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.

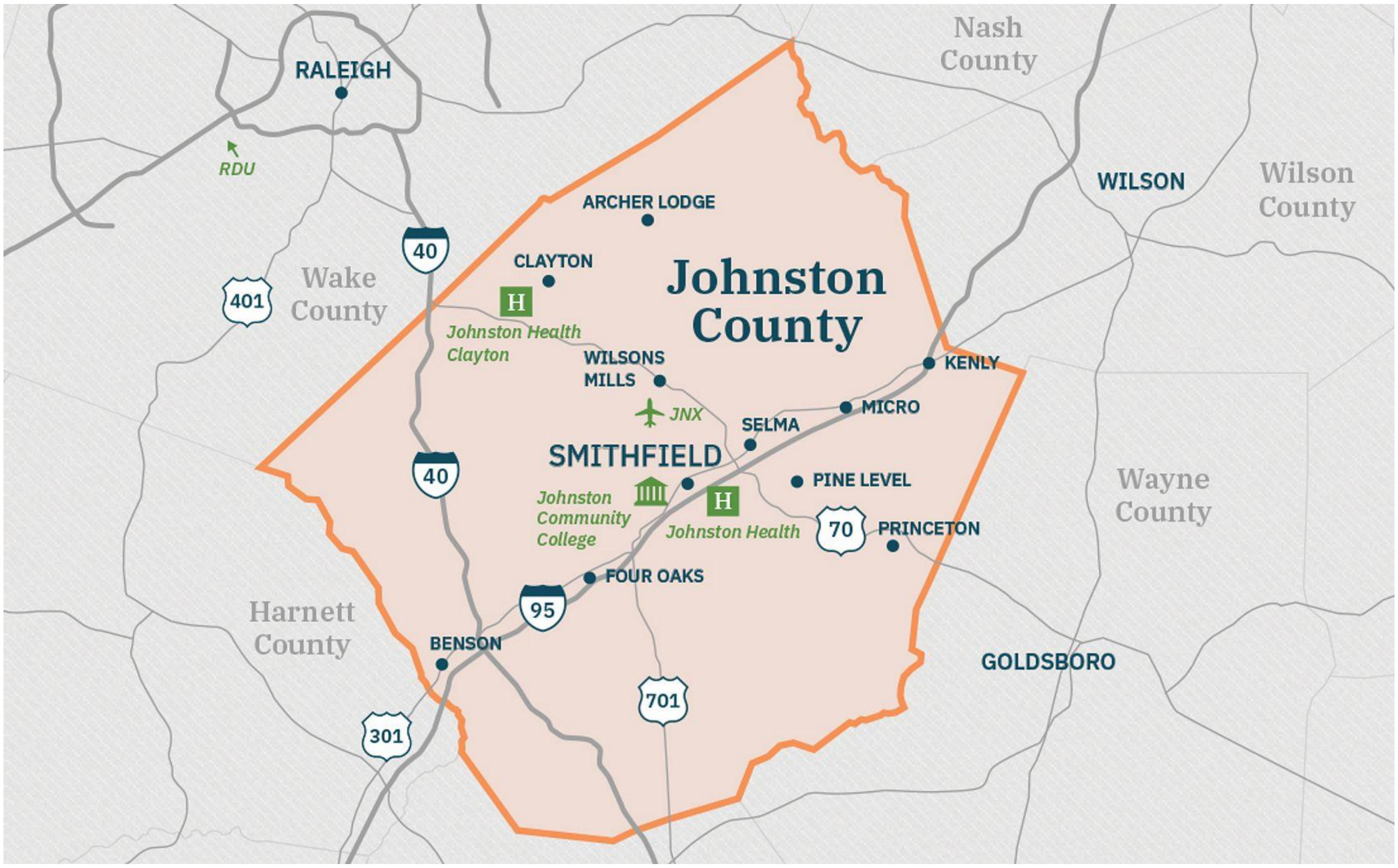

Figure 1: *Johnston County, North Carolina (obtained from* *Johnston County Economic Development*)

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	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.

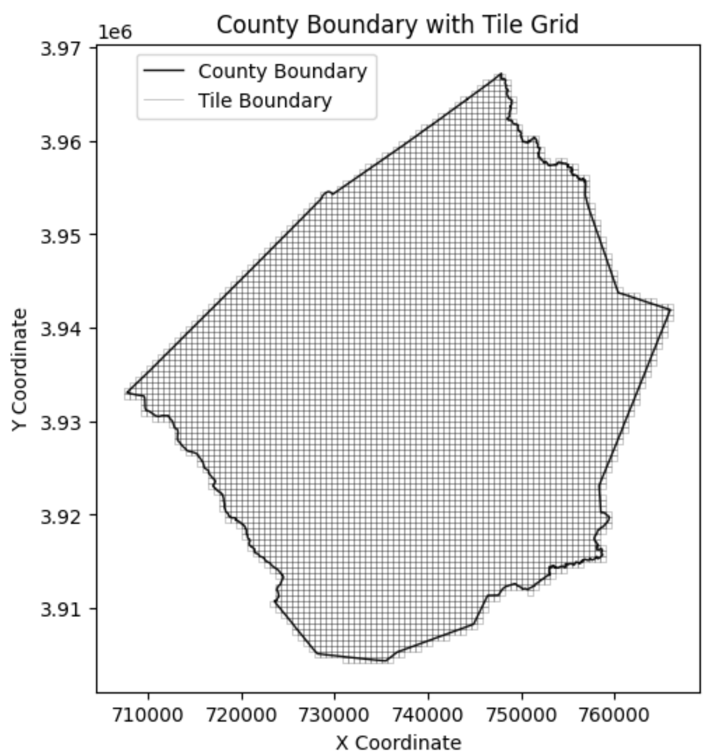

Figure 2: Map displaying the boundary of Johnston County, North Carolina, overlaid with a 600x600-meter tile grid.

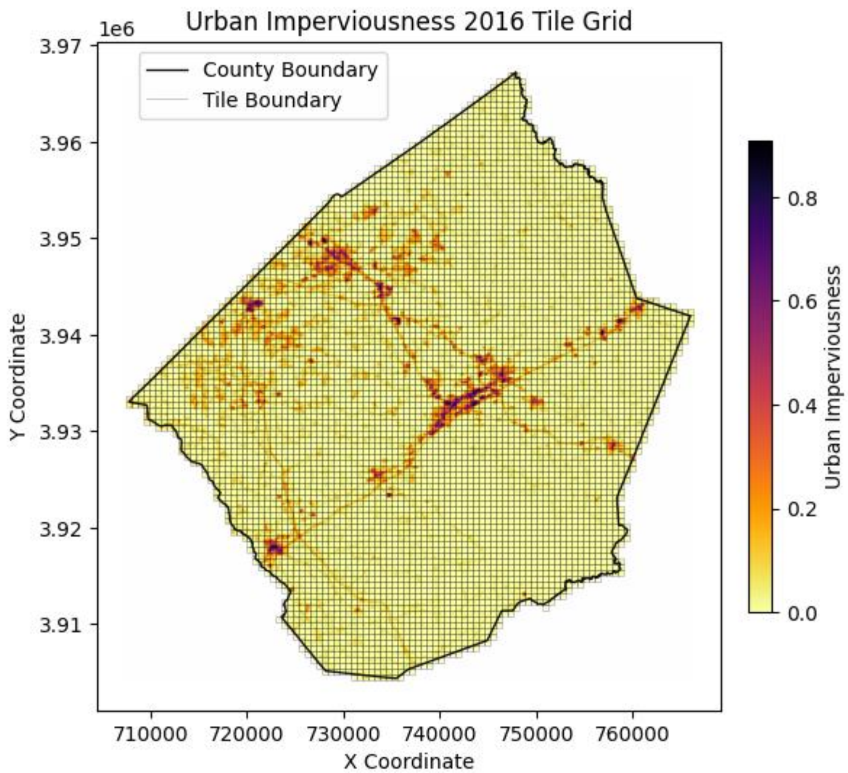

Figure 3: Urban imperviousness across Johnston County, North Carolina, in 2016, with a 600x600-meter tile grid overlay and the county boundary.

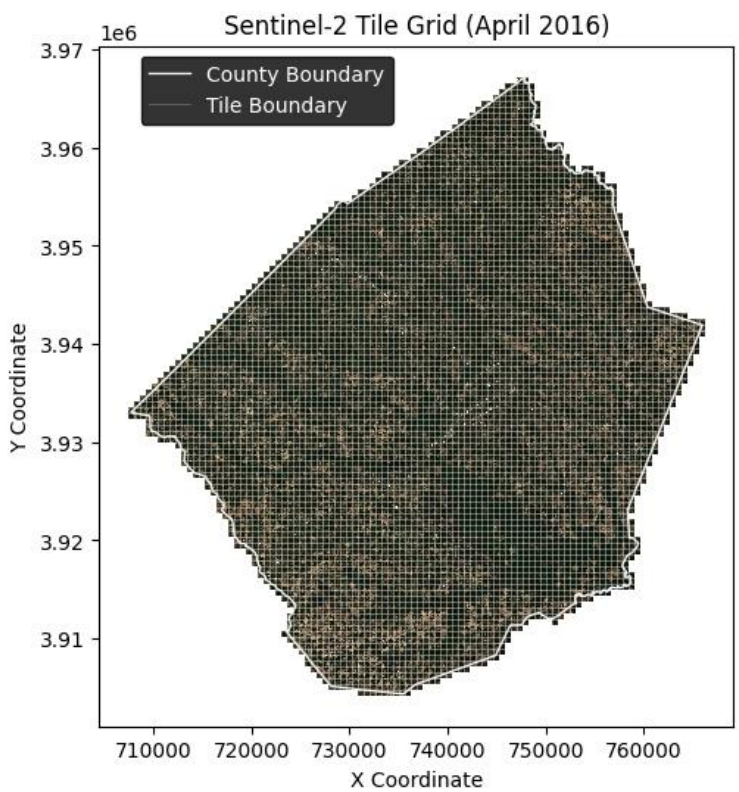

Figure 4: Sentinel-2 imagery of Johnston County in April 2016, overlaid with a 600x600-meter tile grid used and the county boundary.

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