# Utilizing the Clay Foundation Model and Sentinel-2 Imagery for Urban Growth Monitoring in Johnston County, North Carolina

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## Introduction

Urbanization is a transformative process that reshapes landscapes, alters ecosystems, and influences socio-economic dynamics. Monitoring urban growth is essential for sustainable urban planning, environmental conservation, and resource management. Remote sensing technologies, particularly satellite imagery, offer valuable tools for observing and analyzing urban expansion over large areas and time periods. The Sentinel-2 satellite mission provides high-resolution, multispectral imagery that is instrumental in land cover and land use studies.

Advancements in machine learning have enhanced the capacity to process and interpret vast amounts of remote sensing data. The Clay Foundation Model, an open-source artificial intelligence model for Earth observation, leverages self-supervised learning and Vision Transformer architectures to generate embeddings representing spatial and temporal features of the Earth's surface. These embeddings can be utilized for various downstream tasks, including classification, regression, and change detection.

This project aims to develop a proof-of-concept for monitoring urban growth in Johnston County, North Carolina. By integrating Sentinel-2 imagery with the Clay Foundation Model, the study seeks to analyze urban expansion patterns and assess the effectiveness of different modeling approaches.

## Objective

The primary objective is to utilize the Clay Foundation Model and Sentinel-2 imagery to monitor and analyze urban growth in Johnston County, North Carolina.

The project will:

* Develop a methodology for processing and integrating Sentinel-2 imagery with urban density data.
* Generate embeddings using the Clay Foundation Model to capture spatial features.
* Explore modeling approaches such for predicting urban density percentages, and determine the most effective method through testing and evaluation.
* Provide insights into urban growth patterns within the study area.

## Study Site

Johnston County is located in the eastern part of North Carolina, United States, covering approximately 2,050 square kilometers. It lies between latitudes 35.3°N to 35.8°N and longitudes 78.0°W to 78.6°W. The county is part of the rapidly expanding Raleigh-Durham-Chapel Hill metropolitan area, making it a pertinent case study for urban growth analysis.

Coordinates are defined in the Universal Transverse Mercator (UTM) coordinate system, specifically UTM Zone 17N (EPSG:32617), with units in meters. This coordinate system is used by Sentinel-2 imagery in this region and ensures spatial accuracy and consistency in measurements across the study area.

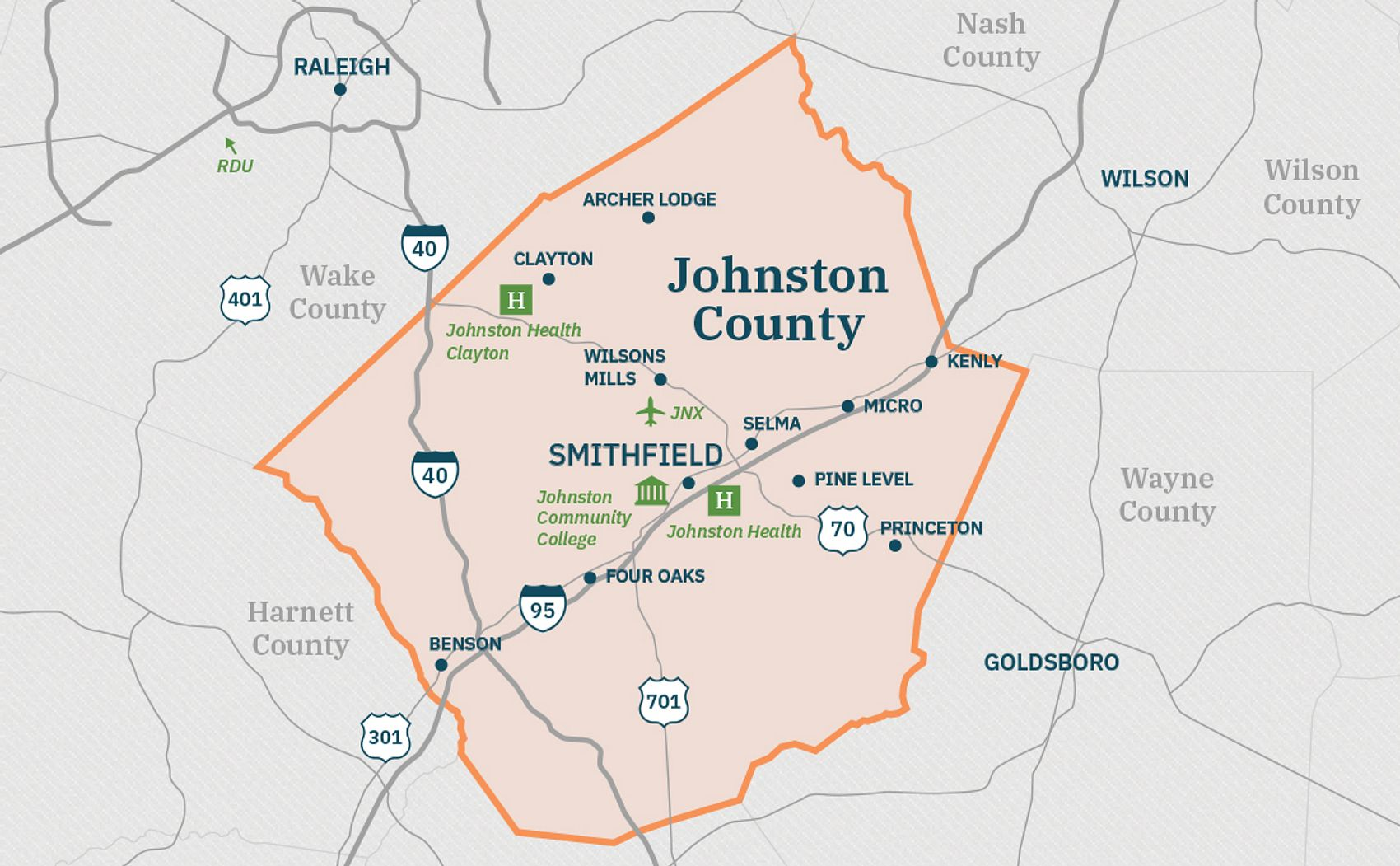


Figure 1: Johnston County, North Carolina (obtained from [*Johnston County Economic Development*](https://www.growwithjoco.com/why-joco/towns/))

## Data

### Johnston County GIS Data

* **Description**: Provides the official county boundary for spatial extent definition.
* **Source**: [Johnston County GIS Data (county boundary)](https://www.johnstonnc.com/gis2/content.cfm?PD=data)

### Sentinel-2 Satellite Imagery

* **Description**: Multispectral imagery with 10-meter spatial resolution.
* **Features**:
  + High temporal resolution with revisit times of approximately five days.
  + Includes 13 spectral bands suitable for land cover analysis.
* **Access Methods**:
  + Accessed via the pystac\_client library from:
    - [Microsoft Planetary Computer STAC API](https://planetarycomputer.microsoft.com/api/stac/v1/)
    - [Earth Search AWS STAC API](https://earth-search.aws.element84.com/v1)

### Urban Density Raster Data

* **Description**: Raster datasets indicating urban impervious surfaces to generate labels.
* **Potential Sources**:
  + **National Land Cover Database (NLCD)**: Provides 30-meter resolution data on land cover and imperviousness.
    - [NLCD Data](https://www.mrlc.gov/data)
* **Usage**: Used to calculate urban density percentages within spatial patches.

## Methods and Tools

### Data Processing

1. **Data Acquisition**:
   * Obtain Sentinel-2 imagery covering Johnston County for the selected dates.
   * Acquire urban imperviousness raster data corresponding to the same period.
2. **Preprocessing**:
   * **Coordinate Alignment**: Ensure all datasets are in the NAD83 coordinate system.
   * **Cloud Masking**: Apply cloud masks to Sentinel-2 imagery to remove cloud-covered areas.
   * **Resampling**:
     + Aggregate data into 600x600-meter patches, equivalent to 60x60 pixels.
     + Resample urban imperviousness data to 200-meter resolution such that each corresponding 600x600-meter patch aligns with a 3x3 pixel urban imperviousness region.
3. **Embedding Generation**:
   * Use the Clay Foundation Model to generate embeddings from the Sentinel-2 image patches.
   * The model leverages self-supervised learning with Masked Autoencoder (MAE) methods.

### Modeling Approaches

The project will evaluate a series of deep learning methodologies to estimate urban imperviousness using spatial embeddings generated by the Clay Foundation Model. These embeddings, created from Sentinel-2 imagery, capture detailed spatial and spectral information suitable for analyzing urban imperviousness at a fine scale. Each target, or label, is a 3x3 matrix of 200x200-meter urban imperviousness values, which aligns spatially with the corresponding 600x600-meter patches used to produce the embeddings. By training models on these continuous urban density labels, the project aims to predict localized urban density patterns over time, preserving spatial granularity without requiring data aggregation.

The modeling approaches include feedforward neural networks of varying depths and complexities, convolutional neural networks (CNNs) to capture embedded spatial relationships within each patch, and recurrent neural networks (RNNs) such as LSTMs, which are intended to leverage both spatial and temporal patterns within the embeddings. By comparing these methods, the project seeks to identify the optimal model architecture for accurately predicting urban imperviousness across Johnston County, providing insight into the broader applicability of the Clay Foundation Model for urban monitoring.

### Tools and Software

* **Programming Language**:
  + **Python**: Selected for its versatility and extensive libraries.
* **Data Processing Libraries**:
  + geopandas, rasterio, xarray, rioxarray: For spatial data handling.
  + numpy: For numerical computations.
* **Machine Learning Libraries**:
  + torch (PyTorch): For utilizing the Clay Foundation Model and implementing deep learning models.
  + scikit-learn: For testing and evaluating model performance.
* **Clay Foundation Model**:
  + Accessed via the Hugging Face repository [made-with-clay/Clay](https://huggingface.co/made-with-clay/Clay) for processing Earth observation data.
* **Satellite Data Access**:
  + pystac\_client: For accessing Sentinel-2 imagery through STAC APIs.
* **Visualization**:
  + matplotlib: For data visualization and plotting.

## Expected Results

The anticipated outcome of this project is the development of a model capable of predicting urban density in Johnston County using Sentinel-2 imagery and embeddings from the Clay Foundation Model. By employing the selected modeling approach, the study aims to generate detailed maps illustrating the distribution of urban density across the county. These visualizations are expected to reveal patterns of urban growth and identify areas experiencing significant development.

Methodologically, the project intends to demonstrate the applicability of the Clay Foundation Model in the context of urban growth monitoring. By providing a framework that integrates advanced machine learning techniques with remote sensing data, the study may offer valuable insights for future research in similar domains. Additionally, the project will address challenges encountered during the process, such as data resolution discrepancies and temporal alignment issues, and will suggest strategies for improving accuracy and extending the methodology in subsequent studies.

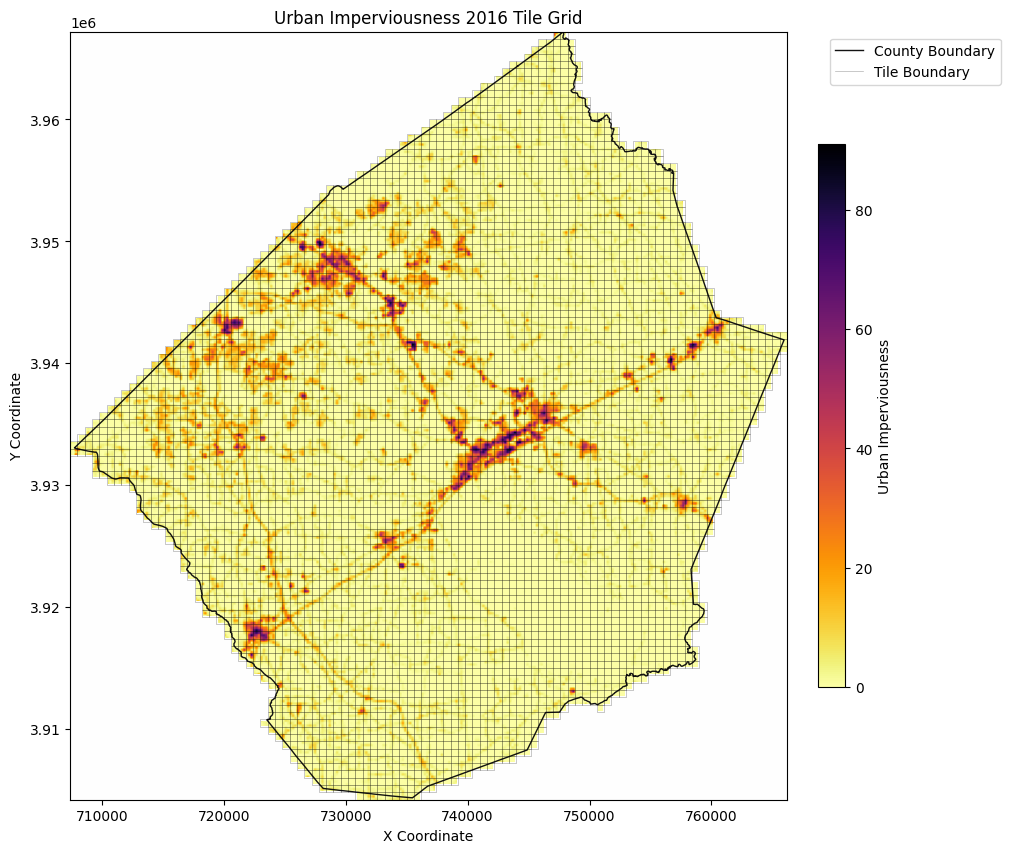
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# Progress Report

This analysis investigates whether embeddings generated from Sentinel-2 imagery through the Clay Foundation Model can effectively model urban growth in Johnston County, North Carolina, over time. Johnston County, located near the Raleigh-Durham-Chapel Hill area, spans approximately 2,050 square kilometers and provides a relevant setting for studying urban expansion due to rapid growth in the surrounding region. Sentinel-2 imagery, acquired from 2016 to 2024 at regular intervals, was accessed via the Microsoft Planetary Computer STAC API, offering high-resolution data essential for generating embeddings that capture both spatial and temporal features. Urban imperviousness data from the National Land Cover Database (NLCD) was also obtained for 2016. To ensure consistent spatial resolution, each Sentinel-2 image was divided into 600x600 meter tiles aligned with the NLCD data.

In the data processing stage, the Clay Foundation Model produced embeddings for each tile across 20 distinct dates, capturing both spatial and temporal patterns in urban growth. These embeddings were combined with corresponding NLCD urban imperviousness values to build a structured dataset for modeling urban density over time. The anticipated outcomes include maps that reveal areas of significant urban growth within Johnston County. By integrating Clay embeddings with traditional imperviousness data, this approach offers an enhanced capability to analyze urban expansion patterns. An additional benefit of this model is its potential to estimate urban growth solely from satellite data, enabling more granular temporal analysis, as NLCD data updates occur only every 4–5 years. Challenges included variability in image availability across tiles for specific dates, requiring the use of a date buffer to iteratively exclude dates where imagery was unavailable within a defined threshold.



# Utilizing the Clay Foundation Model and Sentinel-2 Imagery for Urban Growth Monitoring in Johnston County, North Carolina

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## **Abstract**

**This study examines urban growth in Johnston County, North Carolina, by integrating Sentinel-2 multispectral satellite imagery with the Clay Foundation Model, an open-source deep learning framework for Earth observation. The analysis focuses on monitoring urban expansion using urban imperviousness percentages provided by the National Land Cover Database (NLCD) as a proxy for urbanization. Sentinel-2 imagery, accessed via the Microsoft Planetary Computer and AWS Earth Search APIs, provides high-resolution, multitemporal data, while the Clay Foundation Model generates spatial embeddings that capture detailed spectral information for modeling applications. By combining these resources, the study applies deep learning methodologies, including convolutional and recurrent neural networks, to assess the effectiveness of foundation models in geospatial applications, specifically for urban density analysis. This approach contributes a scalable, data-efficient framework for monitoring urban growth, offering insights into both methodological advancements and the applicability of foundation models for sustainable urban planning.**

## **Introduction**

### I. Urban Growth and Remote Sensing Technologies

Urban growth fundamentally reshapes landscapes, ecosystems, and socioeconomic structures, making it a crucial area of study within environmental and urban planning. The expansion of impervious surfaces, such as roads and buildings, is a key indicator of urbanization that impacts ecosystems by increasing surface runoff, reducing groundwater recharge, and altering local climates. By understanding and tracking these changes, researchers and policymakers can better manage the environmental consequences of urban growth and devise strategies to minimize negative impacts on biodiversity, water cycles, and air quality (Goetzke et al., 2008).

Remote sensing has emerged as an essential technology for monitoring urban growth, offering extensive, consistent data across time and space. Multitemporal satellite imagery, particularly from sources like Sentinel-2, enables precise tracking of land cover changes over large geographic areas and prolonged periods, making it ideal for detecting patterns of urban expansion (Ayush et al., 2021; Zhu et al., 2017). This technology facilitates not only the visualization of urban sprawl but also quantitative analysis of changes in land use and land cover. By providing high-resolution, time-sequenced imagery, remote sensing allows for dynamic monitoring of urbanization processes, yielding insights critical for sustainable urban planning and resource management.

### **II. Deep Learning in Remote Sensing**

Deep learning architectures have revolutionized remote sensing, with Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers each playing pivotal roles. CNNs, which excel at extracting spatial features from images, are widely used for analyzing high-resolution satellite imagery, enabling accurate image classification and object detection. RNNs and their variants, such as LSTMs, are advantageous for capturing temporal patterns within data sequences, allowing the processing of time-series satellite data. Transformers, originally designed for NLP, have been adapted for spatial-temporal analysis, pushing forward new possibilities in remote sensing (He et al., 2022; Jean et al., 2019).

In supervised learning, labeled data is used to train deep learning models to recognize specific patterns, making it suitable for tasks like land cover classification, object detection, and semantic segmentation (Dionelis et al., 2024; Zhu et al., 2017). These tasks require precise pixel-level predictions, which supervised deep learning models, such as CNNs, are adept at performing. However, this approach is often limited by the availability of labeled data, which is both costly and time-consuming to produce. This limitation has led to an increased interest in unsupervised learning and representation learning methods, where models like autoencoders and contrastive learning frameworks learn features from unlabeled data. By enabling models to automatically learn useful representations, these methods make it feasible to work with larger datasets without extensive annotation, enhancing the scope and applicability of deep learning in remote sensing (Ayush et al., 2021; Jean et al., 2019).

### **III. Foundation Models for Geospatial AI**

Foundation models have transformed fields like NLP, where models like BERT and GPT-3 have set new standards in text processing by pretraining on large datasets and then fine-tuning for specific applications. These models provide a flexible framework for handling diverse tasks with minimal additional training, representing a shift from task-specific models to more generalized architectures. By capturing universal patterns within massive datasets, foundation models enable the efficient transfer of knowledge across related tasks, reducing the need for task-specific training data (Mai et al., 2022).

In Earth Observation (EO) and Geospatial AI, foundation models demonstrate significant potential for applications such as land cover classification, object detection, and change detection. Unlike traditional models that are trained for single tasks, foundation models can generalize across a wide range of EO applications, learning to recognize spatial and temporal features across multiple datasets (Dionelis et al., 2024). This generalizability allows these models to be highly adaptable to new tasks, even with limited labeled data, making them particularly valuable in remote sensing where annotation resources are often limited. Their adaptability, combined with label efficiency and robust feature extraction capabilities, positions foundation models as powerful tools for advancing EO and Geospatial AI (Ayush et al., 2021; He et al., 2022).

### **IV. Research Gap and Objectives**

Despite advancements in deep learning and the introduction of foundation models, limited research has focused specifically on using these models to map urban imperviousness. Current methods often struggle with scalability and adaptability, issues that foundation models like the Clay model may address through pretraining on large-scale geospatial datasets (Clay Foundation, 2023). Utilizing such models could improve urban imperviousness mapping by enabling finer-scale predictions with reduced reliance on annotated data, making large-scale urban analysis more feasible.

This study aims to leverage the Clay foundation model, in conjunction with Sentinel-2 imagery, to monitor urban imperviousness and analyze urban growth in Johnston County, North Carolina. Specifically, the study will use the Clay model’s pretrained embeddings to extract features from Sentinel-2 images, evaluating different approaches to predict urban imperviousness at high spatial and temporal resolution. The objective is to create a proof-of-concept for an efficient, scalable framework for urban monitoring, contributing to the growing body of research that employs foundation models for geospatial applications and highlighting their potential for enhancing urban growth studies (Clay Foundation, 2023; Goetzke et al., 2008).

## Study Site

Johnston County is located in the eastern part of North Carolina, United States, covering approximately 2,050 square kilometers. It lies between latitudes 35.3°N to 35.8°N and longitudes 78.0°W to 78.6°W. The county is part of the rapidly expanding Raleigh-Durham-Chapel Hill metropolitan area, making it a pertinent case study for urban growth analysis.

Coordinates are defined in the Universal Transverse Mercator (UTM) coordinate system, specifically UTM Zone 17N (EPSG:32617), with units in meters. This coordinate system is used by Sentinel-2 imagery in this region and ensures spatial accuracy and consistency in measurements across the study area.

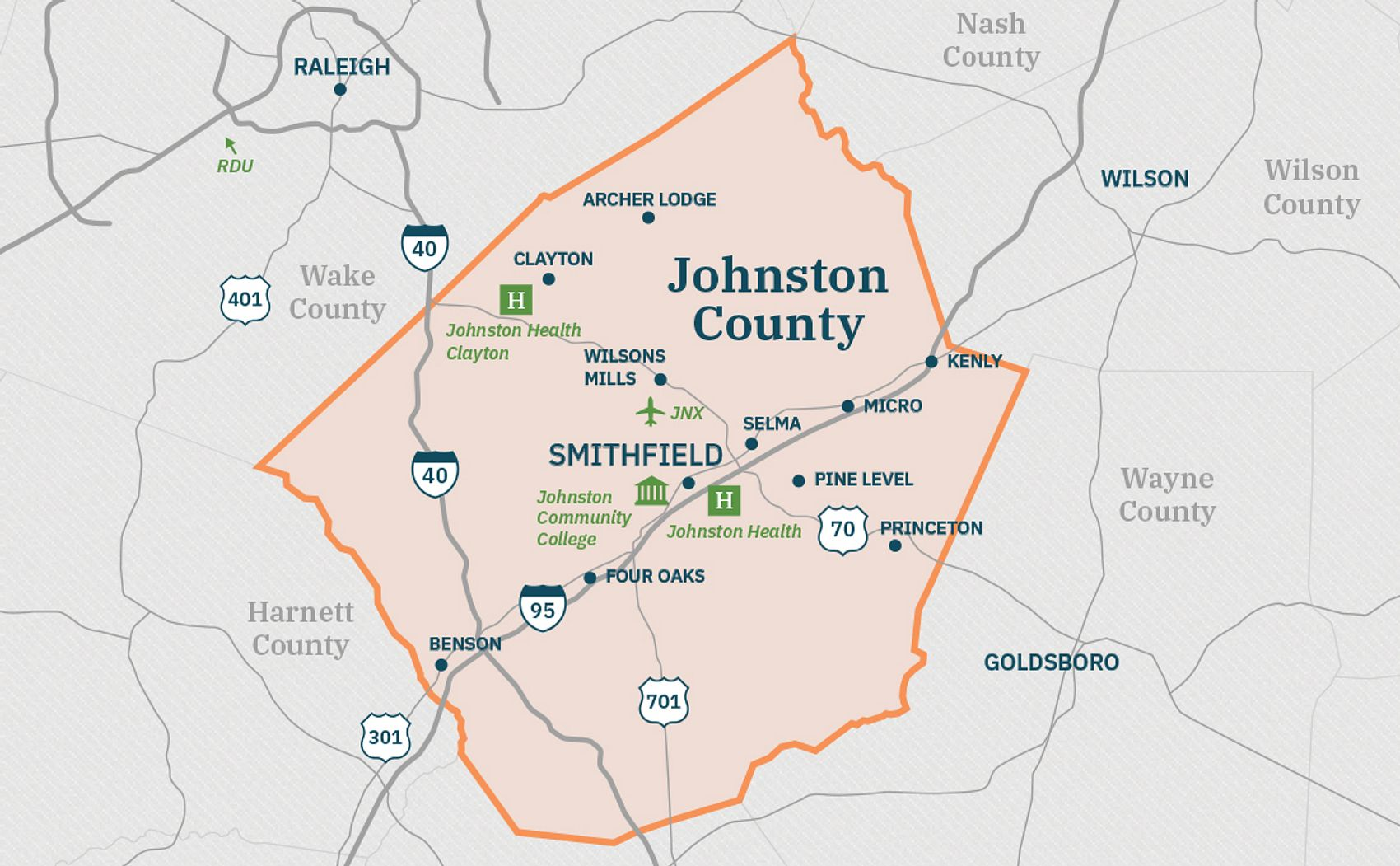


Figure 1: *Johnston County, North Carolina (obtained from* [Johnston County Economic Development](https://www.growwithjoco.com/why-joco/towns/))

## Data Overview

This study utilizes several datasets to define spatial boundaries, analyze land cover, and estimate urban density within Johnston County, North Carolina.

The Johnston County GIS data provides the official county boundary, defining the study’s spatial extent (Johnston County Department of GIS, 2011).

Sentinel-2 satellite imagery from the European Space Agency (ESA) is used as the exclusive source of multispectral data for this study. This dataset, specifically the MSI Level-1C Top of Atmosphere (TOA) Reflectance Product, Collection 1, offers 10-meter spatial resolution and includes 13 spectral bands suitable for land cover analysis. Sentinel-2’s revisit interval of approximately five days allows for frequent monitoring over time (Copernicus Sentinel-2, 2021). Data access is facilitated through the pystac\_client library, drawing from the Microsoft Planetary Computer STAC API (Microsoft Open Source et al., 2022) and the Earth Search AWS STAC API, adhering to the SpatioTemporal Asset Catalog (STAC) API specification (STAC Specification, 2023).

Urban density raster data from the National Land Cover Database (NLCD) provides 30-meter resolution raster data on land cover and impervious surfaces, used to calculate urban density percentages within spatial patches (U.S. Geological Survey, 2021).

|  |  |  |  |
| --- | --- | --- | --- |
| **Dataset** | **Sentinel-2 Satellite Imagery** | **NLCD Urban Imperviousness** | **Johnston County Boundary** |
| **Original CRS** | EPSG:32617 (UTM Zone 17N) | Albers Conical Equal Area (EPSG:4326) | EPSG:32617 (UTM Zone 17N) |
| **Original Spatial Extent** | Queried individually within Johnston County Region | minx: -2493045.0 miny: 177285.0 maxx: 2342655.0 maxy: 3310005.0 | minx: 707750.13 miny: 3904356.29 maxx: 765959.87 maxy: 3967194.75 |
| **Original Resolution / Format** | 10x10 meters / Multispectral GeoTIFF | 30x30 meters / GeoTIFF | Vector |
| **Additional Data Attributes** | Bands:   * B02 (Blue) * B03 (Green) * B04 (Red) * B08 (NIR)   Cloud Cover: < 1% Dates:   * Approximately quarterly spread (where available) * 2016-2024 * 20 dates total | - | - |
| **Transformation Details** | Used as primary spatial reference; no CRS transformation needed. Cropped to the 600x600-meter tiles covering Johnston County boundary. | Reprojected to EPSG:32617 and cropped to Johnston County. Resampled to 200m resolution using bilinear interpolation. | Converted to EPSG:32617 to match Sentinel-2 and NLCD data. Used to define study area bounds, and divided into 600x600-meter tiles for consistent spatial units. |

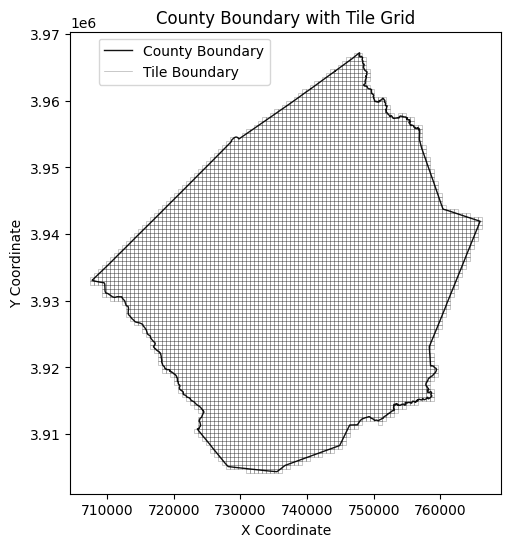


Figure 2: Map displaying the boundary of Johnston County, North Carolina, overlaid with a 600x600-meter tile grid.

## Methods

* Methods for analysis and modeling, focus on general methodology but you can also provide workflow for the specific software, the optional code, scripts and other details should go into appendix.

### Pseudo-code For Initial Data Processing

1. **Setup Libraries and Directories**
   * Import required libraries for geospatial, raster, and deep learning processing.
   * Define the directory paths to store tiles, boundaries, and processed data.
2. **Load and Preprocess County Boundary Data**
   * Load county\_boundary.shp as a GeoDataFrame (GDF).
   * Reproject to **EPSG:32617 (UTM Zone 17N)** to match Sentinel-2 data CRS.
   * Calculate bounding coordinates of the boundary with minx, miny, maxx, and maxy values and align these to a tile size (600m).
3. **Generate Grid Tiles for the County**
   * Create a grid of 600x600-meter tiles that cover the county boundary.
   * Store these as polygons within a new GDF.
   * Ensure each tile intersects with the county boundary; keep full tile geometry.
   * Initialize columns in GDF to track whether each tile has been processed and its associated data files.
   * Save the tiles as a GeoJSON file.
4. **Create Unified Boundaries for All Tiles**
   * Combine all tiles into a single unified boundary polygon.
   * Save this as a **shapefile** and create a **raster mask** with a **10-meter pixel resolution**.
   * Define a transform for the raster that aligns with the bounds and CRS of the tiles.
5. **Load and Mask Urban Imperviousness Data**
   * Load **NLCD urban imperviousness raster** and clip it to the county's bounding box.
   * Save this clipped data as an intermediate TIFF file.
   * Resample the clipped raster to **10m and 200m** resolutions, reprojecting it to **EPSG:32617** with **bilinear resampling**.
   * Save both resampled TIFF files.
6. **Extract Urban Imperviousness Data for Each Tile**
   * For each tile, extract a 200m-resampled urban imperviousness raster corresponding to that tile’s bounding box.
   * Save each extracted tile raster as a TIFF, updating the GDF with the path to each tile’s raster file.
7. **Query Available Sentinel-2 Dates**
   * Set up a query for **Sentinel-2 imagery** within a specified date range (e.g., 2016-01-01 to 2024-08-31).
   * Filter for images with **<1% cloud cover** using Microsoft Planetary Computer STAC API.
   * Save the available dates to a pickle file.
8. **Select Optimal Dates for Data Collection**
   * Group the available dates by year and select a specified number of dates per year (e.g., quarterly).
   * Store the selected dates as the main temporal dataset.
9. **Download and Save Sentinel-2 Image Tiles**
   * For each tile and each selected date, query STAC items for Sentinel-2 imagery in the tile’s bounding box.
   * Extract and save each band (Blue, Green, Red, NIR) as TIFF files, ensuring alignment with the tile bounds and CRS.
   * Update the GDF with the file paths to each downloaded image file.
10. **Generate Mosaics and RGB Composites**
    * Create RGB mosaics for the tiles using bands B02 (Blue), B03 (Green), and B04 (Red).
    * Save the merged mosaics as TIFF files, creating RGB composites for visualization.
11. **Merge Subdivided Urban Data Tiles into a Single Raster**
    * Collect all 200m-resampled urban tiles and merge them into a single **GTiff** raster.
    * Ensure the final merged raster retains the CRS and spatial alignment of the tiles.
12. **Assign Data Files to Dates for Each Tile**
    * For each tile, associate its downloaded Sentinel-2 data with specific dates.
    * Update the GDF to track which dates are associated with available data files, facilitating data retrieval for modeling.
13. **Error Handling and Cleanup**
    * Identify missing files, incomplete downloads, and tiles with multiple files for the same date.
    * Re-query missing data and remove redundant or incomplete files.

## Results

* Present and explain the results qualitative and quantitative, tables, graphs, maps/images; compare with results from other studies – confirms previously observed phenomena, shows something new, which questions remain unresolved.

## Discussion

## Conclusion

* Summary of the most important findings including advances in methodology, future work

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## Appendix

* Workflows, commands, scripts, metadata, software-specific issues