (Building Density)
Measurement	Light intensity at night	Physical presence of buildings
Sensitivity	Human activity, economic activity, electricity usage	Urban development, infrastructure
Temporal Variability	High (changes yearly)	Low (updated every few years)

Comparison of Ideal Power Grid Locations Using Night Lights vs GHSL Data

- Land Use Type Mismatch
  - Some areas with high night light intensity may be commercial or industrial zones with fewer residential buildings.
  - GHSL would underestimate such zones.
- Temporal Mismatch
  - NTL data may be recent (e.g., 2023), while GHSL data may lag (e.g., from 2018), leading to outdated building density.
- Vertical Density Not Captured
  - GHSL mostly reflects horizontal spread; multi-story buildings may appear low-density.
  - Night lights capture actual usage more effectively.
- Data Quality and Resolution
  - NTL may be affected by:
    - Cloud cover
    - Sensor saturation in bright areas (e.g., city centers)
  - GHSL may miss small structures or informal settlements.
- Power Usage Patterns
  - Night lights correlate with electricity usage, which is a better proxy for power demand than just buildings.

HOW DID WE GET THAT ?

GHSL: Global built-up surface 1975-2030 (P2023A)



Dataset Availability

1975-01-01T00:00:00Z–2030-12-31T00:00:00Z

Dataset Provider

EC JRC

Earth Engine Snippet

`ee.ImageCollection("JRC/GHSL/P2023A/GHS_BUILT_S")`

Tags

built · built-environment · builtup · copernicus · ghsl · jrc · landcover · landsat-derived · population · sdg · sentinel2-derived · settlement · urban

Description | Bands | Terms of Use | Citations | DOIs

Pixel Size

100 meters

Bands

Name	Units	Description
`built_surface`	m^2	Built-up surface per grid cell
`built_surface_nres`	m^2	Non-residential built-up surface per grid cell

IDEAL LOCATIONS ?

- we have used four methods for finding ideal locations. each of the methods considers the following :
  - light intensities only
  - temporal aspect of light intensity
  - LULC combined light intensity (for now we only considering the land in use and land not in use).
  - ghsl building density.

LIGHT INTENSITIES

- Histogram Plot
  - We plots a histogram showing how bright each pixel is. This helps decide what pixel intensity should be considered "bright".
- Select Bright Pixels (Top 10%)
  - It uses the 90th percentile of pixel brightness to extract only the brightest pixels — these likely represent areas of high activity.
- use KMeans to group these bright pixels into NUM_GRIDS = 15 clusters. Each cluster center becomes a suggested location for a power grid, ensuring a minimum distance of 50 km between grids.

LIGHT INTENSITIES

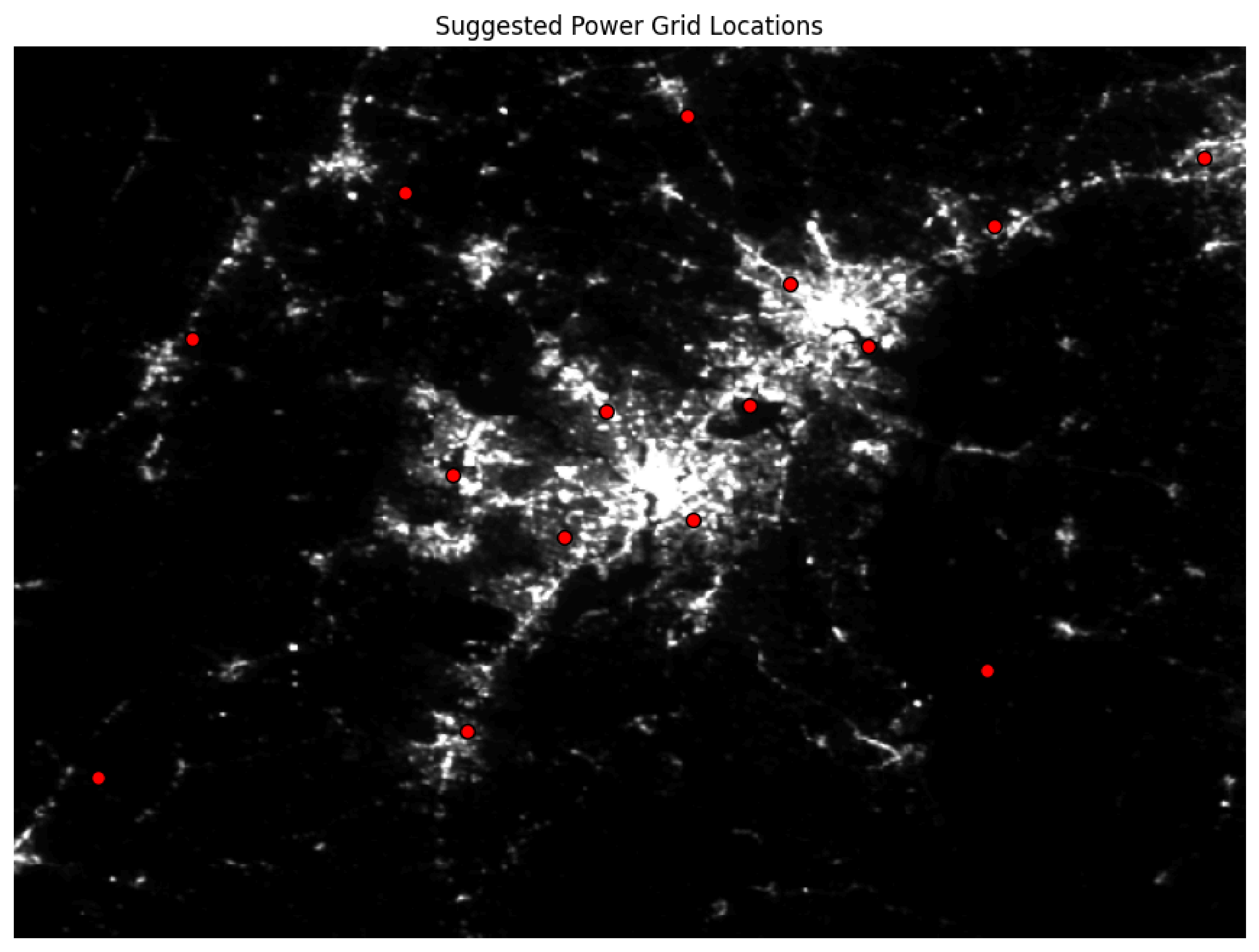
```python
# ========== PARAMETERS ==========
NUM_GRIDS = 15                          # Number of power grids to be placed
MIN_DISTANCE_KM = 50                    # Minimum distance between two grids (in km)
INTENSITY_THRESHOLD = 200               # Brightness threshold to select pixels
# IMAGE_PATH = "./Png_Files/NTL/NightLights_2020.png"
IMAGE_PATH = "./Batch_Loads/Png/NTL_01/NTL_2022.png"

# Coordinates of the image corners (top-left, bottom-left, bottom-right, top-right)
COORDINATES = [
    [-79.6104828125, 42.1057705066091],
    [-79.6104828125, 36.588415552450094],
    [-71.0850921875, 36.588415552450094],
    [-71.0850921875, 42.1057705066091]
]

# ========== GEO MAPPING ==========
lat_top = COORDINATES[0][1]
lat_bottom = COORDINATES[1][1]
lon_left = COORDINATES[0][0]
lon_right = COORDINATES[2][0]
```

TEMPORAL ASPECT

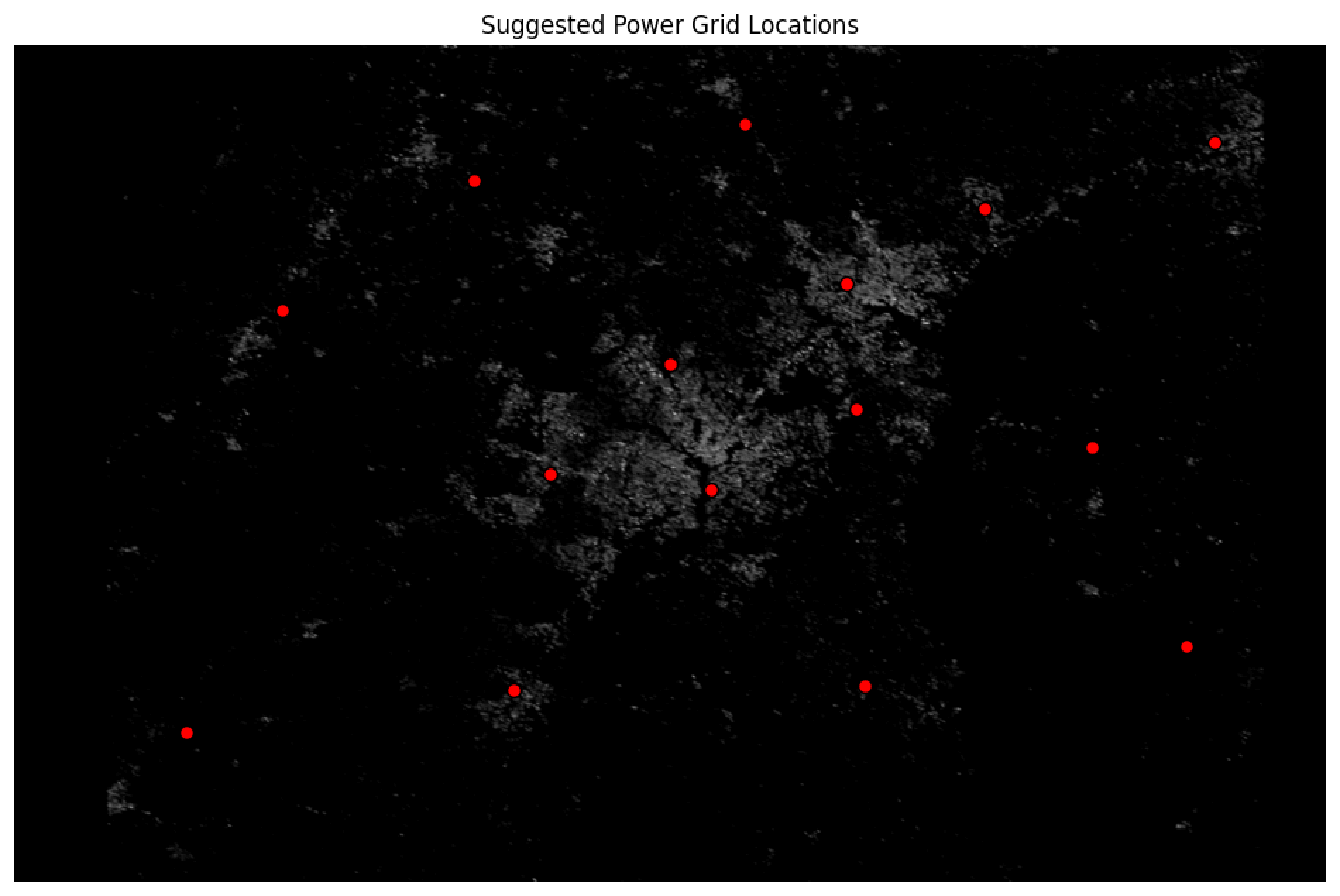
- Load Multiple Yearly Nightlight Images
  - All PNG files from a folder are read and converted to grayscale.
  - Shape: (years, height, width) → a cube of images over time.
- Aggregate Brightness
  - Averages brightness for each pixel over all years → smooths out noise (e.g. seasonal changes, one-time events).
  - we can use other methods too such as weighted averages, median, etc.
- Histogram of Average Brightness
  - Shows distribution of averaged brightness, helps pick a brightness threshold.
- Clustering

LULC INTEGRATED

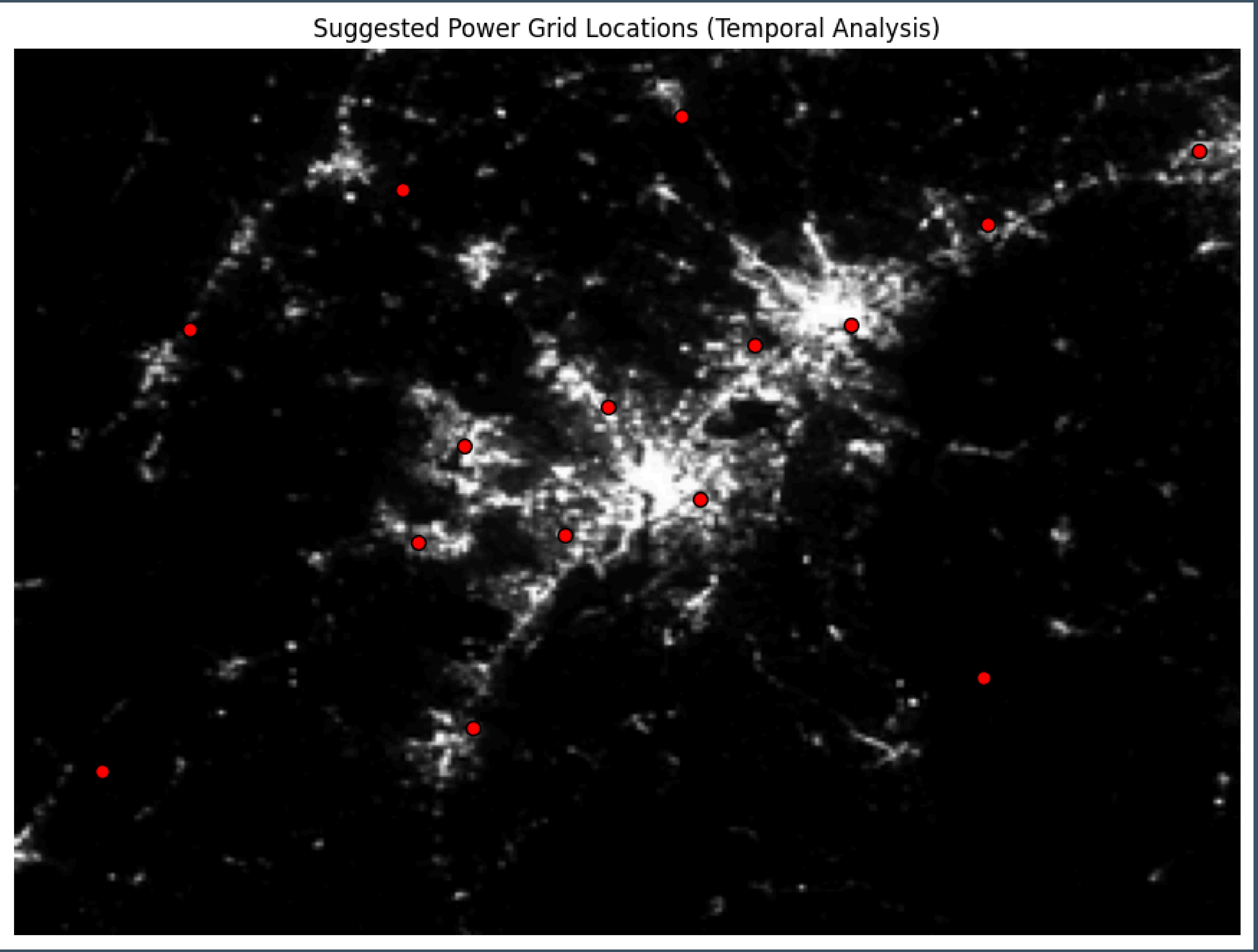
- Load Two Images
  - NTL Image: Shows brightness at night (indicates electricity use).
  - LULC Mask Image: Binary image (white = valid land, black = not valid for grid).
  - Both must be the same size.
- Plot Brightness Histogram
- Cluster Bright Pixels (Only considers bright and land-appropriate regions for grids.)
- Enforce Real-World Distance
- in future we can integrate other layers / bands and provide suggestions such as renewable energy, type of grid etc.



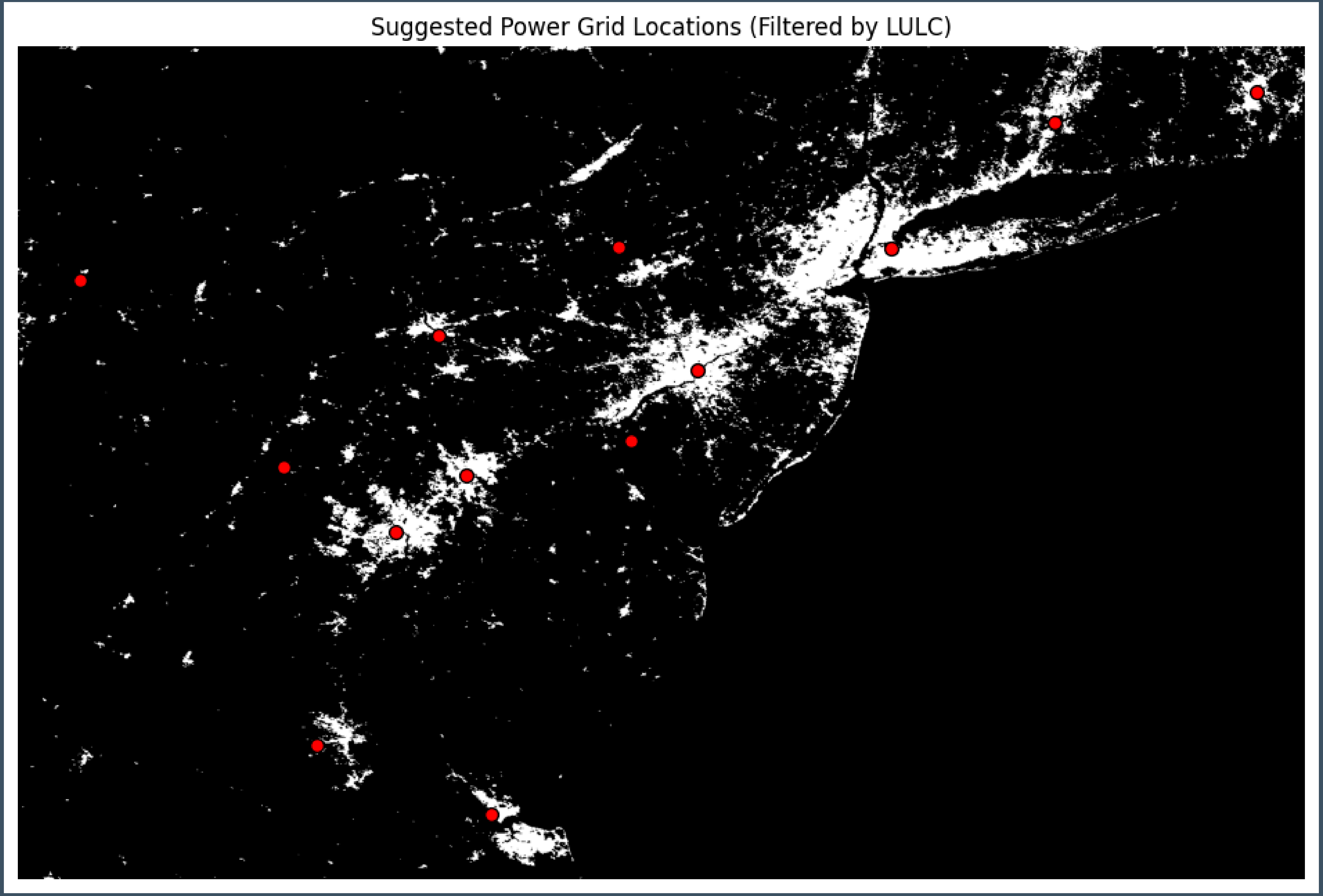
considering light intensities



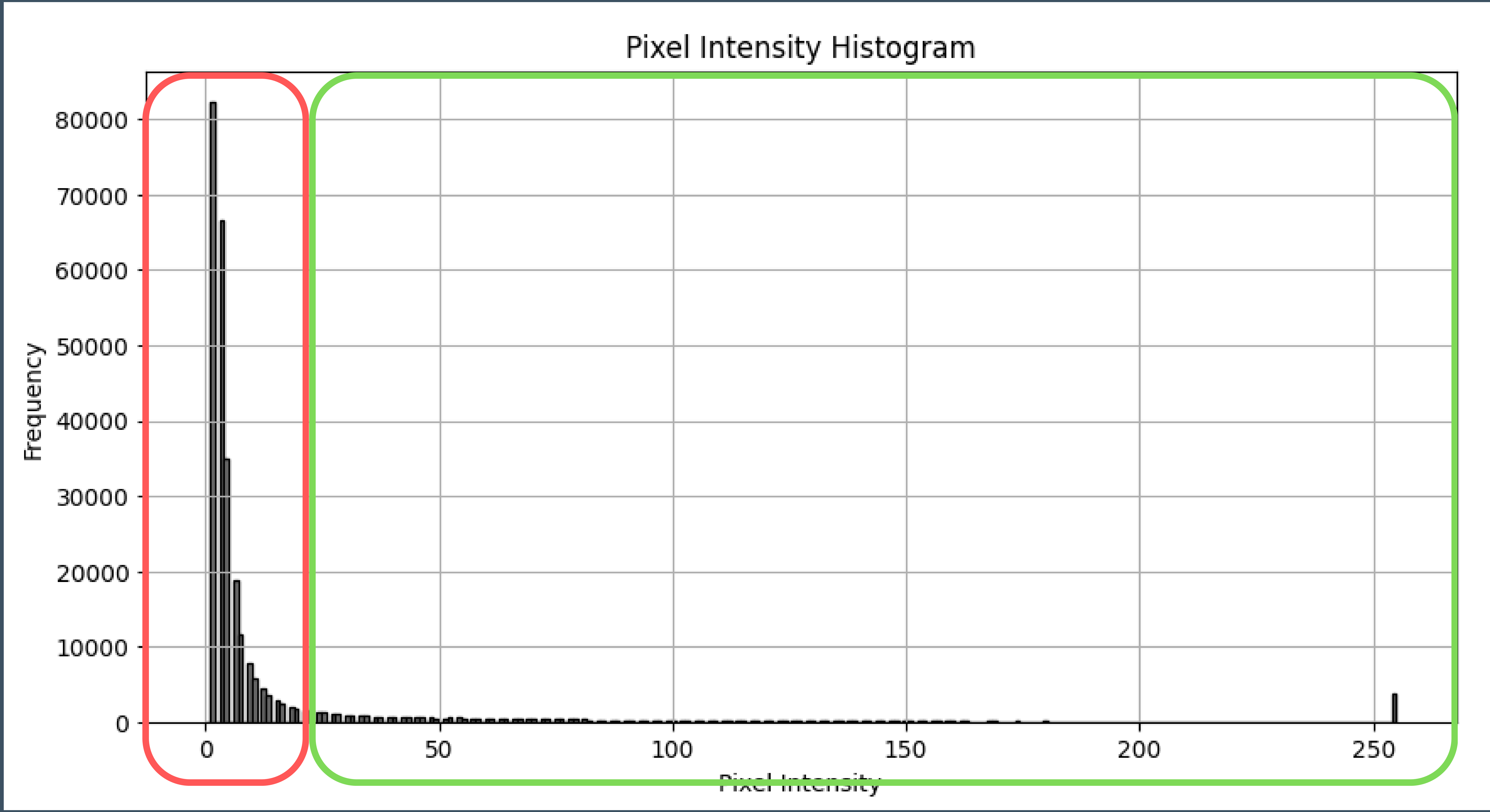
considering GHSL



considering temporal aspect



considering LULC layer

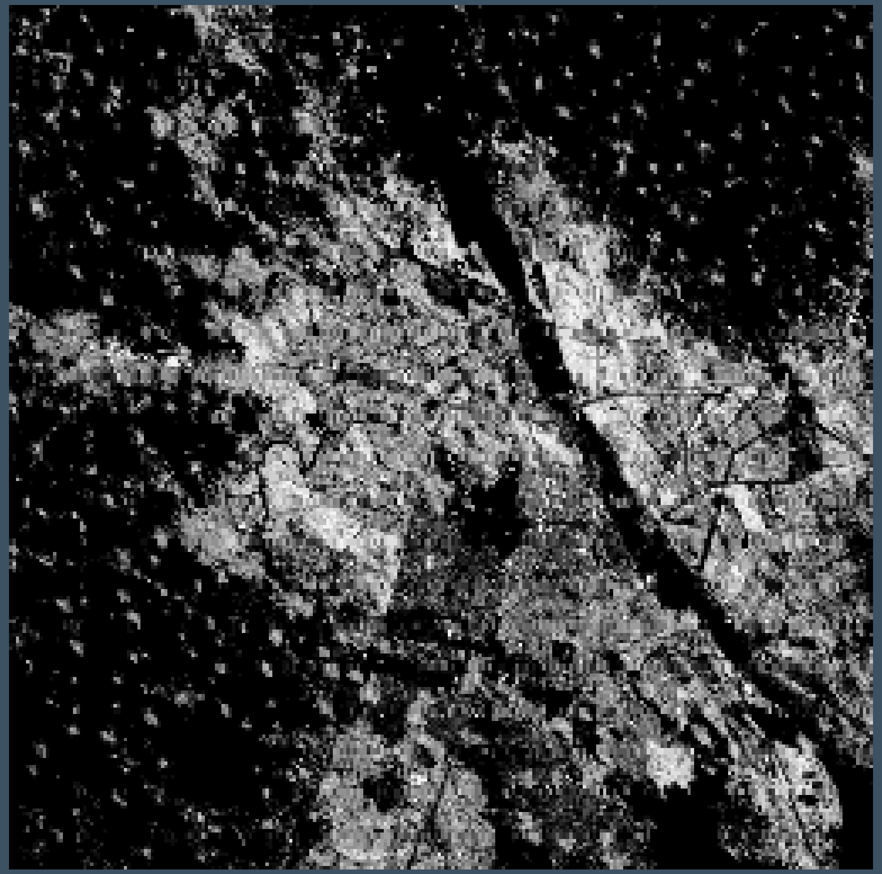


frequency plots

CHALLENGES

CHALLENGES

- We first tried to evaluate our results with the help of OSM data.
- OSM provides polygons with tags such as buildings, industry, home etc.
- but its very high resolution. and our night lights covers nearly 25K sqkm.
- so when we tried to download it, it came out to be 10GB files. and we were not able to process it. thus we used GHSL.



FUTURE WORKS

- we build this project as a prototype version / base version so that others can develop this further.
- we can develop further with integrating other layers for suggesting the renewable resources.
- we have considered less data for training the model. we can train it with multiple places too for better results.
- if we had availability with the smart power grid data, we can analyse our results accurately and we can integrate that data into this project.
- we have defined preprocessing files so, it will be easy for the user to work on huge variable data in future.
- we can work on few general problems of smart grid such as fault detection, demand consumption, integration of renewable energy resources.

Thank You