

Development of On-the-go Nitrogen Application Algorithms for Cotton Production Based on Active Reflectance Sensors

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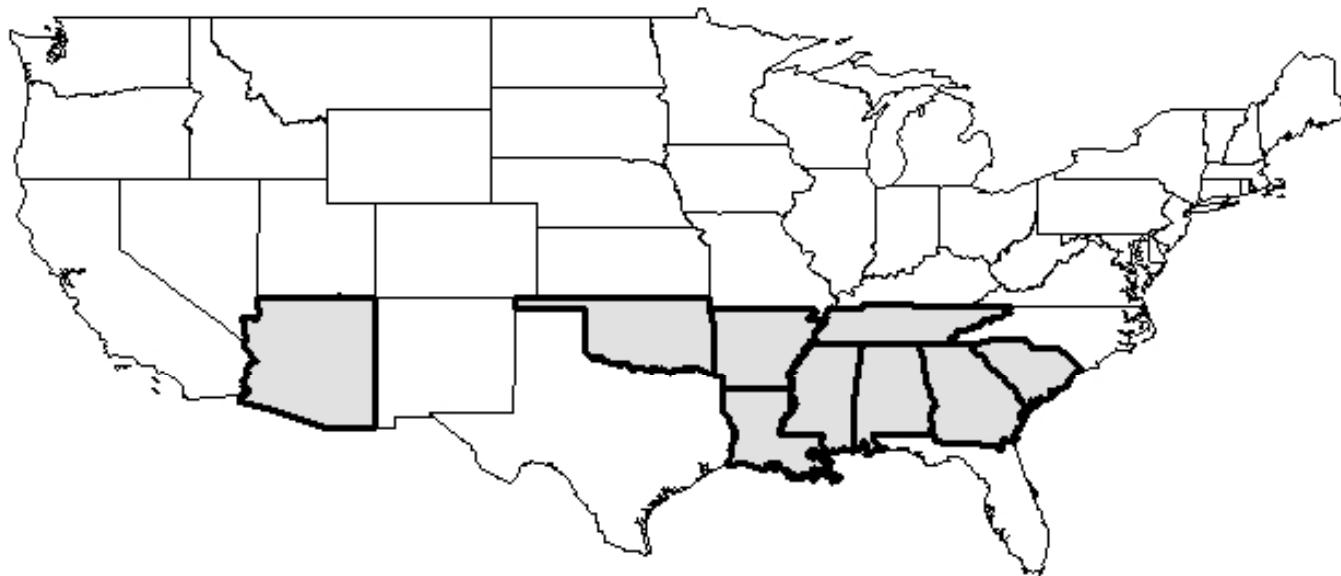
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Cotton NDVI Studies

- Collaborators from 9 states
 - Funding from Cotton Inc.
 - Applied nitrogen studies

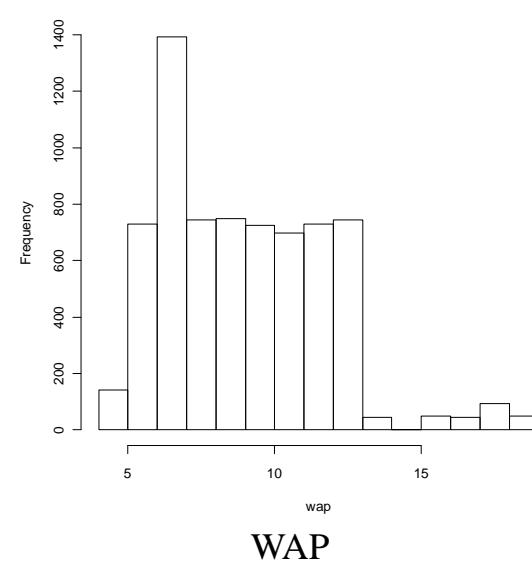
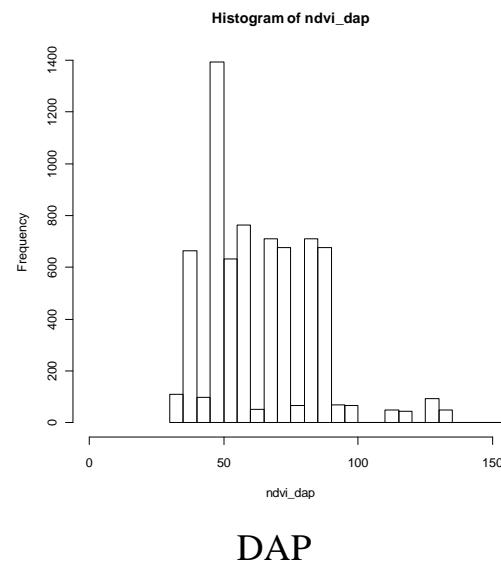
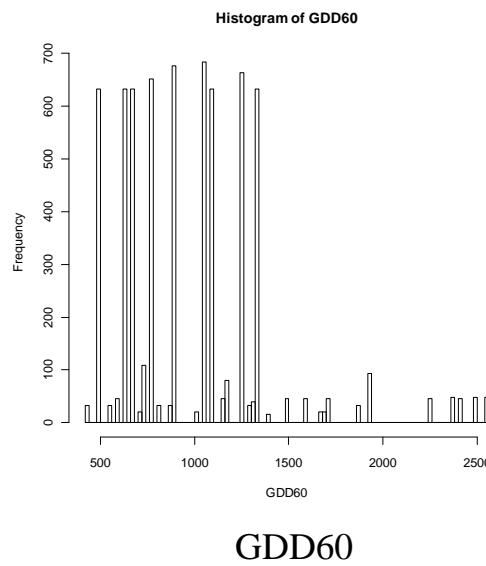


Caveats

- No economic analysis conducted
 - Statistical analysis of bio-physiological data

Choosing Unit of “Time”

- Heat unit accumulation preferred to ‘time’...
 - Algorithm development requires ‘categorized’ time
 - Rather than GDD60, using WAP
 - DAP resulted in too many ‘bins’ for given amount of data



GDD60

DAP

WAP

Precision Ag: The Tale of Two Technologies

Information-intensive & Embodied-knowledge

Information-intensive

- Field level data to make decisions
- Requires additional data and skill
- IPM

Embodied-knowledge

- Information purchased in the form of an input
- Requires minimal additional data/skill
- Round-up Ready or Bt

Two Faces of Precision Agriculture

Information-intensive

- Yield monitors
- Traditional variable rate applications
- *Data

Embodied-knowledge

- Automated guidance
- On-the-go sensors applying variable rates
- *Automated

Motivation and Issue

- Analyses have been conducted for single datasets
- Failed to model multiple climates, systems, etc.
- Global response estimated from all datasets
- Objective: Develop on-the-go N application algorithm



Motivation and Issue

- Analyses have been conducted for single datasets
- Failed to model multiple climates, systems, etc.
- Global response estimated from pooled dataset
- Derive on-the-go nitrogen application algorithms
- Objective: analyze multi-state experiment data to estimate response between active sensor reflectance and cotton yield for on-the-go nitrogen management
 - Develop on-the-go N application algorithm



Data and Methods

- Pooled model
 - Multiple site-years; 9 states, ≥ 11 PI, ≥ 13 studies
 - All data (sites and years) in single dataset
 - Datasets normalized and controlled for heterogeneity
 - Conditioned by year, location
- Correlation among?
 - yield, nitrogen rate, NDVI values and timing
- Regression analysis of pooled dataset

Challenges

- Cotton is a perennial
- N rate sufficient to cause yield penalty
- Identifying appropriate timing for NDVI
 - DAP, GDD60
- No economic analysis conducted
 - Statistical analysis of bio-physiological data

Challenges

- Cotton is a perennial
- N rate sufficient to cause yield penalty
- Identifying appropriate timing for NDVI
 - DAP, GDD60
- Testing functional forms of relationships
- Testing indexes for algorithm
 - Variety, location, and GDD60 specific
 - Global algorithm with local intercept/slope shifters
- No economic analysis conducted
 - Statistical analysis of bio-physiological data

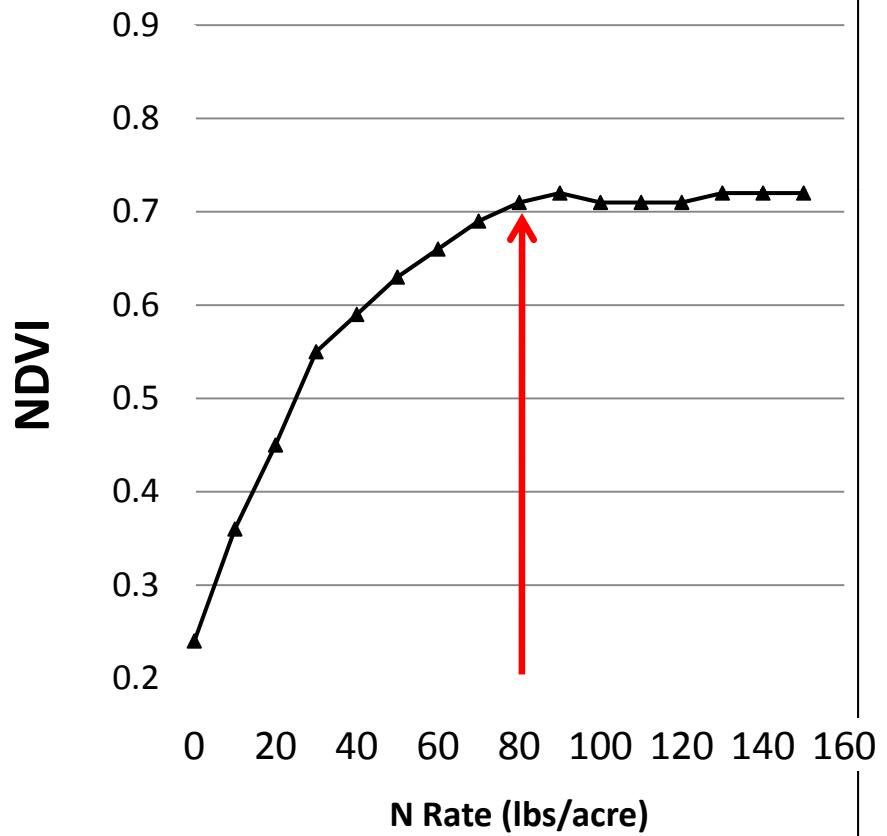
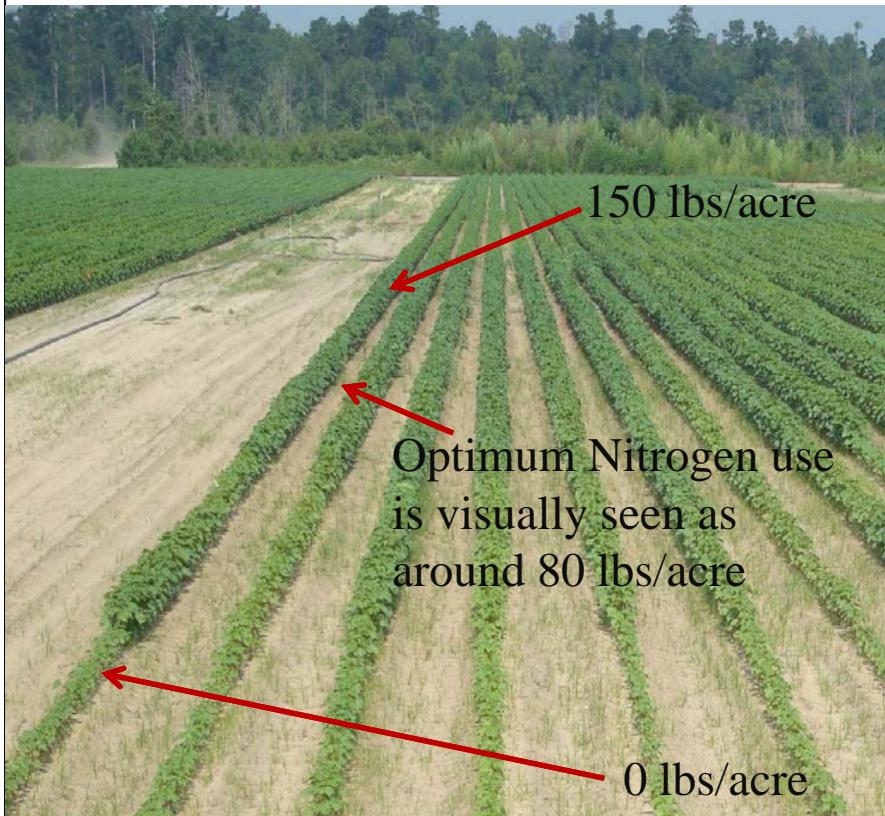
Sensor-Base N Status

- “Yield Potential” approach available for growers not mapping soils
- OSU approached “worked” everywhere evaluated (SC, TN, LA, OK); however:
 - How early can readings be taken? In some cases response not clear until 4-weeks after early bloom
 - Debate if soil specific reference strips needed

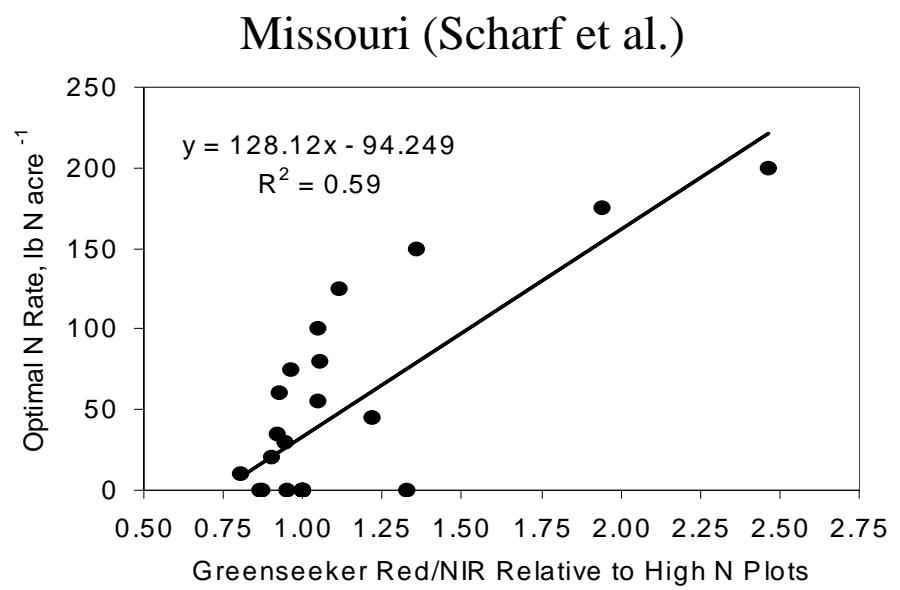
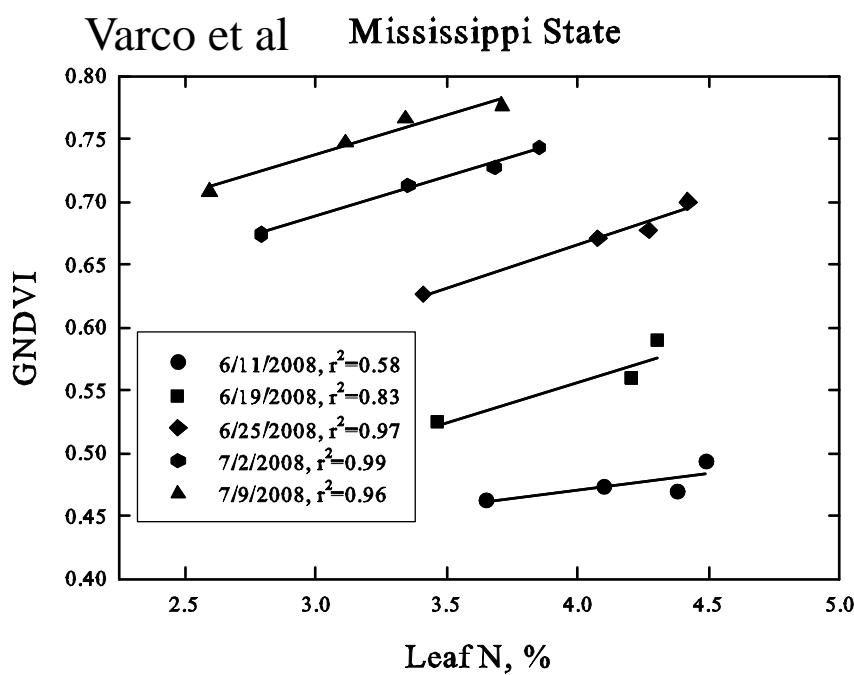


Visual/NDVI use of Ramp Strips

The Green Seeker data collection verified what was seen visually in the ramp strips in SC. 30% N savings over blanket application with no yield reduction US modified OSU approach – 2007 to 2009

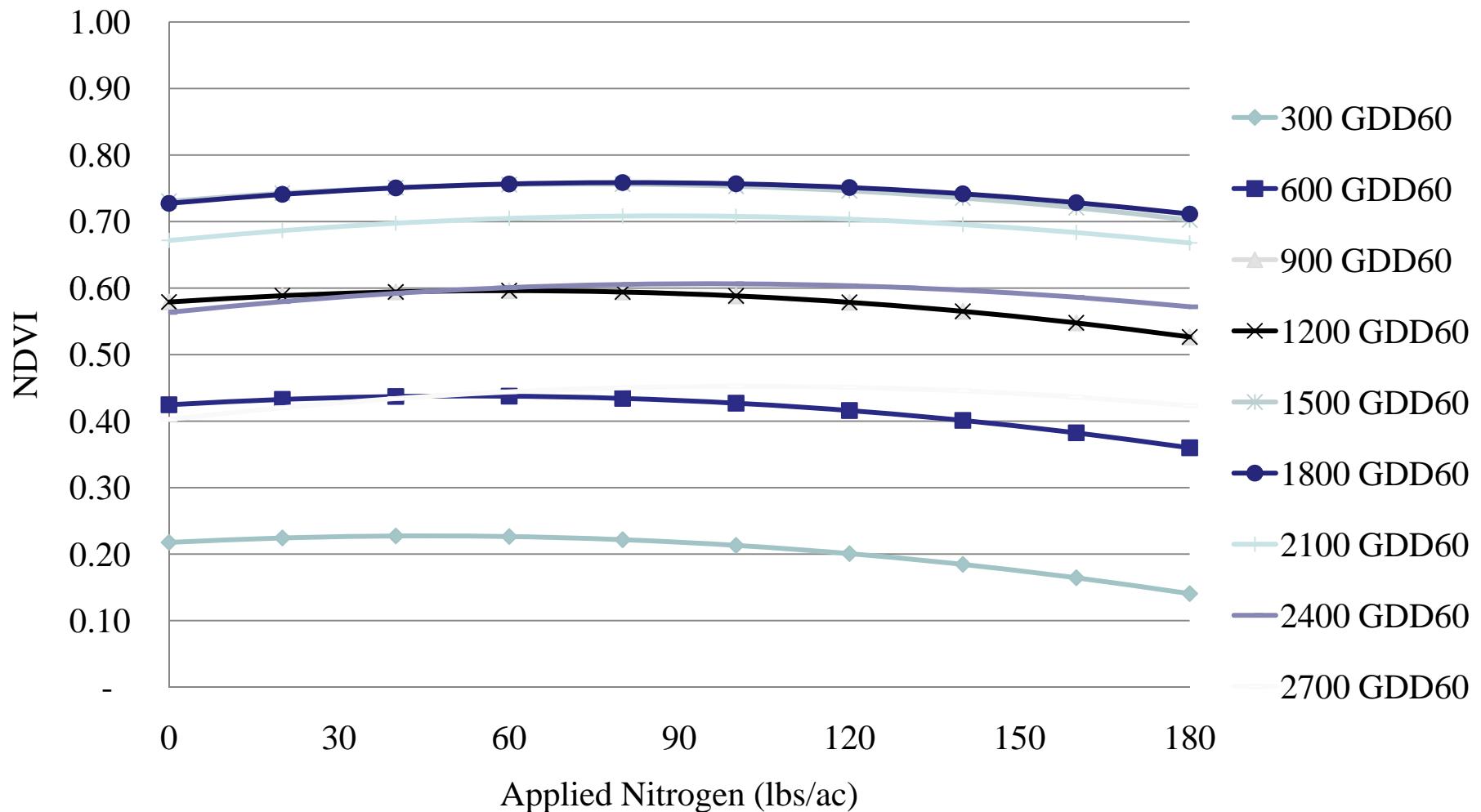


Other Indexes and Relationships

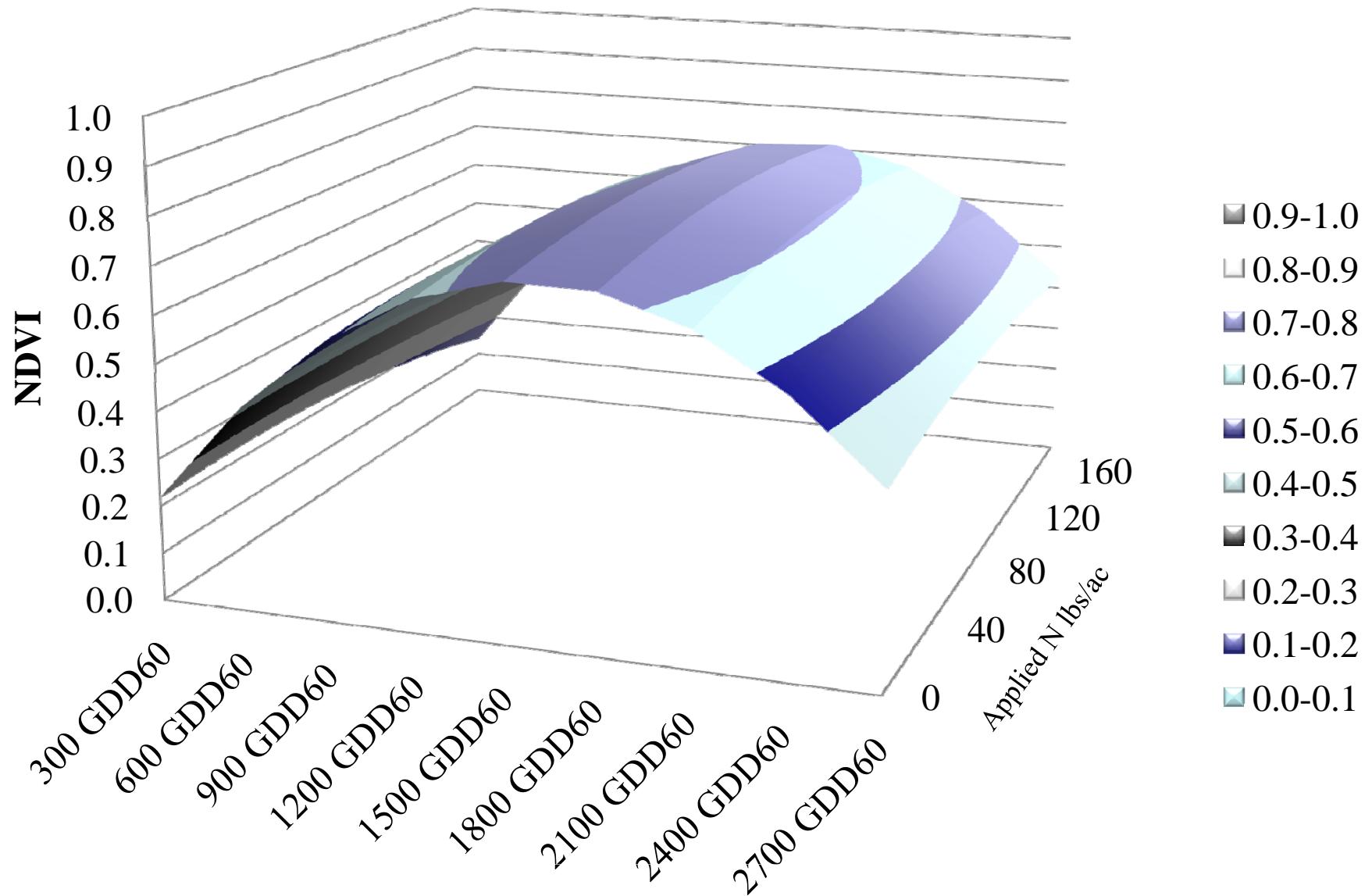


NDVI ~ N by HUA

Not as useful for developing algorithms... need categorical time

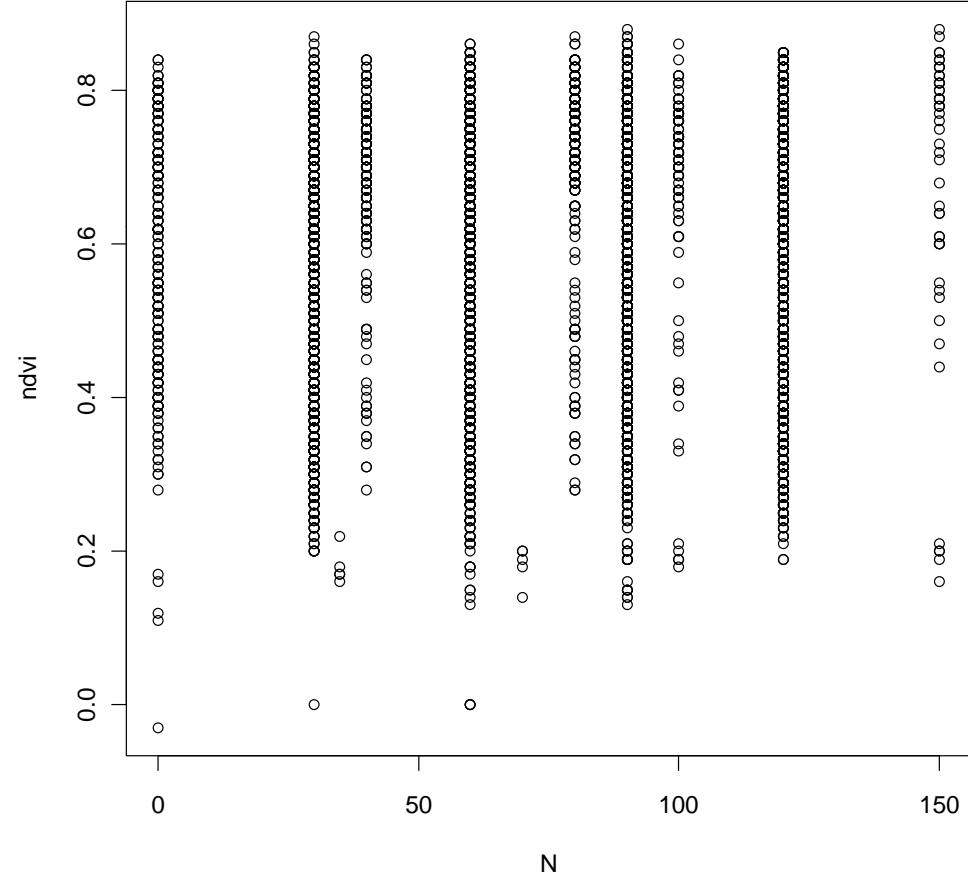


NDVI response to N application by time of measurement



NDVI and Applied Nitrogen

- Determine the shape of the functional form
 - Linear
 - Quadratic
 - Other?
 - No relationship?
- Can NDVI proxy for applied N?



Correlation: N and NDVI by Time

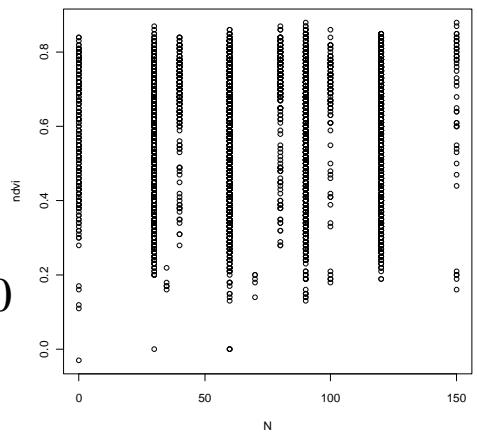
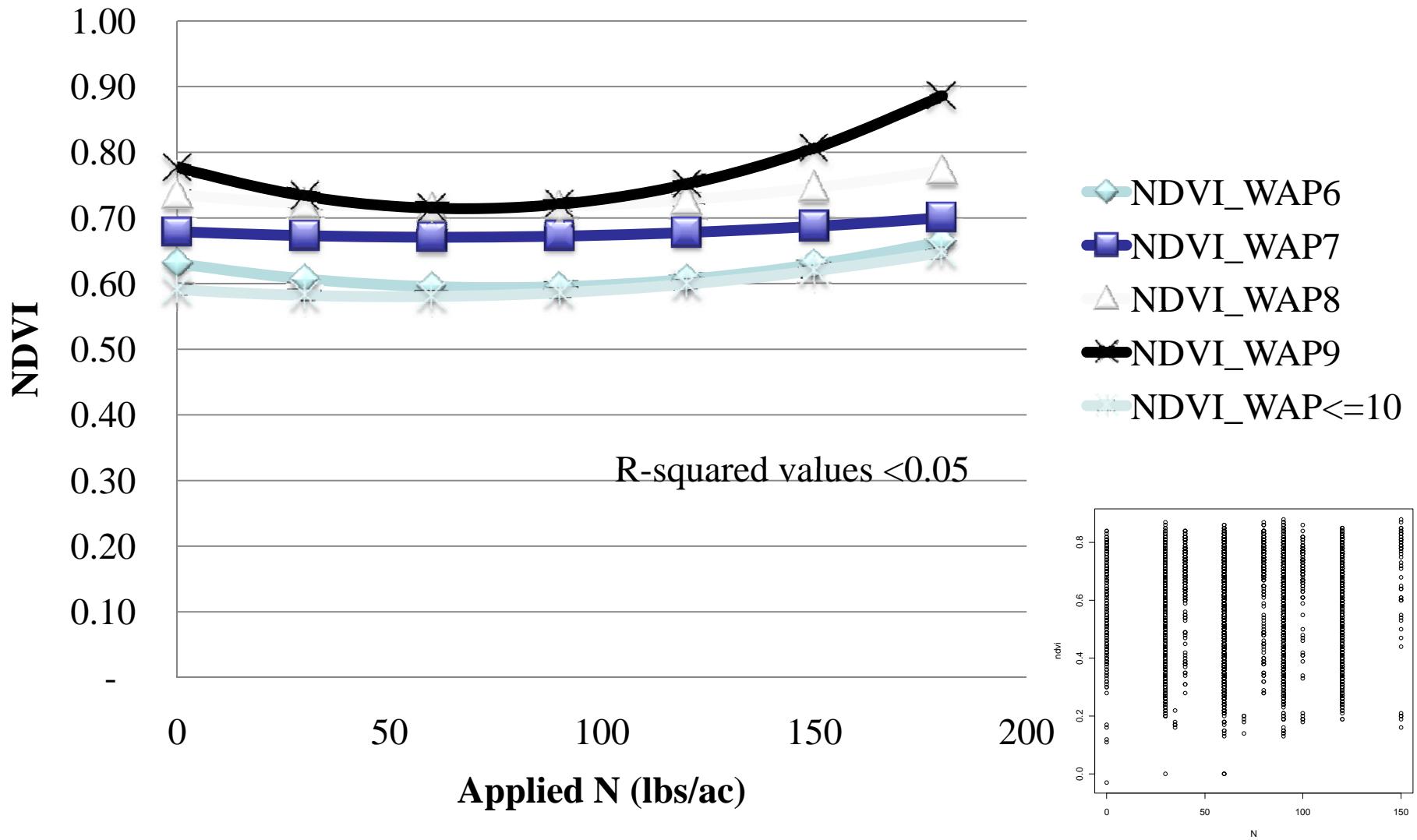
Pearson Correlation Coefficient applies only to linear relationship

Bolded numbers are significant at 90% level

WAP8 and WAP9 become significant at 89 and 88% levels

	N	WAP6	WAP7	WAP8	WAP9	<=WAP10
N	1	0.49	0.73	0.66	0.65	0.83
WAP6		1	0.95	0.98	0.98	0.89
WAP7			1	0.99	0.99	0.99
WAP8				1	1.00	0.97
WAP9					1	0.96
WAP<=10						1

NDVI and Nitrogen by Time



Algorithms

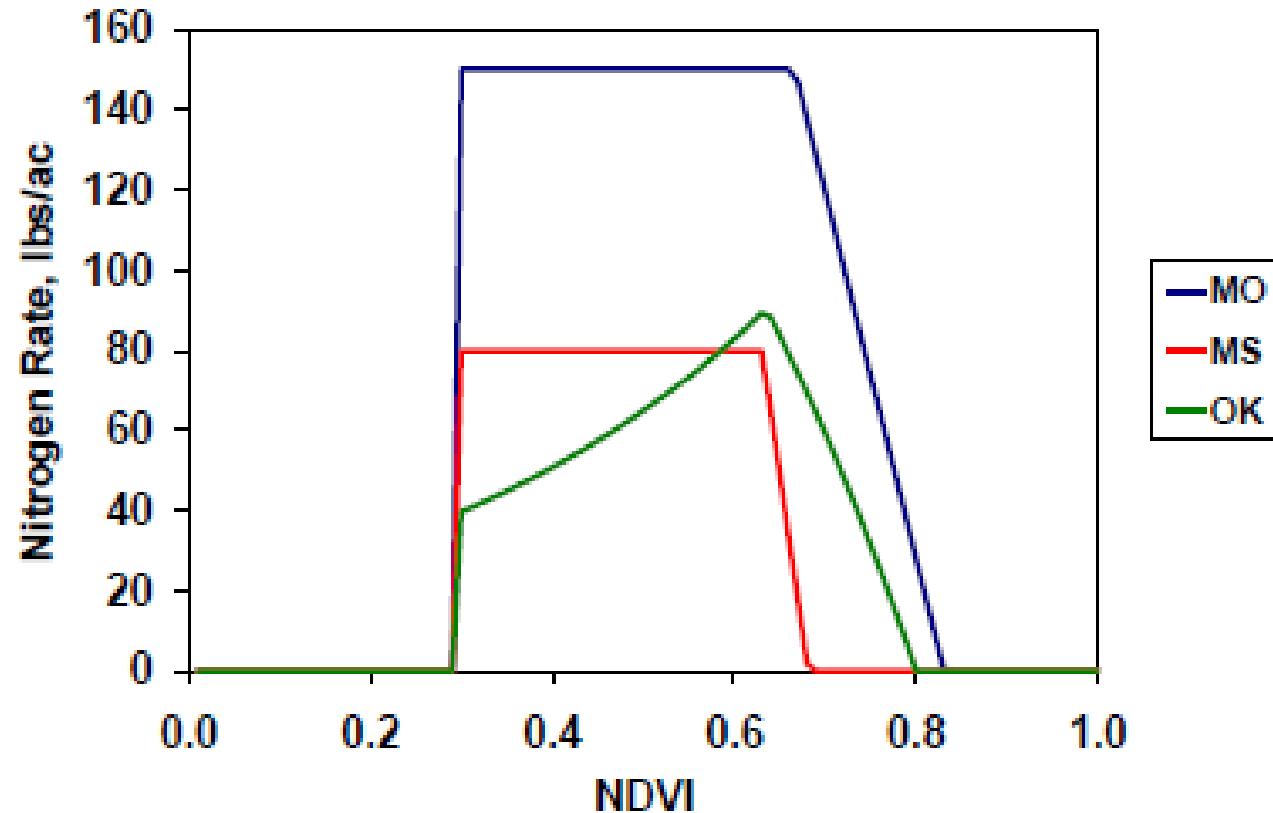


Figure 10. Variable nitrogen prescriptions developed by Missouri (MO), Mississippi (MS), and Oklahoma (OK).

Source: Randy Taylor, Oklahoma State University

Histogram of NDVI Values

Algorithm can be “hard bounded” by 0.2 and 0.8

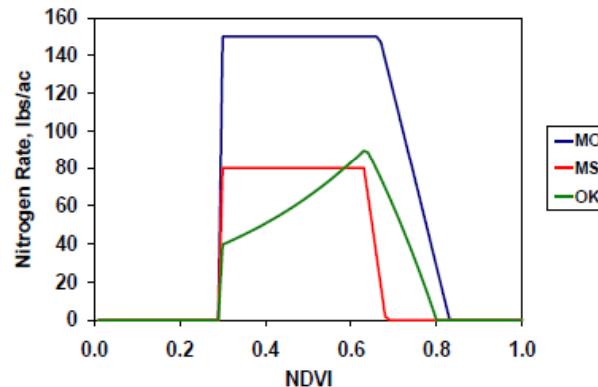
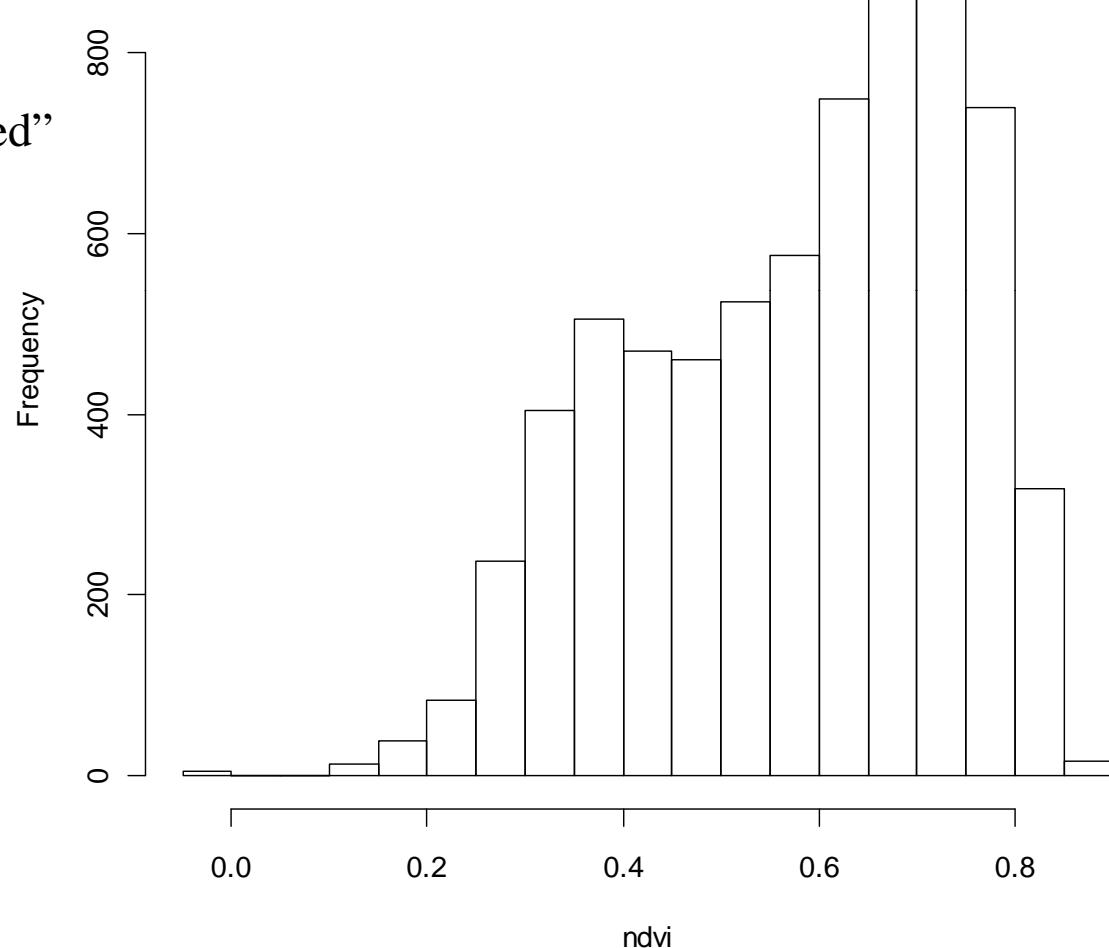
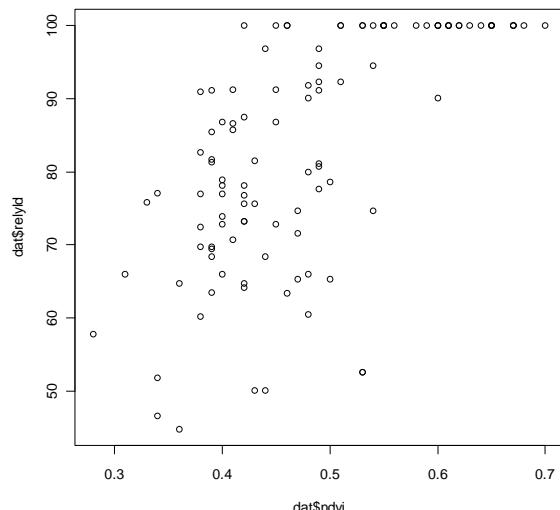


Figure 10. Variable nitrogen prescriptions developed by Missouri (MO), Mississippi (MS), and Oklahoma (OK).

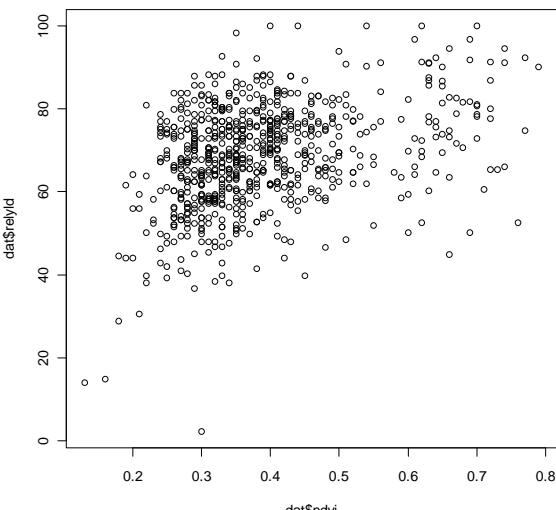
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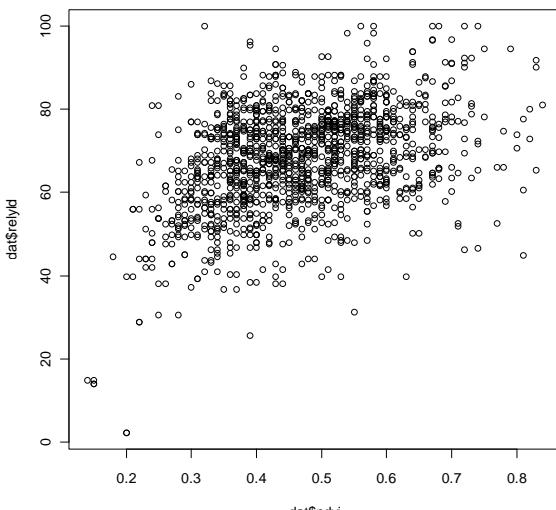
Yield potential as function of NDVI by WAP



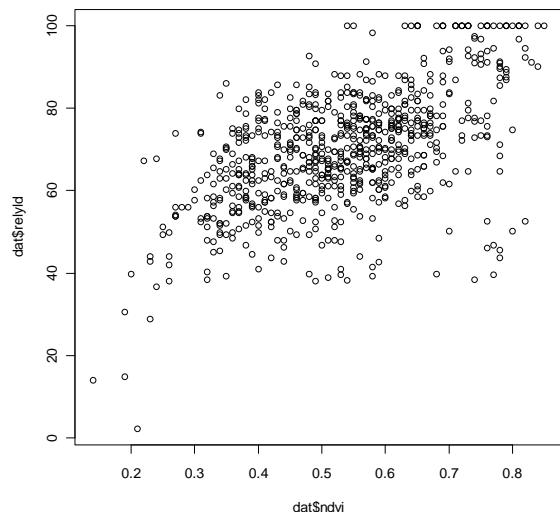
WAP=5



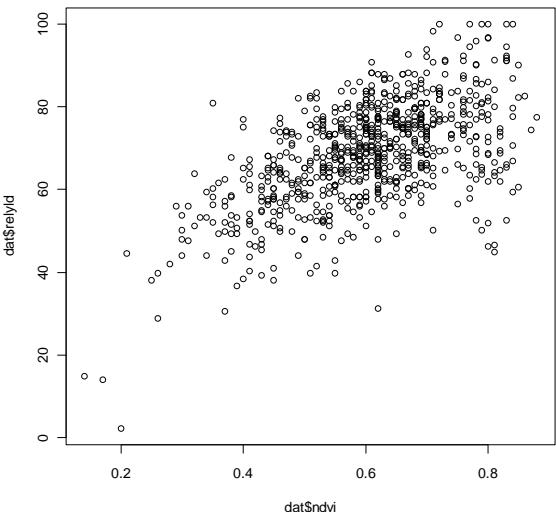
WAP=6



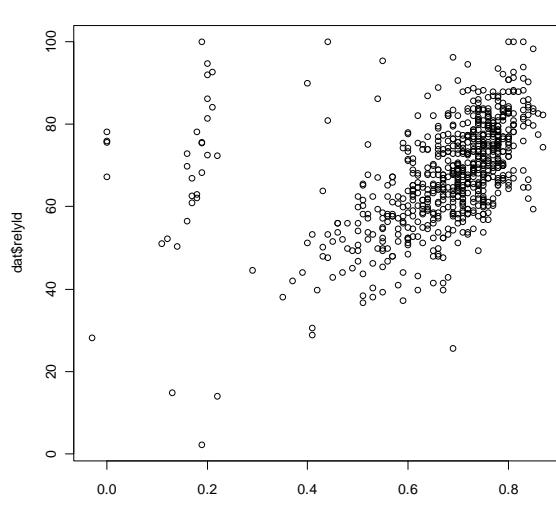
WAP=7



WAP=8

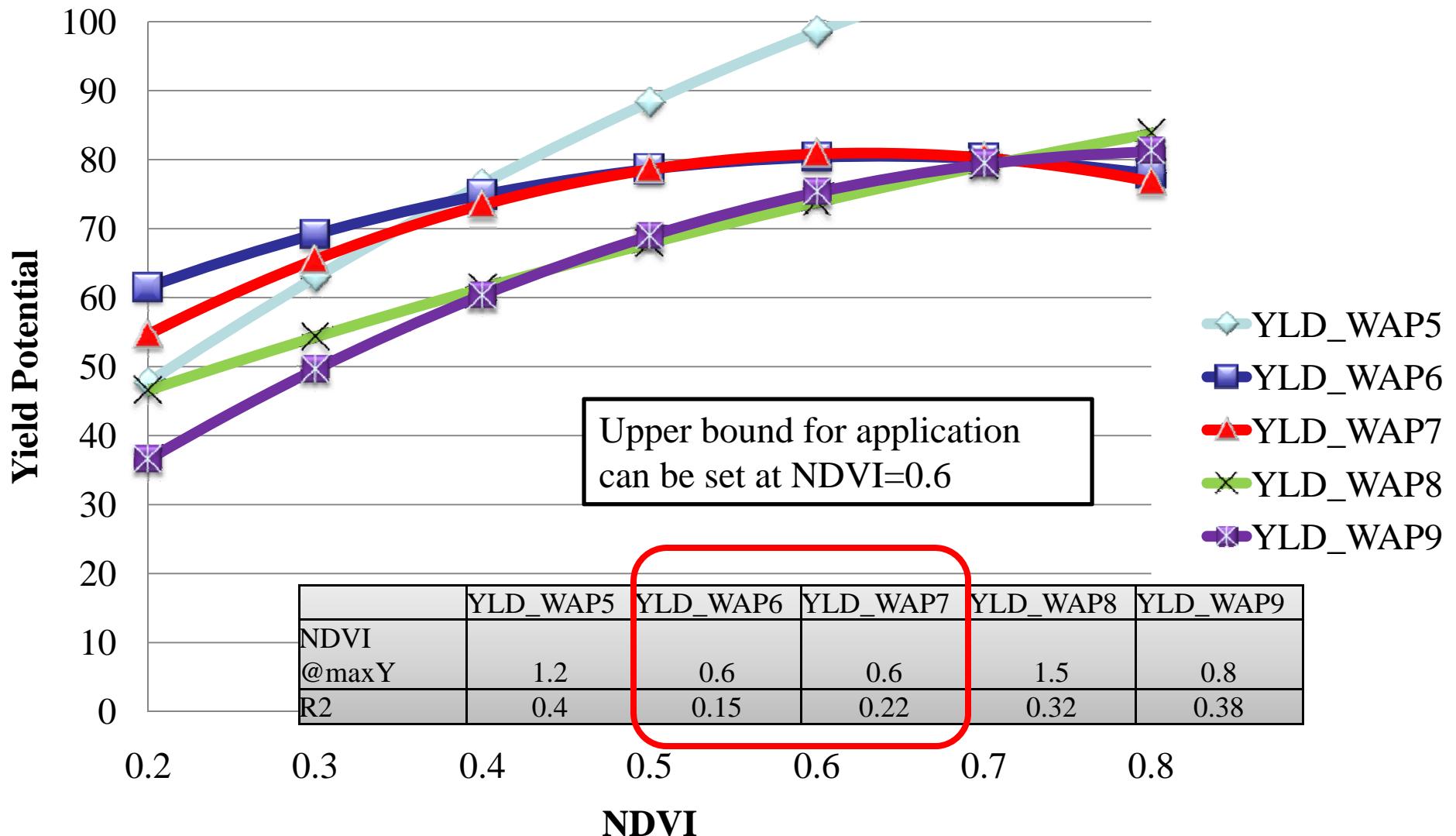


WAP=9

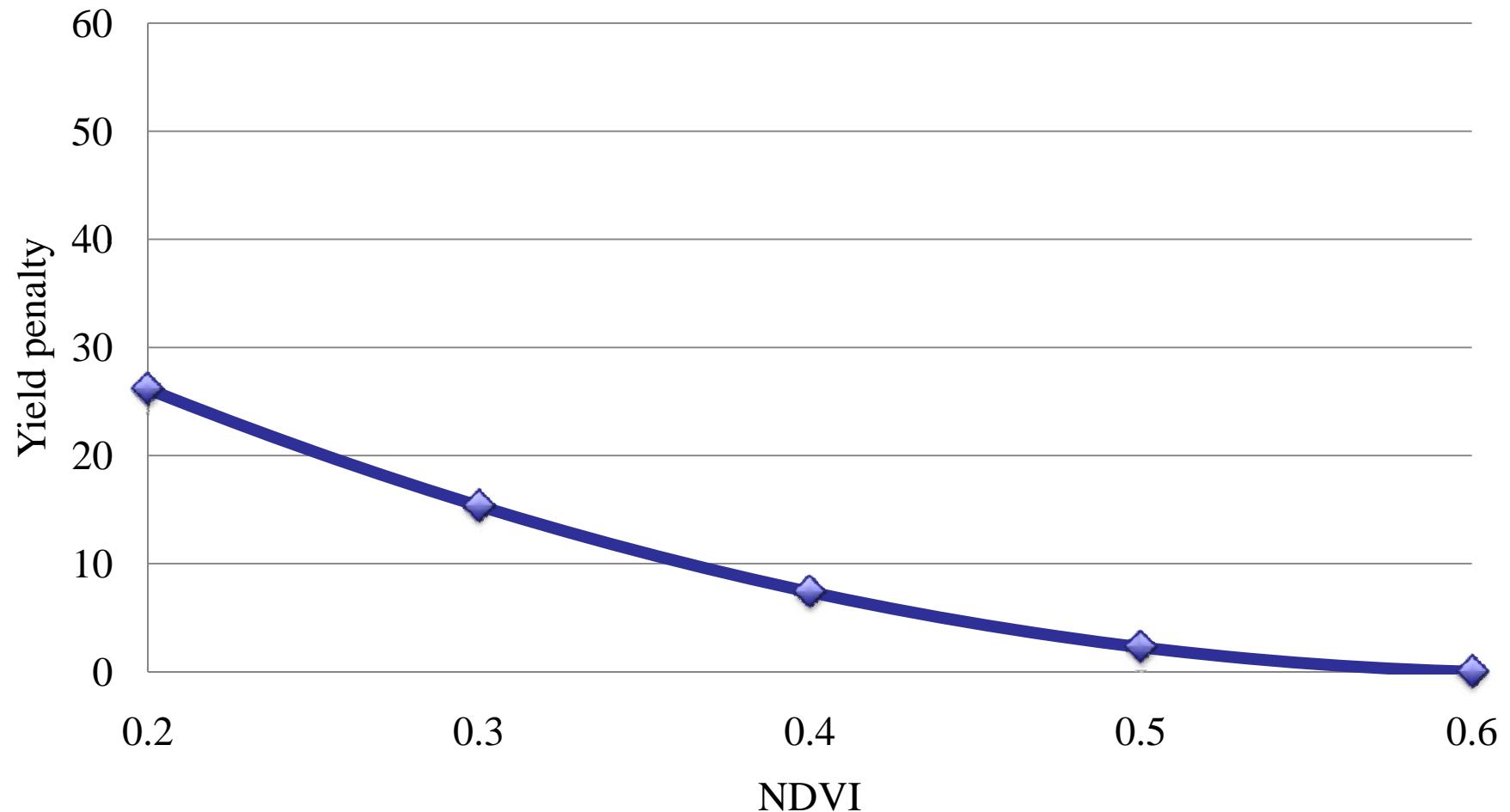


WAP=10

Yield as Function of NDVI by WAP

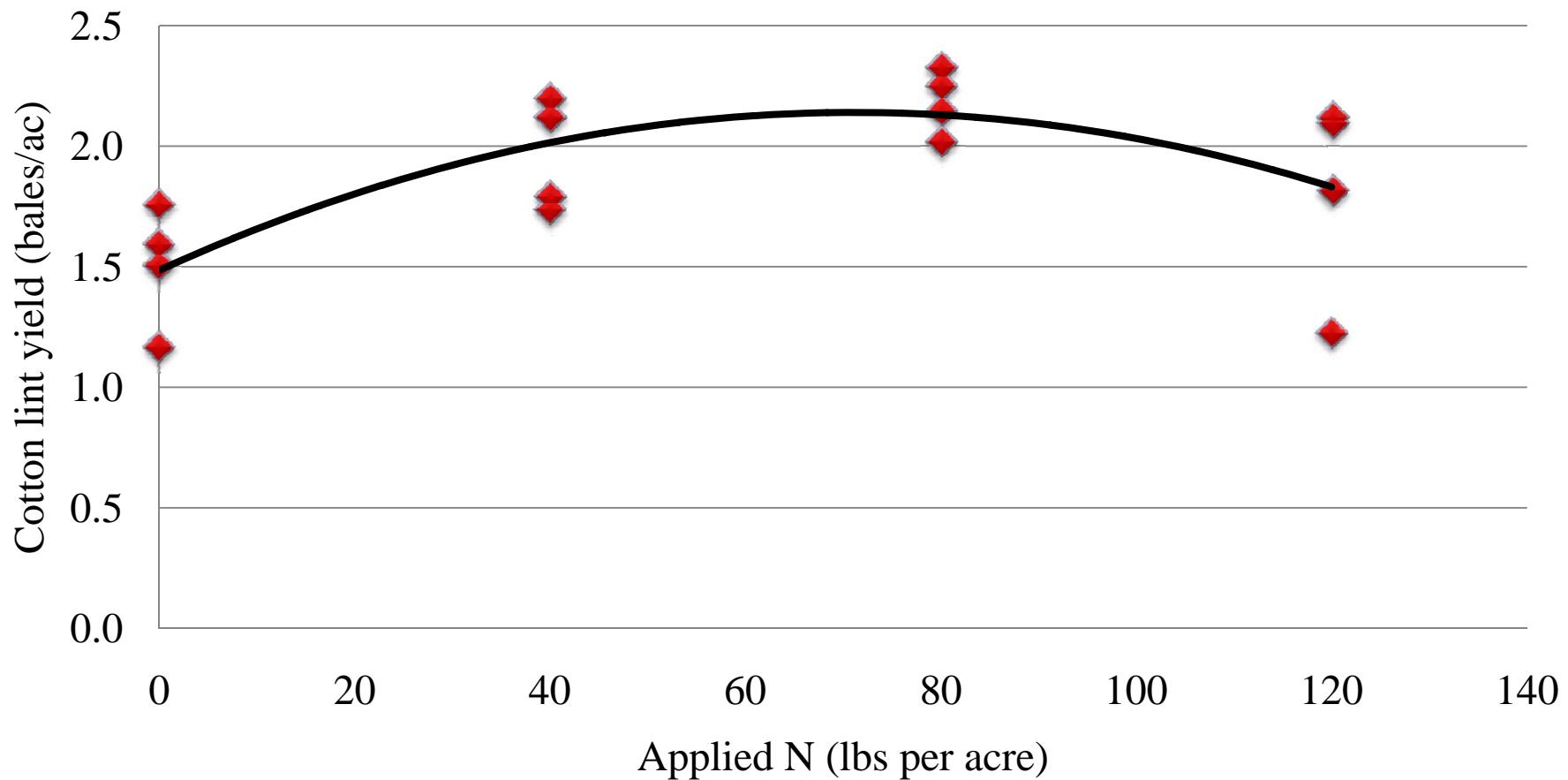


Yield Penalty as Function of NDVI: WAP=7

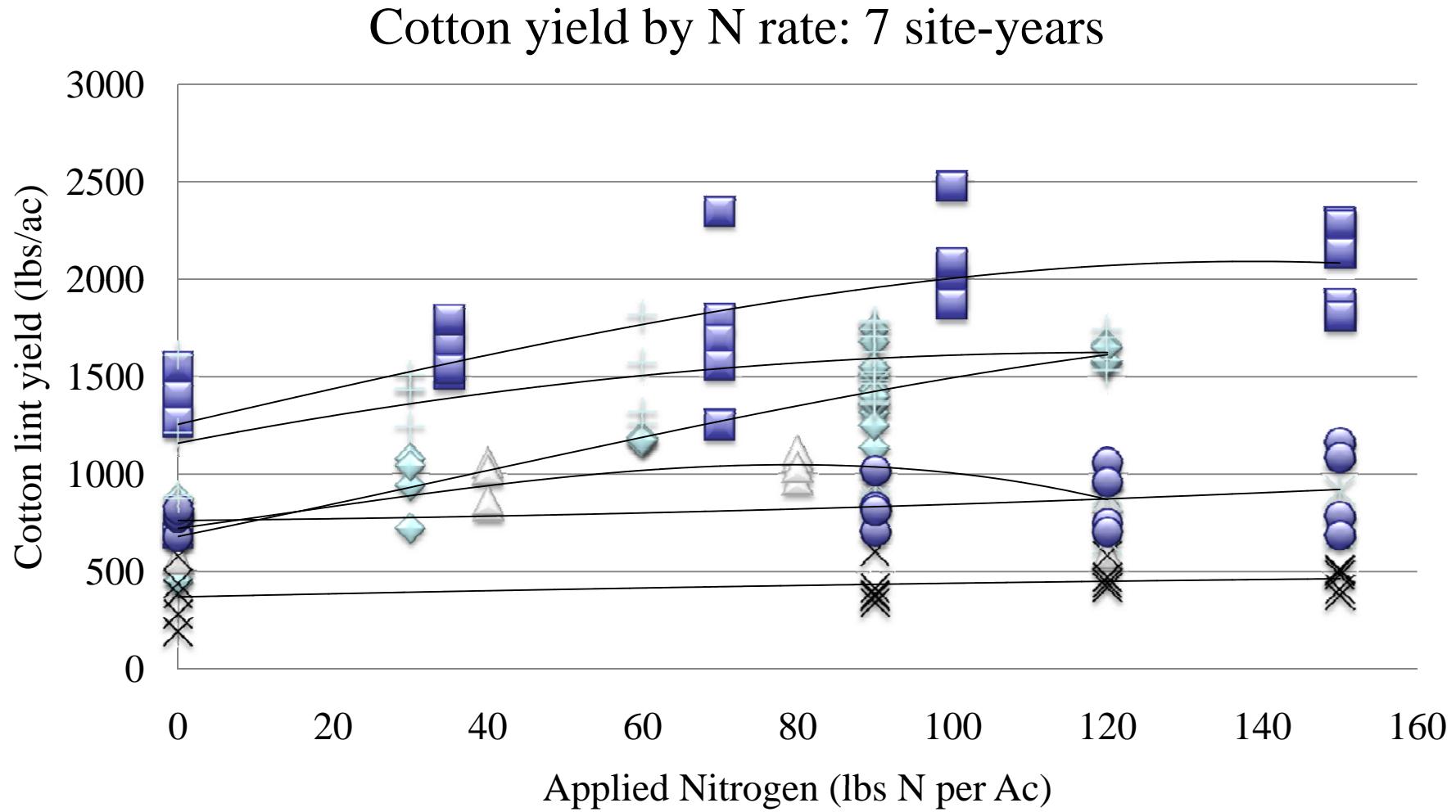


Classic Cotton Lint Response to Applied N

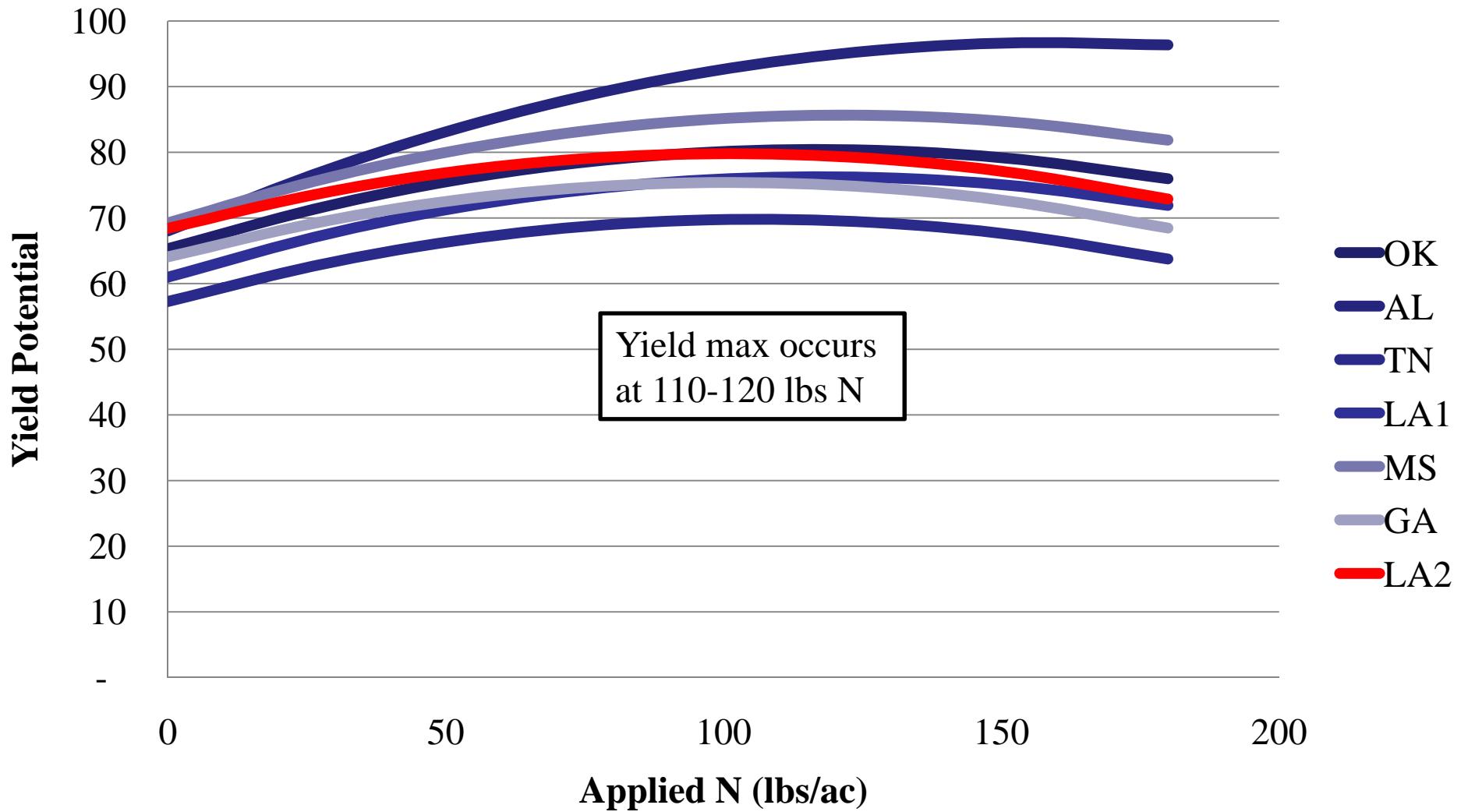
- In theory, quadratic without plateau



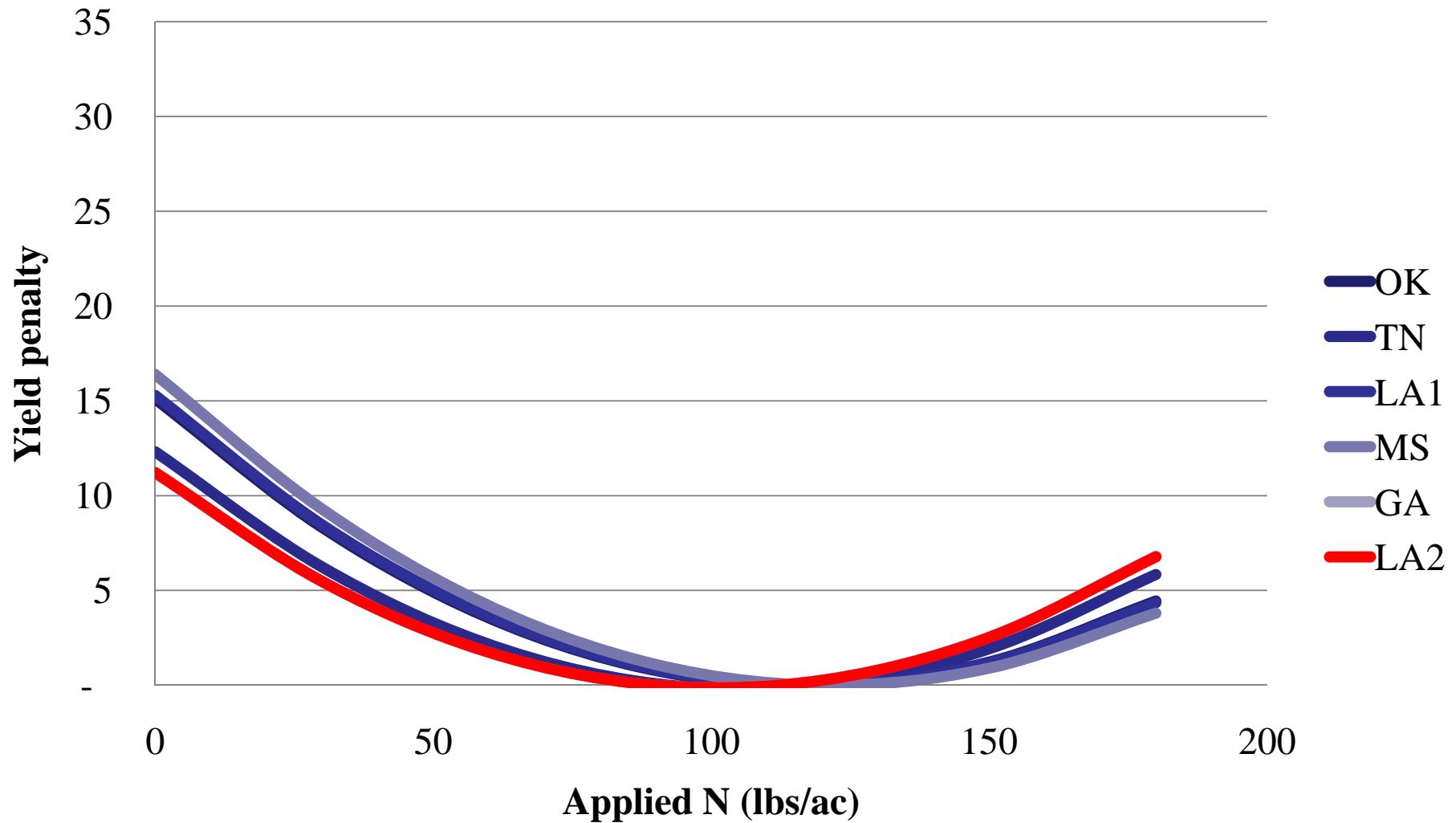
Data is ‘messy’ and ‘all over the place’



Yield Potential by N Rate



Yield Penalty by N Rate



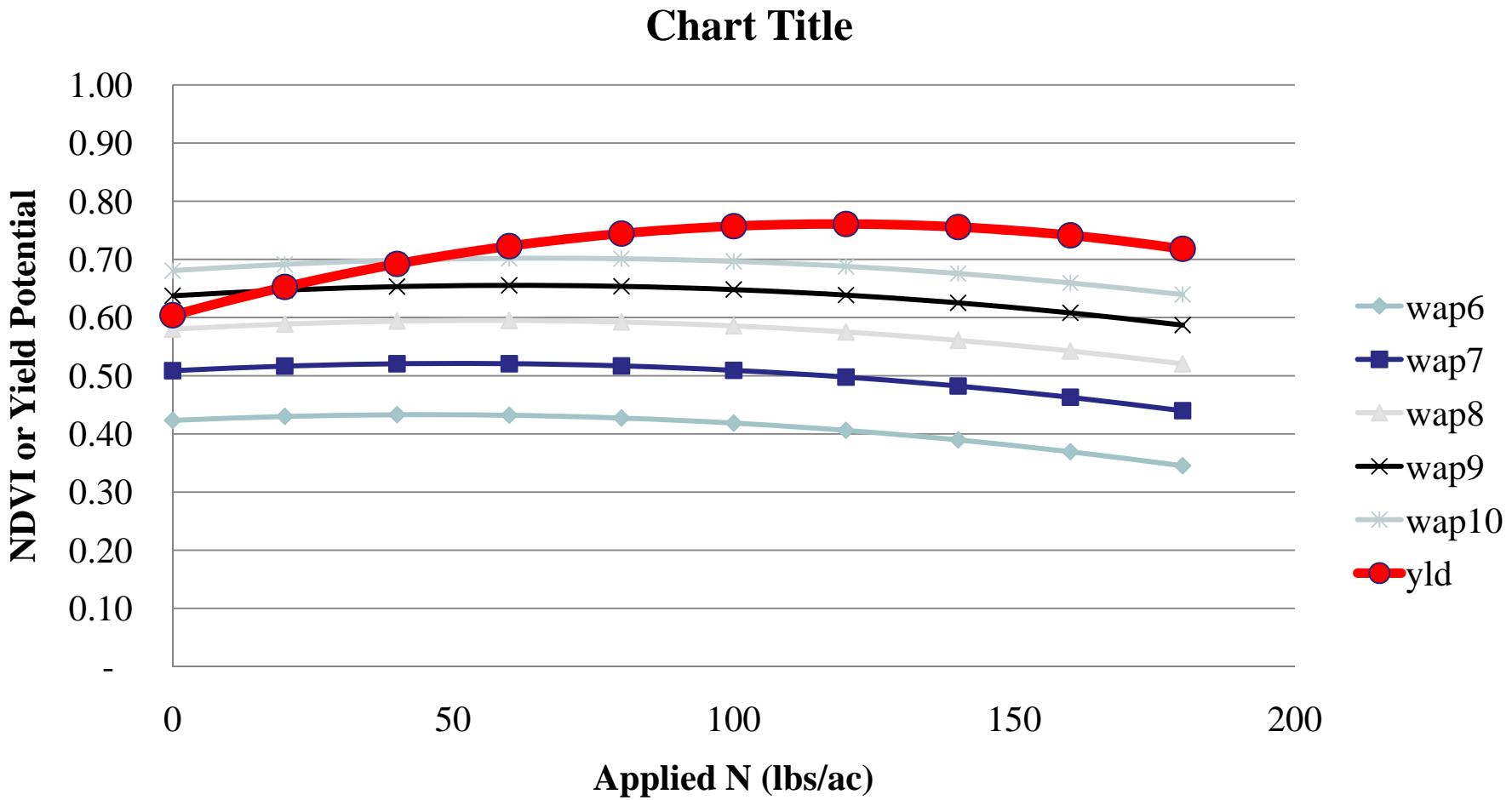
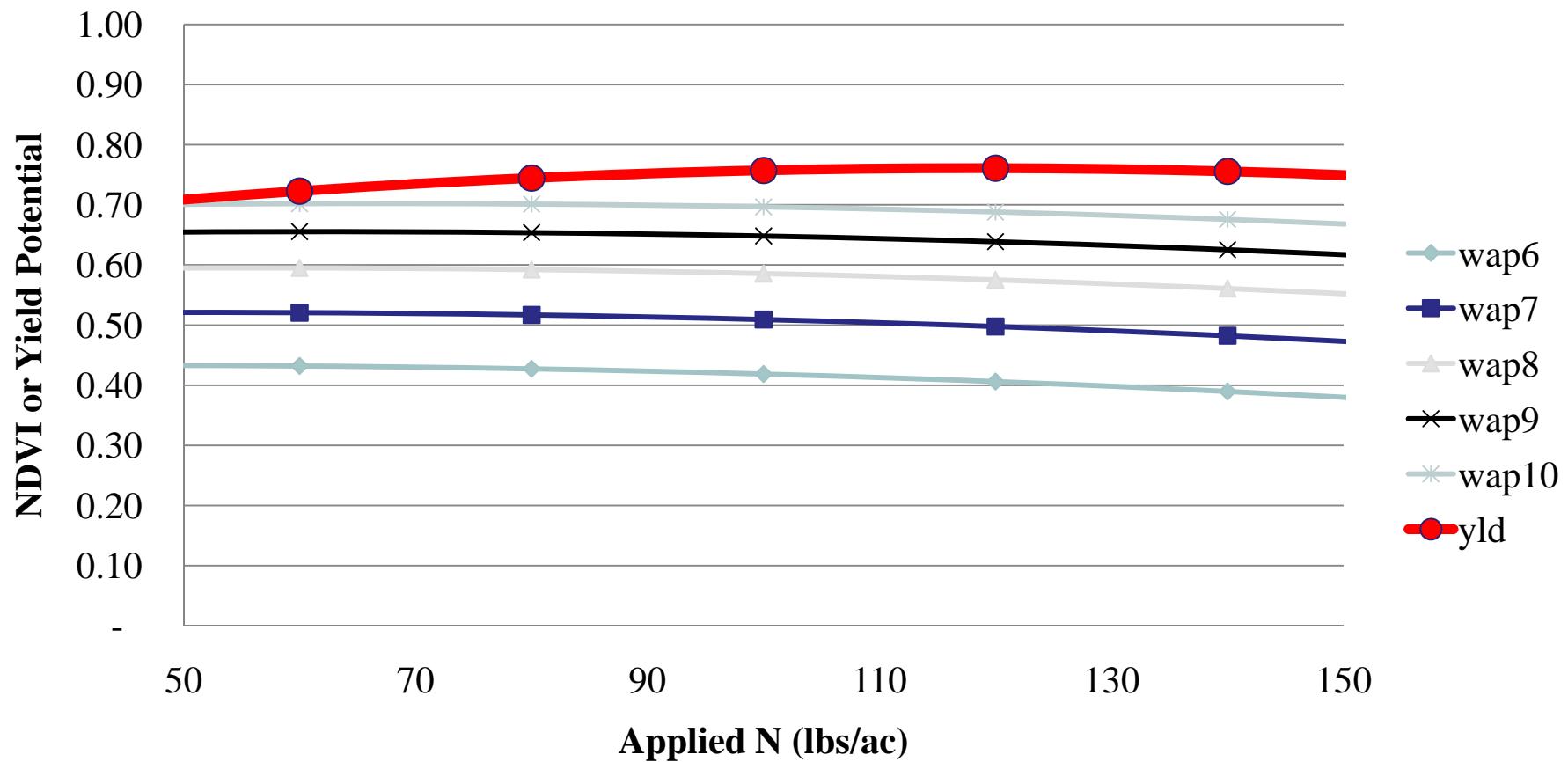


Chart Title



Practical Implications

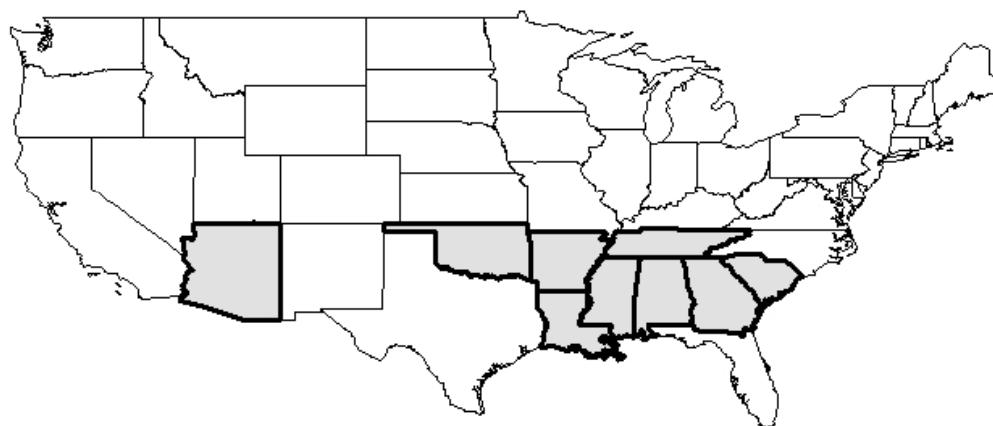
- Lower bound = 0.2
- Upper bound = 0.6
- Difficult to predict total on-the-go applied product
 - Need to take extra product to field
- Some applicators not capable of abruptly varying rates

Limitations

- Cotton is a perennial grown as summer annual
 - Cotton is a tree
- Need more data!
 - Locations, years, varieties
 - DAP/GDD60 of measurements
 - Variables: canopy height, time of day
- Profit maximization has not been evaluated
- Heat unit accumulation metrics
 - Use of GDD60 needs to be revisited

Acknowledgements

- Funding from Cotton Inc.
- Collaborators in 9 states



<u>State</u>	<u>PI</u>
Alabama	Kip Balkcom
Arizona	Ed Barnes
Arizona	Pedro Andrade-Sanchez
Arkansas	Tom Barber
Georgia	George Velidis
Louisiana	Brenda Tubana
Mississippi	Jac Varco
Mississippi	Yufeng
Oklahoma	Randy Taylor
South Carolina	Phil Bauer
Tennessee	John Wilkerson

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Correlation: Yield and GDD60

Pearson Correlation Coefficient applies only to linear relationship

	300 GDD60	600 GDD60	900 GDD60	1200 GDD60	1500 GDD60	1800 GDD60	2100 GDD60	2400 GDD60	2700 GDD60	
YLD	1	-0.32	-0.25	-0.15	-0.02	0.16	0.37	0.60	0.80	0.92
YLD										
300 GDD60		1	1.00	0.98	0.95	0.89	0.76	0.57	0.32	0.07
600 GDD60			1	1.00	0.97	0.92	0.81	0.63	0.39	0.15
900 GDD60				1	0.99	0.95	0.86	0.70	0.48	0.25
1200 GDD60					1	0.99	0.92	0.79	0.59	0.37
1500 GDD60						1	0.98	0.88	0.72	0.53
1800 GDD60							1	0.97	0.86	0.70
2100 GDD60								1	0.96	0.86
2400 GDD60									1	0.97
2700 GDD60										1