

Utilizing Patch Metrics to Improve Classification of Remote Sensing Imagery



THE UNIVERSITY of
TULSA

Michael L. Treglia* and Megan E. Young
Department of Biological Science, University of Tulsa, Tulsa, OK 74104-9700
Departments of Wildlife and Fisheries, Texas A&M University, College Station, TX 77843-2258
*e-mail: mike-treglia@utulsa.edu



Problem: Classified remote sensing imagery is used to inform management of various natural resources, though achieving accurate results is a persistent challenge. In particular, some land cover types that are functionally very distinct can be spectrally similar, thus misclassification errors can yield poor decision-making. Relatively new, object-oriented classification methods that consider the shape of clusters of similar pixels can yield improved results, albeit often at considerable software expense and steep learning curves.

Our Approach: We employ a two-stage classification procedure, that takes advantage of free and open source tools to improve upon per-pixel classification techniques. First we perform supervised classification to obtain a layer with patches of our focal land cover classes. We then calculate descriptive metrics for each patch, characterizing size and shape, and for each land cover class we extract the per-pixel probability of class assignment. Lastly, we perform a second supervised classification based on raster layers representing the aforementioned class probabilities and patch metrics.

Case Study: A Complex Landscape of West Texas

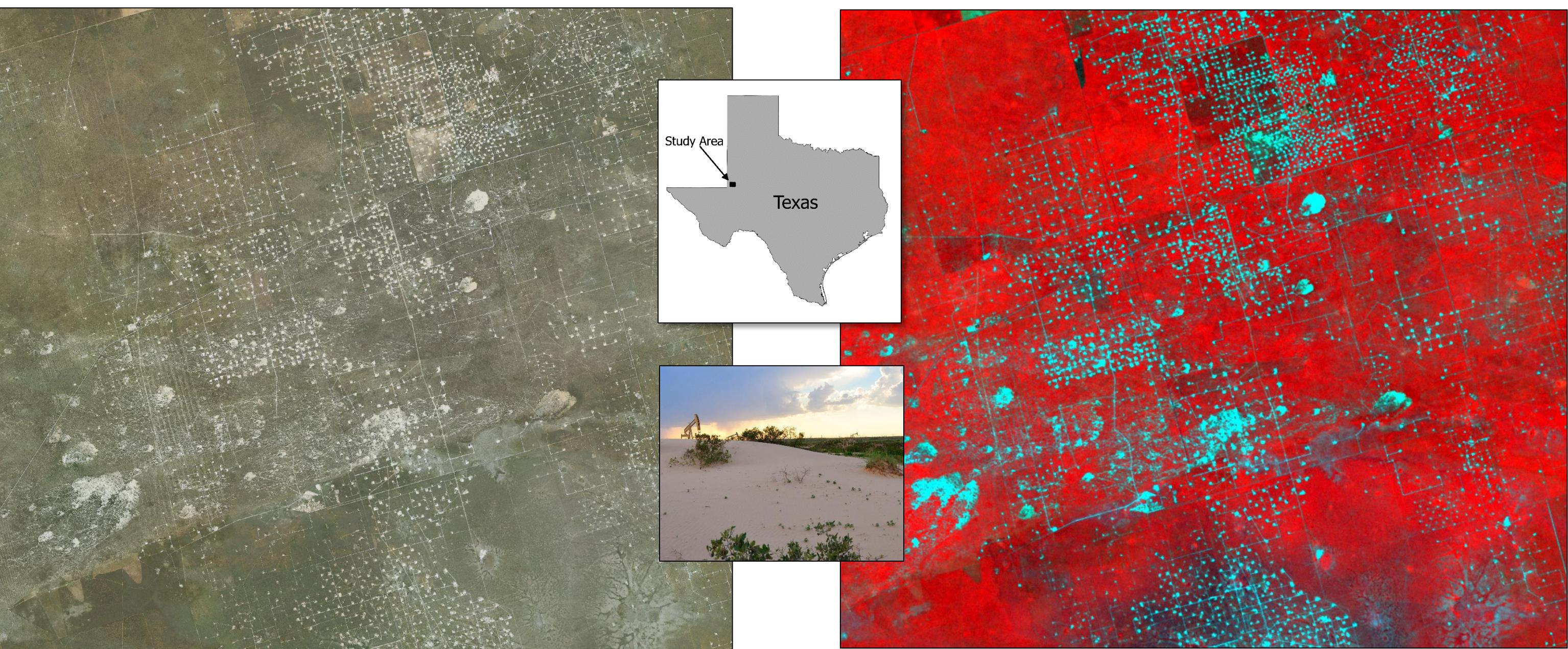


Fig. 1. NAIP 1 m aerial imagery (left) and false color composite from Landsat TM data (right) displaying NDVI, Green and Blue for our study area.

Methods

Stage 1 Classification

- Calculated NDVI and Tasseled Cap metrics for a single Landsat scene (Path 30/Row 38) from 2010 and stacked them with the original Landsat bands using QGIS and R.
- Performed supervised classification using Random Forests (in R), based on 260 training areas derived from 1 m aerial imagery and our knowledge of the system.

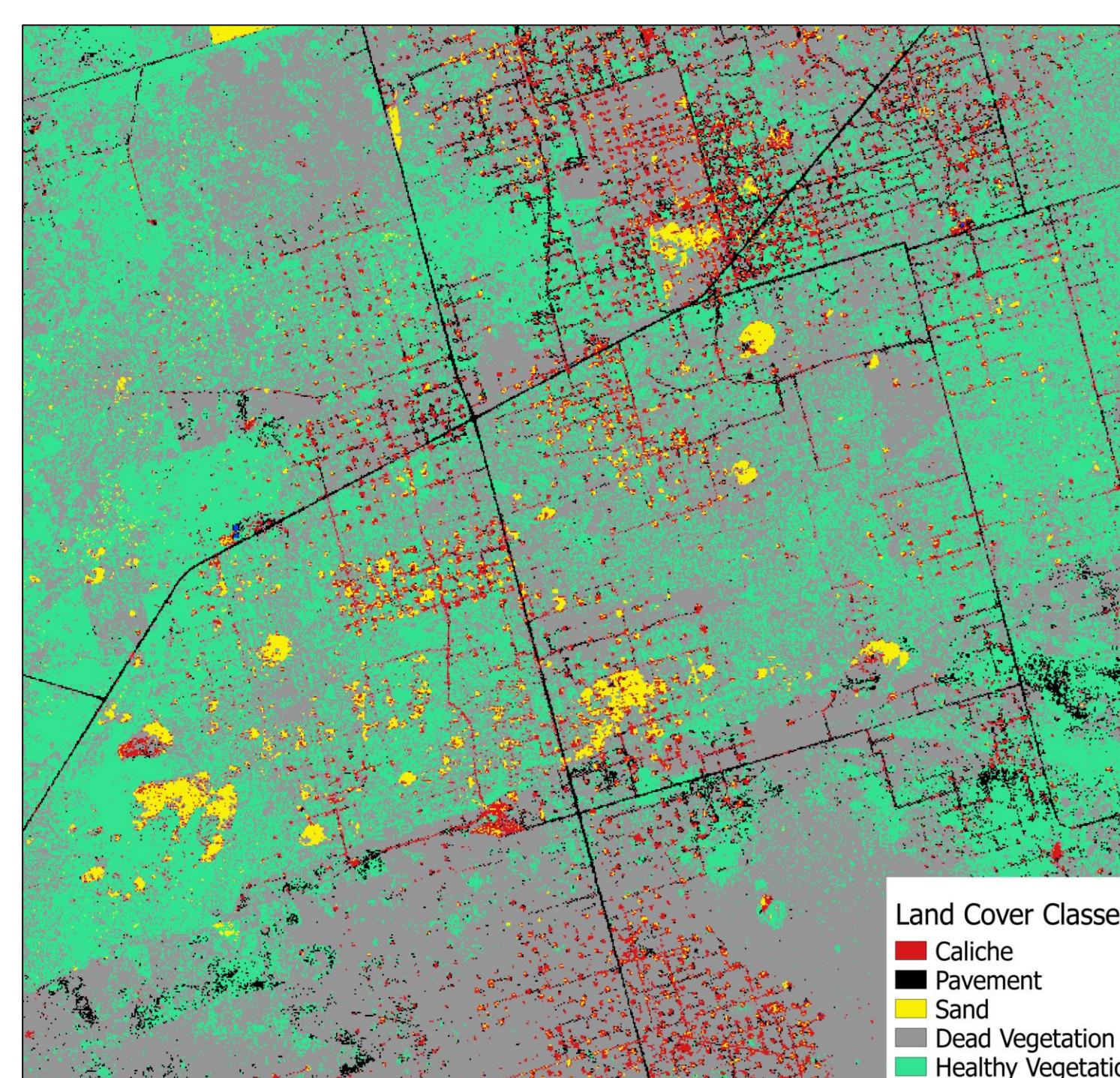
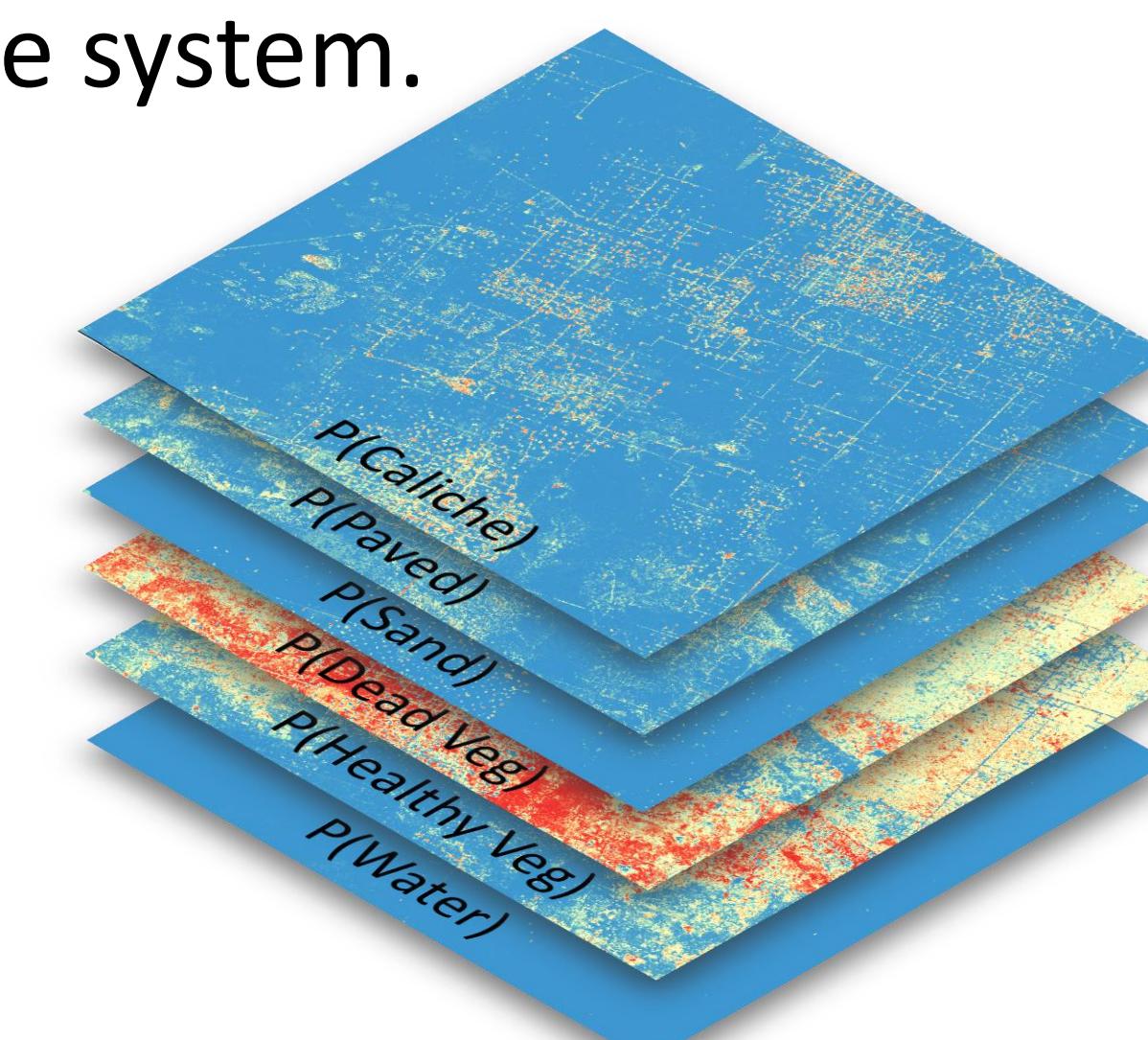


Fig. 2. Result of stage 1 classification (left), and derived data used in the stage 2 classification including patch metrics (bottom-right) and per-pixel class probabilities (top-right).



Patch ID	AREA	PERIM	GYRATE	PARA	SHAPE	Frac	Circle	Contig	ENN
1	6.30	3480	141.52	552.38	3.41	1.23	0.74	0.56	60.00
3	3.06	1500	114.20	490.20	2.08	1.15	0.81	0.57	60.00
4	8965.26	2886300	6022.36	321.94	76.12	1.47	0.77	0.75	60.00
7	0.09	120	15.00	1333.33	1.00	1.00	0.00	0.00	67.08
10	0.36	300	30.00	833.33	1.25	1.05	0.70	0.25	67.08
12	0.09	120	15.00	1333.33	1.00	1.00	0.00	0.00	134.16
13	0.45	300	25.48	666.67	1.00	1.03	0.51	0.43	90.00
14	4.14	2280	116.33	550.72	2.71	1.19	0.79	0.55	60.00
15	0.45	360	32.84	800.00	1.20	1.07	0.68	0.30	60.00

Stage 2 Classification

- Calculated metrics for each distinct land cover patch classified in stage 1, using Fragstats, and created raster layers for each metric.
- Created raster layers of class probabilities from the stage 1 classification for each land cover class.
- Performed supervised classification using Random Forests, on raster layers representing class probabilities and patch metrics.

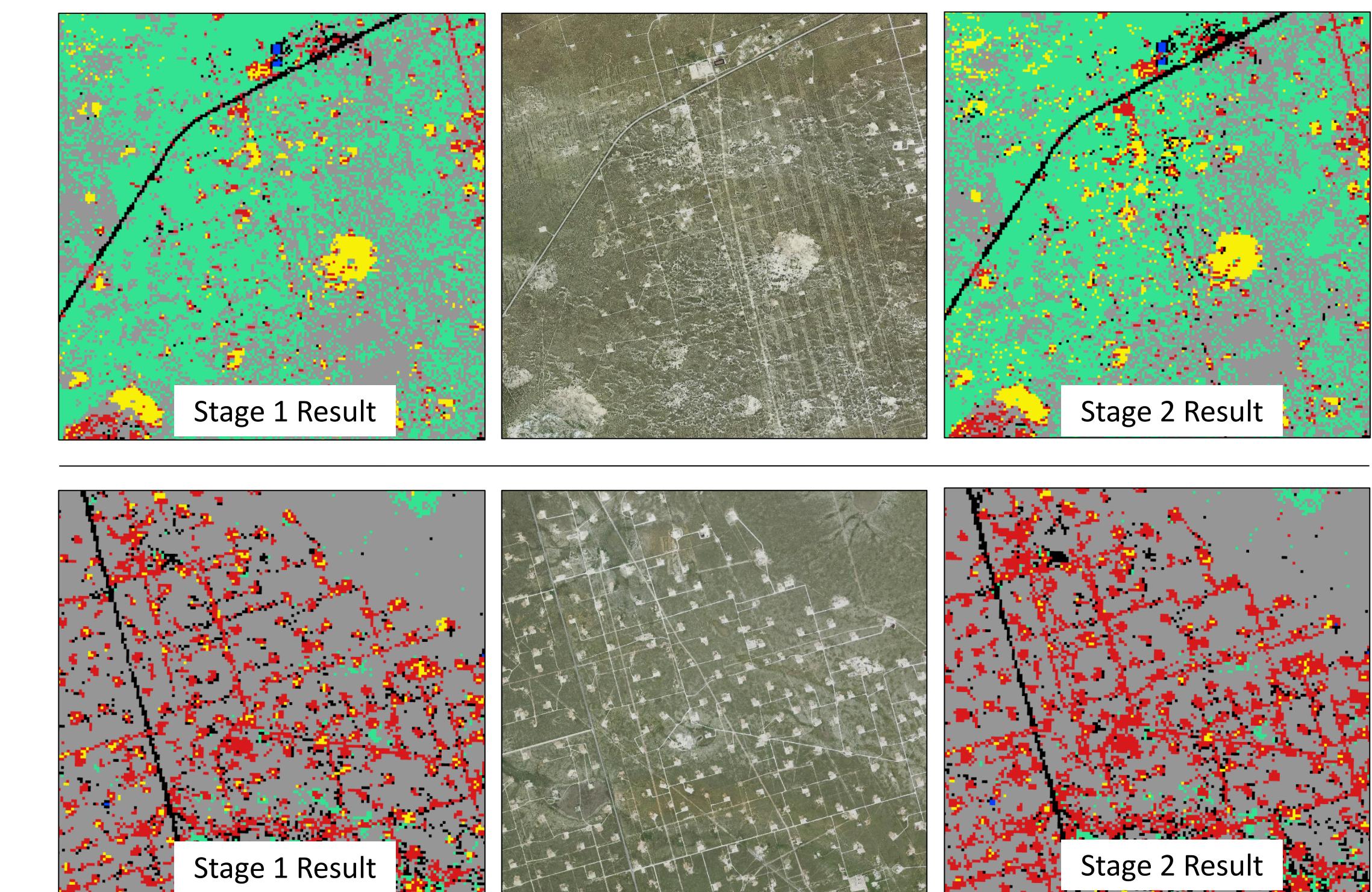


Fig. 3. Classification results for two focal parts of our study area (top and bottom), illustrating the differences in our stage 1 and stage 2 classification, with 1 m aerial imagery in the middle.

Study Area

- We focused on a portion of the Mescalero/Monahans Sand Dunes ecosystem in western Texas, USA, home to unique biodiversity and threatened by oil and gas development.
- The landscape is complex and difficult to classify, particularly with regard to oil/gas roads and well-pads (made of caliche) and natural sand formations.
- We strived to classify on Landsat 5 TM data, available for large portions of the globe for up to 27 years, at 30 m resolution.

Results

Deriving patch statistics from a per-pixel classification for use in a second classification run provided some benefit in our system (Fig. 3). Though there are still classification errors after stage 2, caliche roads and well-pads are better distinguished from sand formations. The stage 2 classification increased overall accuracy on our training dataset, from 94% to 98%. Though these results are positive, neither classification performed well on a smaller evaluation dataset (~50% overall accuracy), with the greatest confusion between living and dead vegetation.

Discussion and Next Steps:

Our two-stage approach for classifying remote sensing imagery effectively uses information about clusters of similar pixels to improve results. It is conceptually simple, and was done exclusively using freely available tools. The example presented here is a first attempt at this method, involving a complex landscape with fine-scale features, perhaps difficult to detect using Landsat imagery. Thus, we suspect this technique will yield greater benefit in landscapes with larger features, or using higher-resolution imagery.