LARGE-AREA LAND USE/LAND COVER CLASSIFICATION OF VERY HIGH-RESOLUTION IMAGERY: ACCOUNTING FOR SPATIAL BIAS IN SAMPLE DATA

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https://scholar.google.com/citations?user=8hXlpL0AAAAJ&hl=en

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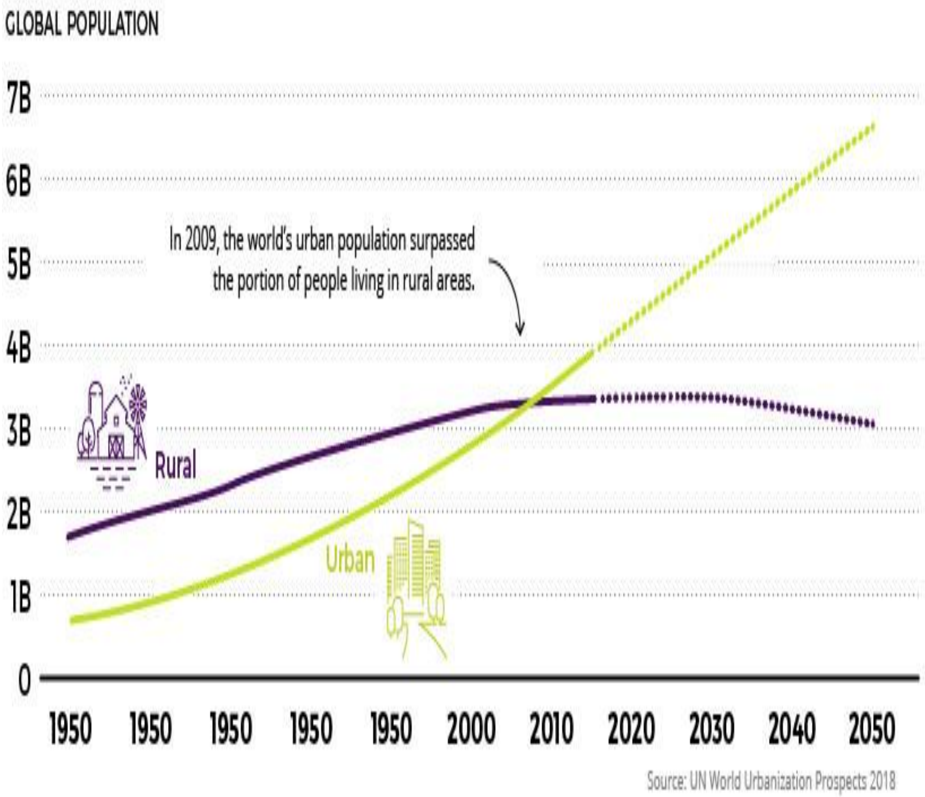
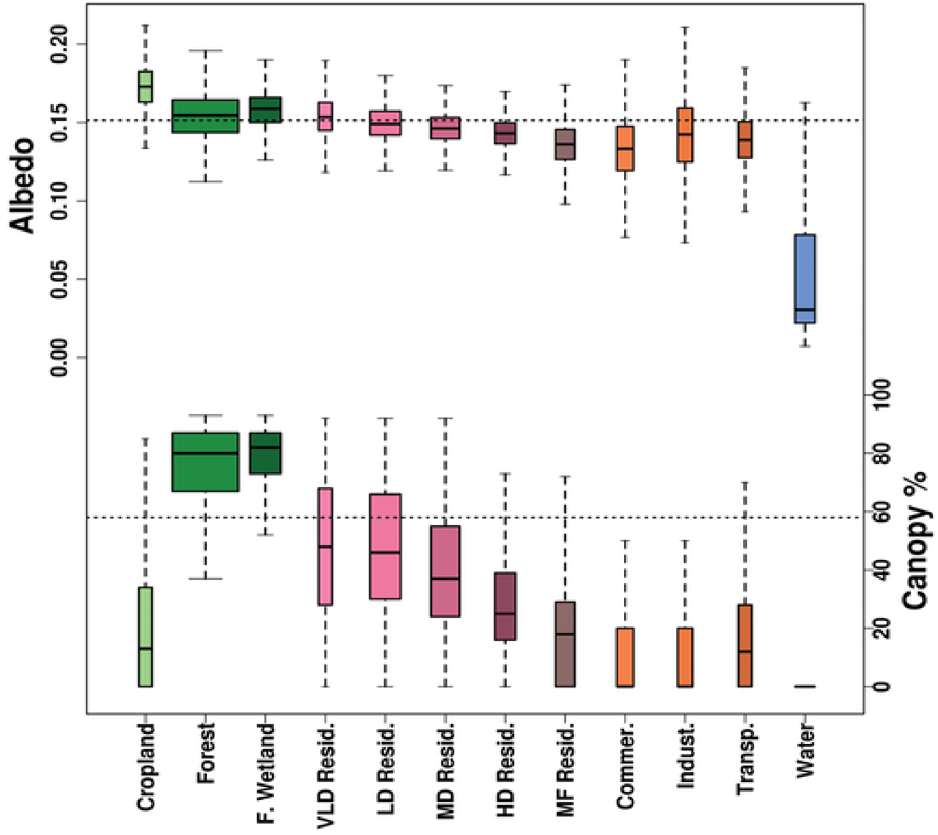
Land Use /Land Cover (LULC)

- Biophysical and human developed features are dynamic



Land cover is an essential climate variable (Hollmann et al., 2013)



Source: (Trlica et al., 2017)

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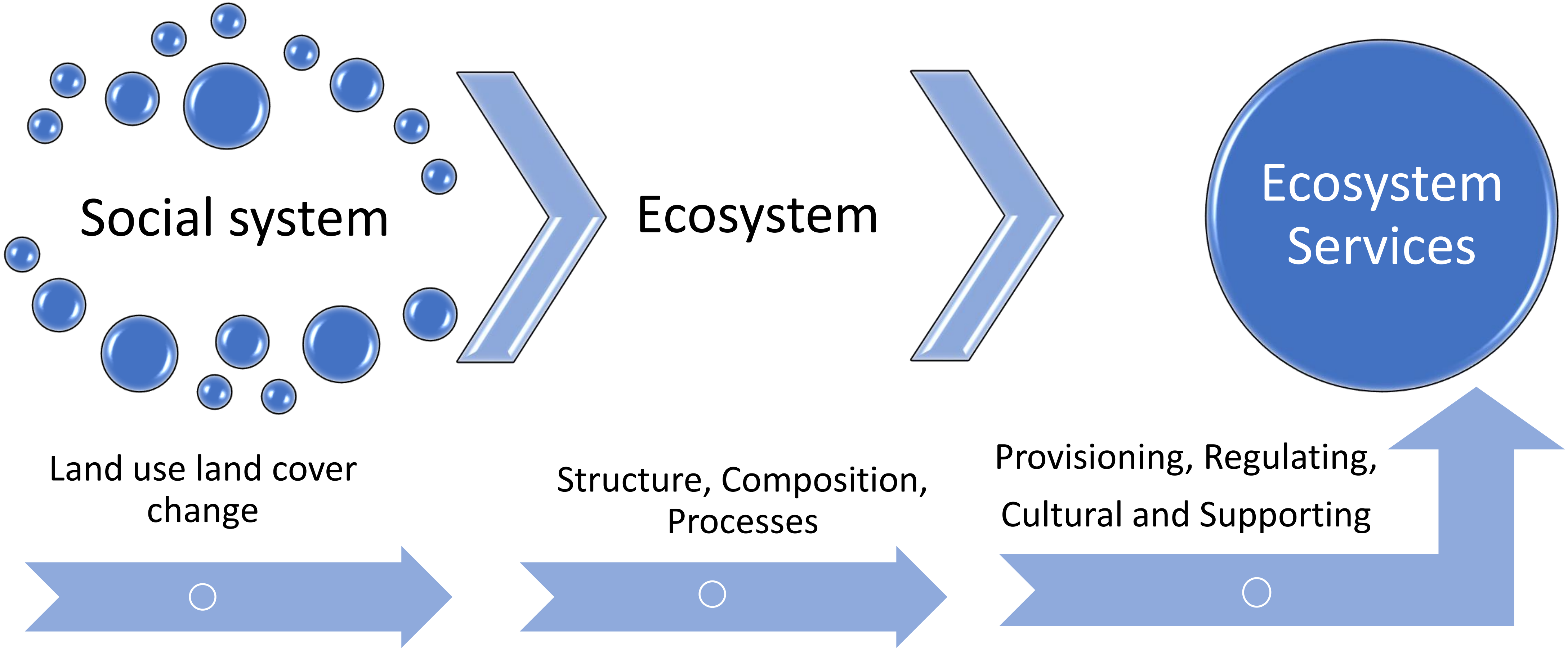
Land Use /Land Cover Change (LULCC)



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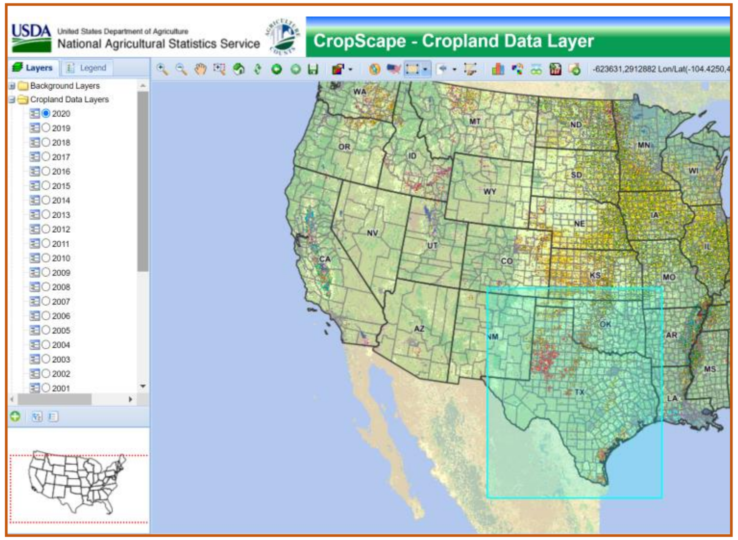
LULC Products in Texas

Multi-temporal LULC change database from 2001 -2019 at every 2–3-year intervals.

Multi-source training data.

Machine learning based land cover classifications.

Availability: FREE

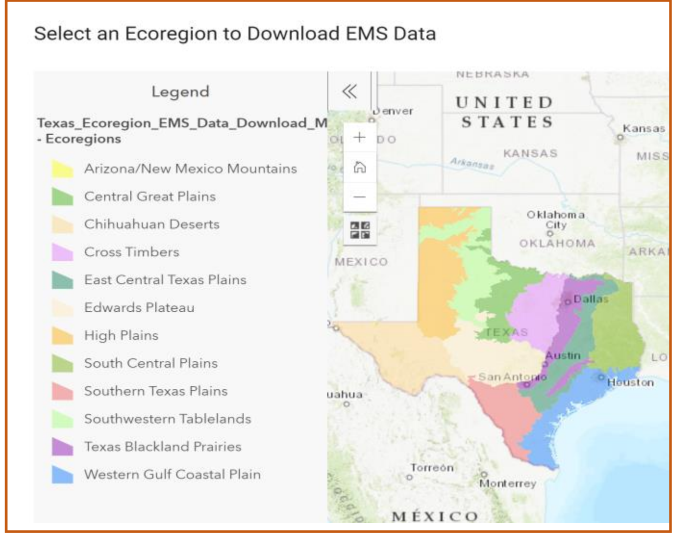


Cropland Data Layer (CDL).

Multi-Temporal/Source LULC data at annual resolution.

Based on moderate resolution satellite imagery and extensive agricultural ground truth.

Availability: FREE



Ecological Mapping System[TPWD].

Based on NAIP objects (10 m) and Expert rules.

70-90% of Overall Accuracy.

Availability: FREE

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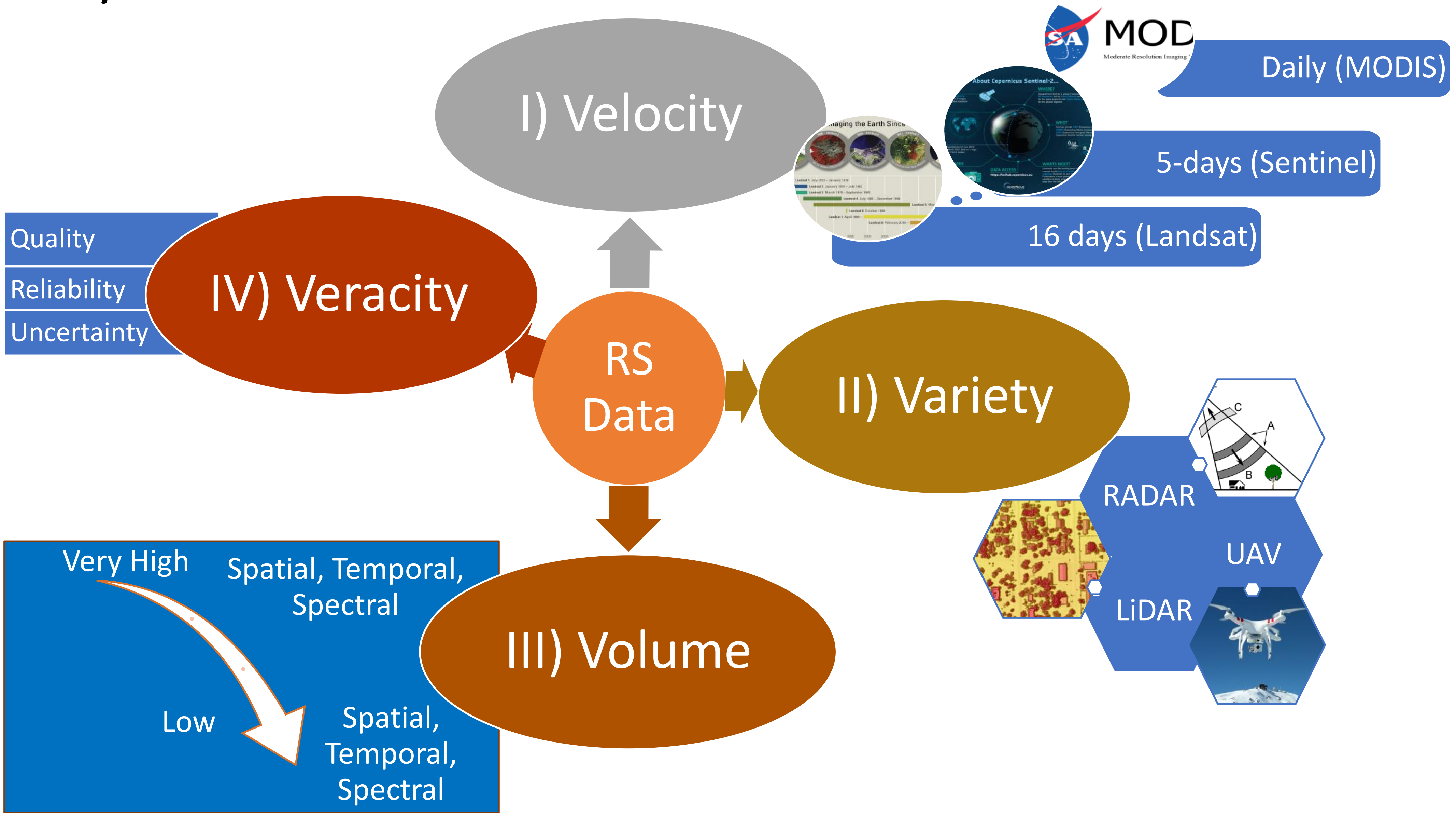
Why Do We Need New LULC Product?



Can We harvest NAIP data for Accurate LULC?

Pros

- ✓ High-Spatial Resolution
- ✓ Free of Cost
- ✓ Low Cloud Contamination (<10%)

Cons

- ➢ Low Spectral Resolution
- ➢ Low Radiometric Resolution
- ➢ Low Temporal Resolution
- ➢ Heterogeneity in data and data acquisition
- ➢ Demand Higher processing power
- ➢ Demand more sophisticated classifier (algorithm)

Processing Scheme: Pixel based or Geographic Object Based (GEOBIA)

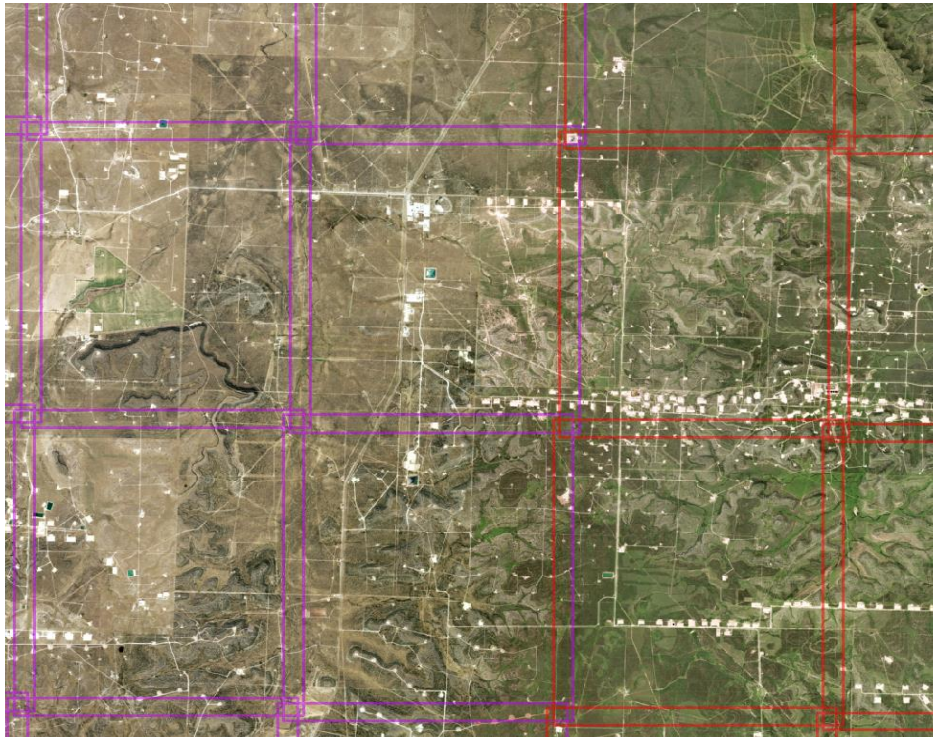
Pixel based/ Object based approaches with ancillary data on NAIP images have shown to produce reasonable accuracy, mostly when resulting LULC classer are fewer(<=5).

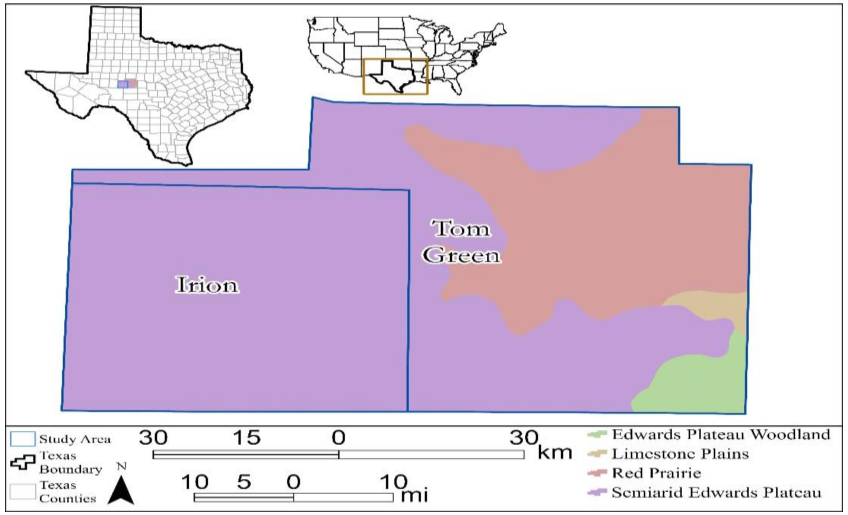
Can We Produce High Resolution Multi-Class Land Use Land Cover Map with National Agriculture Imagery Program (NAIP) Data? If so, How?

How can we utilize NAIP data for LULC?

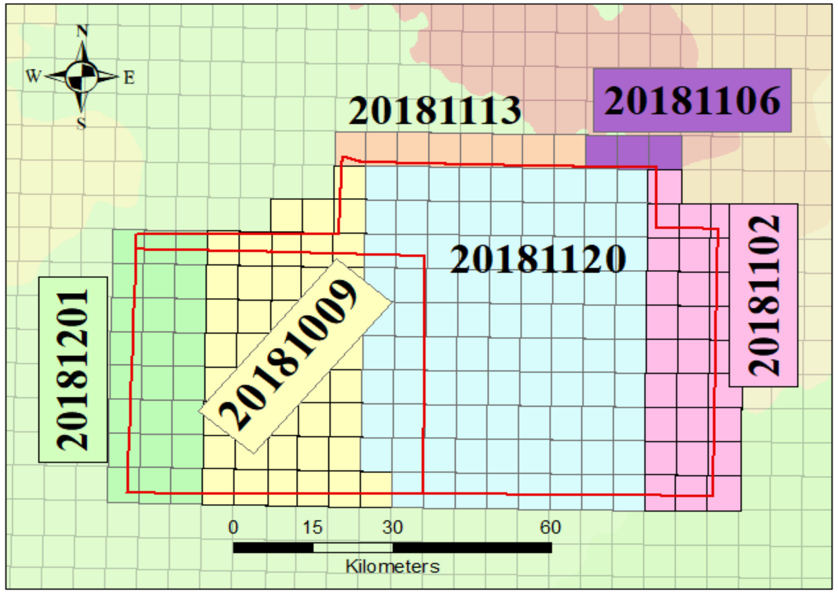
Hypothesis:

- GEOBIA based image classification is effective, and efficient in producing high-quality LULC map harvesting high-resolution orthoimagery (NAIP)data.





Study Area



Data Processing Workflow

Pre-Processing

Median Filter

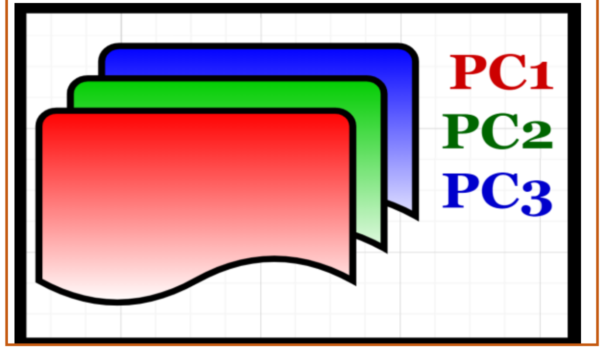
Input

1	4	0	1	3	1
2	2	4	2	2	3
1	0	1	0	1	0
1	2	1	0	2	2
2	5	3	1	2	5
1	1	4	2	3	0

Output

1	4	0	1	3	1
2	1	1	1	1	3
1	1	1	1	2	0
1	1	1	1	1	2
2	2	2	2	2	5
1	1	4	2	3	0

PCA



Segmentation

Feature Extraction

Spectral
- [Total 15]
- [Mean and S.D. on NAIP, and PCA Bands]

Shape
- [Total 7]
- [Object Geometry Feature]

Texture
- [Total 9]
- [Mean and sd of textures]

Index
- [Total 4]
- [Based on NAIP]

Classification

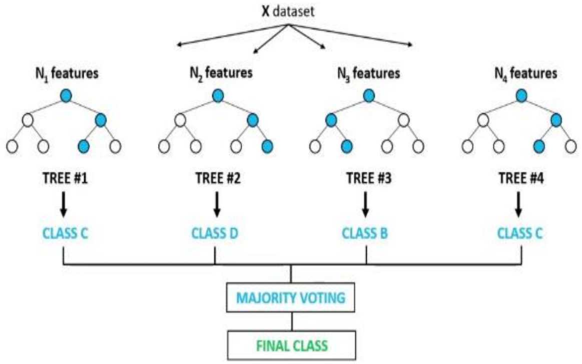
Training Samples

Spatial Analysis

Spatial Filtering

Machine learning

Random Forest Classifier



Map Validation

Final Map

Icon credits: ArcGIS Pro, eCognition, R Core Team , and Rstudio

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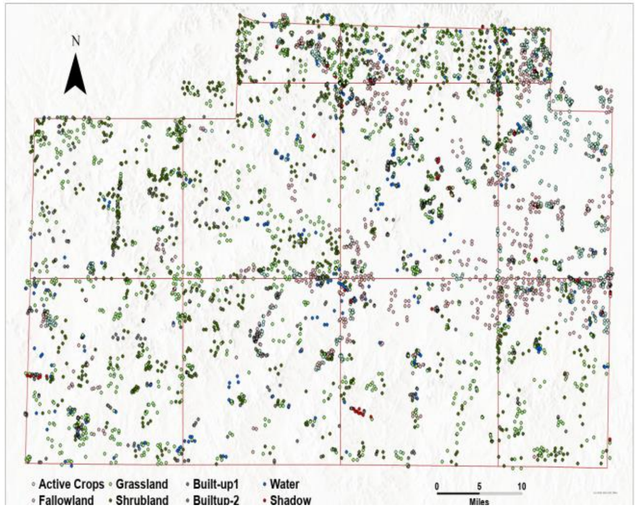
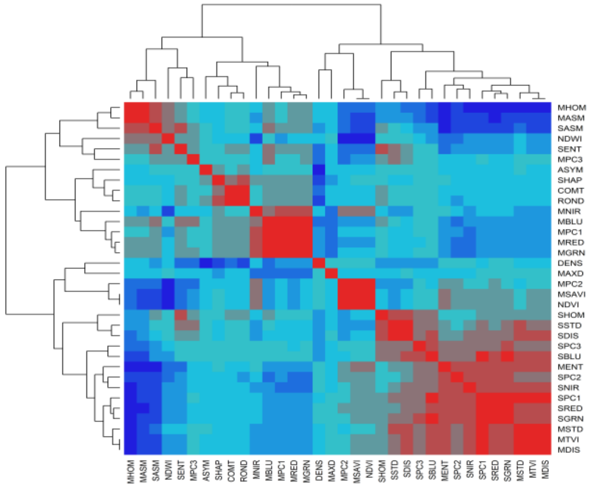
B. LULC Products
C. Data in LULC Mapping
D. Objective/Hypothesis
E. Study Area
F. **Data Processing Workflow**
G. Map Validation/Confusion Matrix
H. Variable Importance
I. Area Under ROC Curve
J. Key Results
K. Way Forward
L. References

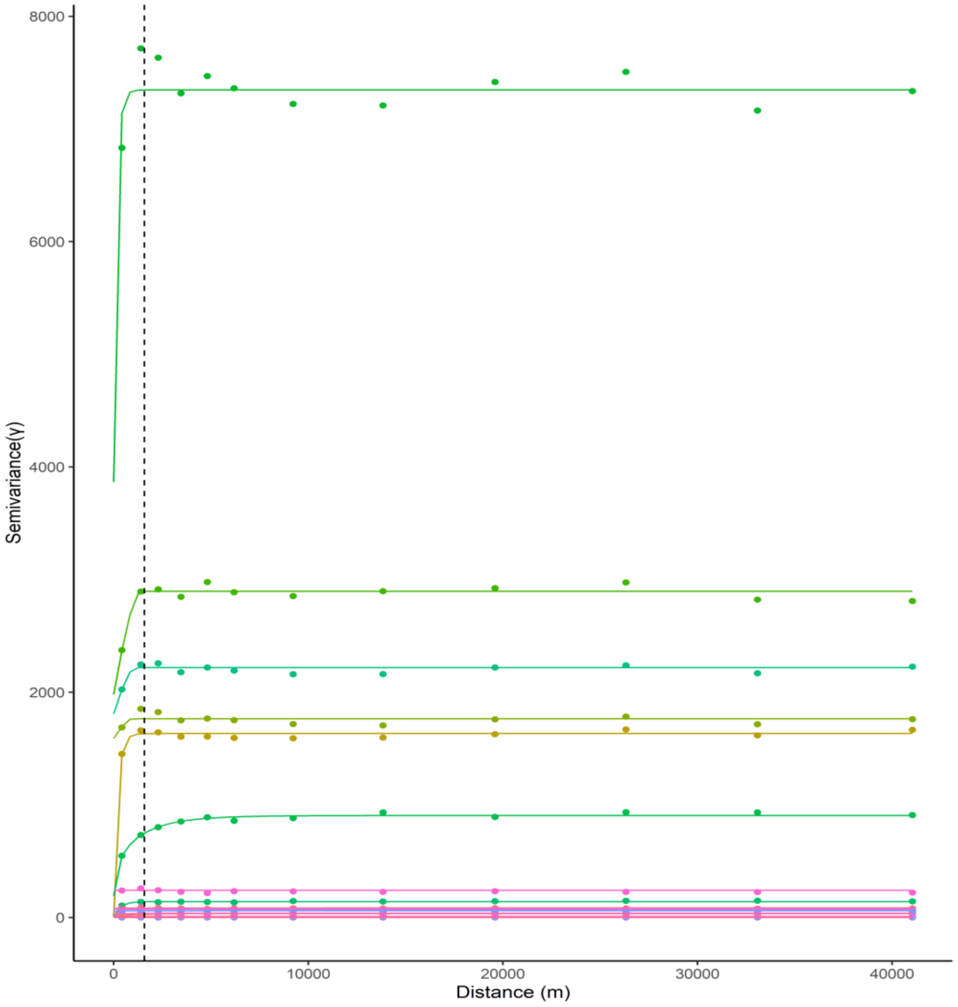
Classification Flow: A Closer Look

Training Samples





Spatial Dependence Analysis



Classification

Thinned Data Splitting

Training (80%)
Testing (20%)

Random Forest Classifier

Hyper-parameters Tuning

Classified Map

Stratification + Sampling (185 *8)

Map Validation and Final Map

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Map Validation

Sampling:- Stratified Random Sampling with Equal Allocation

LULC Class	Accuracy: User's (Precision)	Accuracy: Producer's (Sensitivity)	Specificity†	F1-score@
Active Crops	89.19%	91.16%	99.13%	90.16%
Fallow land	97.84%	95.77%	99.69%	96.79%
Grassland	96.22%	91.75%	99.46%	93.93%
Shrubland	98.38%	93.81%	99.77%	96.04%
Built-up1	92.43%	99.42%	98.93%	95.80%
Built-up2	97.84%	95.26%	99.69%	96.53%
Water	93.51%	96.11%	99.08%	94.79%
Shadow	92.97%	95.56%	99.00%	94.25%
Overall Accuracy		**94.80%**		
Kappa		**94.10%**		

†Specificity indicates the correct prediction of negative values.

@F1-Score is the harmonic mean of precision and sensitivity/recall.

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Map Validation

Predicted Class	Reference Class: Active crops	Fallow land	Grassland	Shrubland	Built-up1	Built-up2	Water	Shadow	Commission/ Users' error	User Accuracy (Precision)
Active crops	165 (17.51%)	1 (0%)	9 (0.15%)	5 (0.04%)	1 (0.01%)	4 (0.01%)	0 (0%)	0 (0%)	10.81% (1.21%)	89.19% (98.79%)
Fallow land	0 (0%)	181 (52.94%)	3 (0.11%)	0 (0%)	0 (0%)	1 (0.04%)	0 (0%)	0 (0%)	2.16% (0.28%)	97.84% (99.72%)
Grassland	5 (0.26%)	1 (0.13%)	178 (8.05%)	1 (0.03%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	3.78% (4.94%)	96.22% (95.06%)
Shrubland	0 (0%)	0 (0%)	3 (0.05%)	182 (10%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1.62% (0.53%)	98.38% (99.47%)
Built-up1	10 (0.26%)	2 (0.19%)	1 (0.04%)	0 (0%)	171 (3.99%)	0 (0%)	1 (0.01%)	0 (0%)	7.57% (10.86%)	92.43% (89.14%)
Built-up2	1 (0%)	2 (0.01%)	0 (0%)	1 (0%)	0 (0%)	181 (0.93%)	0 (0%)	0 (0%)	2.16% (1.52%)	97.84% (98.48%)
Water	0 (0%)	2 (0.03%)	0 (0%)	0 (0%)	0 (0%)	2 (0.02%)	173 (4.45%)	8 (0.05%)	6.49% (2.15%)	93.51% (97.85%)
Shadow	0 (0%)	0 (0%)	0 (0%)	5 (0.01%)	0 (0%)	2 (0.02%)	6 (0.03%)	172 (0.62%)	7.03% (9.45%)	92.97% (90.55%)
Omission/Producer's error	8.84% (2.91%)	4.23% (0.67%)	8.25% (4.12%)	6.19% (0.84%)	0.58% (0.28%)	4.74% (8.38%)	3.89% (0.86%)	4.44% (7.53%)		
Producer's Accuracy (Sensitivity)	91.16% (97.09%)	95.77% (99.33%)	91.75% (95.88%)	93.81% (99.16)	99.42% (99.72)	95.26% (91.62%)	96.11% (99.14)	95.56% (92.47%)		
Overall Accuracy	**94.8% (98.5%)**									
Kappa	**94.1% (97.75%)**									

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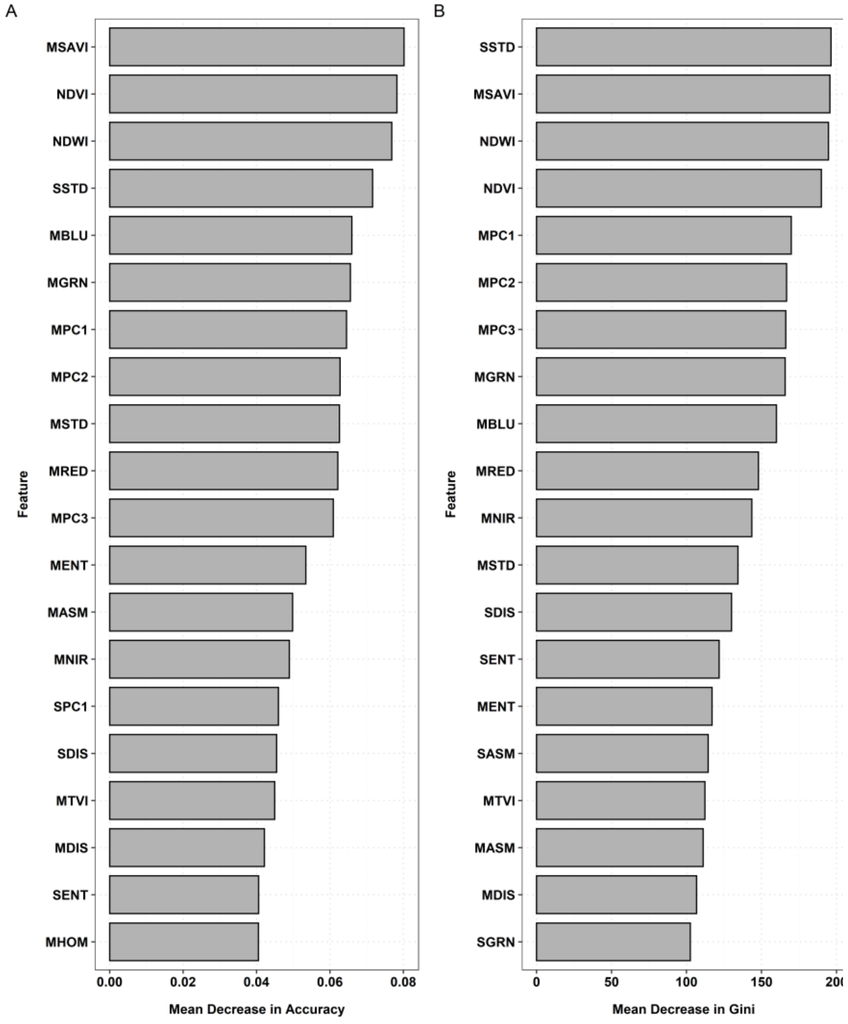
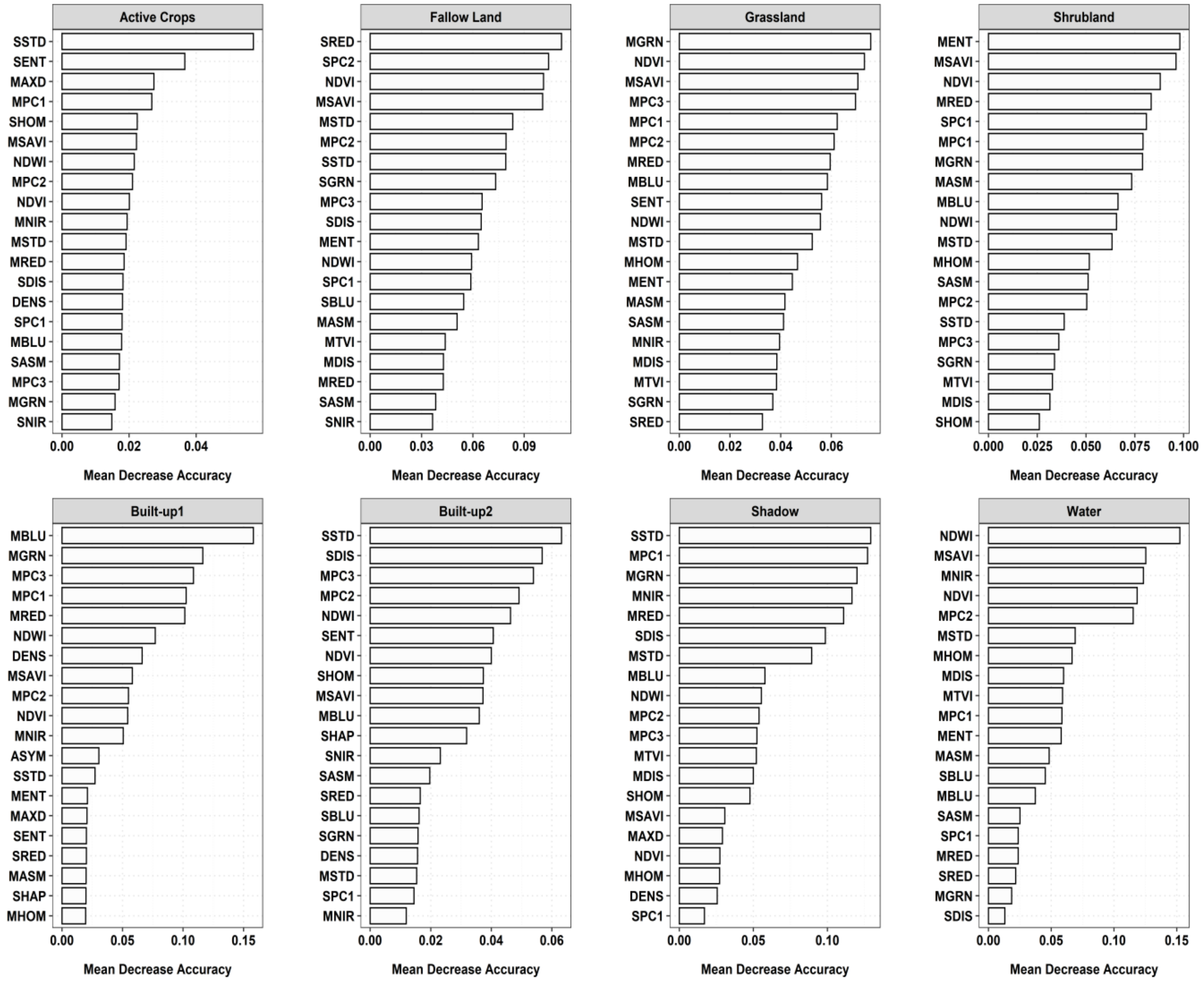
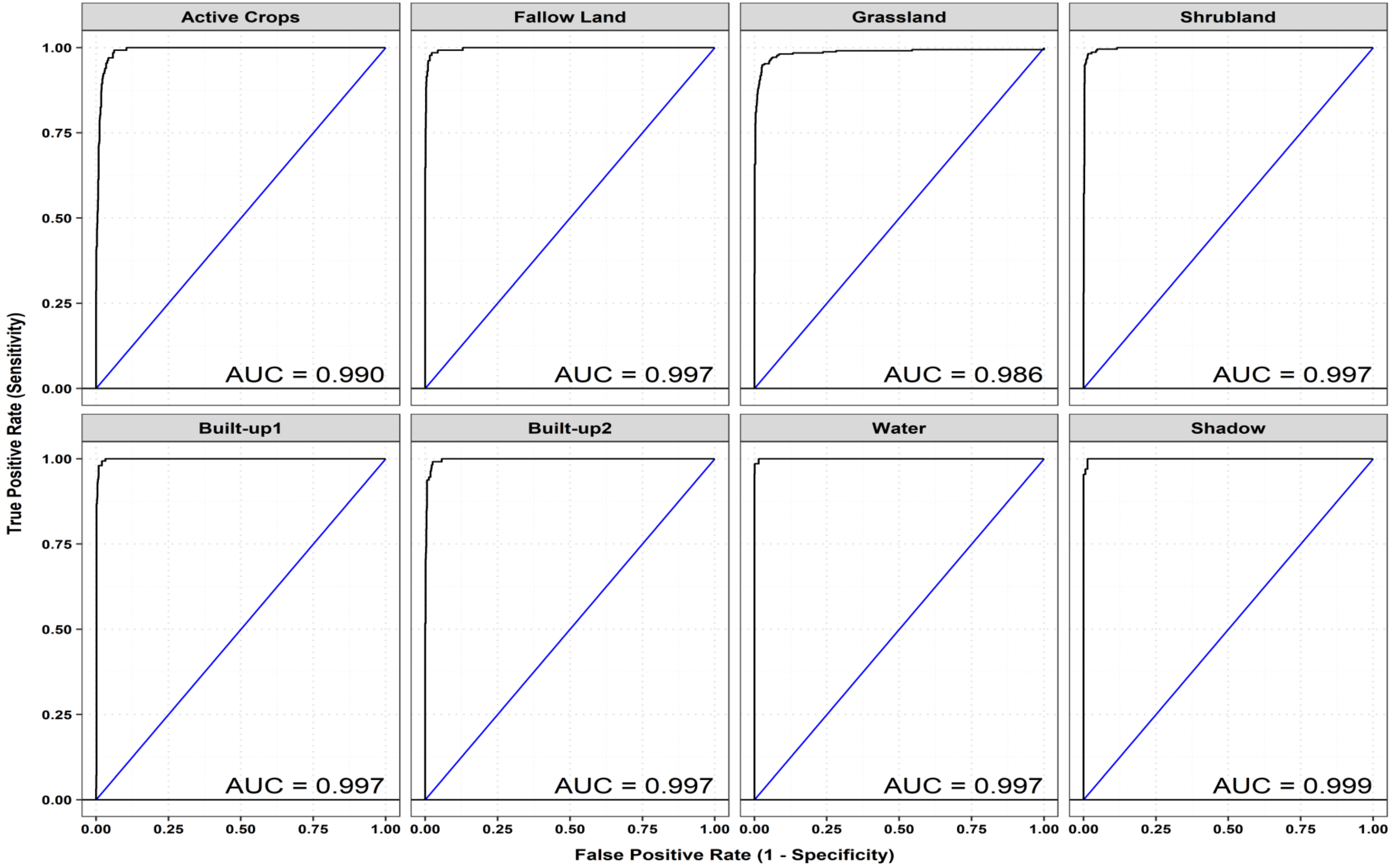
Variable Importance





Area Under ROC Curve



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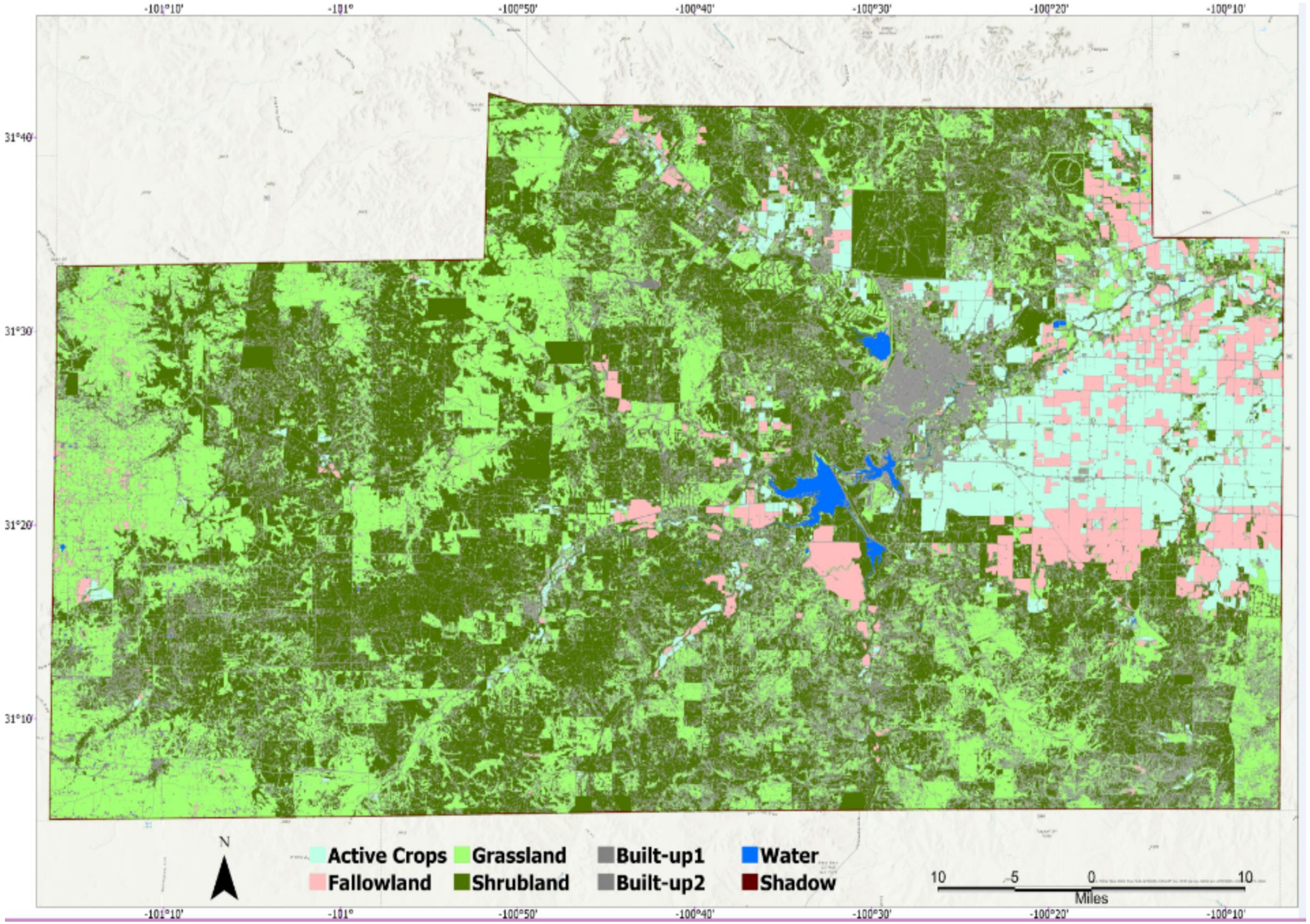
Final Classified Map



Key Results

GEOBIA image classification on NAIP orthoimagery improve LULC map accuracy in comparison to available LULC data products in Texas.

Principal Component Analysis (PCA)on NAIP, GLCM textures, and multiple indices were important in classification process.

We extended spatial thinning method usually applied in presence only data to multi-class classification accounting spatial dependency, which removed spatial bias and over-fitting of model.

Class-level accuracy achieved in the study based on only NAIP data is higher than previous studies; especially in Agriculture.

Higher Producer’s and User’s Accuracies in area-based validation of map indicates misclassification occurred in small objects.

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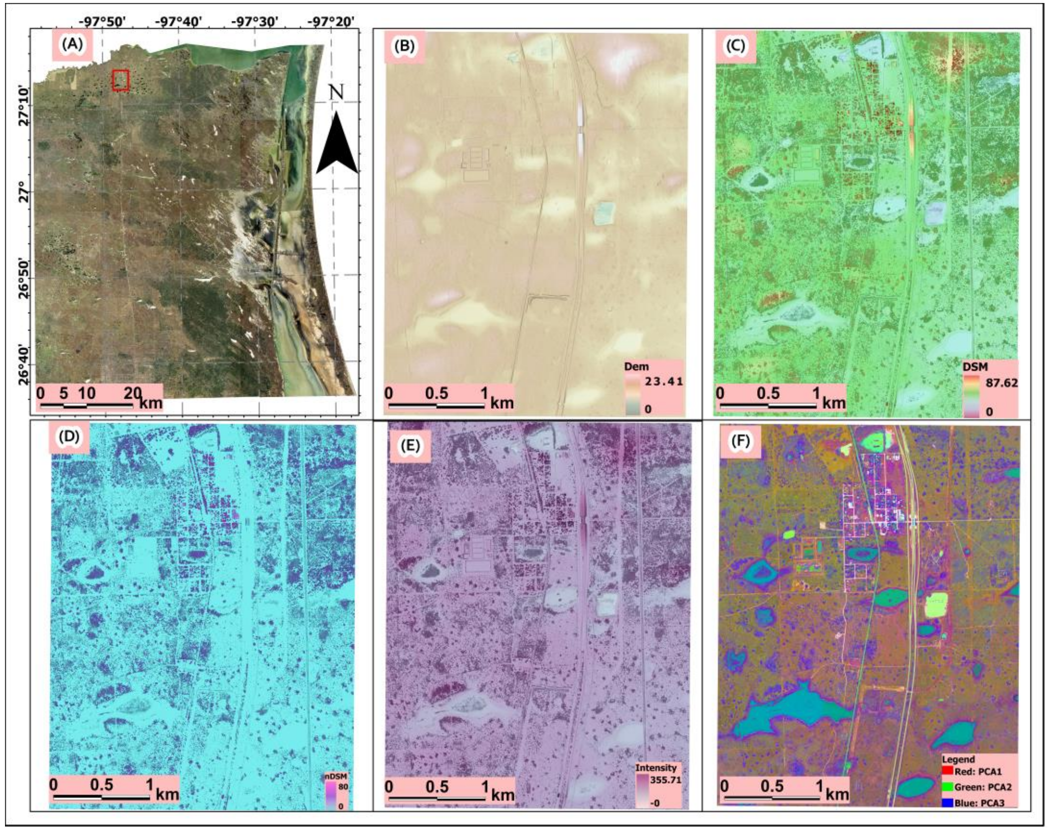
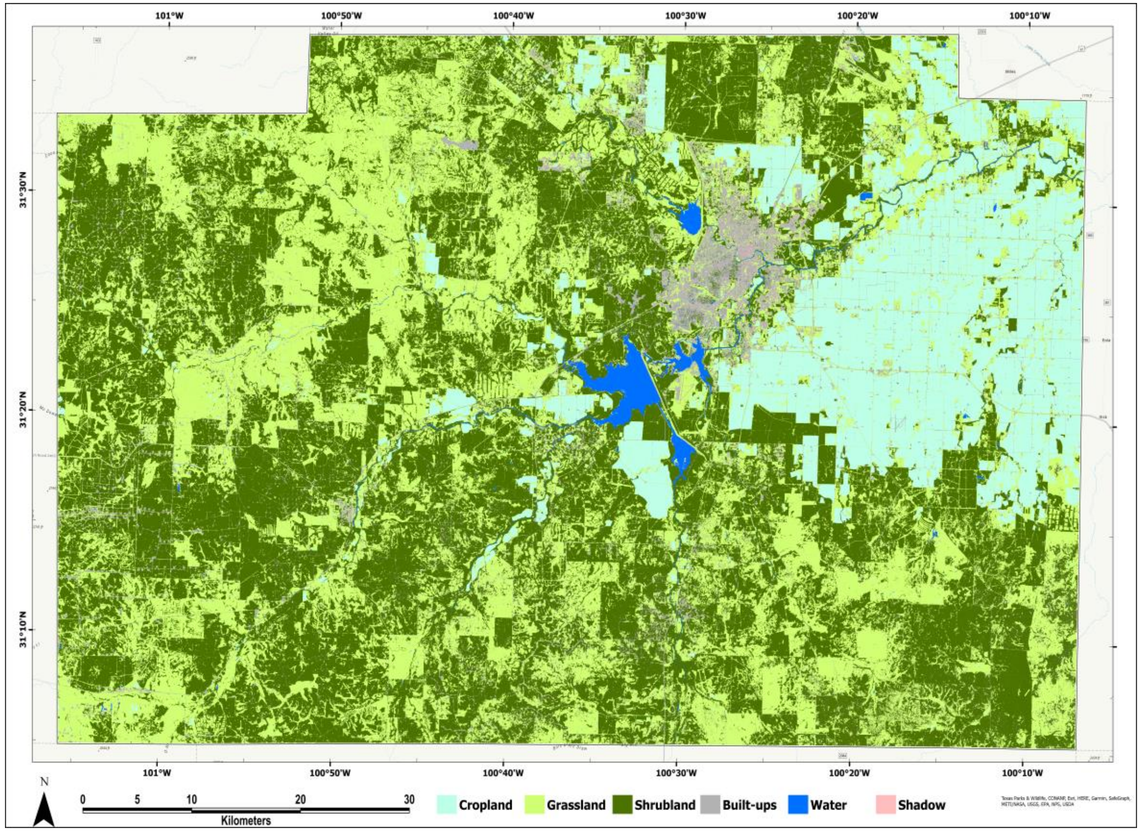
Way Forward:

USGS's 3DEP aim to complete acquisition of nationwide high-resolution topographic elevation data – both bare earth and 3D point clouds



Data Fusion : NAIP + Sentinel Time Series



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- UAV (Wikipedia)
- UN World Urbanization report (published in weforum.org)
- USGS (3D Elevation Program)

Questions?