# 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.

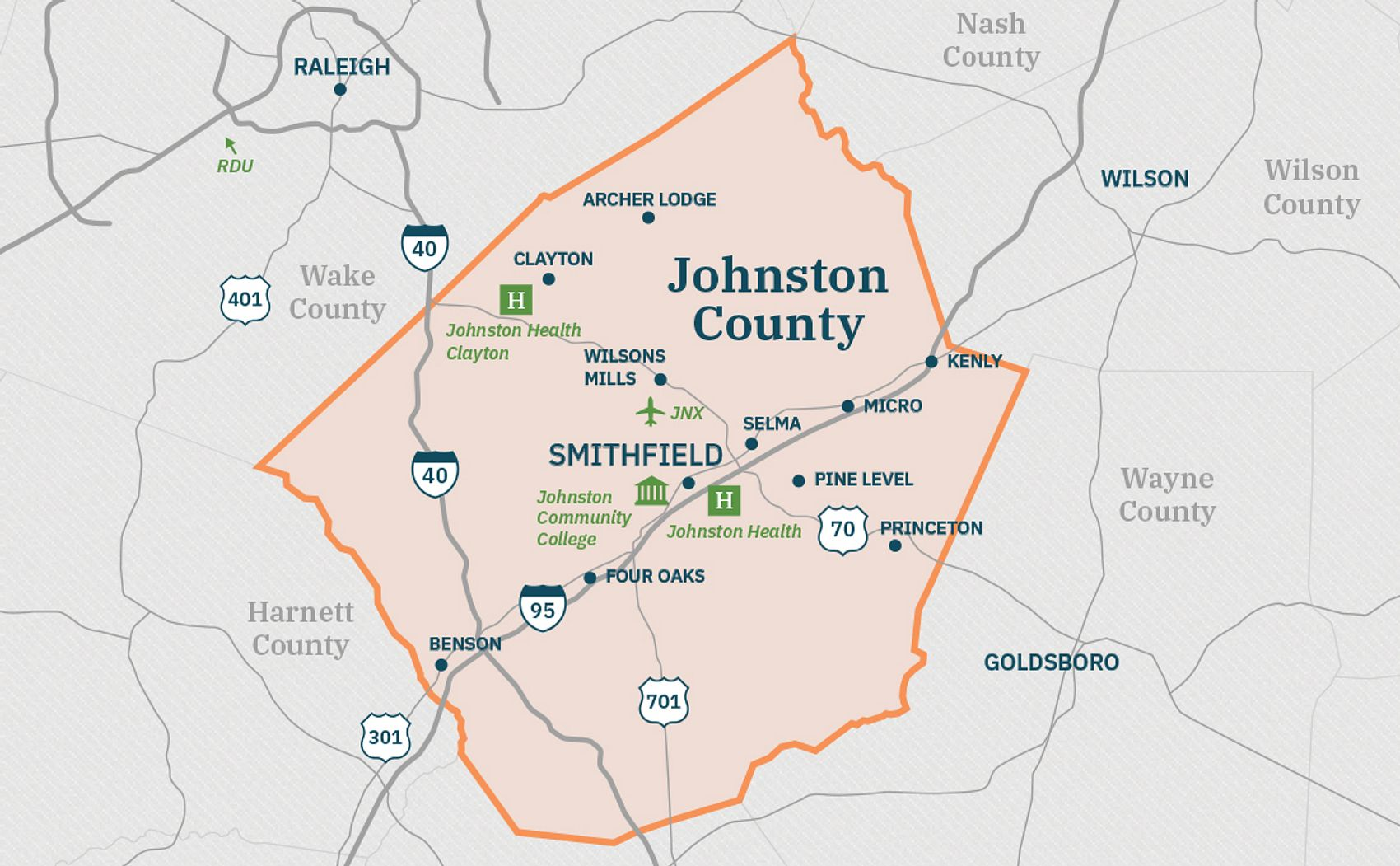


Figure 1: Johnston County, North Carolina (obtained from [*Johnston County Economic Development*](https://www.growwithjoco.com/why-joco/towns/))

## 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.

## References

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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.

