WHERE ARE MOBILE HOME PARKS?

AI-Driven Detection and Mapping of
Manufactured Housing Communities

NORTH CENTRAL REGIONAL CENTER
FOR RURAL DEVELOPMENT

PURDUE
UNIVERSITY

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EDUCATION

- **Doctor of Philosophy in Environmental Design and Planning,** Virginia Tech
  - Advisor: Dr. Andrew McCoy
  - Dissertation Title: Pathways to Sustainable Housing
  - Future Professoriate Certificate, Virginia Tech
- **Master of Building Construction Science and Management,** Virginia Tech
- **Master of Urban and Regional Planning,** Virginia Tech
- **Master of Architectural Engineering,** Iran University of Science and Technology
- **Bachelor of Architectural Engineering,** Tabriz University

TEACHING

CMP 315 Construction Quantity Surveying (Core Undergraduate)

- Create construction project cost estimates
- Analyze construction documents
- Apply electronic-based technology
- Analyze professional decisions based on ethical principles

TEACHING

CMP 891 Data Analytics & Emerging Technologies in Real Estate (Spring Semesters)

- Elective Graduate Course
- Use a data programming language, R or Python
- Program data and create statistical summaries
- Produce and communicate statistical results
- Perform hypothesis tests and regression models
- Apply non-linear statistical methods
- Draw inferences using statistical theory

RESEARCH

Housing, Sustainability, Technology

- Questions on innovative practices and policies that advance construction management, sustainable housing, and real estate development.
- Employing empirical, quantitative research methods to explore the intersection of economic development, environmental protection, and societal equity.

RESEARCH METHODS

- Multivariate Regression Analysis
- Machine Learning and Deep Learning
- Image Processing
- Cost-benefit Analysis (ROI, IRR)
- Monte-Carlo Simulation (Risk and uncertainty analysis)

INTRODUCTION

- Mobile Home Communities (MHCs) are the largest source of unsubsidized, affordable housing in the United States, comprising ~ 6.2% of the American housing stock.

- However, there is limited literature on mobile home parks and there is no systematically collected dataset on the count, footprint, or location of MHCs.

IMPORTANCE

- MHCs provide an affordable housing solution, encouraging individuals to move to rural areas for job prospects, thereby contributing to the local economy.
- Well-managed MHCs can create stable and cohesive communities, leading to community engagement and initiatives aimed at local improvement.

PROPOSED PROJECT

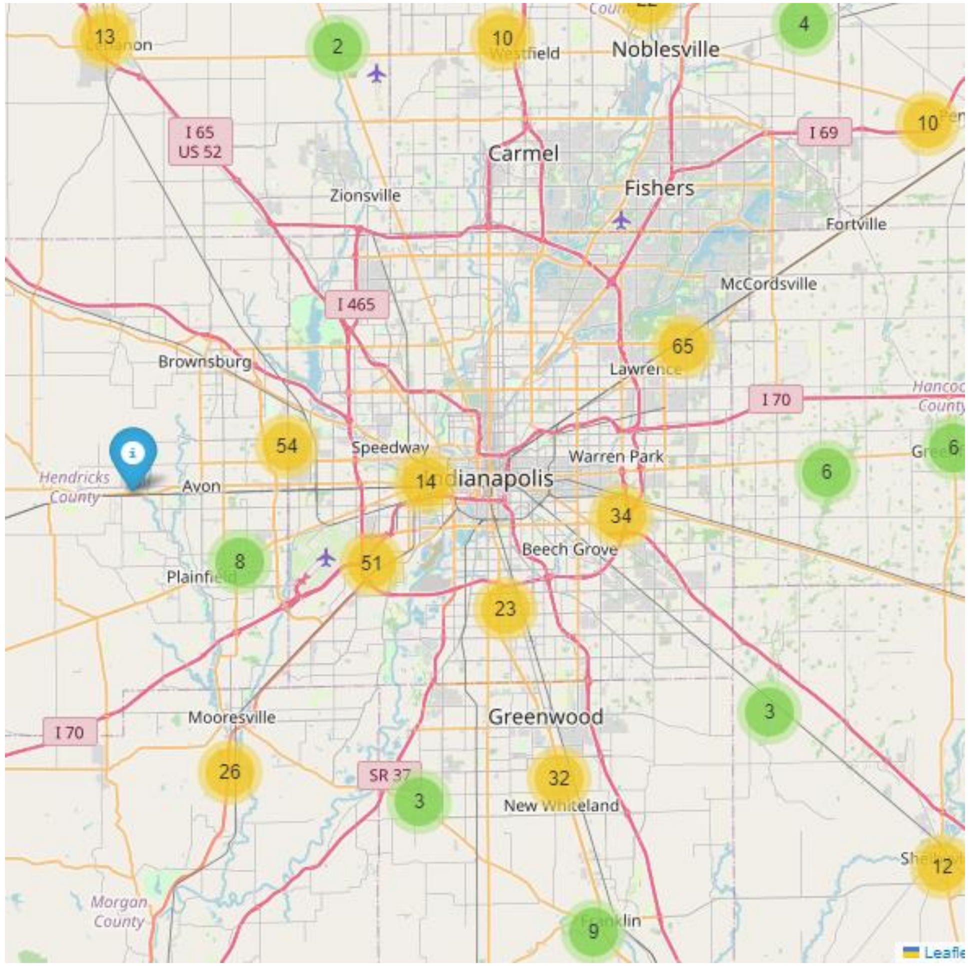
- This project aims to create:
  - The most comprehensive source of MHCs data and shapefiles of the North Central Region.
  - The first automatically created MHCs dataset and mapping in the US, which can be automatically updated for longitudinal analyses with minimal human involvement.

POTENTIAL USERS

- Developers and investors could use the project results to identify locations for new communities and real estate investment.

- Governments, planners, and researchers could use this project for urban planning and zoning decisions and analysis.

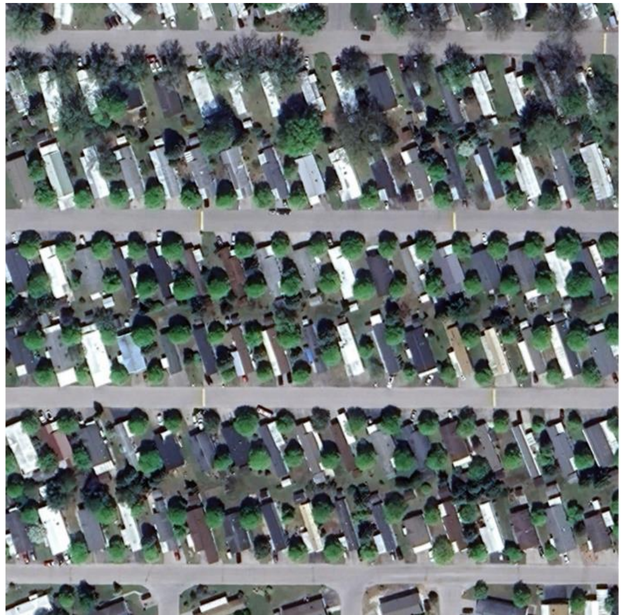
- Environmental organizations, insurance companies, realtors and brokers could use this dataset to obtain insight.



NEIGHBORHOOD TYPOLOGY

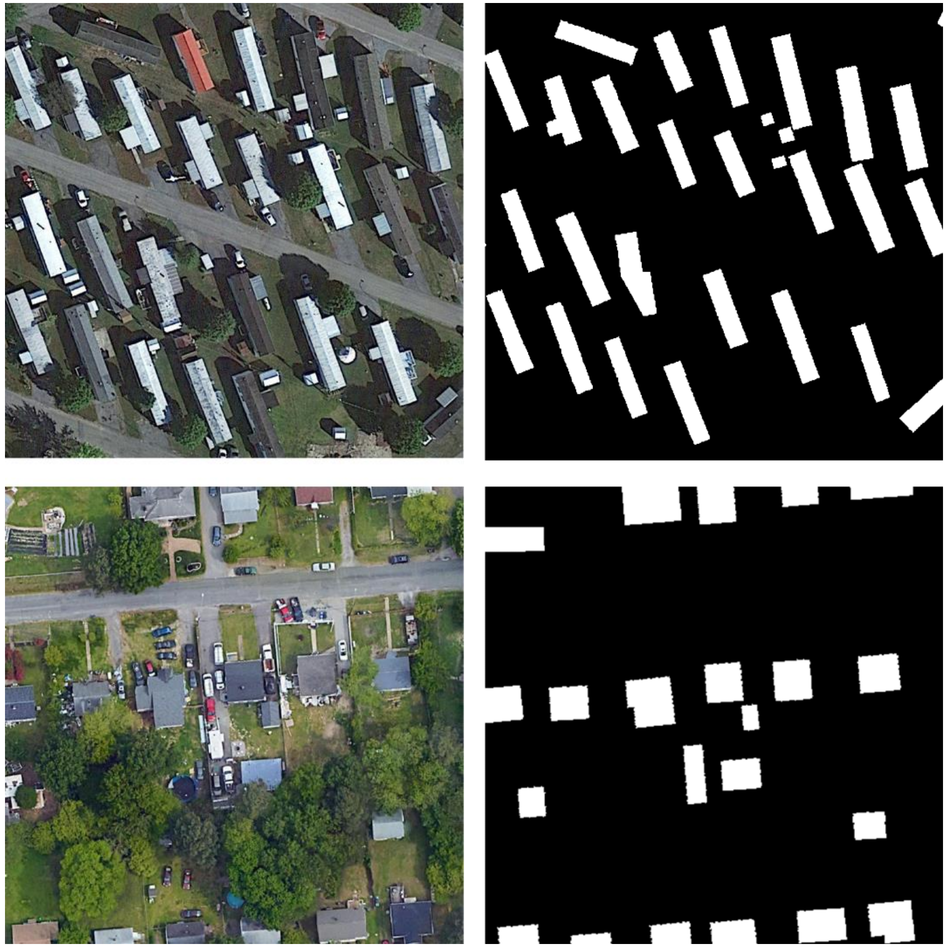
- Formal subdivisions
- Informal subdivisions
- Single-wide MHCs
- Double-wide MHCs



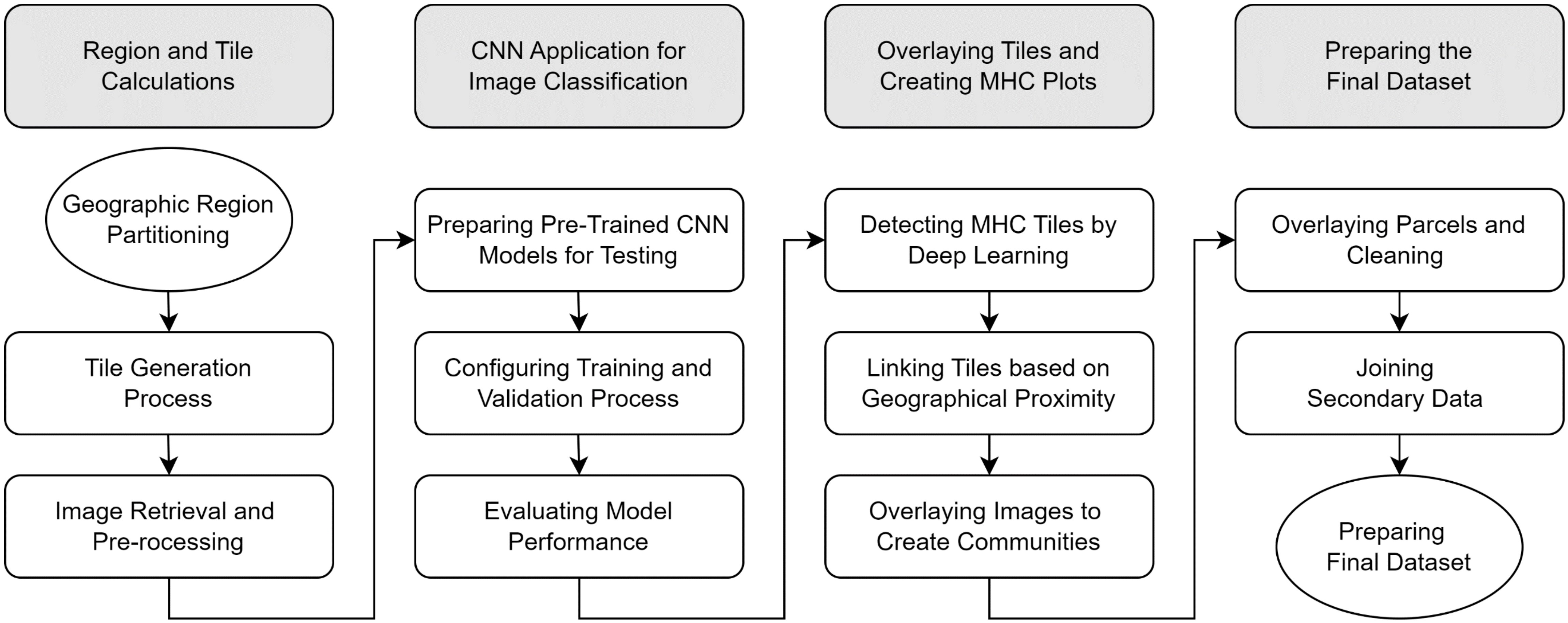



MHC DETECTION & MAPPING

- The NCRCRD has acknowledged the critical need to invest in physical infrastructure as the top priority for the development of rural communities in the next five years.
- This project applies computer vision and satellite imagery as a cost-effective and scalable solution to automated MHC data collection.
- The project output is a publicly available web database and GIS map resource for recording the physical characteristics of mobile/manufactured home communities.

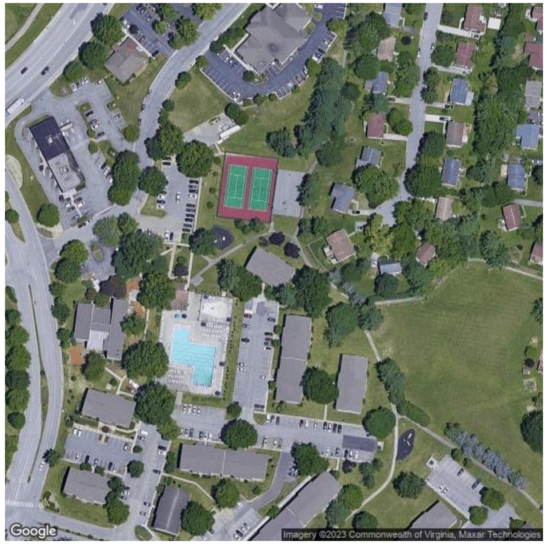


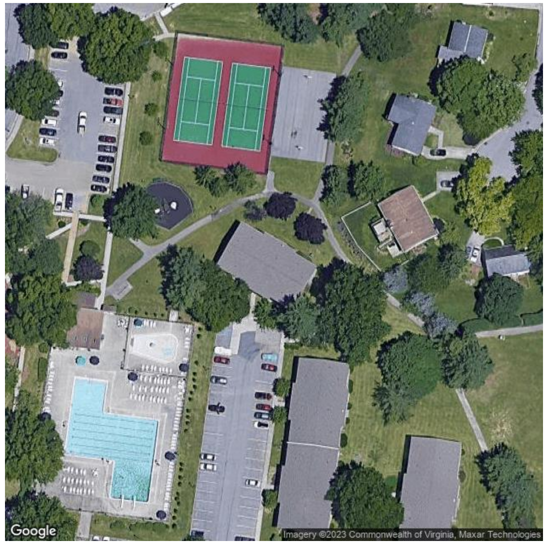
PROCESS



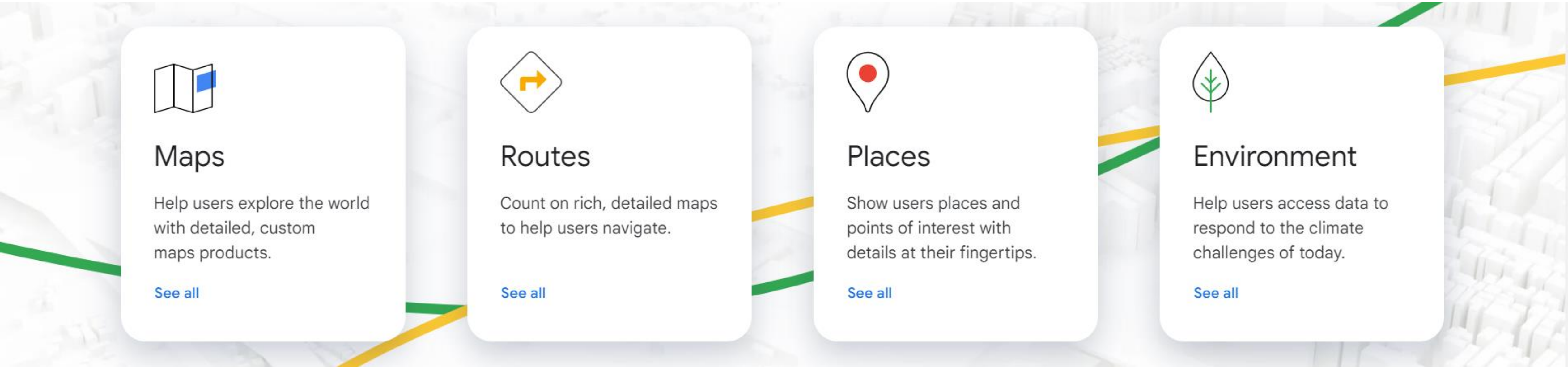
Region and Tile Calculations
Geographic Region Partitioning
Tile Generation Process
Image Retrieval and Pre-rocessing
CNN Application for Image Classification
Preparing Pre-Trained CNN Models for Testing
Configuring Training and Validation Process
Evaluating Model Performance
Overlaying Tiles and Creating MHC Plots
Detecting MHC Tiles by Deep Learning
Linking Tiles based on Geographical Proximity
Overlaying Images to Create Communities
Preparing the Final Dataset
Overlaying Parcels and Cleaning
Joining Secondary Data
Preparing Final Dataset

DATA SOURCE: GOOGLE API





GOOGLE MAPS PLATFORM



DATA SOURCE: leafmap.org

Welcome to leafmap

Open Studio Lab | Open in Colab | launch binder | pypi v0.38.0 | downloads 754k | recipe leafmap
conda-forge v0.38.0 | downloads 184k | docs passing | Linux build passing | pre-commit.ci passed
License MIT | YouTube Channel | JOSS 10.21105/joss.03414

A Python package for geospatial analysis and interactive mapping in a Jupyter environment.

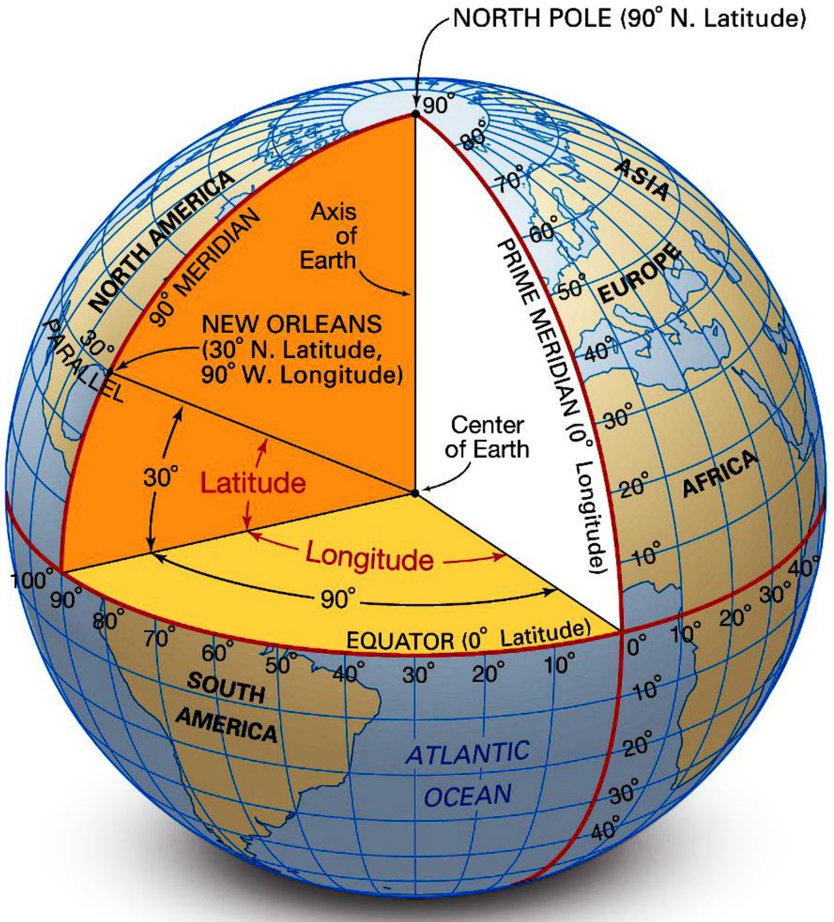
- GitHub repo: https://github.com/opengeos/leafmap

LATITUDE AND LONGITUDE

Geographical coordinate used to specify the location of any point on the Earth's surface.

Latitude is a measurement of location north or south of the Equator, ranging from 0° at the Equator to 90° at the poles (+90° or 90°N for North Pole and -90° or 90°S for South Pole).

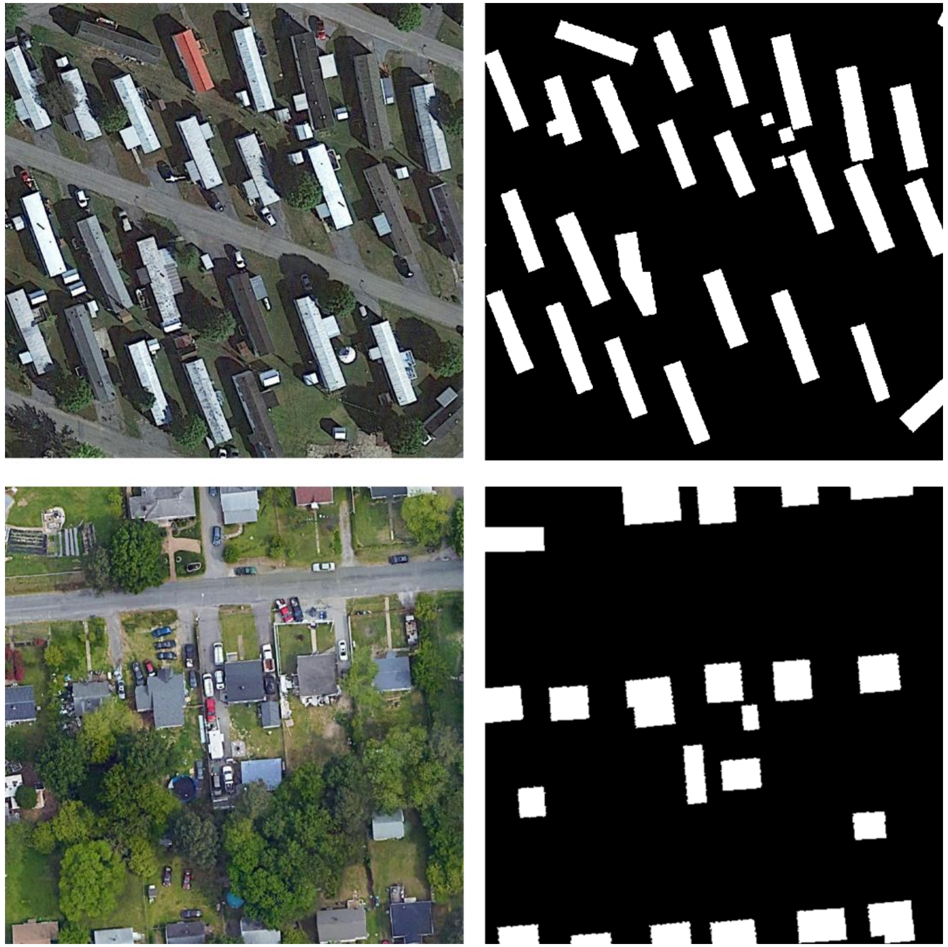
Longitude ranges from 0° at Prime Meridian to -180° or 180°W westward and +180° or 180°E eastward.



UNIT OF ANALYSIS

The chosen fundamental unit of analysis is a tile with a height equivalent to one-thousandth of a degree of latitude.

We calculate the required number of latitude-based tiles within the predefined state bounding box and the dimensions of each tile to obtain square images while considering the distortions introduced by the curvature of the Earth at different latitudes.



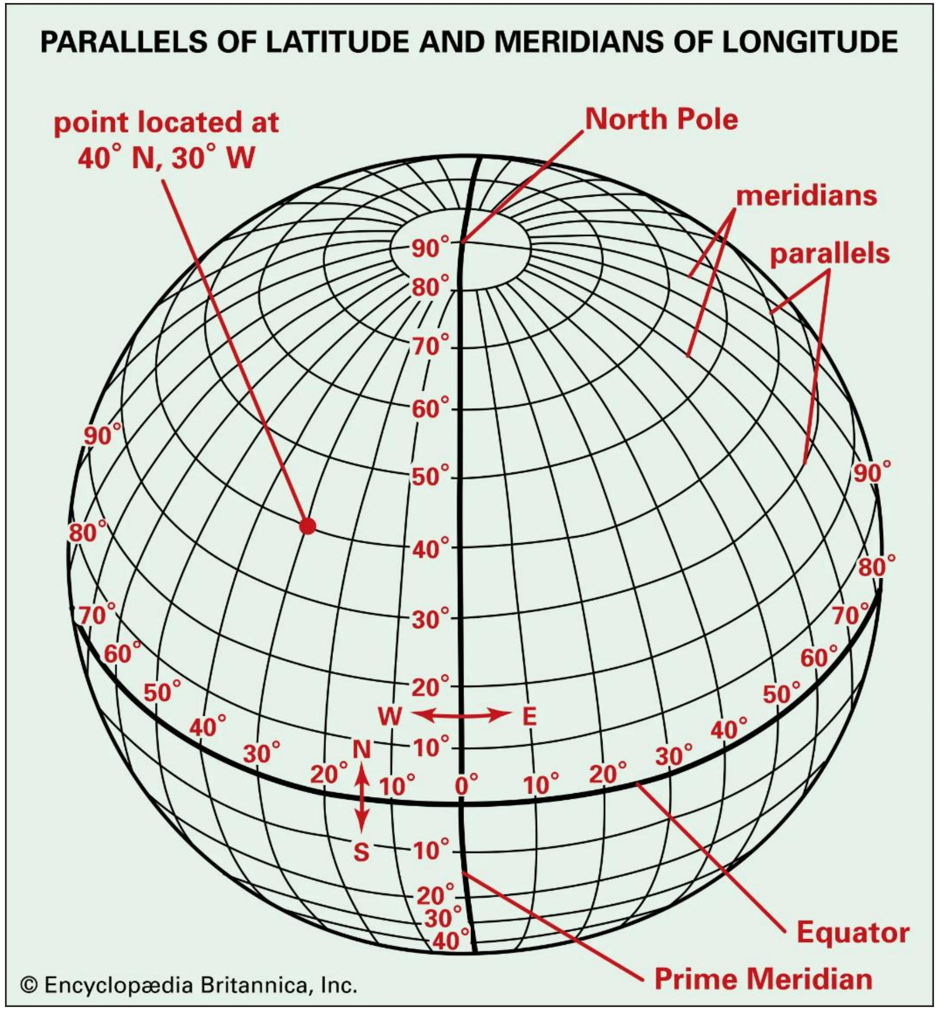
PARTITIONING METHOD

The bounding box data for the geocoded tiles is computed using the following equations. The formula utilizes the cosine function to account for the Earth's curvature, which affects the actual distance covered by one degree of longitude at different latitudes.

(More on this in the papers.)

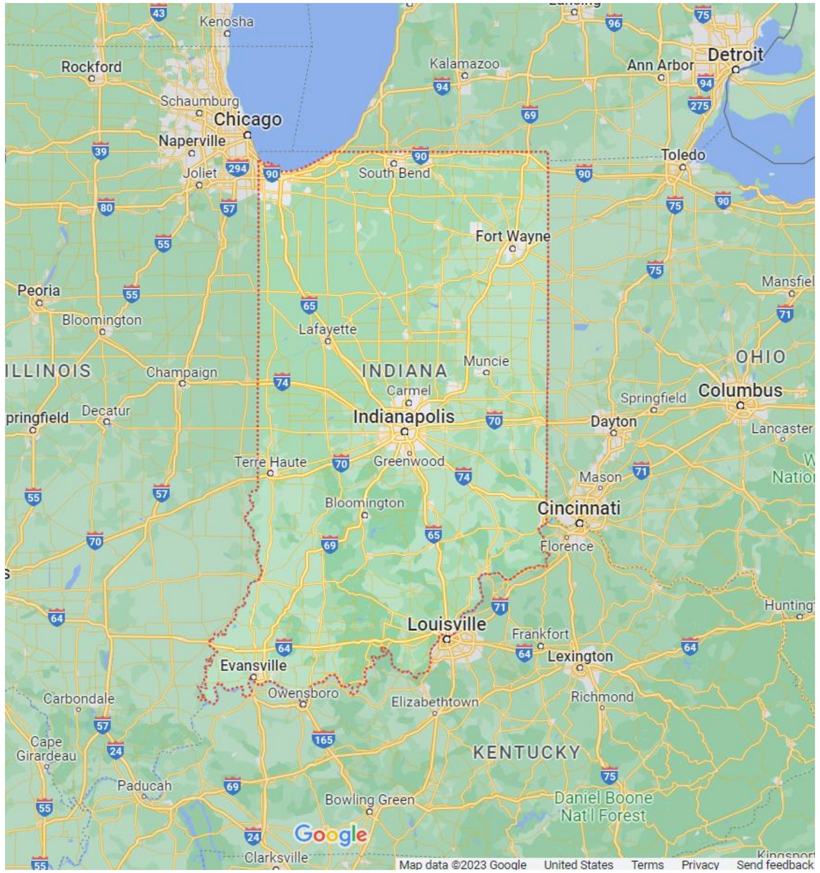
$$W = \frac{H}{\left|\cos\left(\frac{\pi}{180} \times Lat\right)\right|}$$

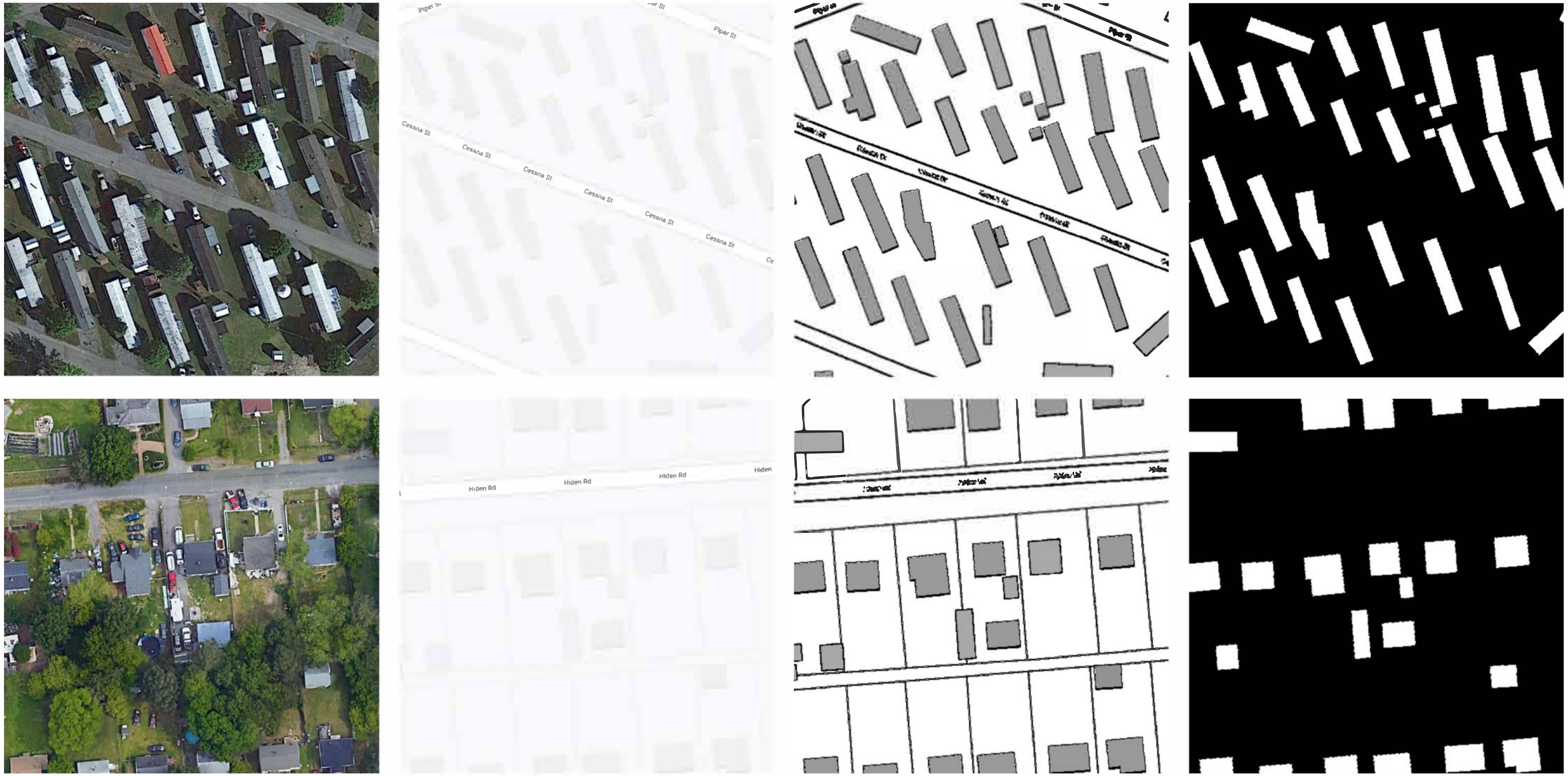
$$N = \frac{B_{IN}[3] - B_{IN}[2]}{\mathrm{W}}$$



DATA COLLECTION BY PARTITIONING

```
[ ] # Define the bounding box coordinates for Indiana
    indiana_bbox = (41.8, 37.7, -87.6, -84.7)

    # Calculate the number of tiles needed
    tile_height = 0.001  # One-thousandth of a degree latitude

    # Calculate the number of tiles in the latitude direction
    num_tiles_latitude = int((indiana_bbox[0] - indiana_bbox[1]) / tile_height)

    # Create a list to store the bounding box data
    bounding_box_data = []

    # Calculate the width of a tile based on latitude
    for y in range(num_tiles_latitude):
        latitude = indiana_bbox[0] - y * tile_height
        tile_width = tile_height / abs(math.cos(math.radians(latitude)))
        num_tiles_longitude = int((indiana_bbox[3] - indiana_bbox[2]) / tile_width)

        for x in range(num_tiles_longitude):
            tile_bbox = (
              latitude,
              latitude - tile_height,
              indiana_bbox[2] + x * tile_width,
              indiana_bbox[2] + (x + 1) * tile_width,
            )
        # Append the data to the list
        bounding_box_data.append((x, y, *tile_bbox))

    # Define the CSV file name
    # csv_file_name = "/content/drive/MyDrive/research/projects/mhp/tiles/in/bounding_boxes.csv"
```

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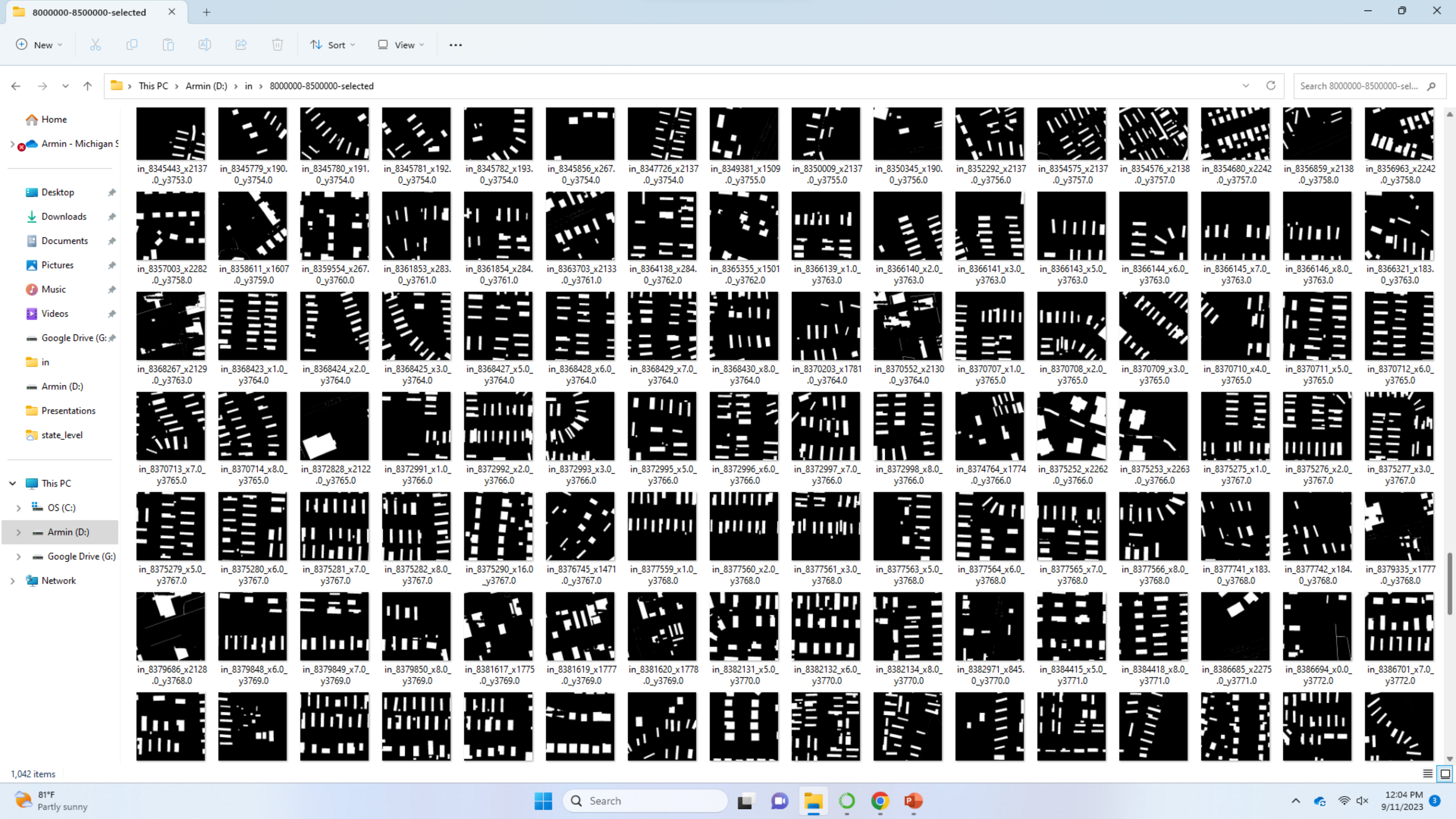
Cessna St
Hiden Rd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TRAINING: MHC

TRAINING: Non-MHC

PERFORMANCE METRICS FOR CNNs

$$Accuracy = \frac{T_p + T_N}{T_p + T_N + F_p + F_N}$$ Equation 3

$$Precision = \frac{T_p}{T_p + F_p}$$ Equation 4

$$Recall = \frac{T_p}{T_p + F_N}$$ Equation 5

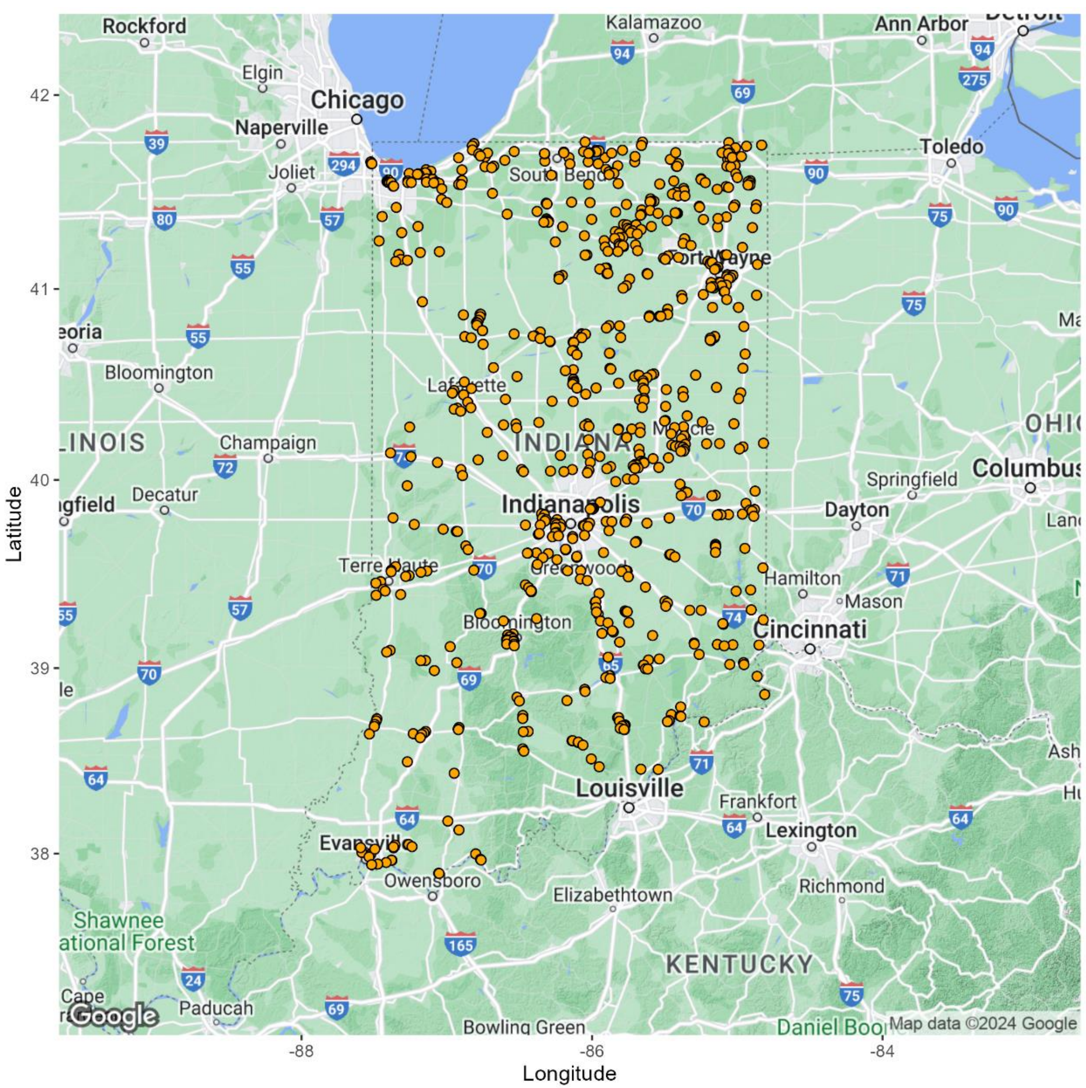
$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$ Equation 6

PERFORMANCE RESULTS FOR CNNs

Table 1 Single-wide deep learning model evaluation results after 10 epochs

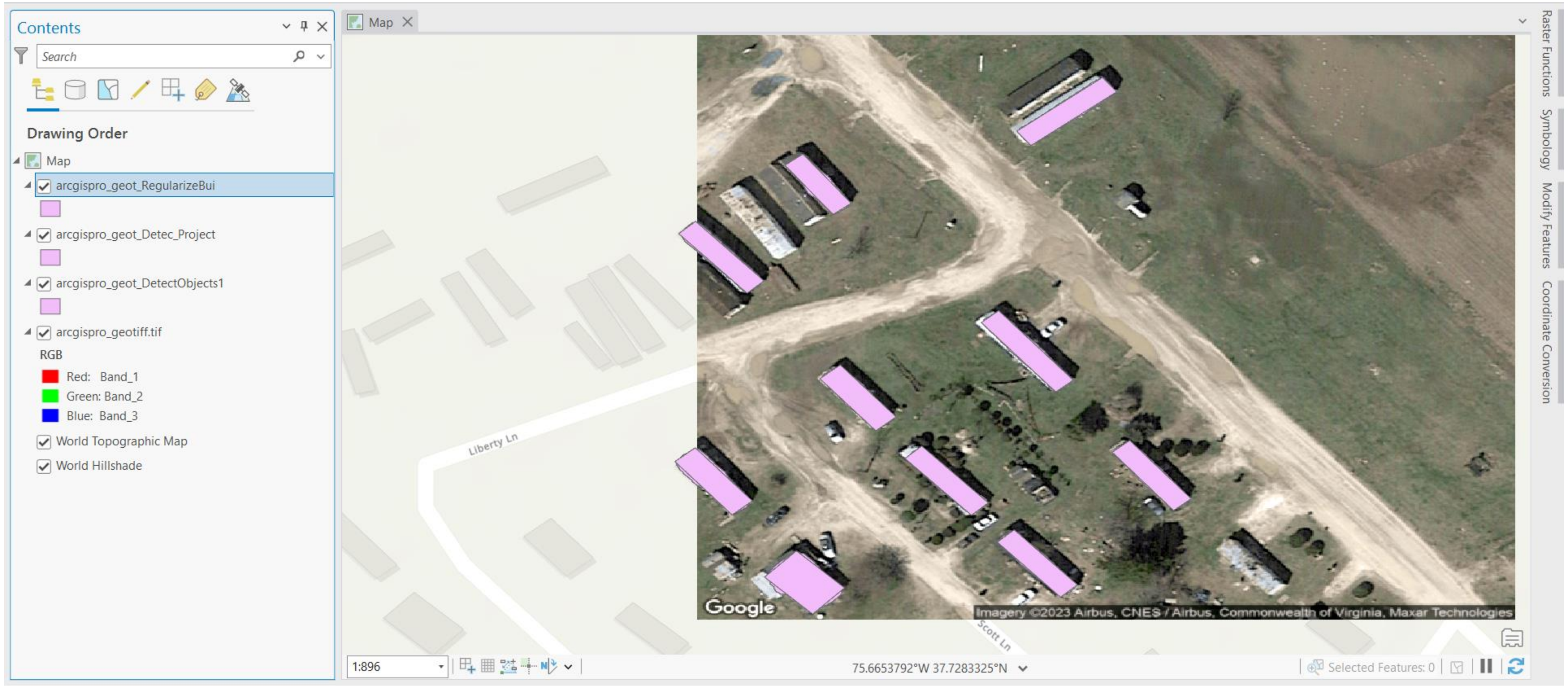
Model	Neurons	Loss	Accuracy	Precision	Recall	F1 Score
DenseNet121	128	0.09	0.96	0.97	0.96	0.96
	32	0.11	0.96	0.96	0.96	0.96
EfficientNetB0	128	0.69	0.50	0.50	1.00	0.67
	32	0.69	0.50	0.00	0.00	0.00
InceptionV3	128	0.18	0.92	0.98	0.87	0.92
	32	0.14	0.94	0.95	0.93	0.94
MobileNet	128	0.06	0.98	0.98	0.97	0.98
	32	0.08	0.97	0.97	0.97	0.97
ResNet	128	0.69	0.50	0.00	0.00	0.00
	32	0.69	0.50	0.00	0.00	0.00
VGG16	128	0.21	0.93	0.92	0.95	0.93
	32	0.19	0.93	0.93	0.92	0.93

LOCATION DETECTION RESULTS

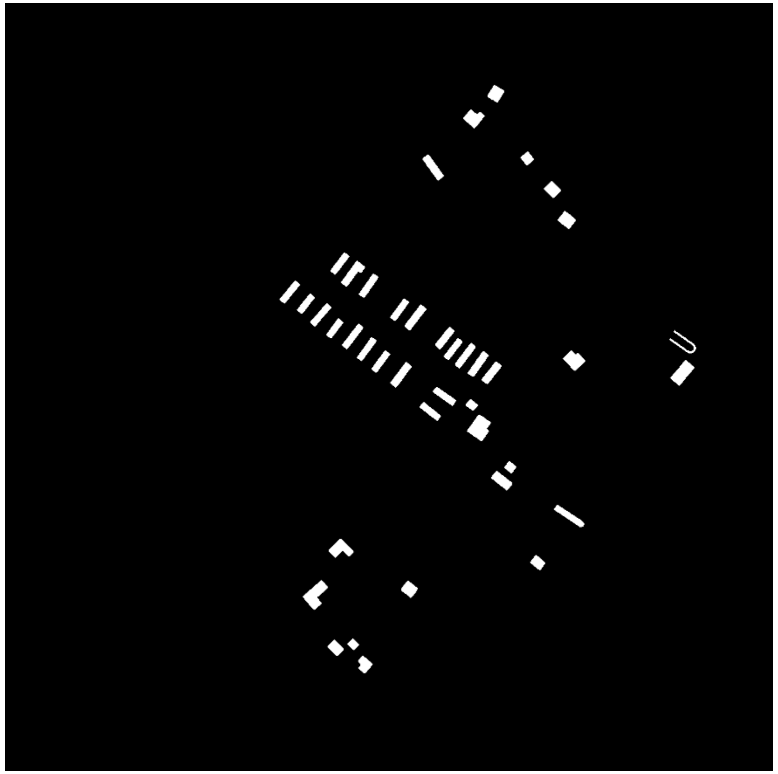


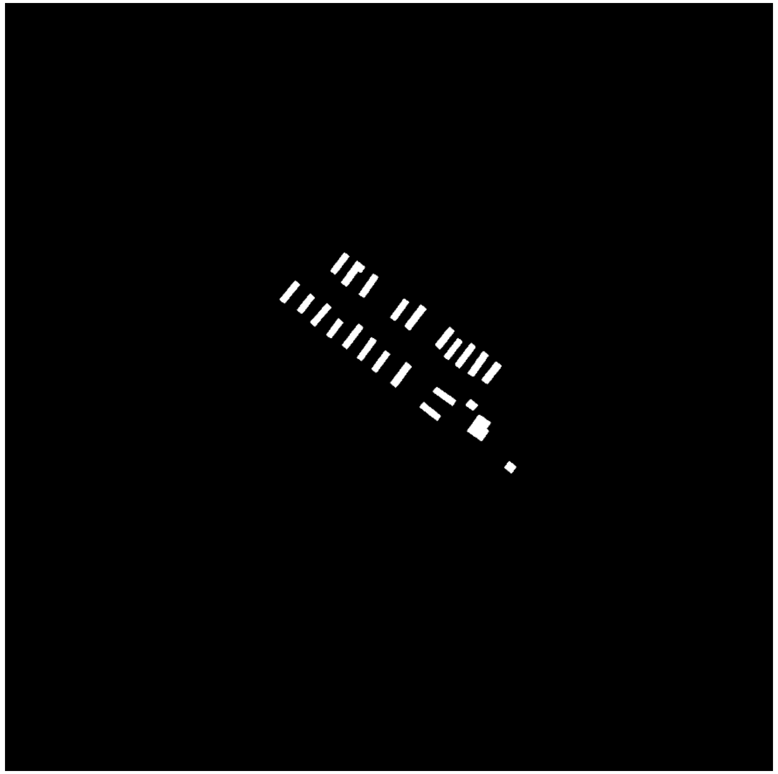
FOOTPRINT EXTRACTION TESTS

POST REGULARIZATION



AUTOMATED OUTLIER CLEANING TESTS





DRIVERS OF MHC GROWTH AND DECLINE

This study aims to identify and understand the socioeconomic drivers behind the growth and decline of these communities.

We join the obtained results with community surveys data from the US Census Bureau to identify the drivers of growth and decline of MHCs over the last two decades.

H1: TOTAL POPULATION

- Population growth has reduced MHC development.
- In growing regions, alternative affordable housing options, e.g., multi-family housing units, subsidized housing, and other programs, might be more suitable to meet the diverse needs of growing populations.

H2: ELDERLY POPULATION

- Elderly population growth has increased MHC development.
- Policies should support MHCs including amenities and services that enhance accessibility and elderly quality of life. Investors should target regions experiencing growth in elderly populations.

H3: ETHNIC DIVERSITY

- Growth in ethnic diversity has increased MHC development.

- Policies should support housing minority residents in MHCs. Economic development strategies should target MHCs for inclusive growth. Investments in education and training can help uplift these communities. MHC developers benefit from diversity.

H4: HOUSEHOLD SIZE

- Larger households have a positive, but weak association with growing MHCs.

- Smaller households, linked to higher education, prime-age residents would prefer townhouses, apartments, and condos. Investors should target markets with larger household sizes or other characteristics that support MHC growth.

H5: HOUSEHOLD INCOME

- As median household income increases, the demand for MHCs tends to decline.

- Policies should ensure affordable housing remains accessible, e.g., encourage mixed-income developments and protect existing affordable housing. Areas with increasing household income may not be the best MHC investment opportunity.

H6: UNEMPLOYMENT RATE

- Higher unemployment rates reduce financial resources and increase MHCs.

- Policies should create incentives to maintain the attractiveness of MHCs for a broader range of residents. Stronger employment might drive residents towards other housing options; thus, MHC investors should focus on enhancing the value proposition of their communities.

H7: POVERTY

- Areas with a high percentage of people living below the poverty line have seen growth in MHCs.

- Policies should support MHCs in high poverty areas. Economic development should improve financial stability, reducing reliance on MHCs as a sole housing option. Areas with lower income and minority populations have a stronger than average demand for manufactured housing.

H8: RENTAL HOUSING COST

- Higher rental costs may not attract renters to MHCs as the relationship is weak, negative, and insignificant.

- As traditional housing market prices increase, making homeownership less affordable, more people turn to manufactured homes as a more affordable homeownership option.

H9: RENTER HOUSEHOLDS

- As the share of renters increases, the growth in MHCs tends to decline.

- Housing policies should address affordability across all housing types, including but not limited to MHCs. For developers, this trend suggests an opportunity in areas with rising homeownership costs, as demand for affordable alternatives may increase.

H10: HOUSING SUPPLY

- Areas with higher housing construction rates might see an increase in MHCs.

- Policymakers should recognize the role of MHCs as a viable, growing segment of the housing market in areas with active construction. Developers can use this insight to identify regions where new construction activities may signal opportunities for expanding MHCs.

H11: URBAN DESIGNATION

- MHCs closer to urban centers or with improved infrastructure (like transportation links) are more likely to grow.

- Policymakers should consider strategies that enhance urban characteristics in areas targeted for MHC development or with declining MHCs. This could include zoning reforms, investment in urban infrastructure, and incentives for urban development.

PUBLICATIONS IN REVIEW

Yeganeh, et al. (2024). Detecting and Mapping Manufactured Housing Communities. Scientific Data.

Yeganeh, et al. (2024). Leveraging Longitudinal Aerial Imagery to Identify Drivers of Growth and Decline in Manufactured Housing Communities. Housing Policy Debate.

nature portfolio

scientific data

QUESTIONS?

THANK YOU!

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https://www.youtube.com/@Armin_Yeganeh

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