Exploiting Multisensor Spectral Data to Improve Estimates of Agricultural Crop Residue Cover

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Outline

- Introduction
  - Estimation of Crop Residue
- Research Motivation
  - Evaluation of Hyperspectral / Multispectral Sensor data for residue estimation
  - Investigation of approaches for large scale applications
- Methodology
- Experimental Results
- Summary and Future Directions

Introduction

- **<u>Residue Cover</u> (RC):** Plant material remaining in field after grain harvest and possible tillage

  - Nutrients

  - Organic material (soil)

  - Agricultural ecosystem stability
  - ↓ water evaporation
  - ↑ water infiltration
  - moderates soil temperature

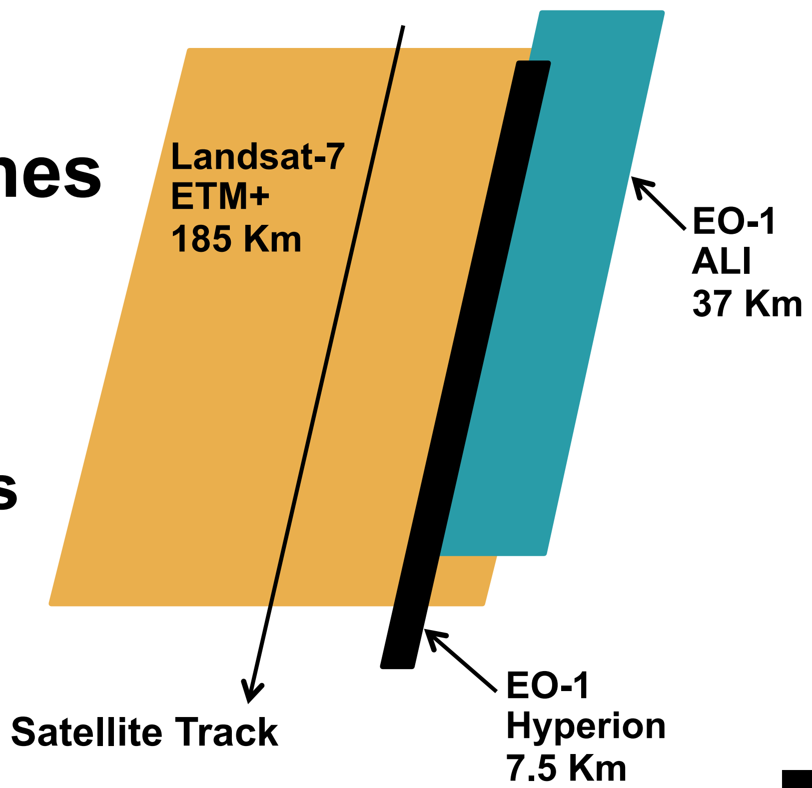
  - Critical in sustaining soil quality
  - erosion
  - runoff rates

- **Ecosystem-based management approaches** (monitoring and impact assessments)

Introduction

- **Manual methods of analysis**
  - **Statistical sampling of fields via windshield surveys**
    - **Costly, requires trained personnel, subjective**
  - **Line transect method**
    - **Time and labor intensive**

- **Remote sensing based approaches**
  - **Detect within field variability**
  - **GREATER coverage area**
  - **Potentially reduce subjective errors**



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Research Motivation

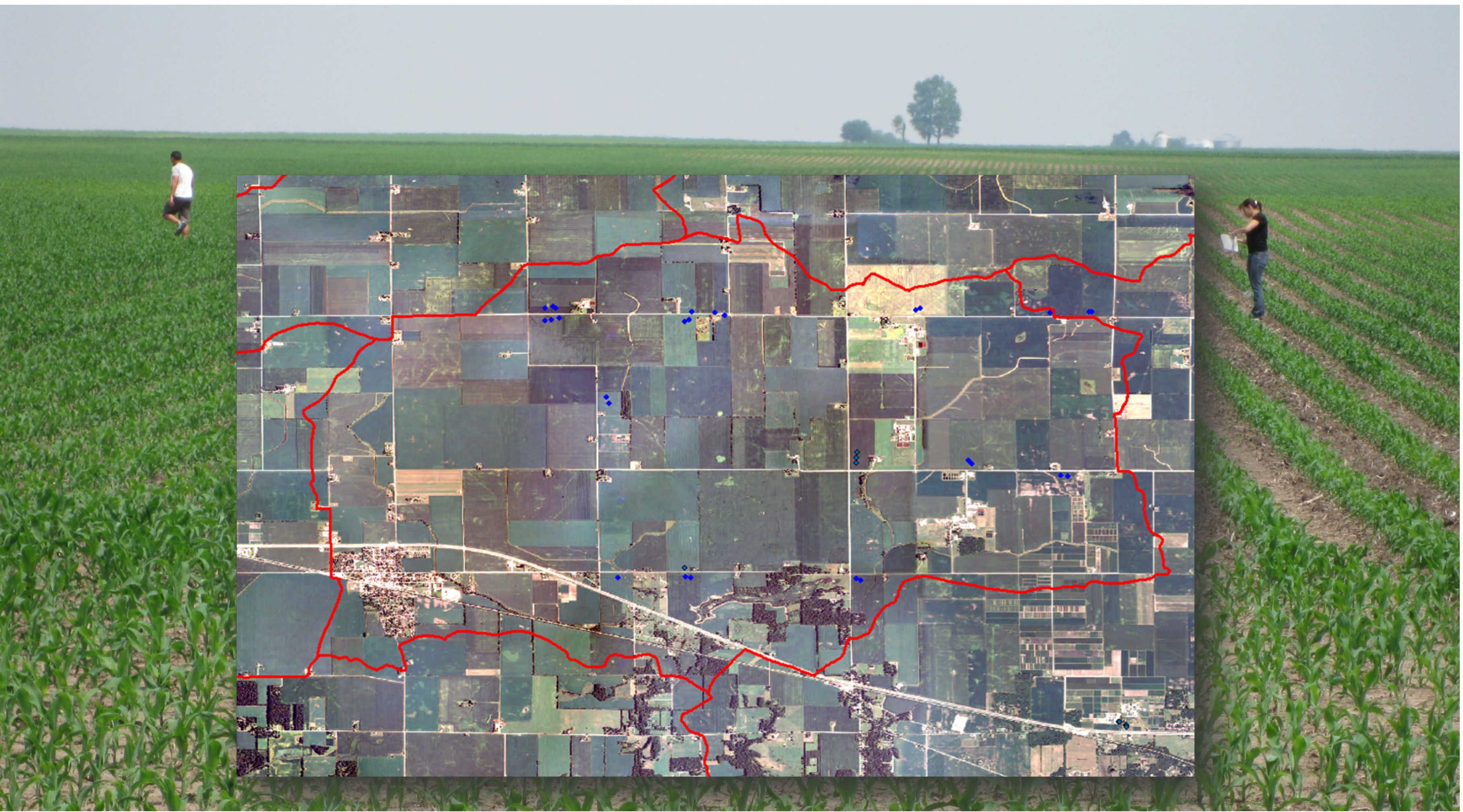
- Evaluate performance of *Multispectral* and *Hyperspectral* data for estimating residue cover over local and extended areas
- Evaluate performance of next generation multispectral sensors
  - Landsat 8 Operational Land Imager (OLI)
- Investigate sensor fusion scenarios
  - Potential contribution of *Hyperspectral* data for improving (calibrating) residue cover estimates derived from wide coverage, *Multispectral* data
- Challenges
  - Residue cover can only be estimated between harvest and planting the following year
  - Vegetation in fence rows/waterways, weeks, etc
  - Cloud cover and limited extent of airborne/Hyperion data

Research Motivation

Transect Method vs. Remote Sensing based Method

Research Motivation

- **Land Cover Characteristics**
  - **Agricultural Cover Discrimination and Assessment**



Proposed Approaches - NDTI

- **Classification or unmixing**
  - Discrete vs continuous estimates; extraneous endmembers
- **Band based Indices**
  - Based on the absorption characteristics (reflectance) of RC
  - Linear relationship between RC and indices exploited via regression models
- Multispectral **NDTI** (Normalized Difference Tillage Index)
  - Empirical models developed and validated locally
  - Applicable to multiple sensors: ASTER, Landsat, ALI (EO-1)

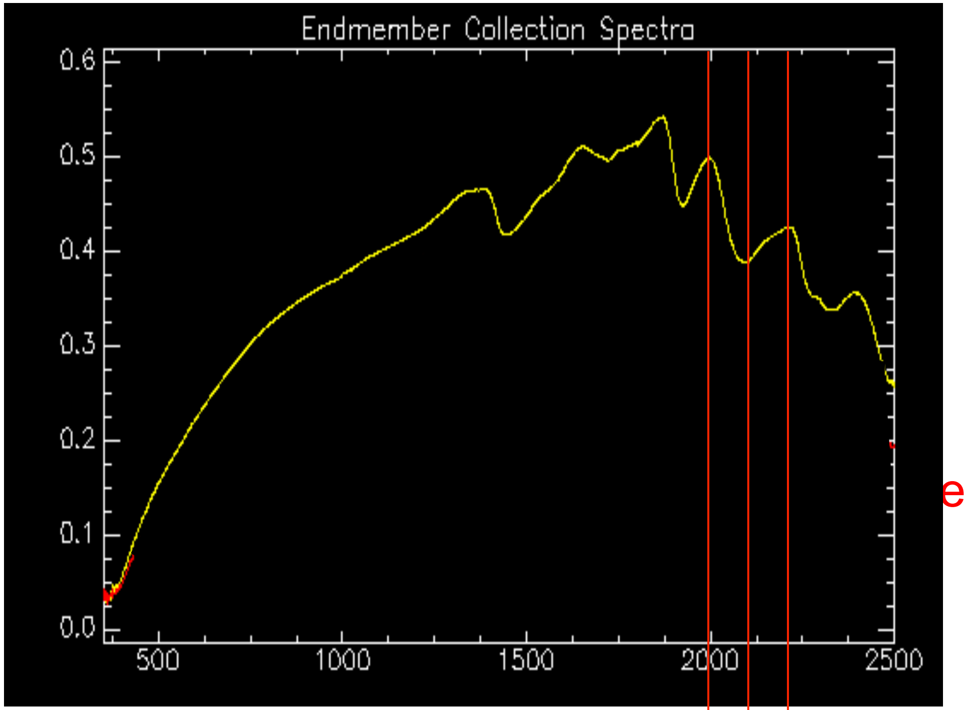
$$\boxed{NDTI = (TM5 - TM7)/(TM5 + TM7)}$$

Where:

- TM7: Landsat TM band 7 or equivalent
- TM5: Landsat TM band 5 or equivalent

Proposed Approaches - CAI

- Hyperspectral **CAI -** (Cellulose Absorption Index)
  - Physically based
  - Demonstrated to accurately RC [Daughtry, 2008]
  - Robust to crop and soil types
  - Limited coverage and



2000
2100
2200

CAI = 0.5 * (R2.0 + R2.2) – R2.1

Where:

- R2.0, R2.1, R2.2: average response of 3 bands centered at 2000 nm, 2100 nm and 2200 nm respectively

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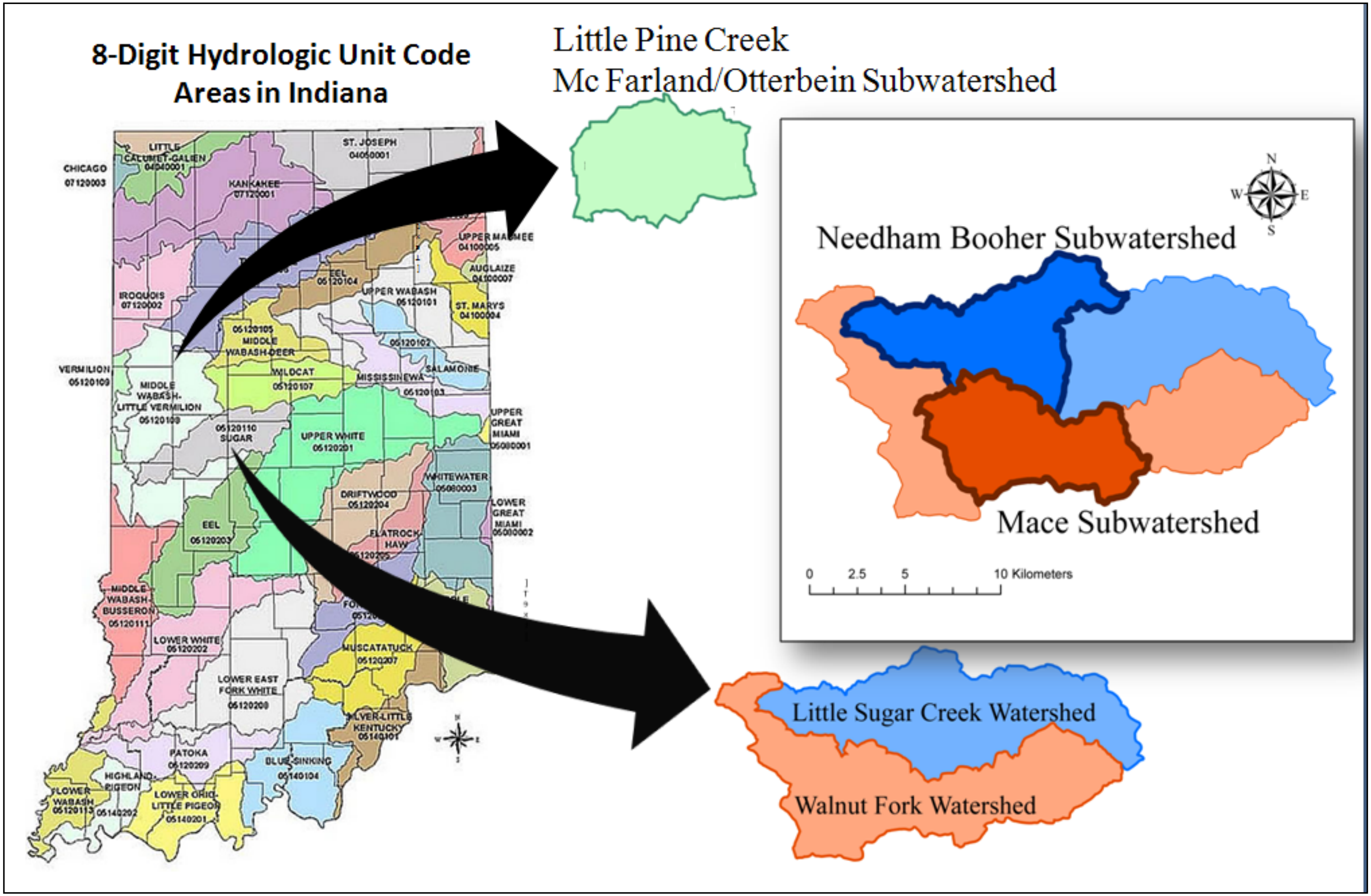
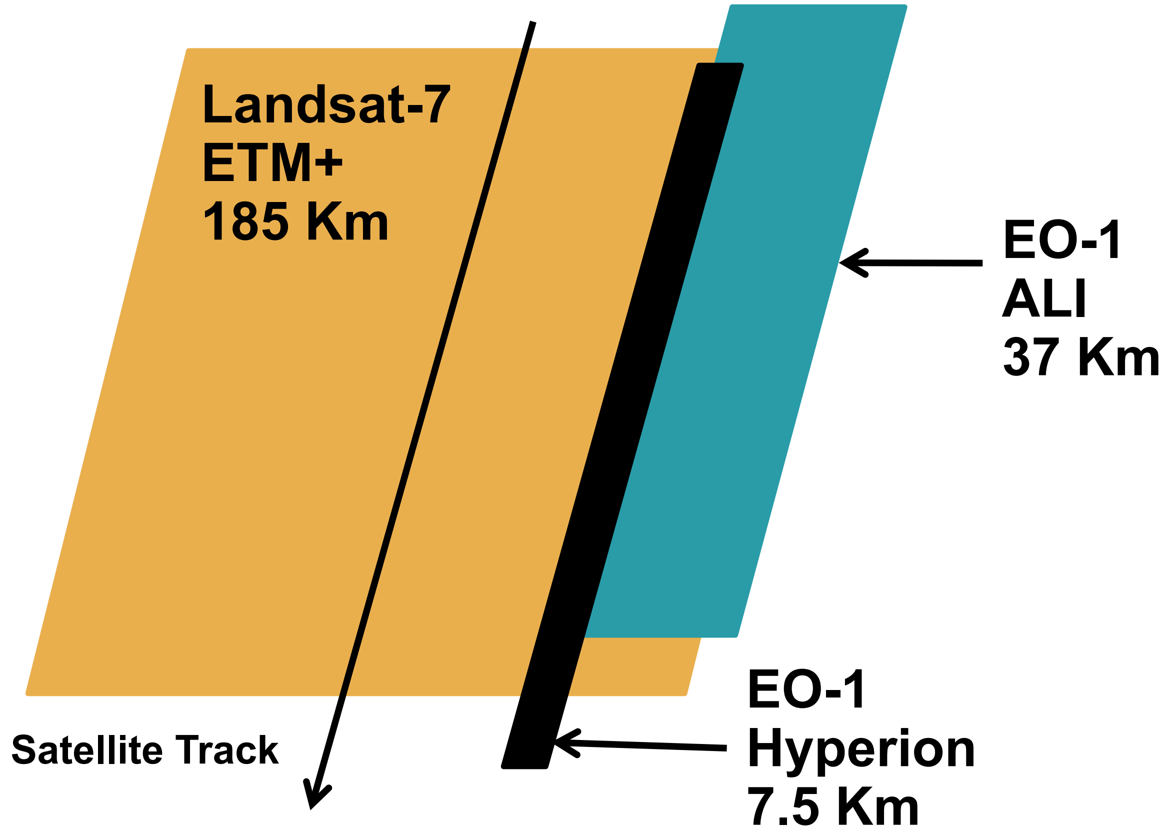
Study Location / Field Data



Remote Sensing Data (2008-2010)

Data Available	Spring 2008	Fall 2008	Spring 2009	Fall 2009	Spring 2010	Fall 2010
EO-1 ALI/Hyperion	May 6	Nov 1	No Data	Oct 11	May 23	Nov 2
Landsat TM	June 11	Nov 2	May 29	Oct 20	April 22	Nov 8
SpecTIR Airborne	No Data	Nov 3	June 5	No Data	May 24	No Data

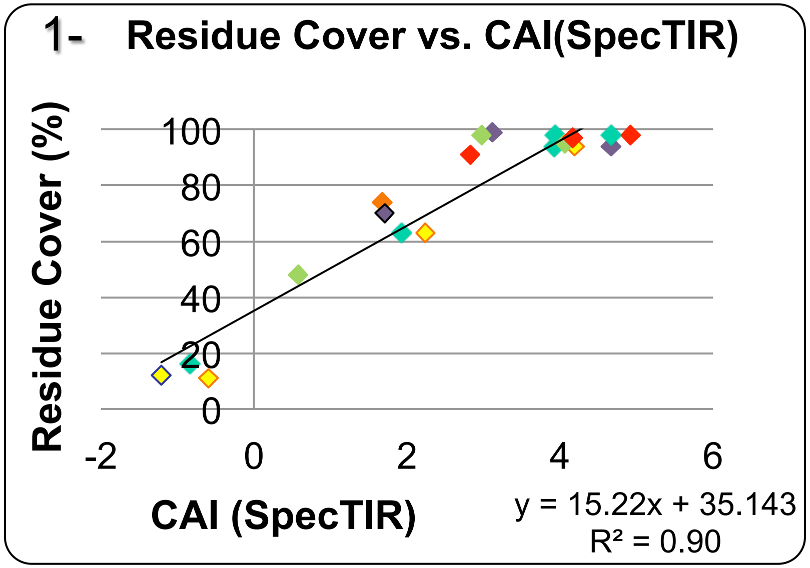


Linear Models

1- $y_i = \beta_0^1 + \beta_1^1 CAI_i + \varepsilon_i^1 \rightarrow \varepsilon_i^1 : \; N(0,\sigma_1^2)$

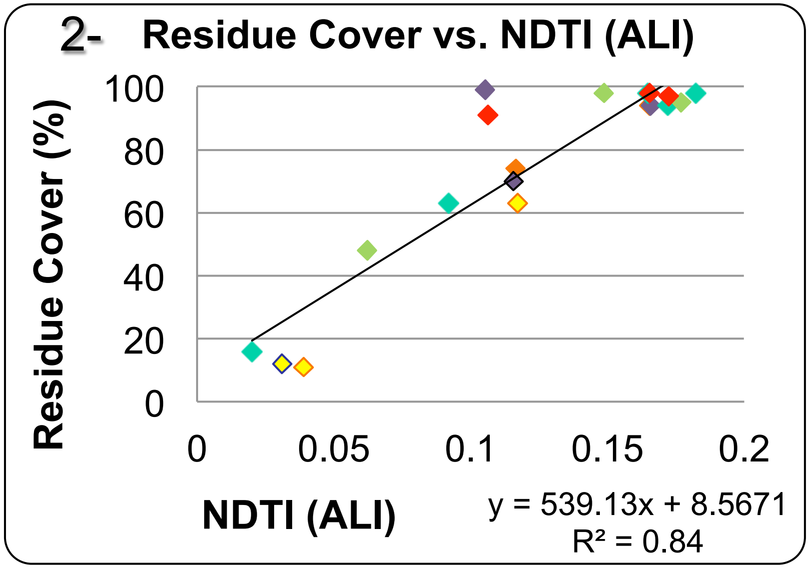
2- $y_i = \beta_0^2 + \beta_1^2 NDTI_i + \varepsilon_i^2 \rightarrow \varepsilon_i^2 : \; N(0,\sigma_2^2)$

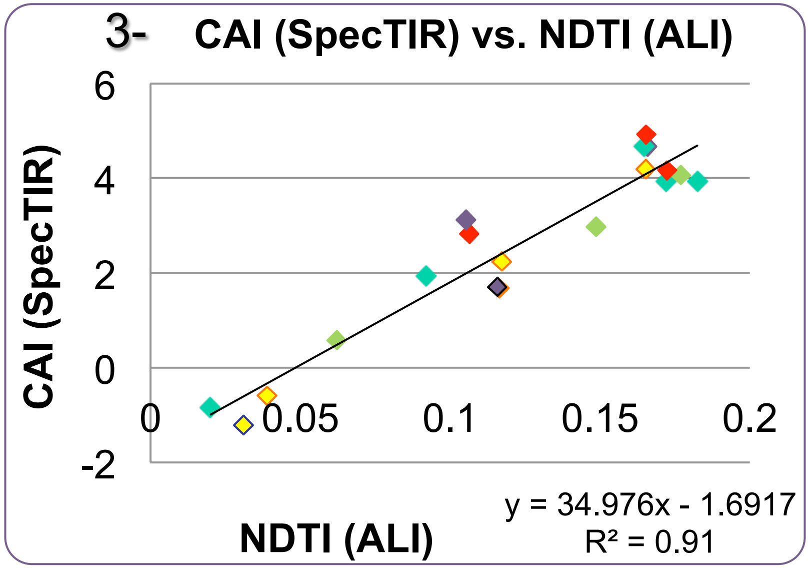
3- $CAI_i = a_0 + a_1 NDTI_i + \varepsilon_i^3 \rightarrow \varepsilon_i^3 : \; N(0,\sigma_3^2)$



Substitute in Model 1

$$y_i = \beta_0^1 + \beta_1^1(a_0 + a_1 NDTI_i) + \varepsilon_i^1$$





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Linear Models

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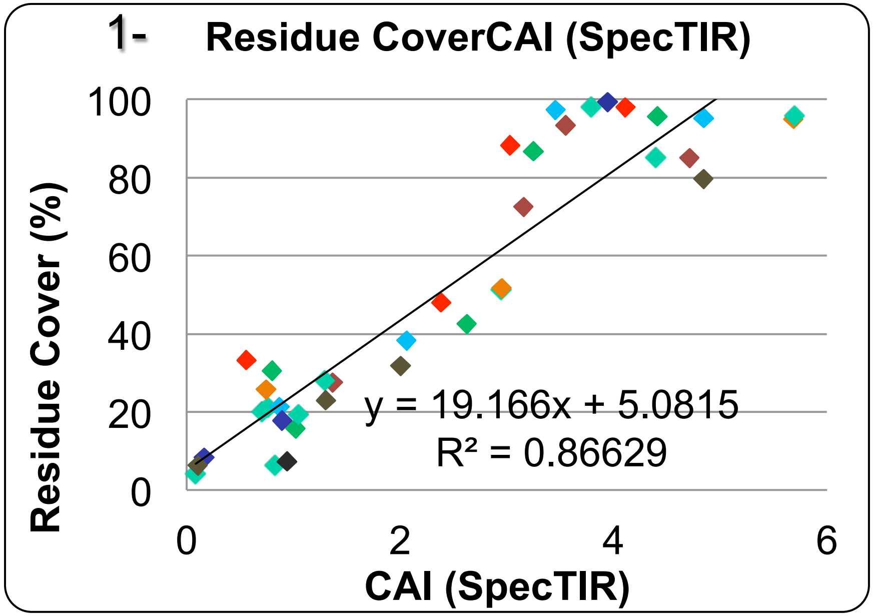
2- $y_i = \beta_0^2 + \beta_1^2 NDTI_i + \varepsilon_i^2 \rightarrow \varepsilon_i^2 : \; N(0,\sigma_2^2)$

3- $CAI_i = a_0 + a_1 NDTI_i + \varepsilon_i^3 \rightarrow \varepsilon_i^3 : \; N(0,\sigma_3^2)$



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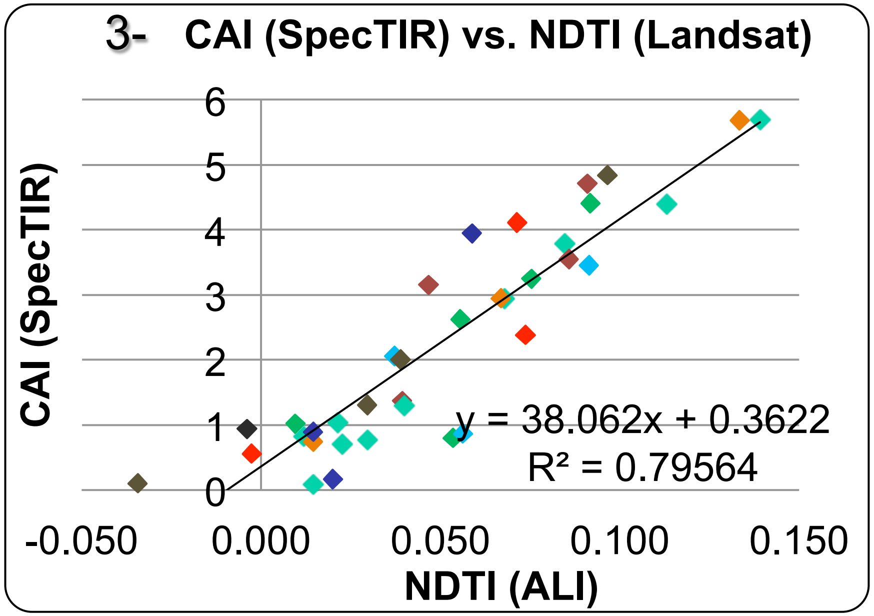

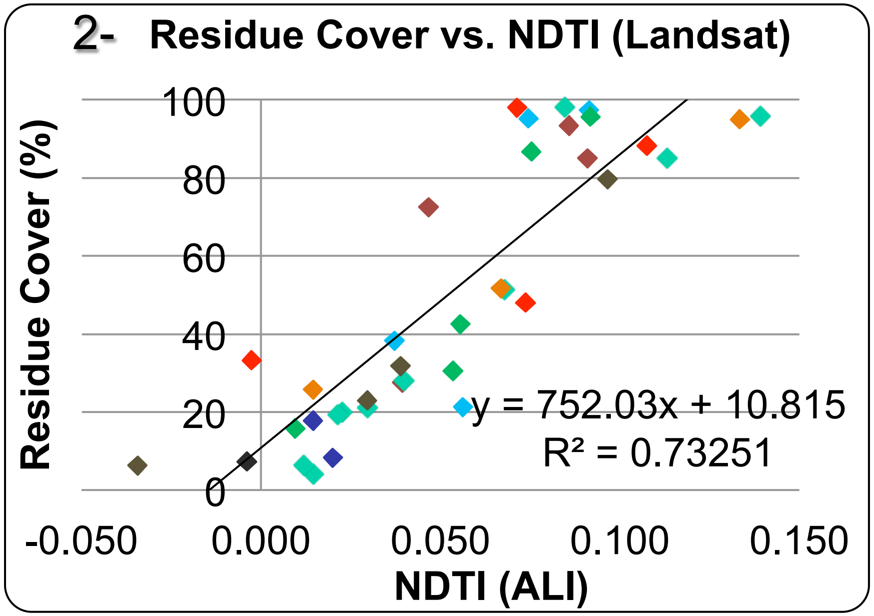

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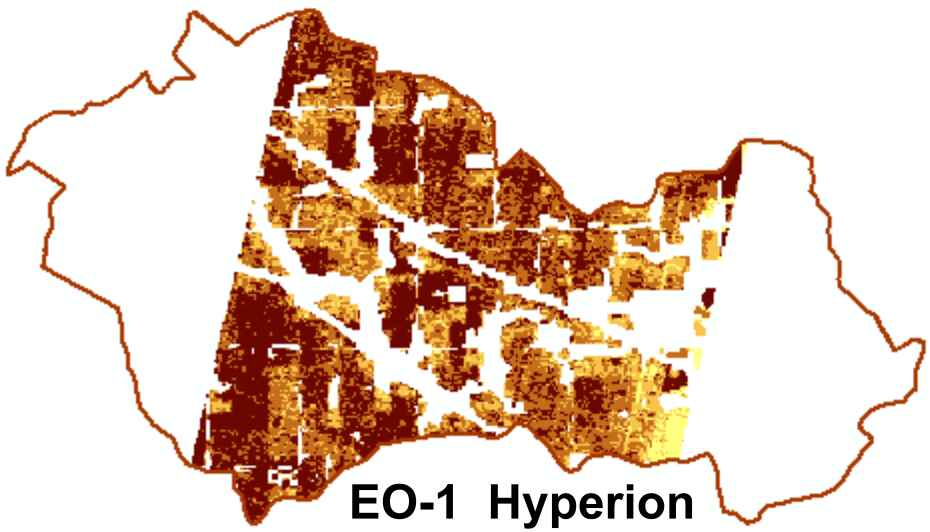
Model 1 - CAI Index

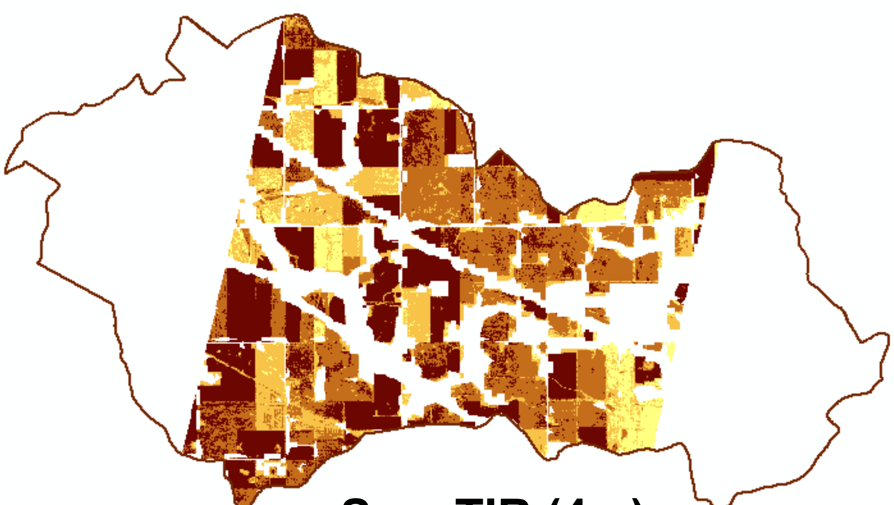
$$y_i = \beta_0 + \beta_1 CAI_i + \varepsilon_i^1 \rightarrow \varepsilon_i^1 : \; N(0, \sigma_1^2)$$

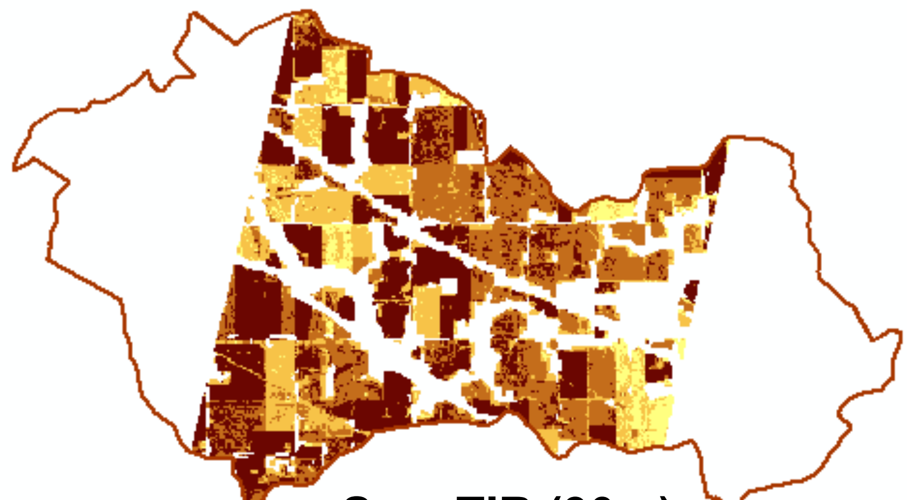
0% - 25%	
26% - 50%	
51% - 75%	
76% - 100%	

Watershed Scale Evaluation

Residue Cover (%)	SpecTIR 4m (hec)	SpecTIR 30m (hec)	Hyperion (hec)
0% - 25%	34.97	26.49	4.87
26% - 50%	138.37	157.82	124.02
51% - 75%	498.19	464.81	525.65
76% - 100%	738.02	768.55	774.59


EO-1 Hyperion


SpecTIR (4m)


SpecTIR (30m)

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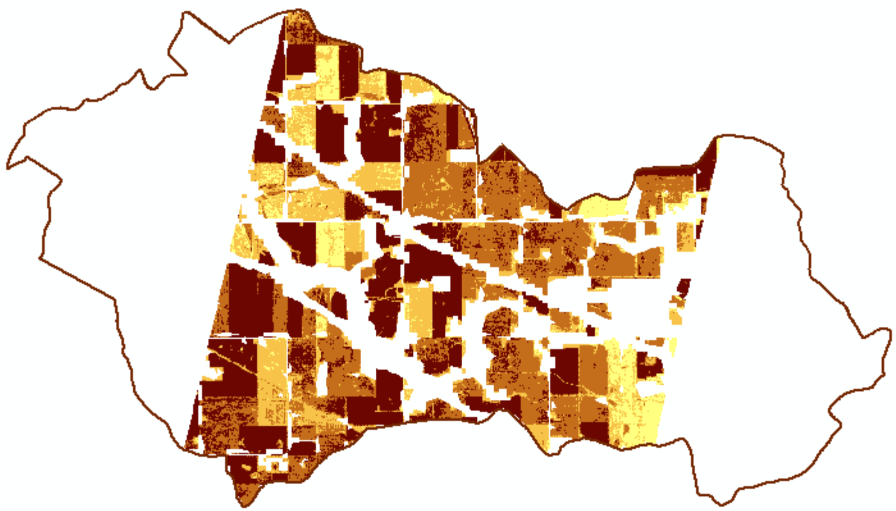
Model 2 – NDTI Index

$$y_i = \beta_0 + \beta_2 NDTI_i + \varepsilon_i^2 \rightarrow \varepsilon_i^2 : \; N(0,\sigma_2^2)$$

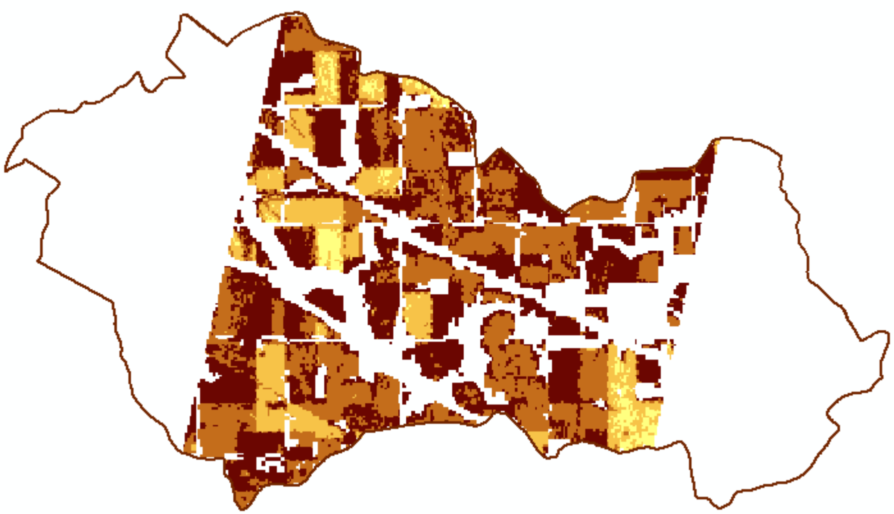
- 0% - 25%
- 26% - 50%
- 51% - 75%
- 76% - 100%



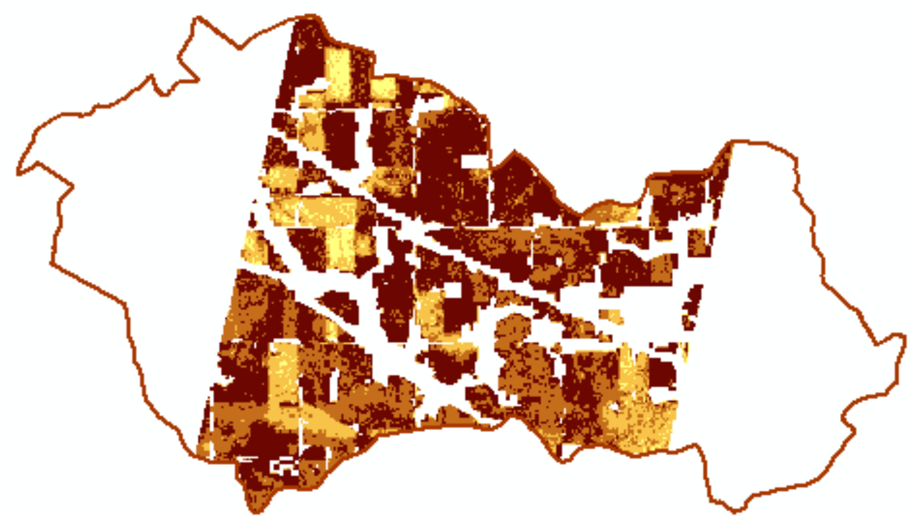
CAI Model – SpecTIR (4m)

Watershed Scale Evaluation

Residue Cover (%)	Landsat (hec)	ALI (hec)	SpecTIR 4m (hec)
0% - 25%	12.03	14.31	34.97
26% - 50%	99.91	97.41	138.37
51% - 75%	405.14	550.35	498.19
76% - 100%	1061.03	835.68	738.02



NDTI Model - ALI



NDTI Model – Landsat TM

Generalization: Little Pine Creek Model Applied to Darlington Region

Model 2

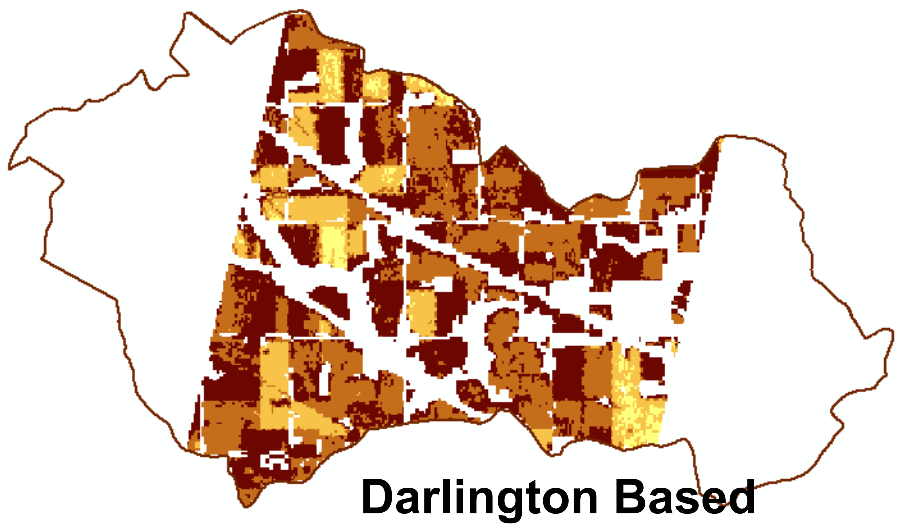
$$y_i = \beta_0 + \beta_2 NDTI_i + \varepsilon_i^2$$

- 0% - 25%
- 26% - 50%
- 51% - 75%
- 76% - 100%

Watershed Scale Evaluation

Residue Cover (%)	ALI (hec)	ACRE Model (hec)
0% - 25%	62.82	0.63
26% - 50%	276.48	195.12
51% - 75%	808.47	149.13
76% - 100%	961.83	1766.16

Little Pine Creek Model Applied to Darlington



Darlington Based Model (ALI)

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Model 3 – NDTI Substition in CAI Model

$$CAI_i = a_0 + a_1 NDTI_i + \varepsilon_i^3 \rightarrow \varepsilon_i^3 : \ N(0, \sigma_3^2)$$

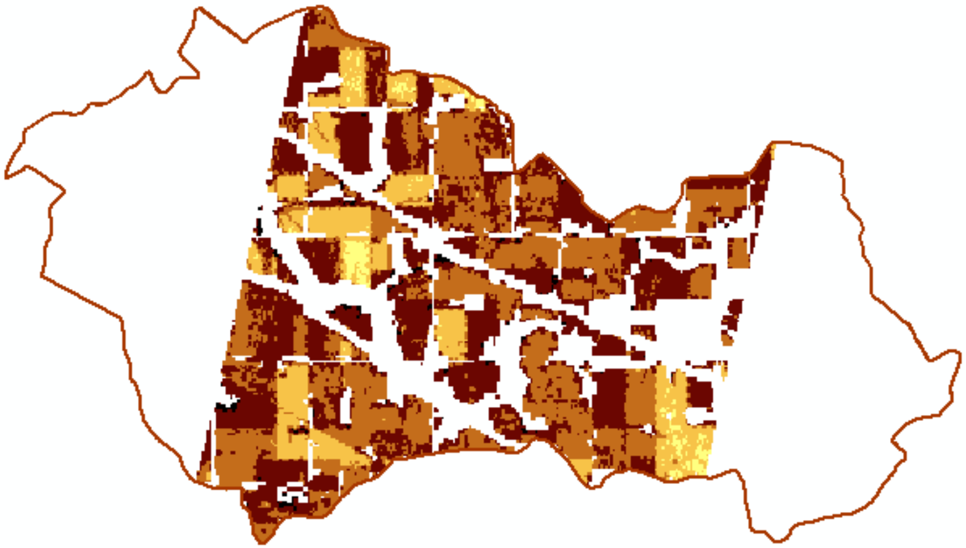
Substitute in Model 1

$$y_i = \beta_0 + \beta_1 (a_0 + a_1 NDTI_i) + \varepsilon_i^1$$

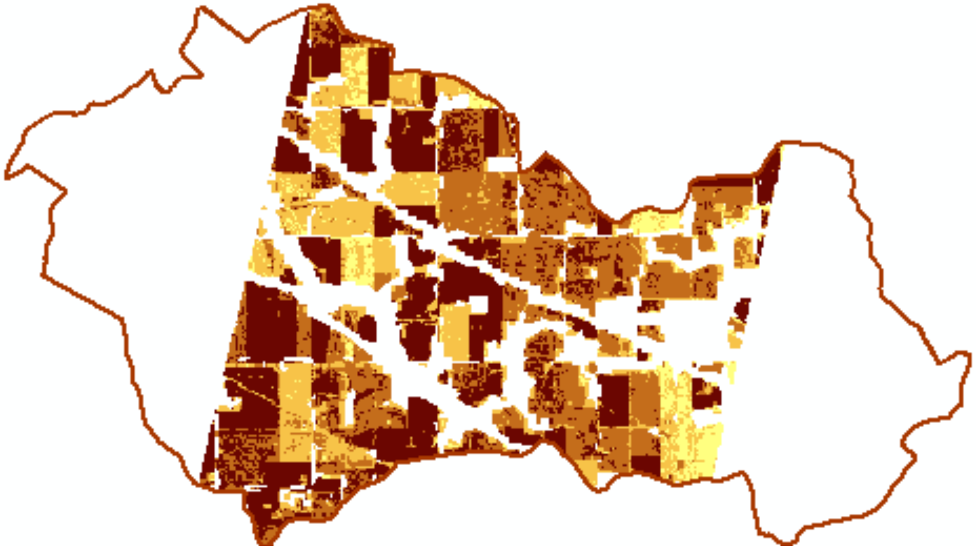
- 0% - 25%
- 26% - 50%
- 51% - 75%
- 76% - 100%

Watershed Scale Evaluation

Residue Cover (%)	Model 3 (hec)	SpecTIR (hec)
0% - 25%	38.43	131.49
26% - 50%	297.36	441.27
51% - 75%	825.75	693.81
76% - 100%	949.50	844.56



Model 3 - (Substitution Model)



Model 1 – SpecTIR (30m)

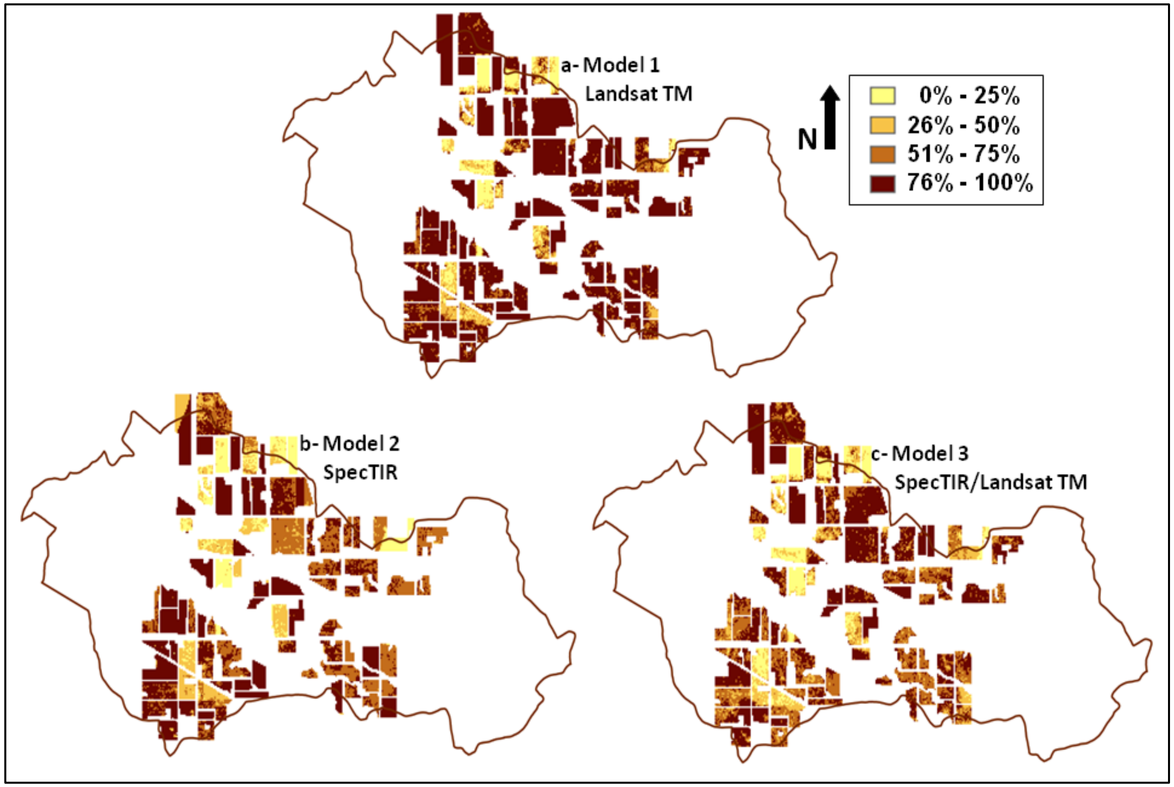
Model 4 – CDF Based Rescaling

- **Matching Multi-source CDF**
  - Rank samples for the data sets CAI (I_h) and NDTI (I_m).
  - Compute differences between corresponding elements of the ranked data sets:
    - $I_{d,i} = I_{h,i} - I_{m,i}$

  where $I_{h,i}$ and $I_{m,i}$ are the ranked CAI and NDTI values for $i=1\ldots n$;
  n = no. of samples.

  - Approximate the CDF using a global polynomial or piece-wise linear approaches

Knowledge Transfer via CDF Based Rescaling



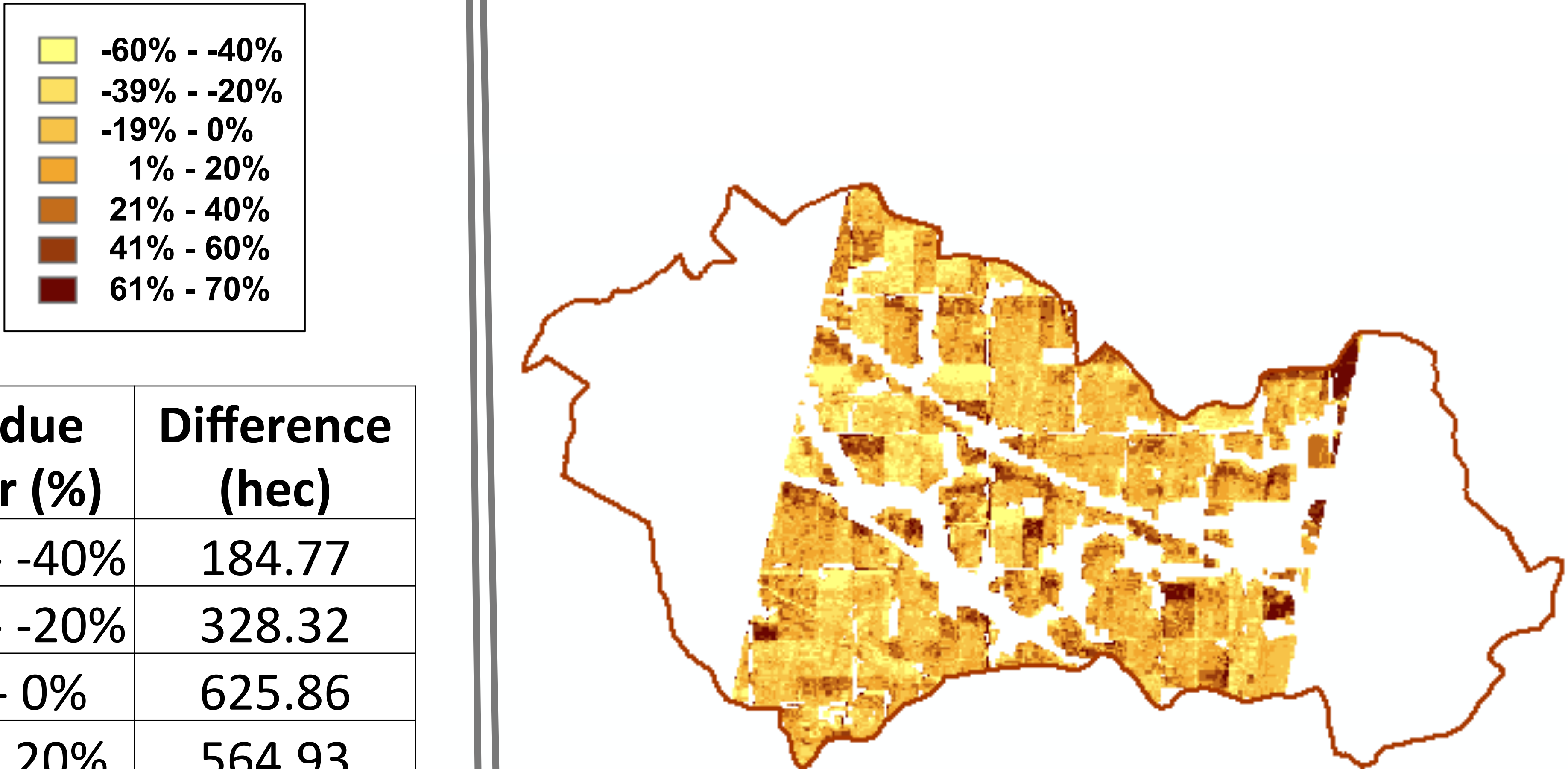
Field Residue Cover (%)	Residue Coverage				
	Model 1	Model 1	Model 2	Model 3	Model 3
	Landsat TM (ha)	ALI (ha)	SpecTIR (ha)	LandsatTM (ha)	ALI (ha)
0% - 25%	11.7	27.1	23.9	16.1	24.2
26% - 50%	35.2	47.5	48.5	52.6	49.6
51% - 75%	81.5	321.2	249.2	258.3	249.1
76% - 100%	883.3	485.1	556.0	541.1	554.7

Field Residue Cover (%)	Residue Coverage					
	MFOW in MW			MW		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Landsat TM (ha)	SpecTIR (ha)	Landsat TM (ha)	LandsatTM (ha)	SpecTIR (ha)	Landsat TM (ha)
0% - 25%	12.4	23.2	37.3	11.7	23.9	16.1
26% - 50%	31.5	56.6	50.7	35.2	48.5	52.6
51% - 75%	122.26	221.15	289.6	81.5	249.2	258.3
76% - 100%	863.6	647.0	592.6	883.3	556.0	541.1

Period	RMSE (Residue Cover Percent)				
	Model 1	Model 1	Model 2	Model 3	Model 3
	ALI	Landsat TM	Hyperion	ALI	Landsat TM
Fall 2008	12.9	19.7	18.9	16.1	19.8
Fall 2009	16.6	20.3	23.9	20.2	28.3
Fall 2010	12.2	13.8	17.1	12.3	14.5

Thank You

SpecTIR 30m vs. Hyperion 30m



Residue Cover (%)	Difference (hec)
-60% - -40%	184.77
-39% - -20%	328.32
-19% - 0%	625.86
1% - 20%	564.93
21% - 40%	268.92
41% - 60%	99.36
61% - 70%	38.88

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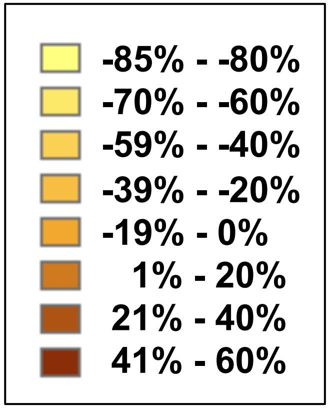
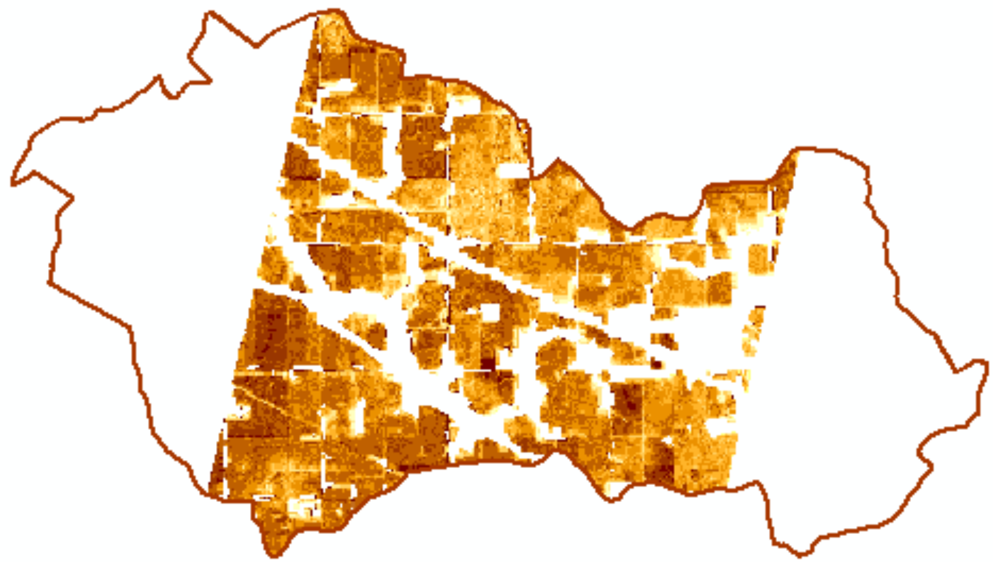
CAI (SpecTIR) vs. NDTI (Landsat/ALI)



Residue Cover (%)	Landsat Difference (hec)	ALI Difference (hec)
-85% - -80%	67.41	34.2
-79% - -60%	69.21	65.52
-59% - -40%	146.52	92.45
-39% - -20%	**339.93**	**179.37**
-19% - 0%	**607.95**	**628.39**
1% - 20%	**925.75**	**682.47**
21% - 40%	177.66	174.79
41% - 60%	19.89	5.49

SpecTIR vs. ALI



SpecTIR vs. Landsat TM

Model 1 vs. Model 3

- -85% - -80%
- -70% - -60%
- -59% - -40%
- -39% - -20%
- -19% - 0%
- 1% - 20%
- 21% - 40%
- 41% - 60%

Residue Cover (%)	Difference (hec)
-85% - -80%	49.14
-79% - -60%	49.77
-59% - -40%	90.9
-39% - -20%	180
-19% - 0%	653.94
1% - 20%	899.19
21% - 40%	183.06
41% - 60%	5.04

Little Pine Creek Model Applied to Darlington Region

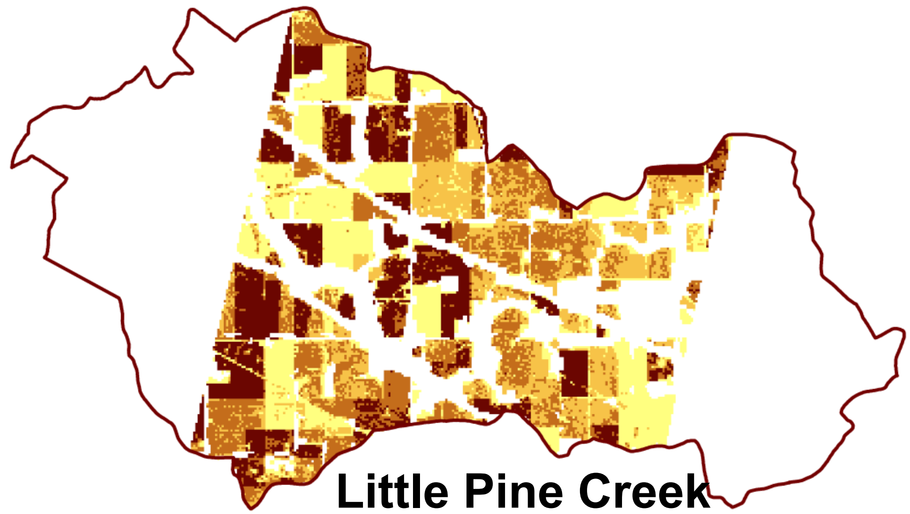
Model 2

$$y_i = \beta_0 + \beta_1 CAI_i + \varepsilon_i^1 \rightarrow \varepsilon_i^1 : \ N(0,\sigma_1^2)$$

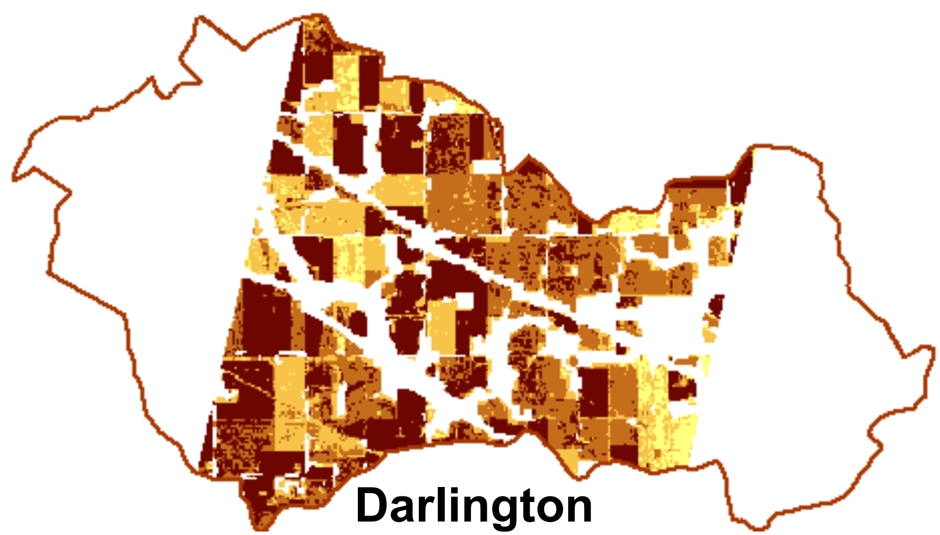
- 0% - 25%
- 26% - 50%
- 51% - 75%
- 76% - 100%

Watershed Scale Evaluation

Residue Cover (%)	SpecTIR (hec)	ACRE Model (hec)
0% - 25%	131.49	584.01
26% - 50%	441.27	491.85
51% - 75%	693.81	553.32
76% - 100%	848.56	481.86



Little Pine Creek Data (Model 1)



Darlington Data (SpecTIR)