Northeastern Permanent Forest Land Clearing

Overview

Forests in the Northeastern United States serve as critical reservoirs of biodiversity, carbon storage, and ecosystem services, playing a central role in regional climate resilience and sustainable resource management (Foster & Aber, 2004). Despite their importance, monitoring forest health, detecting deforestation, and differentiating between temporary management disturbances (e.g., shelterwood harvesting, planned rotations) and permanent forest conversion remain ongoing challenges (Hansen et al., 2013; Tropek et al., 2014; Olofsson et al., 2021).

Many existing global and regional land cover products conflate cyclic forest management events with permanent deforestation, misrepresenting forest dynamics and potentially informing misguided policy decisions (Ahmed et al., 2021; Cohen et al., 2022). In the Northeast, where active forest management and natural regeneration after harvest are commonplace, such misclassifications obscure true forest conditions and trends. For instance, clearcutting followed by rapid regrowth is a managed cycle, not permanent forest loss, yet conventional methods often treat these temporary reductions in canopy cover as deforestation (Kennedy et al., 2010; Griffiths et al., 2021). This project addresses these limitations by leveraging higher-resolution (10 m) satellite imagery and time-series analysis to:

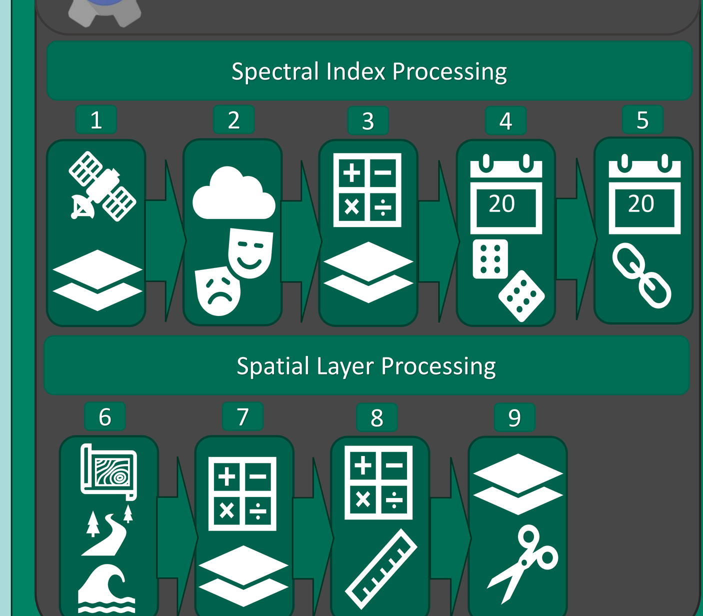
- Generate updated land cover maps focused on Northeastern U.S. forests, reflecting fine-scale spatial heterogeneity.
- Distinguish between short-term, management-related forest disturbances and long-term, permanent deforestation that leads to temporally stable non-forest land covers.
- Incorporate multi-year satellite observations—such as those from the Landsat and Sentinel programs—to track forest regeneration, ensuring that cyclical harvest-and-recovery processes are not mistaken for irrevocable land cover changes (Hermosilla et al., 2022; White et al., 2021).
- Provide a clearer picture of drivers behind permanent forest loss, including urbanization, agricultural expansion, and solar energy installations etc, by identifying true land cover transformations rather than cyclical vegetation dynamics (Hansen et al., 2022; Fagan et al., 2013).

Model Overview

Data Acquisition & Preprocessing | Training Data Preparation | Model Development & Classification | Time-Series Analysis for Change Detection | Quantification & Interpretation of Drivers

Data Processing

Processing Visual



Processing Description

1. Filtering and Data Selection: Identify and process regions and times of interest.
2. Cloud Masking: Remove cloud-contaminated pixels.
3. Index Calculation: Generate multiple spectral indices.
4. Temporal Smoothing and Imputation: Apply rolling means to reduce gaps and noise.
5. Annual Composite: Aggregate data to yearly median values.
6. Topographic and Vector Layers: Get the DEM and other vector layers for processing
7. Rasterize: Build and calculate raster layers
8. Compute secondary layers: For layers of distance to features, calculate Euclidean distance raster
9. Clip raster: Clip to northeast

Simplified NLCD Classes

- Forest: Dominated by tall, mature trees (deciduous, evergreen, or mixed). Represents continuous woody canopies.
- Shrub: Characterized by shorter woody vegetation (shrubs, scrub).Includes shrub-dominated wetlands.
- Grass/Crops: Herbaceous vegetation (natural grasslands, pasture, hay, cultivated fields). Incorporates herbaceous-dominated wetlands.
- Urban: Built environments, from scattered housing to dense city centers. Encompasses all development intensities in a single class.
- Water: Open water bodies and water-dominated wetlands. Lakes, ponds, rivers, and flooded areas.
- Bare: Exposed soil, rock, sand, or minimal vegetation cover. Reflects areas with sparse or no plant growth.

Training Data and Classification Methodology

To ensure a high quality, reliable classification, we collected over 5,000 training points relatively evenly distributed across key land cover classes. Using Google Earth Engine (GEE), our team visually interpreted satellite imagery for each year (2016–2024), verifying class assignments following a standardized protocol. We included both stable sites (no land cover transitions) and areas identified as having changed classes, informed by Hansen et al. (2022) forest loss data. Importantly, we did not classify short-term forest harvesting as land cover change, focusing only on lasting transitions such as forest to shrub or urban. This approach allowed us to accurately quantify and characterize meaningful shifts in land cover composition over time.

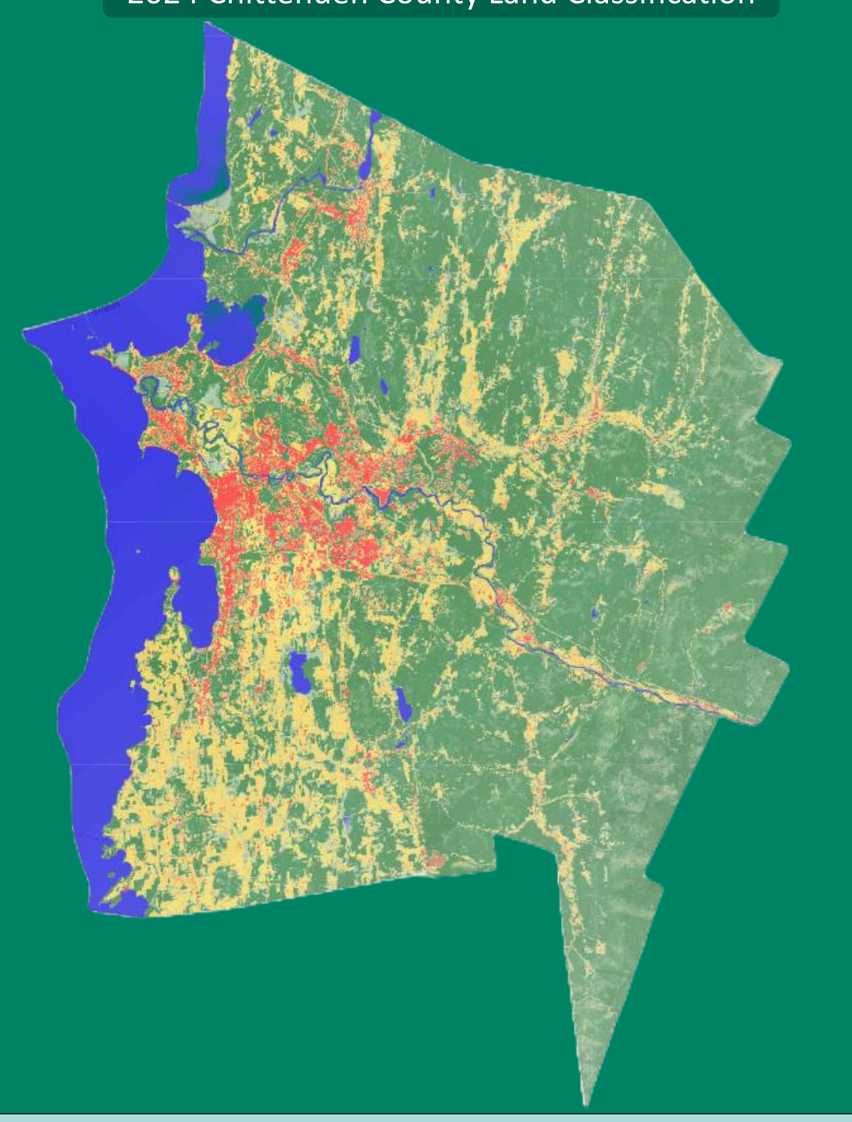
Example: Chittenden 10m Land Classification 2016-2024

2016 Preclearing

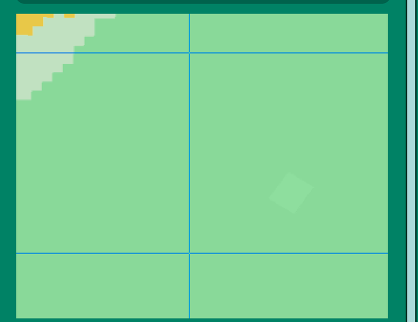
2024

Classified Forest Loss

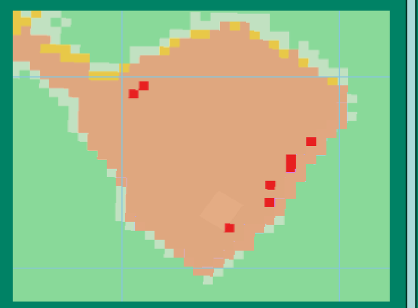
2024 Chittenden County Land Classification



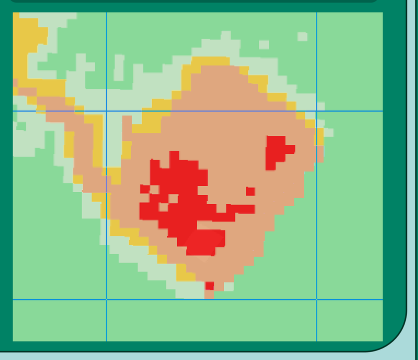
2016 Preclearing



2017 Clearing Year



2024 Classes

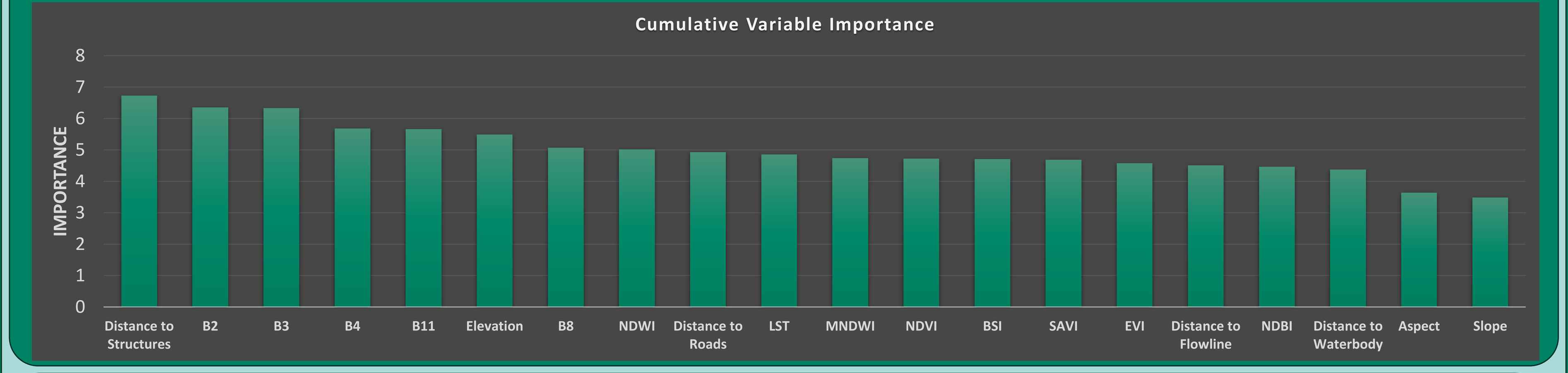


Variable Importance

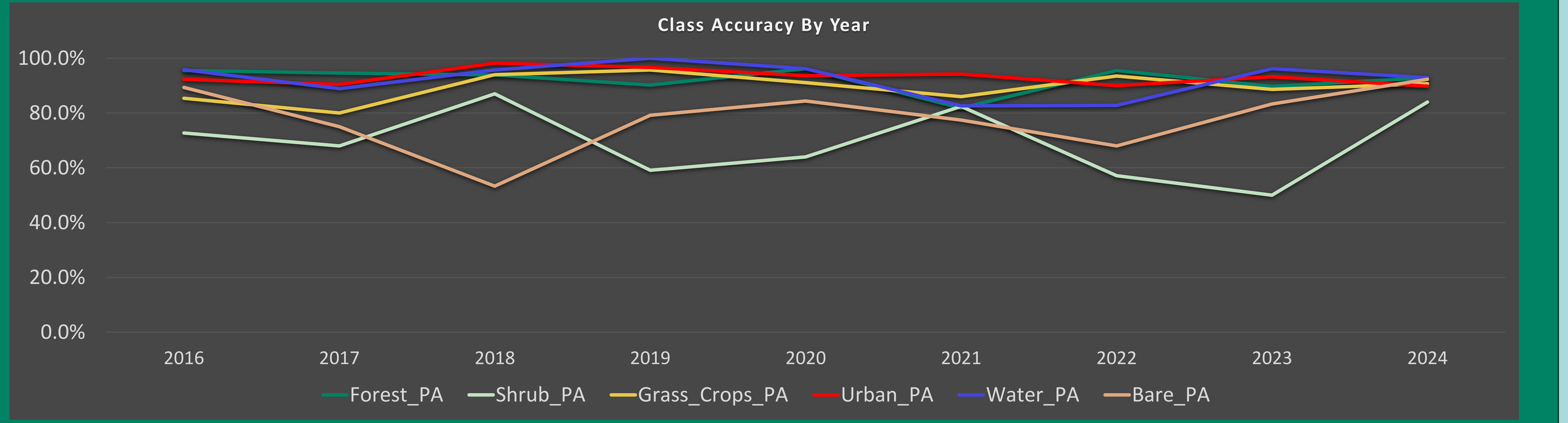
The cumulative variable importance ($IV^{(j)}_{cumulative}$) in land cover classification using Random Forest evaluates the overall contribution of the jj-th predictor variable in explaining the variability of the target classification output (Y) over multiple years. It builds on the conditional expectation function, $\tau(X) = E[Y \mid X]$ which represents the expected value of the target (Y) given the predictors (X). By removing the j-th variable from the predictors (X^{-j}), the importance of this variable is measured as the reduction in explained variance in $\tau(X)$ To capture this effect cumulatively over T years, we define:

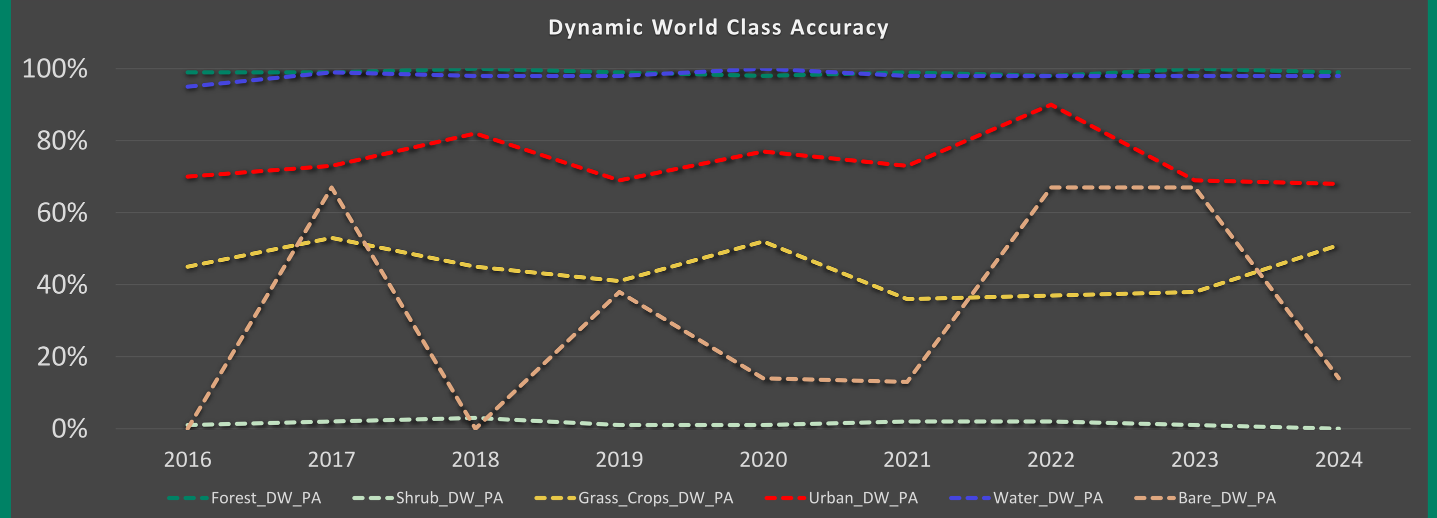
$$IV^{(j)}_{\text{cumulative}} = \frac{\sum_{t=1}^{T} E\left[V\left[\tau(X_t) \mid X_t^{(-j)}\right]\right]}{\sum_{t=1}^{T} V[Y_t]}$$

This measure highlights the j-th variable's overall contribution to explaining the output variance across time, helping identify key drivers of land cover changes in temporal datasets.



Classification Accuracy Compared With Dynamic World

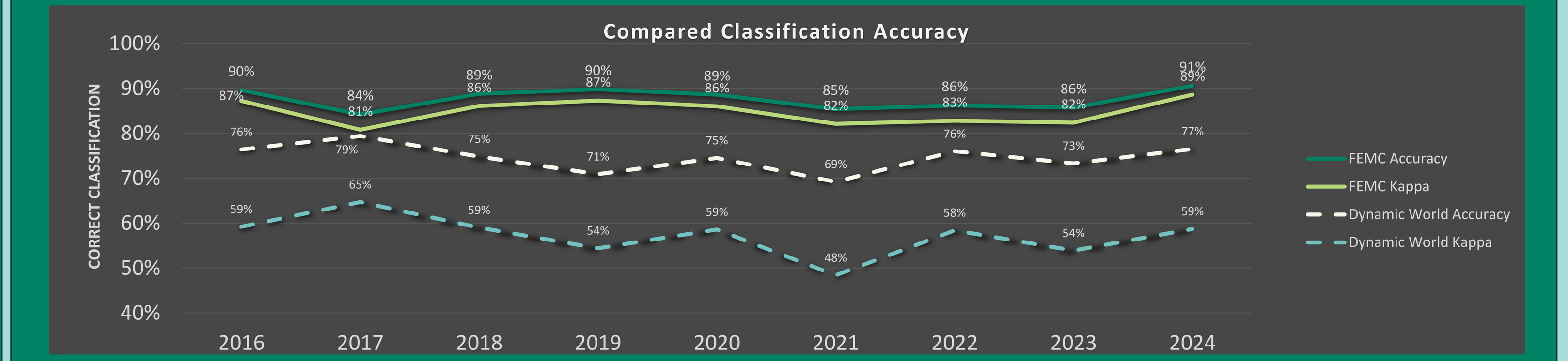




DW Class Code	DW Class Name	Mapped FEMC Code	FEMC Class Name
0	Water	4	Water
1	Tree	0	Forest
2	Grassland	2	Grass & Crops
3	Flooded Vegetation	1	Shrub
4	Crops	2	Grass & Crops
5	Shrubland	1	Shrub
6	Built-up	3	Urban
7	Bare Ground	5	Bare

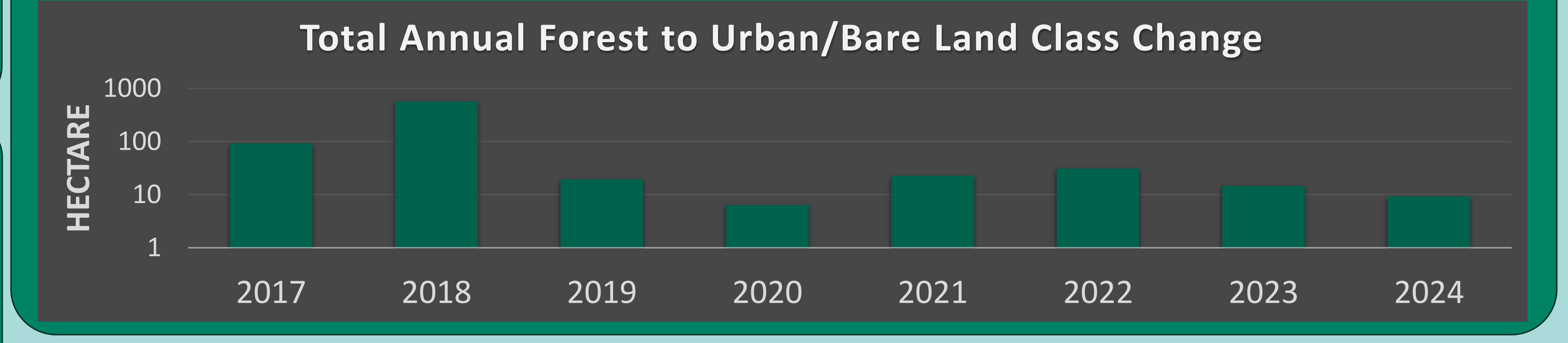
Land Classification Accuracy

The figures comparing accuracy in classes and overall accuracy highlight the superior performance of the FEMC Classification System, consistently achieving over 85% accuracy compared to the variability of Dynamic World (DW), which struggles with transitional land classes. DW nearly fails to classify Shrub while the FEMC model excels at identifying regenerating forests, capturing transitions between forest and shrub more effectively. Forest is the most consistently classified class across all systems, while Urban and Water show moderate accuracy. The FEMC model's ability to classify dynamic land categories demonstrates its robustness compared to DW's limitations. The better the yearly classification, the better the temporal classification of persistent forest loss.



Data Visualization

The data indicate a significant disparity between the Total Forest-to-Urban Change Area and the Total Permanent Forest Loss Area, highlighting differences in land-use dynamics. The Forest-to-Urban/Bare Change Area is substantial at 758.55 ± 19.7 hectares, reflecting conversion of forested areas into urban environments. This underscores urbanization as a major driver of forest cover change. In contrast, the Total Permanent Forest Loss Area is much smaller at 27.29 hectares (3.6%), indicating that while some forest loss is irreversible (e.g., due to development or infrastructure), the overall scale of permanent loss is relatively limited. This distinction is crucial for targeting conservation and reforestation efforts. Where permanent forest loss is the long-term conversion of forest to Urban or Bare for at least 3 consecutive years without regrowth to shrub or forest.



Summary

The process of annual land classification involves filtering Sentinel-2 imagery by region, date range, and cloud cover. A cloud masking function removes contaminated pixels, and key spectral indices such as NDVI, EVI, SAVI, and others are computed. A temporal smoothing technique using a 20-day rolling mean reduces noise caused by cloud gaps. For each year, a median composite of the indices is generated, producing an annual summary image. These annual composites are classified using predefined land classes such as forest, water, agriculture, and built-up areas.

The classification of permanent loss focuses on detecting areas where forest cover has transitioned permanently to non-forest categories like urban areas, agriculture, or bare ground. This involves comparing annual classified layers to identify consistent changes across multiple years. If a previously forested area remains classified as non-forest for several consecutive years, it is labeled as a permanent loss. This approach filters out temporary disturbances such as seasonal clearing or thinned forests, ensuring that only irreversible land-use changes are marked as permanent loss.

Why Are These Data Useful?

- Improved Land Monitoring: Highlight the strengths of the FEMC Classification System in accurately capturing transitions, such as regenerating forests, critical for tracking land-use changes over time.
- Identifying Gaps in Other Models: Show the limitations of models like Dynamic World, particularly its low accuracy for shrub classification, aiding in refining remote sensing methodologies.
- Enhanced Conservation Planning: Provide robust, accurate classifications to support ecosystem monitoring, conservation strategies, and resource management efforts.
- Adaptation for Climate Monitoring: Enable better tracking of dynamic land-cover changes, vital for understanding climate impacts and informing mitigation policies.
- Comparative Model Assessment: Offer a benchmark for assessing the performance of multiple classification systems across various land classes.

Next Steps

- Finalize entire Northeast region models and temporal classification.
- Publication of summary and technical reporting on regional drivers.
- Provide hosting and download capability for land class modeling classification and product layers.

Acknowledgements & Authors

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