Enhanced Forest Cover Mapping using Spectral Unmixing and Object-based Classification of Multitemporal Landsat Imagery

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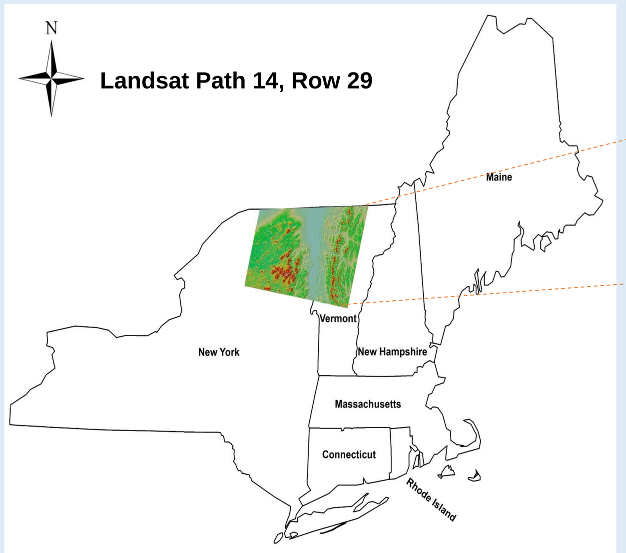
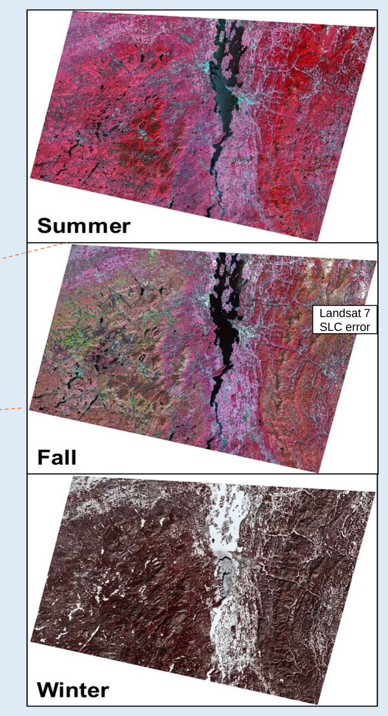
Background

Spatially-explicit tree species distribution maps are increasingly valuable to forest managers and researchers, particularly in light of the effects of climate change and invasive pests on forest resources. Advanced remote sensing techniques, such as spectral unmixing and object-based image analysis (OBIA), utilize spectral and ancillary environmental data to provide information on proportional species composition and enable more precise forest cover mapping. This is especially useful in Northeastern forests where species composition is often highly mixed. **Here, we:**

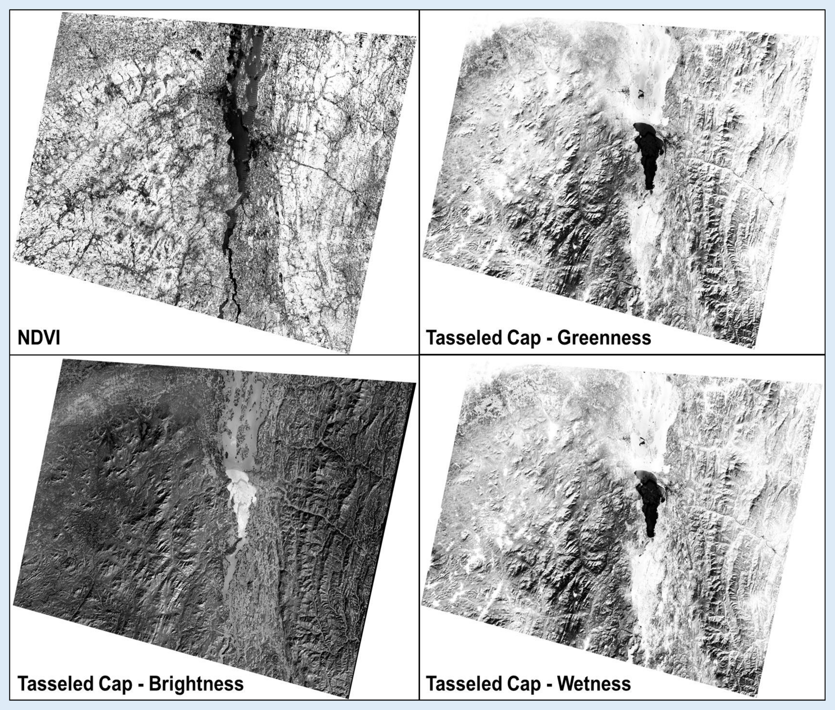
1. **Develop a novel method for classifying tree species/genera across a heterogeneous landscape that integrates spectral unmixing and OBIA methods using multitemporal Landsat imagery and ancillary environmental data.**
2. **Compare the accuracy of our approach to large-scale forest mapping products, including the National Land Cover Database (NLCD), LANDFIRE Existing Vegetation Type (EVT Group), and the National Forest Type Map (USFS NFTM).**

Pixel-based Spectral Unmixing Workflow

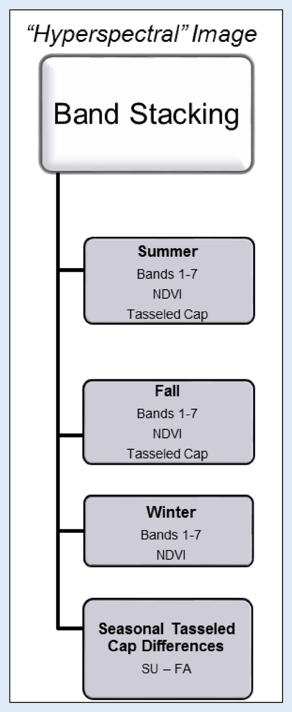


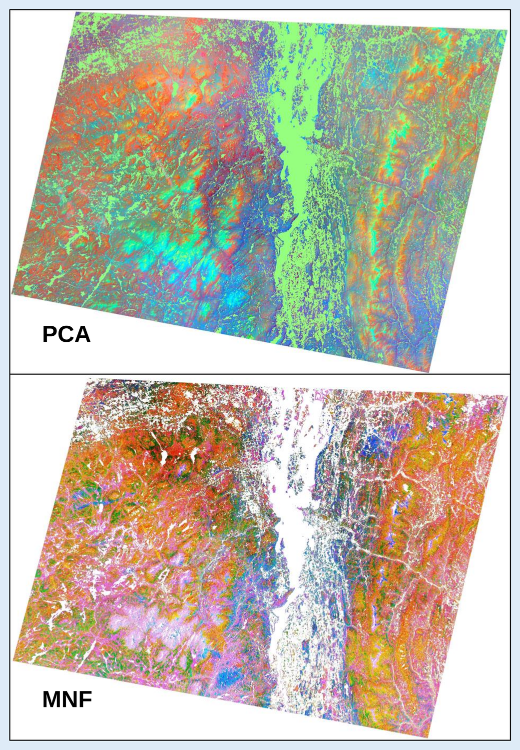


Seasonal Landsat ETM imagery, backfilled with nearby dates when necessary due to cloud cover.

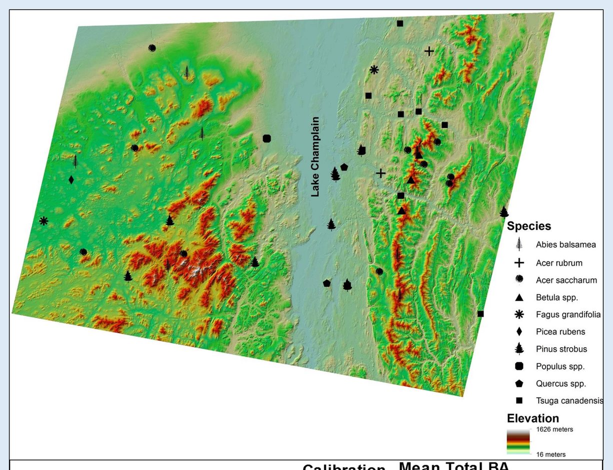


Derived vegetation indices: the **Normalized Difference Vegetation Index** (NDVI) for each season, **Tasseled Cap (TC) transformation** for the summer and fall imagery, and **seasonal TC differences**.





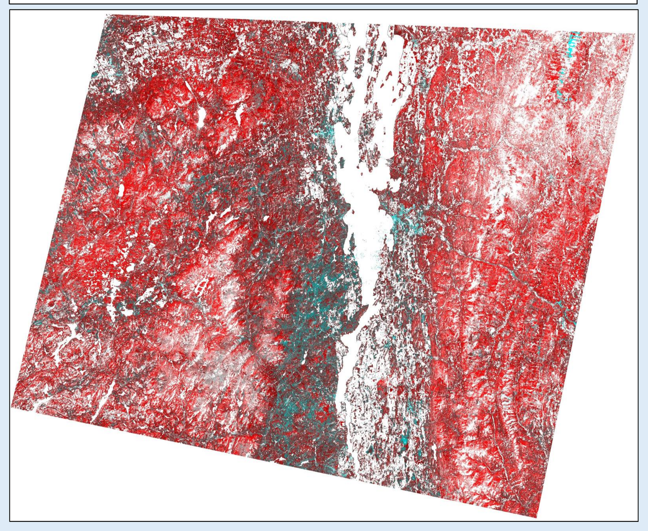
Principal components analysis (PCA) reduces spectral autocorrelation in the "hyperspectral" image. Following restacking of the PCA, summer, fall, and seasonal tasseled cap difference bands, a **Minimum Noise Fraction (MNF) transformation** condenses this spectral data into primary signal and noise bands for spectral unmixing.



Species	Common Name	Calibration Plots	Mean Total BA m^2h^{-1} (±SD)	Mean %BA
Abies balsamea	Balsam Fir	8	23.5 (9.9)	89.7
Acer rubrum	Red Maple	2	27.2 (1.2)	89.4
Acer saccharum	Sugar Maple	10	28.6 (8.8)	86.8
Betula spp.	Birches	6	23.2 (1.6)	90.4
Fagus grandifolia	American Beech	2	32.8 (5.6)	81.5
Picea rubens	Red Spruce	1	24.9 (--)	92.0
Pinus strobus	Eastern White Pine	11	36.1 (9.6)	93.1
Populus spp.	Aspens	1	27.8 (--)	86.5
Quercus spp.	Oaks	2	26 (17.4)	89.3
Tsuga canadensis	Eastern Hemlock	11	35 (13.4)	85.9

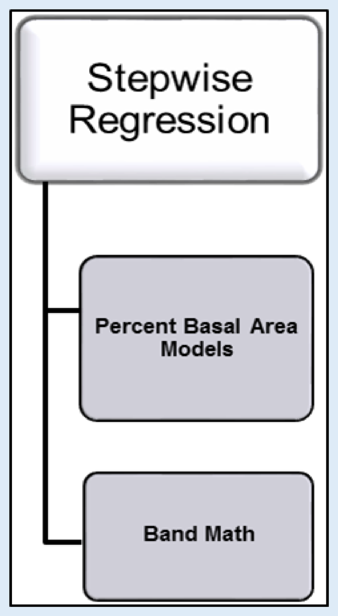
The number, structure, and spatial distribution of our **spectral unmixing calibration plots**. Calibration data consisted of FIA and state field inventory plots with >80% basal area comprised of one target species/genus (i.e. "pure pixels"/spectral endmembers). A **Pixel Purity Index** was used to retain only those pixels with highest spectral similarity, excluding outliers influenced by shadow or non-forested surfaces.

Example MTMF image (Sugar Maple)



A **Mixture-tuned Matched Filtering (MTMF)** algorithm matches the target endmember (i.e. tree species) signatures at a subpixel level (Matched Filter; MF), and also provides a false positive likelihood value (Infeasibility; INF). High MF scores with low INF mean the species is likely present; low MF means the species is likely absent; and high MF and high INF signify a likely false positive.

Percent Basal Area Results and OBIA Workflow

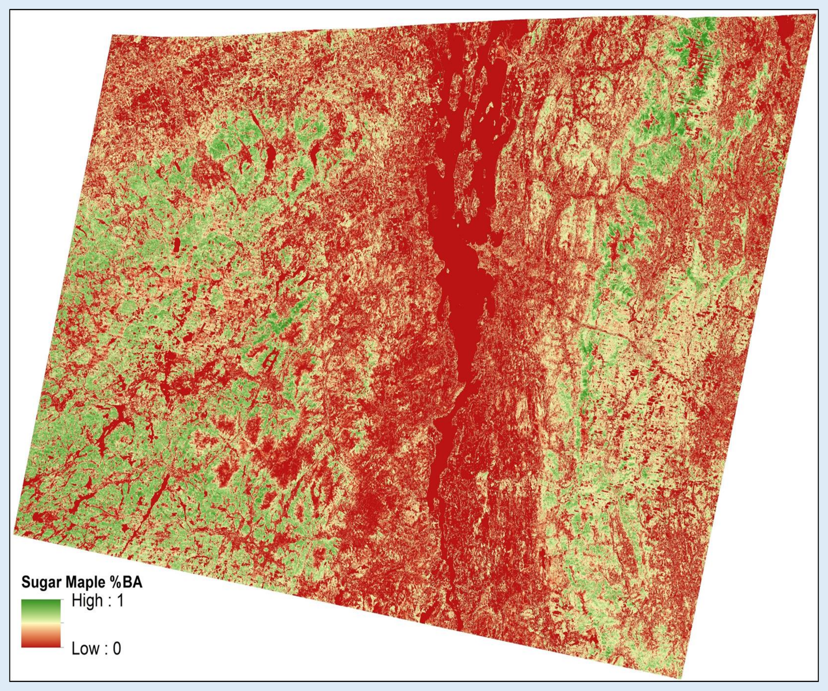


Regression modeling of MTMF values provides **% basal area equations** that are applied on a pixel by pixel basis to create **% basal area rasters.**

Species	r^2	Mean	RMSE	PRESS	# Spp. Dominant Plots*
Balsam Fir	0.34	0.15	0.11	0.12	9
Red Maple	0.47	0.08	0.06	0.06	1
Sugar Maple	0.46	0.28	0.16	0.17	17
Birches	0.32	0.13	0.08	0.09	6
American Beech	0.6	0.07	0.06	0.07	1
Red Spruce	0.52	0.07	0.06	0.06	1
Eastern White Pine	0.3	0.1	0.1	0.1	5
Aspens	0.25	0.04	0.04	0.04	1
Oaks	0.49	0.05	0.05	0	1
Eastern Hemlock	0.32	0.11	0.09	0.1	5

* Species considered dominant at >0.4 (40%) basal area.

Results of % basal area modeling for ten common Northeastern tree species/genera from **54 federal and state forest inventory field plots.**



Example % basal area map – maps for each species/genus are loaded into **eCognition®** along with Landsat spectral data, vegetation indices, and digital elevation models for thematic forest classification in a decision tree framework.

Object-based Classification – a decision tree-type analysis to classify imagery via user-defined thresholding of spectral and ancillary data layers.

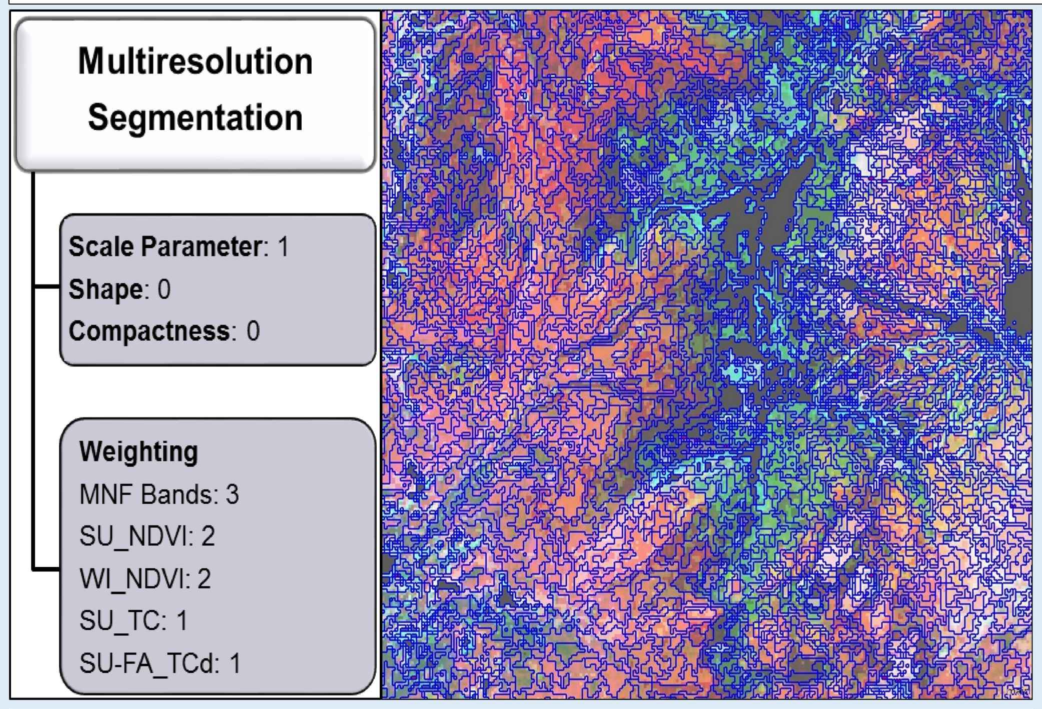
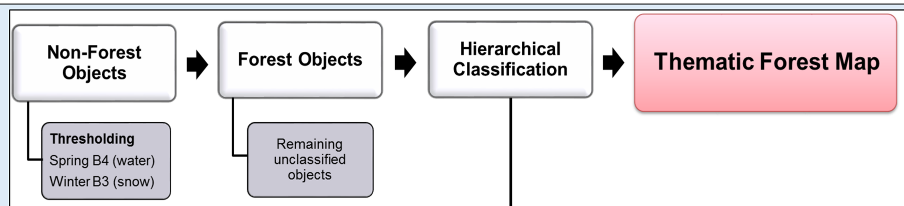


Image object segmentation parameters and spectral data weighting to classify forest cover at a stand- versus pixel-level.



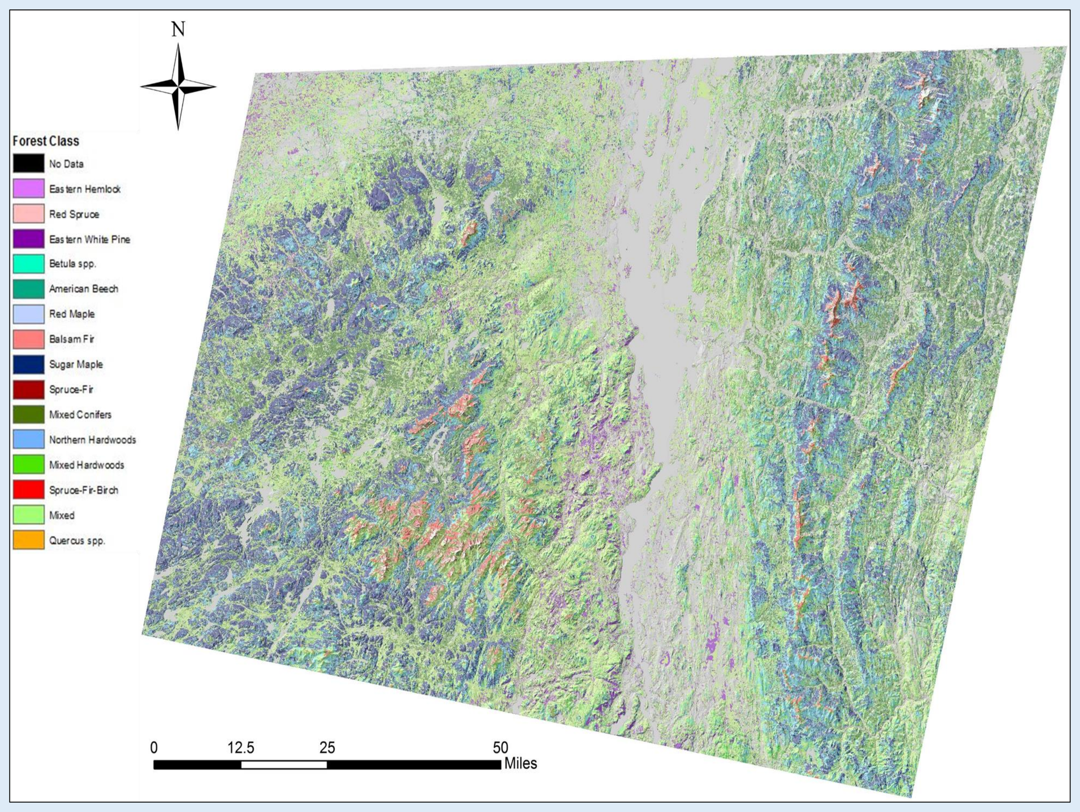
Order	Class	Condition (%BA and elevation thresholds)
1	No Data	Sum %BA for all spp = 0
2	*Populus* spp. (POPU)	POPU ≥ 0.4 AND > all other spp./genera AND DEM ≤ 910m
3	*Quercus* spp. (QUER)	QUER ≥ 0.4 AND > all other spp./genera AND DEM ≤ 430m
4	Red Spruce (PIRU)	PIRU ≥ 0.4 AND > all other spp./genera
5	Red Maple (ACRU)	ACRU ≥ 0.4 AND > all other spp./genera
6	*Betula* spp. (BETU)	BETU ≥ 0.4 AND > all other spp./genera AND FAGR ≤ 0.25 AND ACSA ≤ 0.25
7	American Beech (FAGR)	FAGR ≥ 0.4 AND > all other spp./genera AND ACSA ≤ 0.25 AND BETU ≤ 0.25 AND DEM ≤ 980
8	Eastern Hemlock (TSCA)	TSCA ≥ 0.4 AND > all other spp./genera AND DEM ≤ 730m
9	Eastern White Pine (PIST)	PIST ≥ 0.4 AND > all other spp./genera AND DEM ≤ 460m
10	Balsam Fir (ABBA)	ABBA ≥ 0.4 AND > all other spp./genera AND PIRU < 0.05
11	Sugar Maple (ACSA)	ACSA ≥ 0.4 AND > all other spp./genera AND BETU ≤ 0.25 AND FAGR ≤ 0.25 AND DEM ≤ 760
12	Northern Hardwoods	ACRU+ACSA+FAGR+BETU ≥ 0.6
13	Spruce-Fir-Birch	ABBA+PIRU+BETU ≥ 0.6 AND AND BETU ≥ 0.05 DEM ≥ 650m
14	Spruce-Fir	ABBA+PIRU ≥ 0.4 AND DEM ≥ 650m
15	Mixed Hardwoods	ACRU+ACSA+BETU+FAGR+POPU+QUER ≥ 0.6
16	Mixed Conifers	ABBA+PIRU+PIST+TSCA ≥ 0.6
17	Mixed	All remaining unclassified forest pixels

Image classification scheme to discriminate forest from non-forest using the spectral data, then **classify forest cover based on mean % basal area values and elevation thresholds.**

Forest Classification and Accuracy Assessment

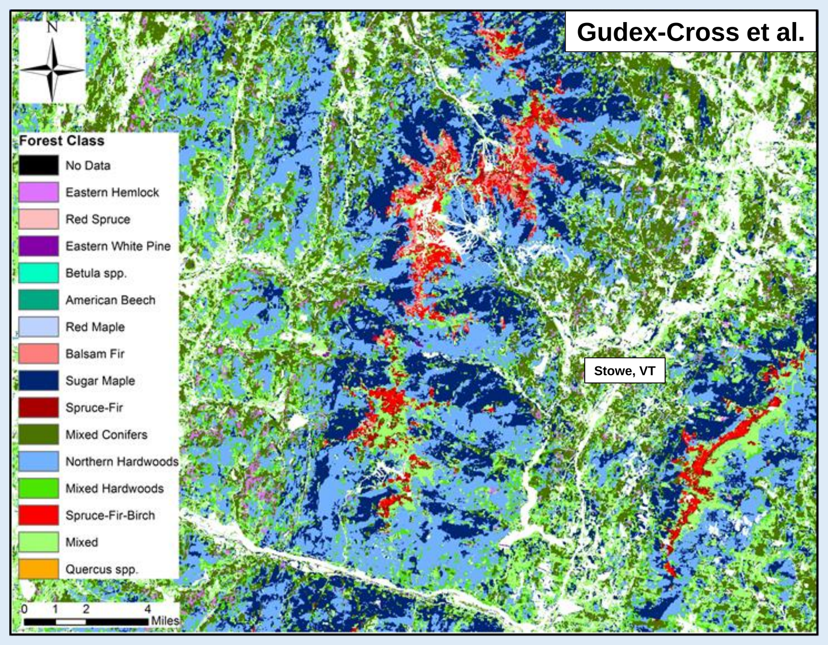
Species-type and coarse level (i.e. Deciduous, Evergreen, or Mixed) accuracy based on 50 independent federal and state forest inventory plots from across Vermont.

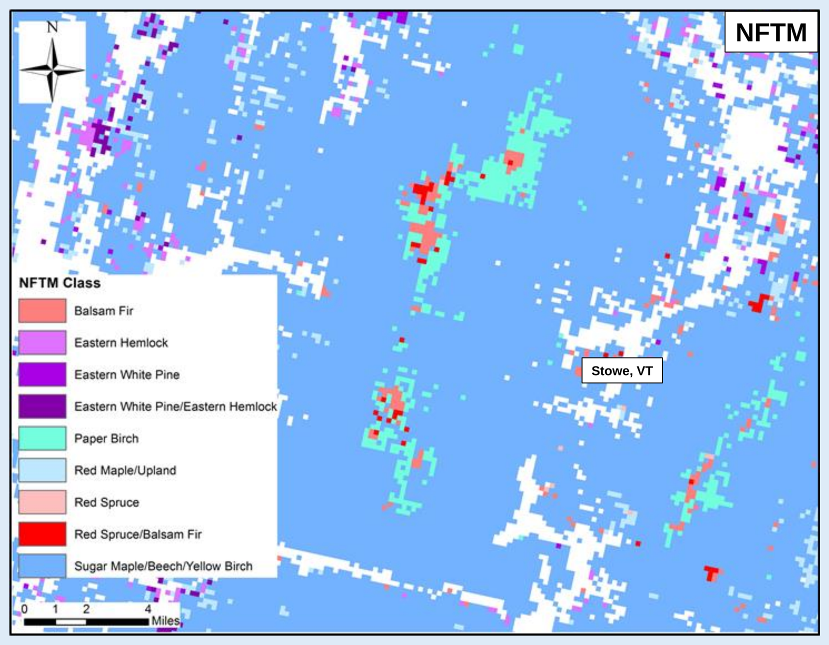
Product	Species-Type Level			Coarse Level	
	# Forest Classes	Overall Accuracy	Fuzzy Accuracy	# Forest Classes	Overall Accuracy
Gudex-Cross et al.	16	38%	84%	10	74%
NFTM	6	18%	70%	6	62%
LANDFIRE	6	28%	80%	3	66%
NLCD	--	--	--	3	56%

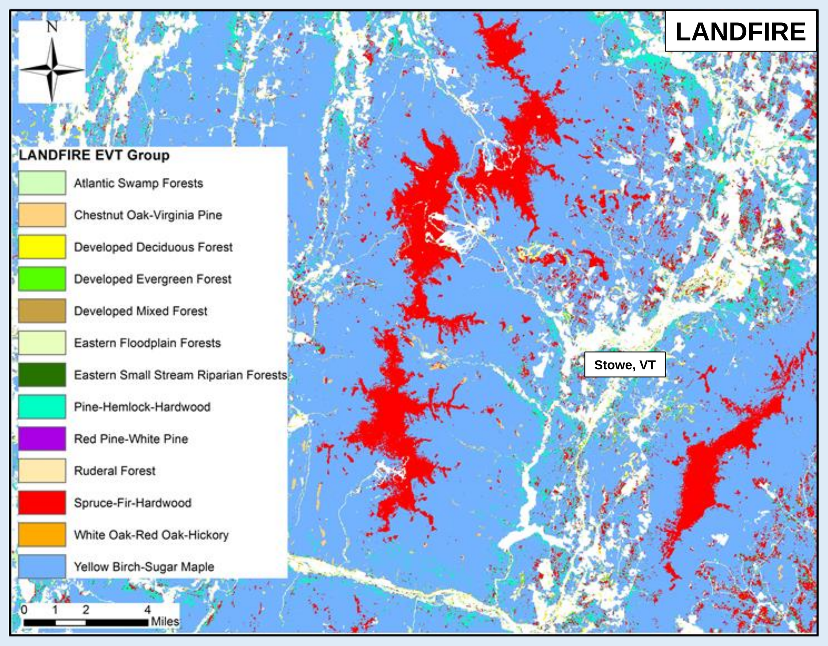


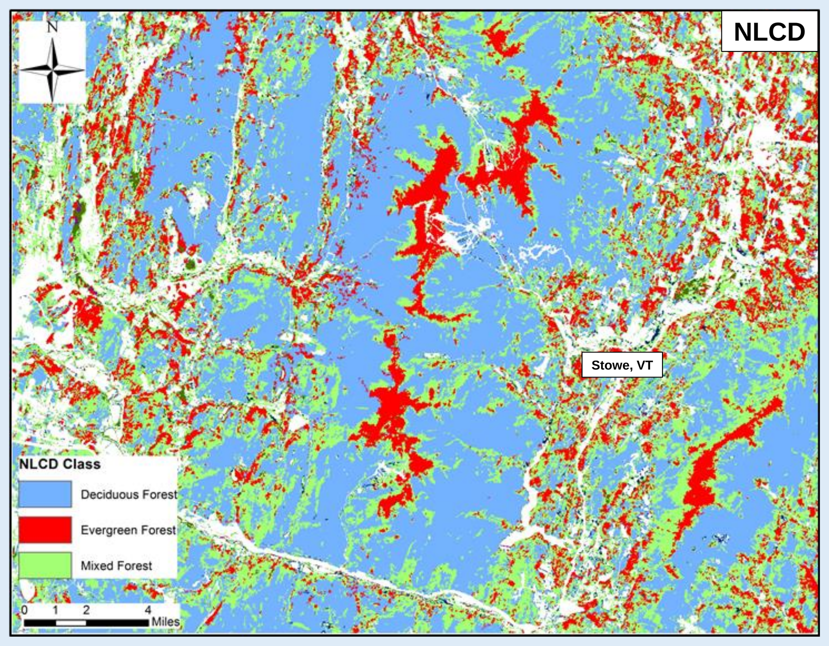
Final thematic forest classification from our integrated spectral unmixing-OBIA method across northern New York and Vermont (Landsat Path 14, Row 29).

Zoomed-in look at the difference in classification detail across the four forest classification products.









Conclusions

1. **Our integrated unmixing-OBIA approach to forest cover mapping provides increased accuracy and specificity over existing large-scale forest mapping products.**
2. **Utilization of publicly-available imagery and ancillary data ensures that this approach could be applied across larger regions at minimal cost.**
3. **Provides a forest classification product that can be used in management decisions (e.g. invasive insect host distributions) and modeling studies (e.g. aboveground carbon storage).**
4. **Basal area mapping and classification errors are influenced by: the number and quality of "pure" calibration sites for unmixing algorithms; limited availability of cloud and error free imagery from all seasons; and the spectral similarities among compatriot species. These issues highlight the importance of field inventories, image selection, and preprocessing in integrated classification schemes.**
5. **Current efforts include mapping species composition from the Adirondacks to southern Maine at 5 year intervals to understand how and where species distributions may be shifting across the landscape over the past three decades. This information can guide management (e.g. invasive insect host distributions) and modeling efforts (e.g. carbon storage) into the future.**