

2012

# Evaluation of WorldView-2 and Landsat Data to Differentiate and Map Freshwater Marsh Plant Communities at Different Spatial Scales for Two Everglades Landscapes

Daniel Gann

*GIS-RS Center, Florida International University, gannd@fiu.edu*

Jennifer H. Richards

*Department of Biological Sciences, Florida International University, richards@fiu.edu*

Andrew Gottlieb

*Atkins*

Follow this and additional works at: <http://digitalcommons.fiu.edu/gis>



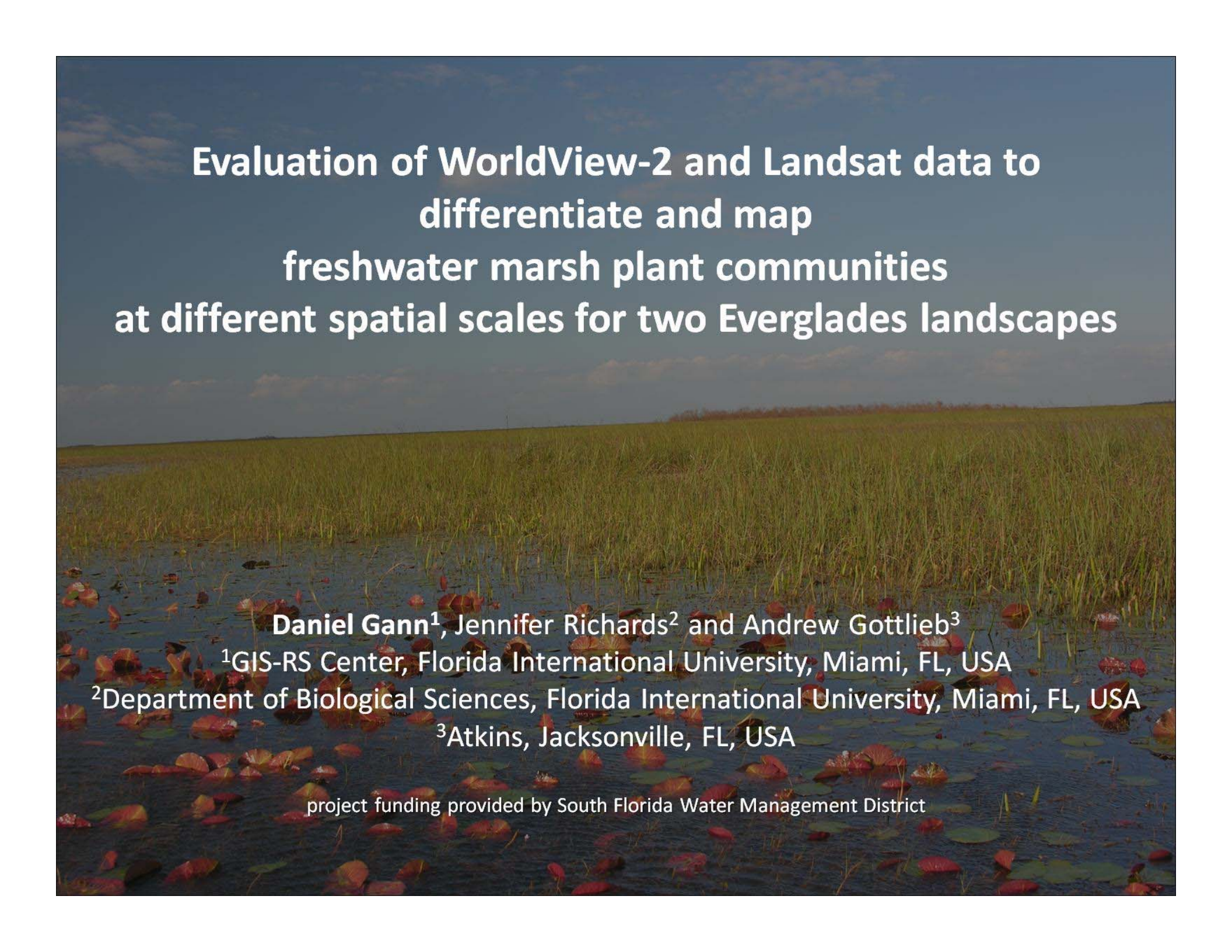
Part of the [Remote Sensing Commons](#)

---

## Recommended Citation

Gann, Daniel; Richards, Jennifer H.; and Gottlieb, Andrew, "Evaluation of WorldView-2 and Landsat Data to Differentiate and Map Freshwater Marsh Plant Communities at Different Spatial Scales for Two Everglades Landscapes" (2012). *GIS Center*. Paper 28.  
<http://digitalcommons.fiu.edu/gis/28>

This work is brought to you for free and open access by the GIS Center at FIU Digital Commons. It has been accepted for inclusion in GIS Center by an authorized administrator of FIU Digital Commons. For more information, please contact [dcc@fiu.edu](mailto:dcc@fiu.edu).



**Evaluation of WorldView-2 and Landsat data to  
differentiate and map  
freshwater marsh plant communities  
at different spatial scales for two Everglades landscapes**

**Daniel Gann<sup>1</sup>, Jennifer Richards<sup>2</sup> and Andrew Gottlieb<sup>3</sup>**

<sup>1</sup>GIS-RS Center, Florida International University, Miami, FL, USA

<sup>2</sup>Department of Biological Sciences, Florida International University, Miami, FL, USA

<sup>3</sup>Atkins, Jacksonville, FL, USA

project funding provided by South Florida Water Management District

# Introduction

Goal: monitor wetland plant communities

- over **large spatial extents**
- at **multiple spatial resolutions**
- **reliable, repeatable and inexpensive**

Value of vegetation map to monitoring

- not only determined by **accuracy**
- but also by **spatial precision**
  - i.e., spatial resolution -> **minimum mapping unit (MMU)**
  - i.e., **spatial variability** of vegetation -> **Classification Scheme**

Method of choice: Remote Sensing → **“Detection” and “Scaling”**



# Objective : Detection

Determine overall and class-specific detection accuracies

2 different **spatial resolutions** (spatial precision)

(1) WorldView2 → **high spatial resolution**

(2) Landsat → **medium spatial resolution**

2 levels of **classification scheme precision**

(1) plant community level

(2) structural level

# Objective : Scaling

Determine how **spatial aggregation** algorithms compare to maps classified at same resolution

- (1) **morphological** aggregation algorithm
- (2) **grid-based** (arbitrary origin) majority rule

aggregated vs. classified resolution:

- (1) 30x30 m Landsat

# Methods : Detection

prediction level	model name	variable set	classifier
community class (comClass)	wetSeason	8 refl. bands of 11/2010	randomForest (rndFor)
	drySeason	8 refl. bands of 5/2011	
	biSeason	16 refl. bands of 2010/2011	
community structure (comStruc)	wetTexture	8 refl. bands and 16 text. layers of 11/2010	Ctree (cTree)
	dryTexture	8 refl. bands and 16 text. layers of 5/2011	
	biTexture	16 refl. bands and 32 text. Layers of 2010/2011	

- 1) **variable set**: spectral reflectance, first-order textural derivatives (variance) and for single- and dual-date imagery
- 2) **classifier**: single tree (cTree) vs. randomForest recursive partitioning
- 3) **prediction level**

evaluation metrics: overall and class-specific accuracies and Kappa

- 1) **model-based** cross-validated results
- 2) **design-based** post-classification stratified random samples

# Methods : Scaling

## 1) hierarchical thematic aggregation

e.g., Short Graminoid (GS) *Rhynchospora* and Short Graminoid *Eleocharis* aggregated to GS

## 2) grid-based spatial aggregation

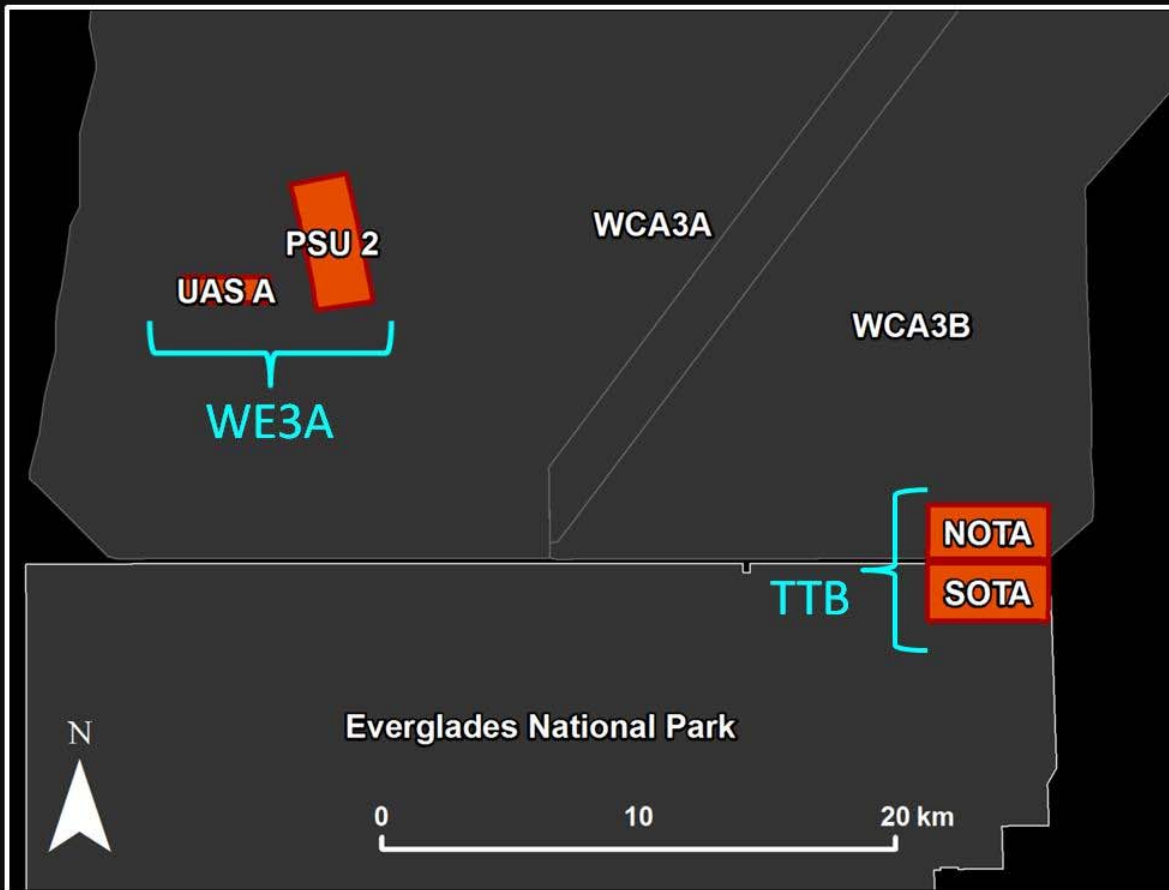
e.g., an area of 25 2x2 m grid cells are aggregated to one grid cell of 10x10 m

## 3) morphological spatial aggregation algorithm

e.g., contiguous grid cells with the same class membership with area less than the minimum mapping unit are absorbed by the surrounding polygon

evaluation metrics: areal coverage change of plant community abundances and changes in class diversity

# Methods : Study Areas



2 landscape formations

1) *Wet Prairie, Shrubland*  
Tamiami Trail Bridge (TTB)

NOTA & SOTA

2) *Ridge, Slough, Tree Island*

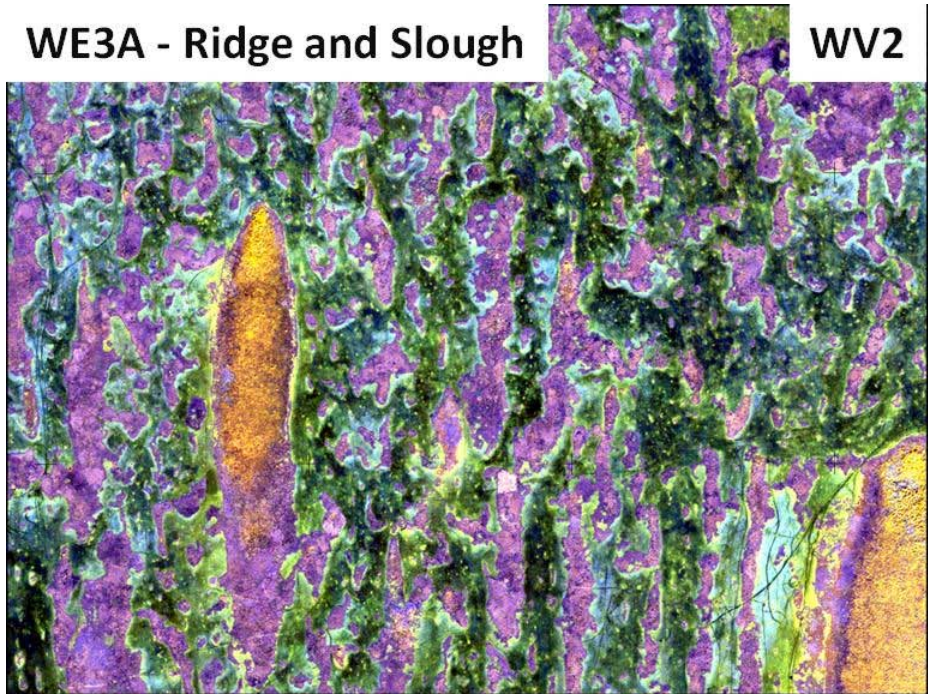
WEstern 3A (WE3A)

PSU 2 & UAS A



**WE3A - Ridge and Slough**

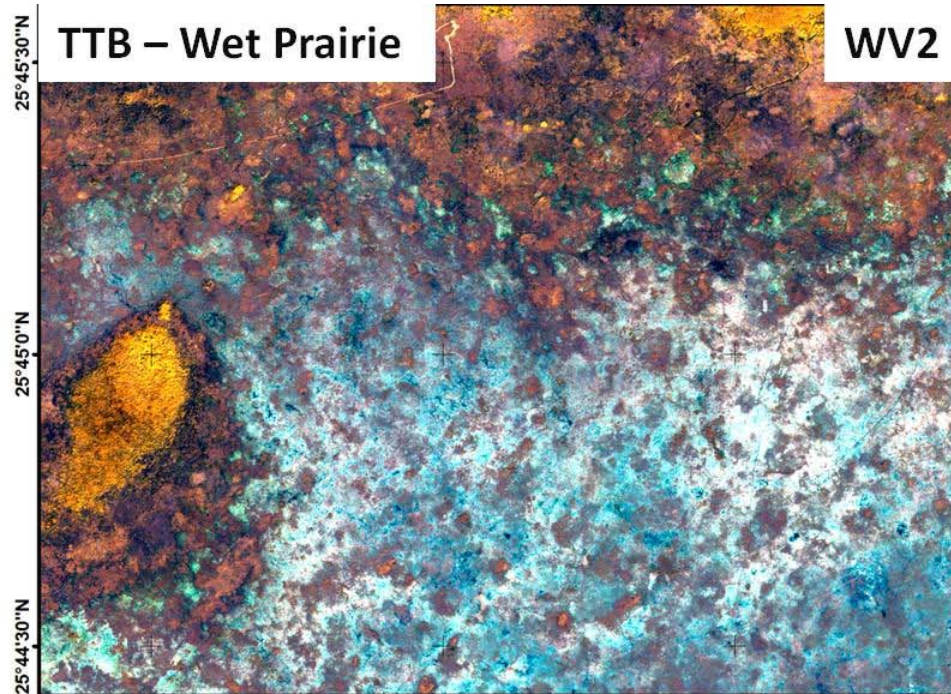
**WV2**



80°46'0\"W 80°45'30\"W 80°45'0\"W 80°44'30\"W  
80°46'0\"W 80°45'30\"W 80°45'0\"W 80°44'30\"W

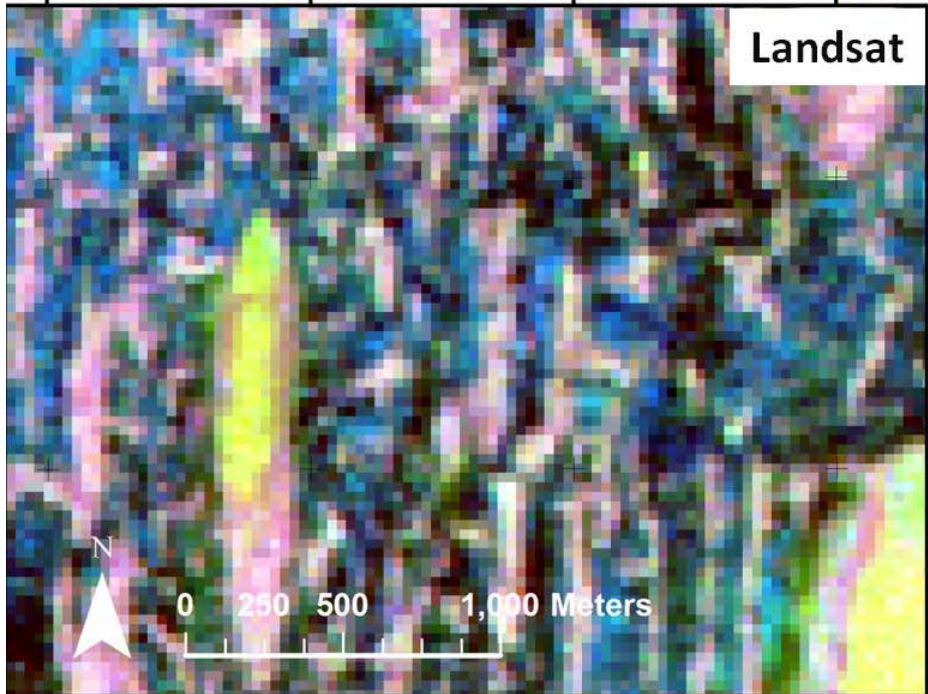
**TTB - Wet Prairie**

**WV2**

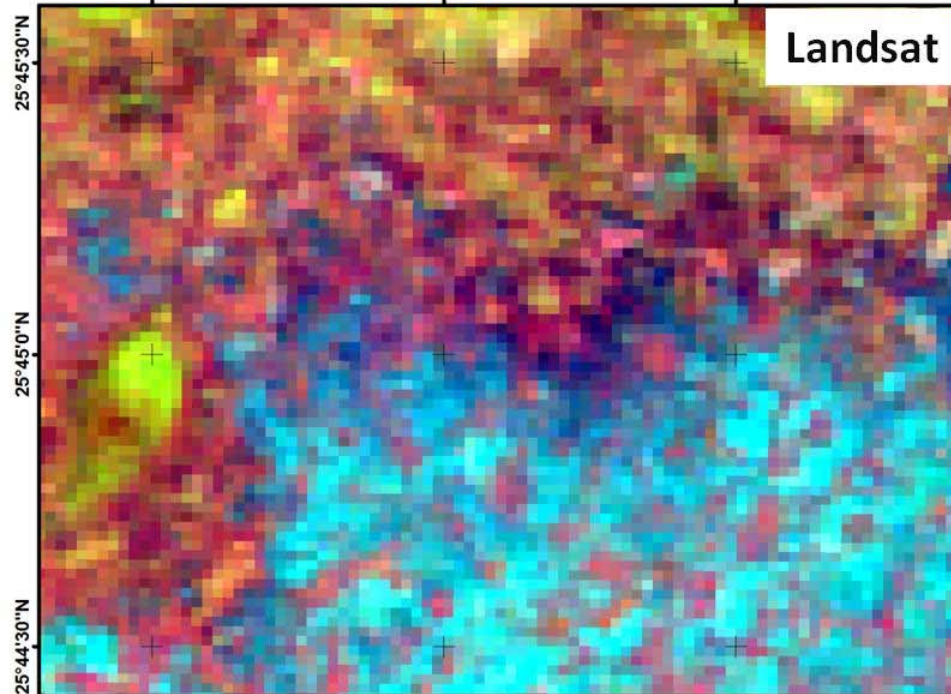


80°31'30\"W 80°31'0\"W 80°30'30\"W  
80°31'30\"W 80°31'0\"W 80°30'30\"W

**Landsat**



**Landsat**





# Methods : Classification Scheme

community structure	community class	community class description	TTB	WE3A
SL	Flno	<i>Nymphaea odorata</i>	0	1
SL	FLu	<i>Utricularia ssp.</i>	0	1
SL	_Pf	floating periphyton mat	0	1
SL	_OW	open water in Slough matrix	0	1
BL	BLmix	Broadleaf mix (i.e., <i>Sagittaria</i> , <i>Pontederia</i> , <i>Crinum</i> , <i>Peltandra</i> )	1	1
BL	BLpv	<i>Peltandra virginica</i>	1	1
BL	BLbs	<i>Blechnum serrulatum</i>	1	1
WP	GS_BL	short graminoid broadleaf mix	1	0
WP	GSmix	short graminoid mix (i.e., <i>Eleocharis</i> , <i>Panicum</i> , <i>Rynchospora</i> )	1	0
WP	Gse	<i>Eleocharis ssp.</i>	1	0
WP	GSrt	<i>Rynchospora tracyi</i>	1	0
WP	_Pb	benthic periphyton mat	1	0
WP	_BGp	bare ground peat (w/wo water)	1	0
GT	GTcj	<i>Cladium jamaicense</i>	1	1
GT	GTcjS	<i>Cladium jamaicense</i> Short	1	0
GT	GTcjT	<i>Cladium jamaicense</i> Tall	1	1
GT	GTt	<i>Typha ssp.</i>	1	1
S	Ssc	<i>Salix caroliniana</i>	1	1
S	SB	Bayhead (i.e., <i>Annona</i> , <i>Myrica</i> , <i>Persea</i> , <i>Magnolia</i> )	1	1
T	TB	Bayhead (i.e., <i>Annona</i> , <i>Myrica</i> , <i>Persea</i> , <i>Magnolia</i> )	1	1
T	Tag	<i>Annona glabra</i>	1	0
total number of classes			17	13

2 landscape formations

*Wet Prairie, Shrubland*

TTB (NOTA; SOTA)

*Ridge, Slough, Tree Island*

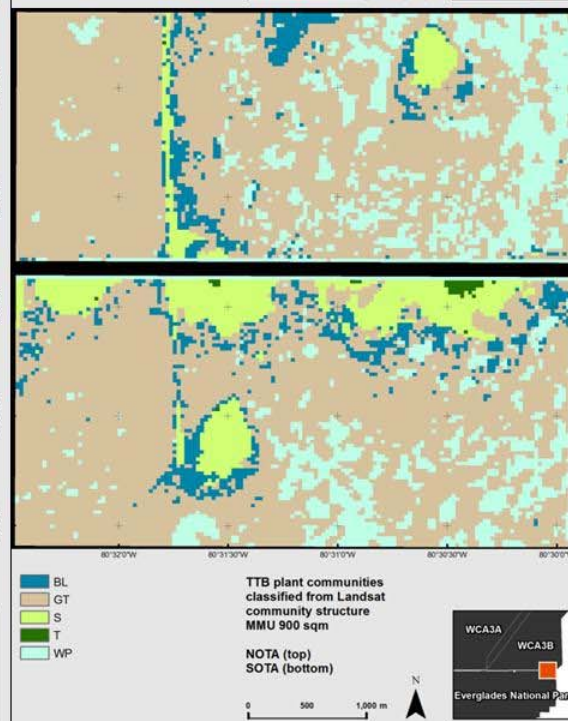
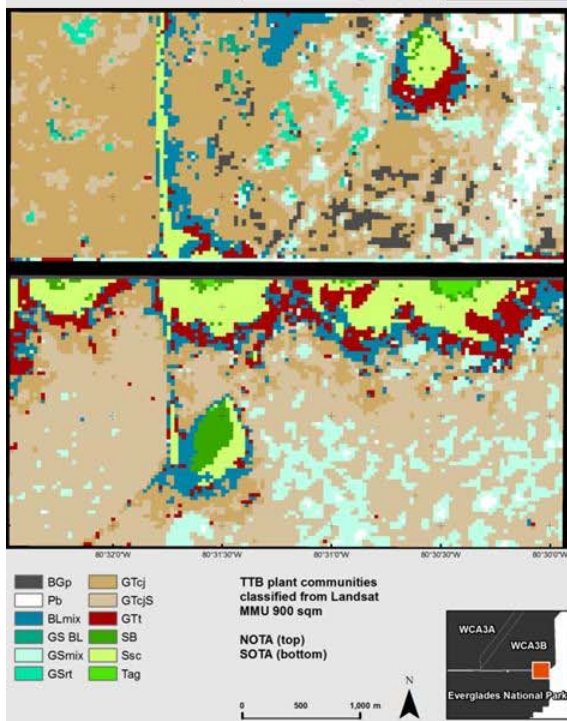
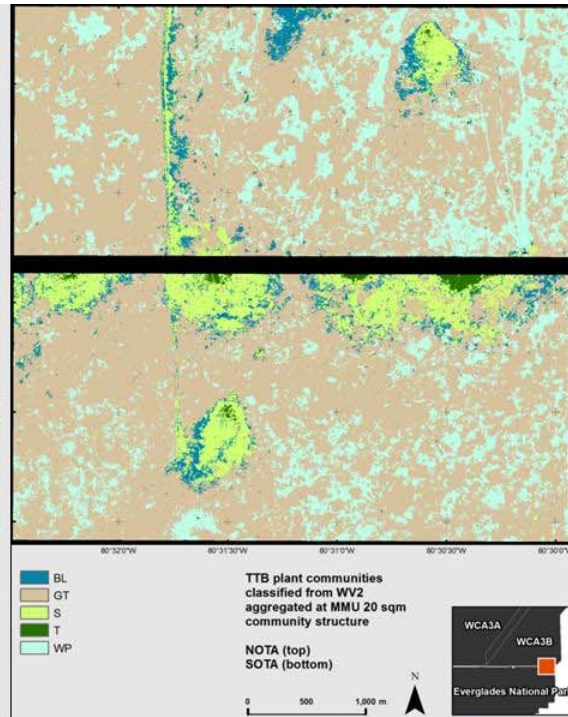
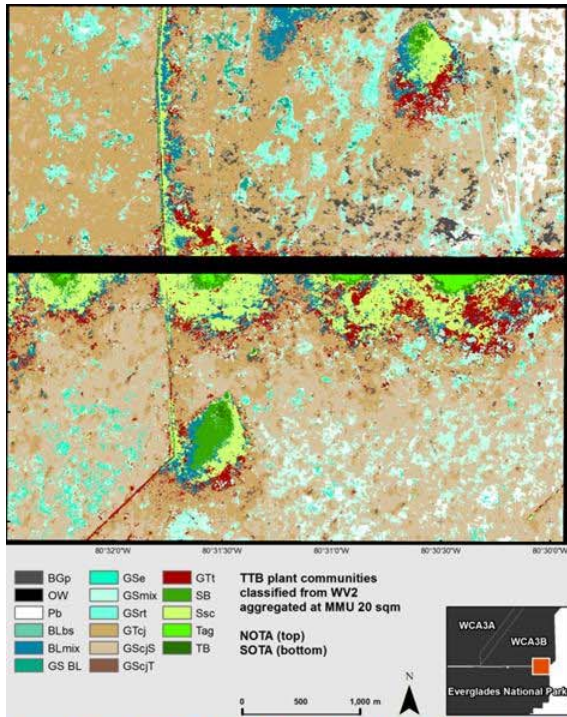
WE3A (PSU 2; UAS A)

# Results : Detection TTB

top: WV2

left: Community level

right: Structural level

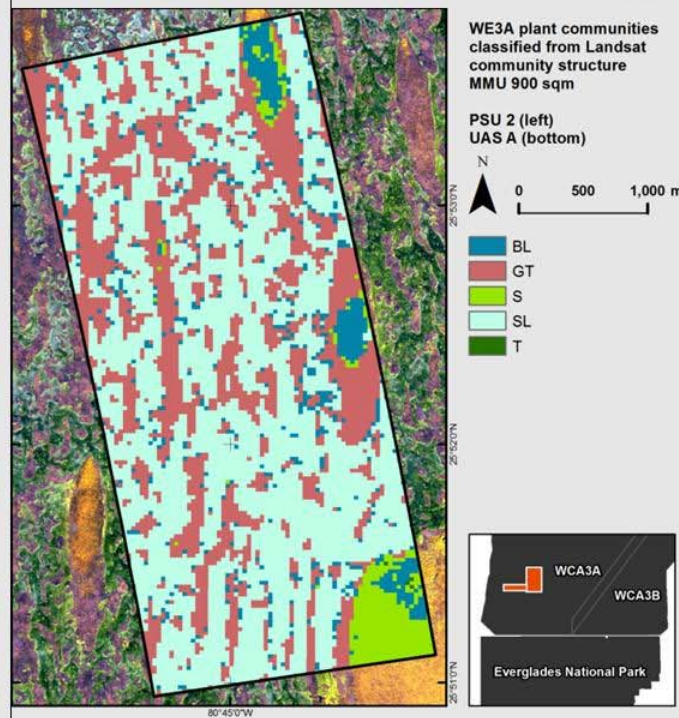
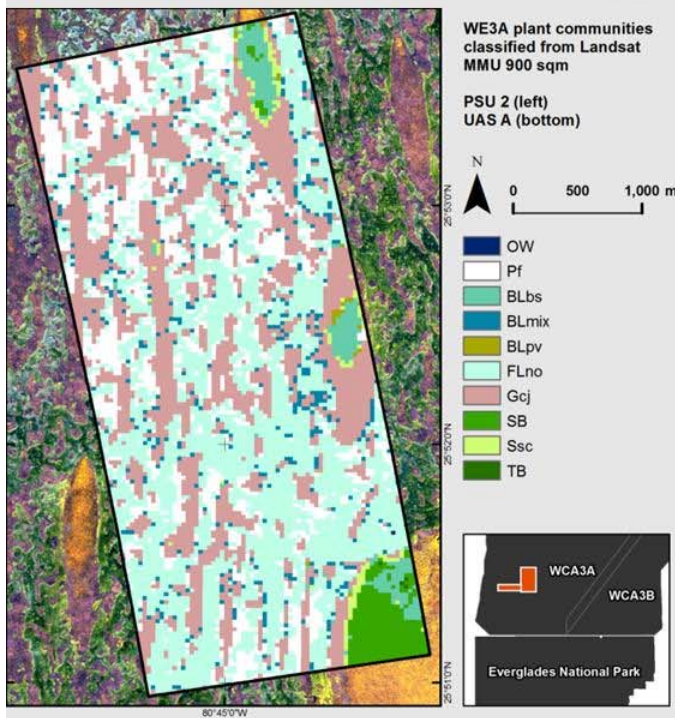
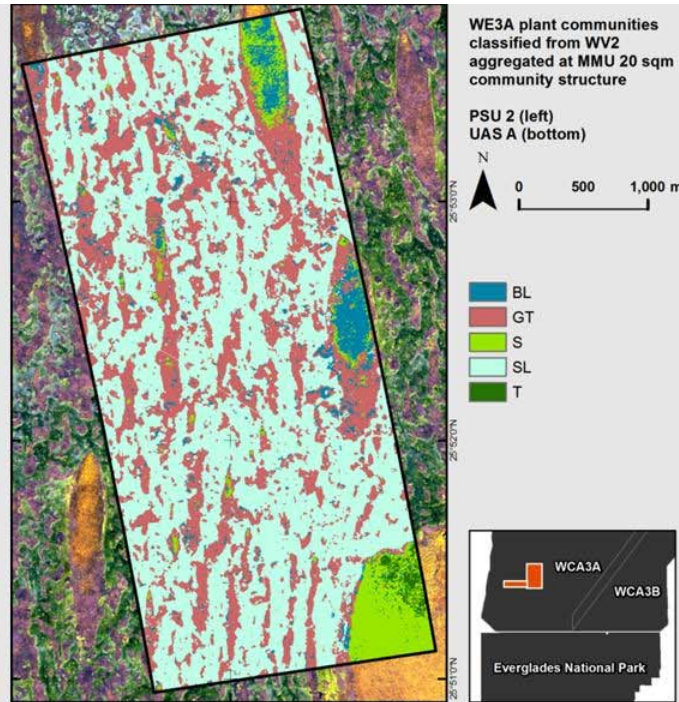
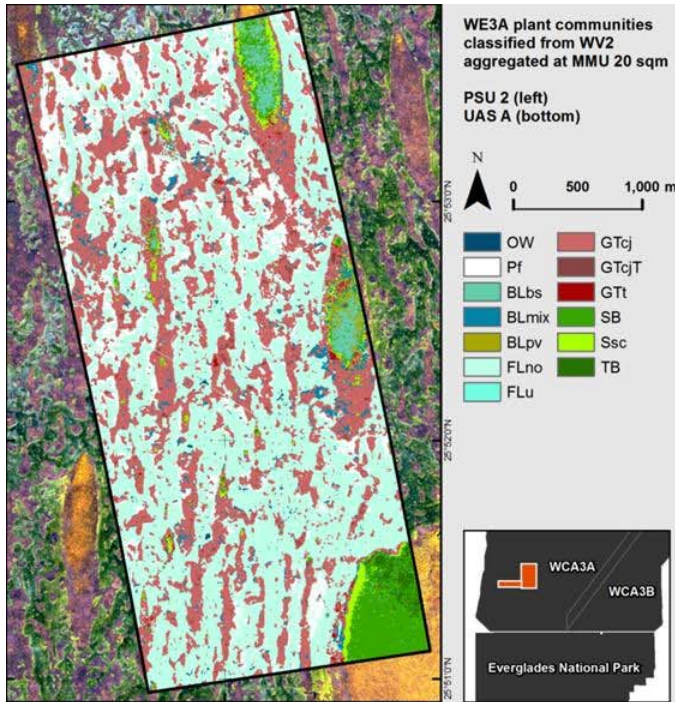


bottom: Landsat

left: Community level

right: Structural level





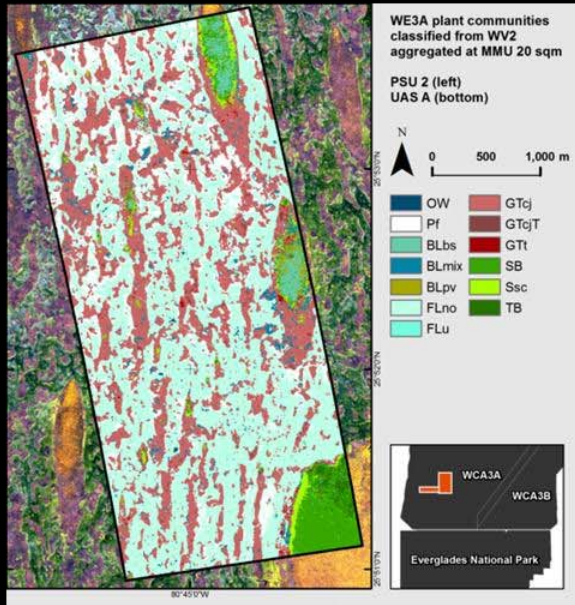
# Results : Detection WE3A

top: WV2  
left: Community level  
right: Structural level

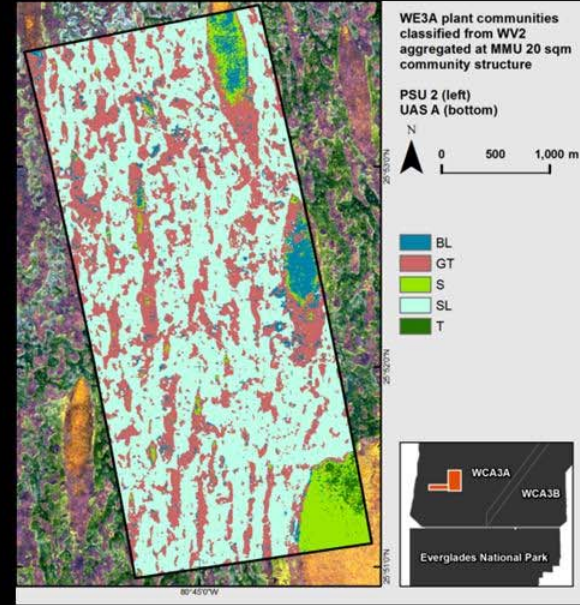
bottom: Landsat  
left: Community level  
right: Structural level







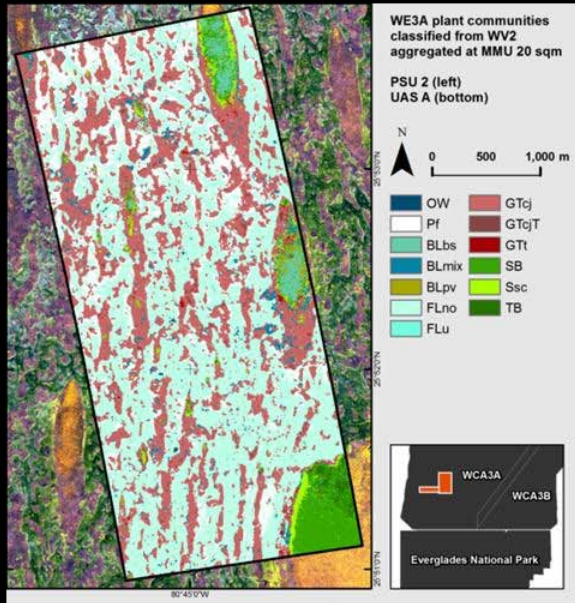
evaluation: overall and class-specific accuracies and Kappa statistic estimates



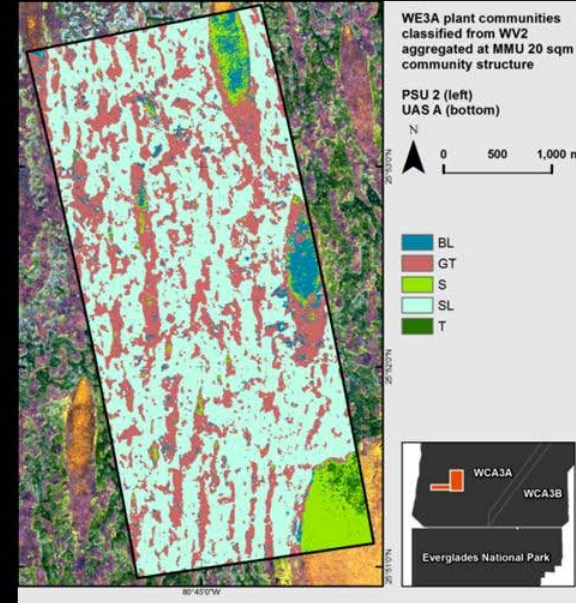
	_OW	_Pf	BLbs	BLmix	BLpv	FLno	FLu	GTcj	GTcjT	GTt	SB	Ssc	TB	r.T	c.E	c.E (%)
_OW	95	0	0	0	0	6	0	0	0	0	0	0	0	101	0.06	5.94
_Pf	0	578	0	3	0	44	12	0	0	1	0	0	0	638	0.09	9.40
BLbs	0	0	44	4	0	0	0	0	0	0	6	0	2	56	0.21	21.43
BLmix	1	0	0	197	7	4	0	7	0	0	0	0	2	218	0.10	9.63
BLpv	0	0	1	3	51	1	0	1	0	0	0	2	0	59	0.14	13.56
FLno	4	50	0	21	9	1060	0	6	1	0	0	0	0	1151	0.08	7.91
FLu	0	2	0	0	0	0	68	0	0	0	0	0	0	70	0.03	2.86
GTcj	0	0	0	9	7	5	0	520	24	11	0	3	0	579	0.10	10.19
GTcjT	0	0	0	0	1	0	0	7	70	2	0	0	0	80	0.13	12.50
GTt	0	0	0	0	0	0	0	8	0	82	0	1	0	91	0.10	9.89
SB	0	0	3	0	0	0	0	0	5	0	67	2	3	80	0.16	16.25
Ssc	0	0	1	3	0	0	0	1	0	4	0	92	0	101	0.09	8.91
TB	0	0	1	0	0	0	0	0	0	0	2	0	93	96	0.03	3.13
c.T														3017	3320	
o.E														3320		
o.E (%)	5.00	8.25	12.00	17.92	32.00	5.36	15.00	5.45	30.00	18.00	10.67	8.00	7.00			
acc (%)	95.00	91.75	88.00	82.08	68.00	94.64	85.00	94.55	70.00	82.00	89.33	92.00	93.00			
oa (%)														90.87		
K̂														88.69		

	SL	BL	GT	S	T	r.t	c.E	c.E (%)
SL	1922	36	16	0	0	1974	0.03	2.63
BL	4	300	8	9	4	325	0.08	7.69
GT	4	22	714	3	0	743	0.04	3.90
S	0	6	12	160	3	181	0.12	11.60
T	0	1	0	3	93	97	0.04	4.12
c.T						3189	3320	
o.E	0.00	0.18	0.05	0.09	0.07			
o.E (%)	0.41	17.81	4.80	8.57	7.00			
acc (%)	99.59	82.19	95.20	91.43	93.00			
oa (%)						96.05		
K̂						93.30		





evaluation: overall and class-specific accuracies and Kappa statistic estimates



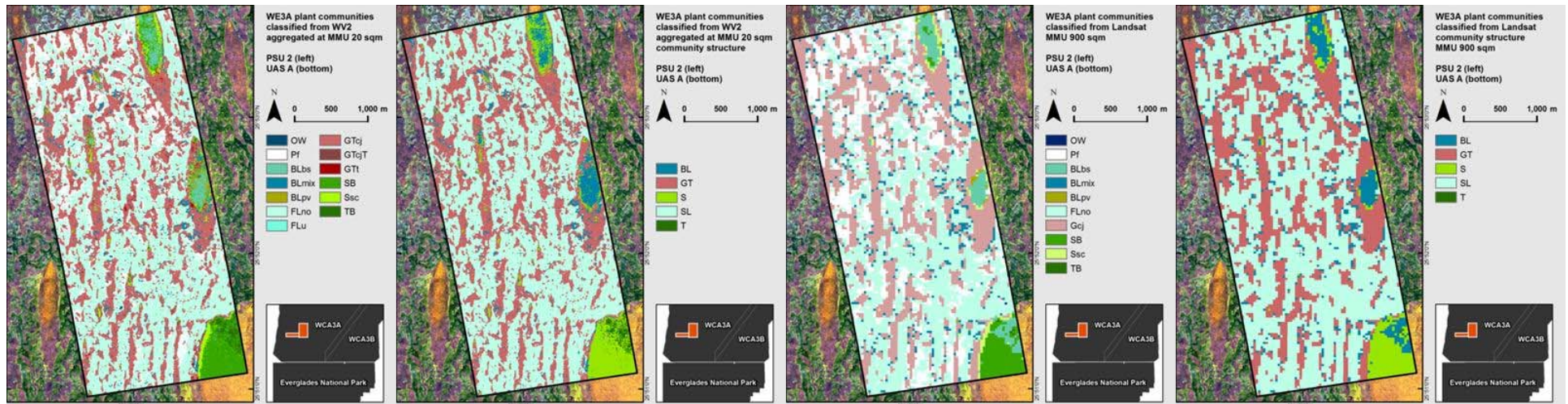
	_OW	_Pf	BLbs	BLmix	BLpv	FLno	FLu	GTcj	GTcjT	GTt	SB	Ssc	TB	r.T	c.E	c.E (%)	
_OW	95	0	0	0	0	6	0	0	0	0	0	0	0	101	0.06	5.94	
_Pf	0	578	0	3	0	44	12	0	0	1	0	0	0	638	0.09	9.40	
BLbs	0	0	44	4	0	0	0	0	0	0	6	0	2	56	0.21	21.43	
BLmix	1	0	0	197	7	4	0	7	0	0	0	0	2	218	0.10	9.63	
BLpv	0	0	1	3	51	1	0	1	0	0	0	2	0	59	0.14	13.56	
FLno	4	50	0	21	9	1060	0	6	1	0	0	0	0	1151	0.08	7.91	
FLu	0	2	0	0	0	0	68	0	0	0	0	0	0	70	0.03	2.86	
GTcj	0	0	0	9	7	5	0	520	24	11	0	3	0	579	0.10	10.19	
GTcjT	0	0	0	0	1	0	0	7	70	2	0	0	0	80	0.13	12.50	
GTt	0	0	0	0	0	0	0	8	0	82	0	1	0	91	0.10	9.89	
SB	0	0	3	0	0	0	0	0	5	0	67	2	3	80	0.16	16.25	
Ssc	0	0	1	3	0	0	0	1	0	4	0	92	0	101	0.09	8.91	
TB	0	0	1	0	0	0	0	0	0	0	2	0	93	96	0.03	3.13	
c.T														3017	3320		
o.E														3320			
o.E (%)	5.00	8.25	12.00	17.92	32.00	5.36	15.00	5.45	30.00	18.00	10.67	8.00	7.00				
acc (%)	95.00	91.75	88.00	82.08	68.00	94.64	85.00	94.55	70.00	82.00	89.33	92.00	93.00				
oa (%)														90.87			
R														88.69			

	SL	BL	GT	S	T	r.t	c.E	c.E (%)
SL	1922	36	16	0	0	1974	0.03	2.63
BL	4	300	8	9	4	325	0.08	7.69
GT	4	22	714	3	0	743	0.04	3.90
S	0	6	12	160	3	181	0.12	11.60
T	0	1	0	3	93	97	0.04	4.12
c.T						3189	3320	
o.E	0.00	0.18	0.05	0.09	0.07	3320		
o.E (%)	0.41	17.81	4.80	8.57	7.00			
acc (%)	99.59	82.19	95.20	91.43	93.00			
oa (%)						96.05		
R						93.30		

	SL	BL	GT	S	T	r.t	c.E	c.E (%)
SL	1919	33	8	0	0	1960	0.02	2.09
BL	6	307	8	8	4	333	0.08	7.81
GT	5	17	724	4	0	750	0.03	3.47
S	0	7	10	161	3	181	0.11	11.05
T	0	1	0	2	93	96	0.03	3.13
c.T						3204	3320	
o.E	0.01	0.16	0.03	0.08	0.07	3320		
o.E (%)	0.57	15.89	3.47	8.00	7.00			
acc (%)	99.43	84.11	96.53	92.00	93.00			
oa (%)						96.51		
R						94.09		





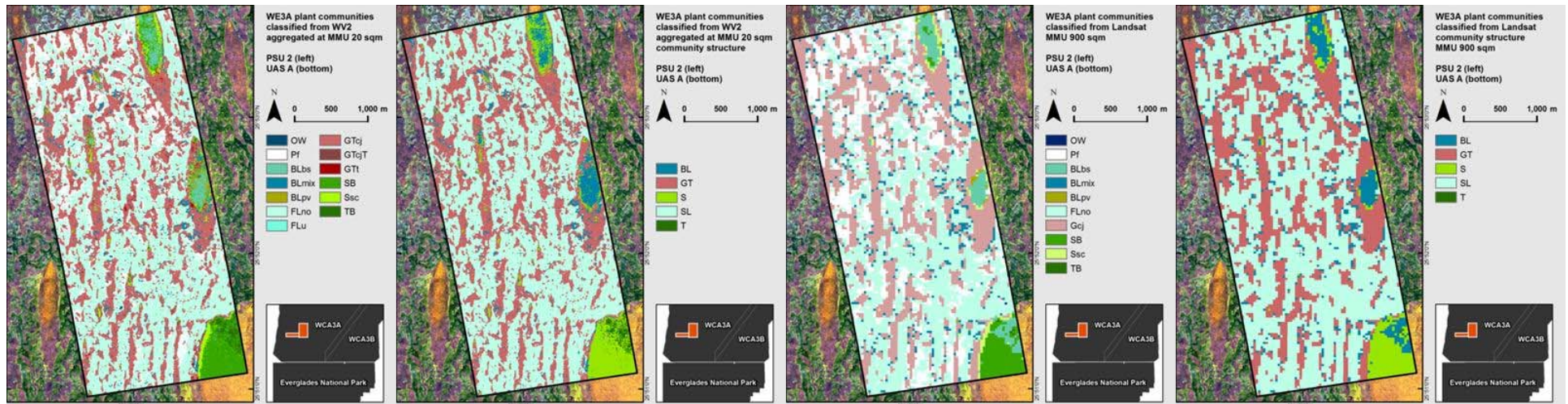


models				accuracy				model based overall accuracy by variable set					
roi	img	clf	predLevel	oaMod	kaMod	oaDes	kaDes	wet	dry	bi	wetTxt	dryTxt	biTxt
WE3A	wv2	cTree	comClass	87.68	84.76	-	-	81.27	63.64	84.10	84.91	69.55	87.68
WE3A	wv2	cTree	comStruc	94.61	90.81	-	-	90.96	85.24	93.16	91.60	89.34	94.61
WE3A	wv2	rndFor	comClass	90.87	88.69	-	-	81.36	64.67	86.99	86.66	73.10	90.87
WE3A	wv2	rndFor	comStruc	96.05	93.30	88.89	85.56	91.27	86.81	94.04	93.77	90.51	96.05
WE3A	wv2	rndFor	classAggStruc	96.51	94.09	-	-	-	-	-	-	-	-
WE3A	ls	rndFor	comClass	93.07	91.22	73.56	61.06	90.10	79.46	93.07	-	-	-
WE3A	ls	rndFor	classAggStruc	96.29	94.70	85.13	73.48	-	-	-	-	-	-

evaluation: overall and class-specific accuracies and Kappa statistic estimates

1) model-based - cross-validated results (oaMod; kaMod)

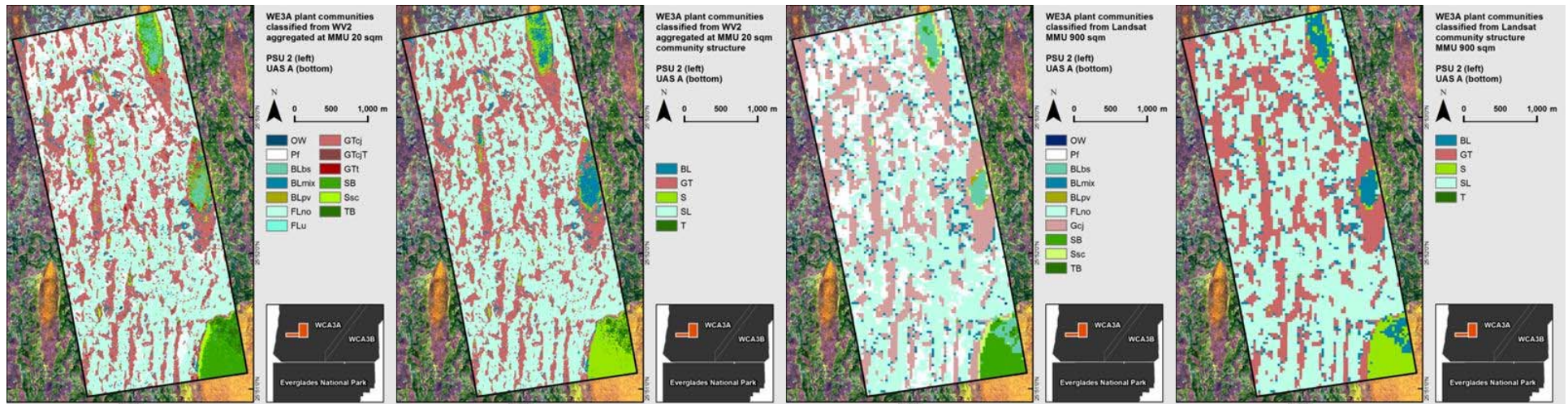




models				accuracy				model based overall accuracy by variable set					
roi	img	clf	predLevel	oaMod	kaMod	oaDes	kaDes	wet	dry	bi	wetTxt	dryTxt	biTxt
WE3A	wv2	cTree	comClass	87.68	84.76	-	-	81.27	63.64	84.10	84.91	69.55	87.68
WE3A	wv2	cTree	comStruc	94.61	90.81	-	-	90.96	85.24	93.16	91.60	89.34	94.61
WE3A	wv2	rndFor	comClass	90.87	88.69	-	-	81.36	64.67	86.99	86.66	73.10	90.87
WE3A	wv2	rndFor	comStruc	96.05	93.30	88.89	85.56	91.27	86.81	94.04	93.77	90.51	96.05
WE3A	wv2	rndFor	classAggStruc	96.51	94.09	-	-	-	-	-	-	-	-
WE3A	ls	rndFor	comClass	93.07	91.22	73.56	61.06	90.10	79.46	93.07	-	-	-
WE3A	ls	rndFor	classAggStruc	96.29	94.70	85.13	73.48	-	-	-	-	-	-

evaluation: overall and class-specific accuracies and Kappa statistic estimates

1) model-based - cross-validated results (oaMod; kaMod)

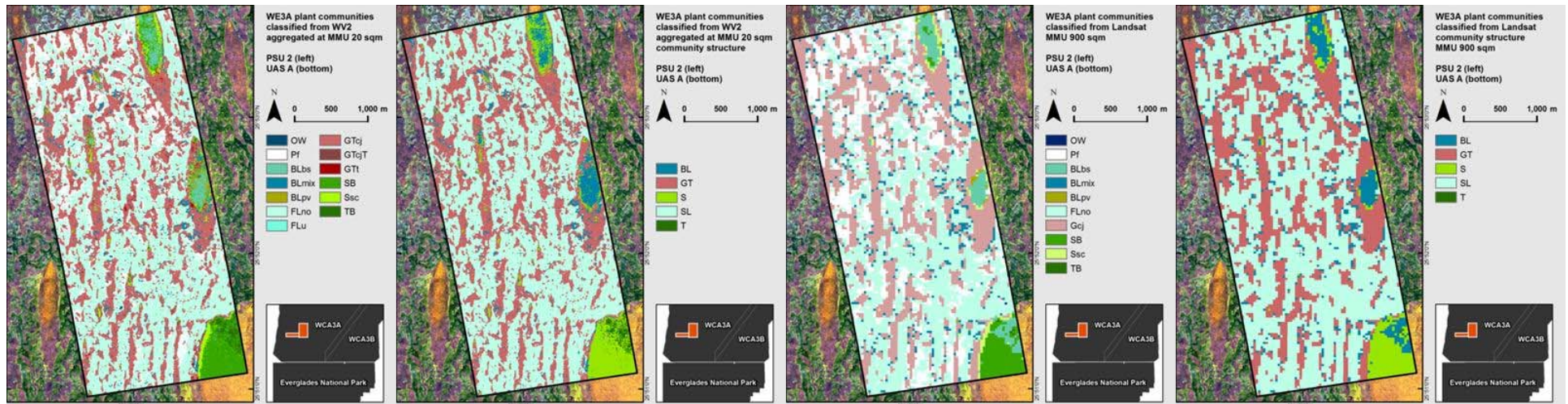


models				accuracy				model based overall accuracy by variable set					
roi	img	clf	predLevel	oaMod	kaMod	oaDes	kaDes	wet	dry	bi	wetTxt	dryTxt	biTxt
WE3A	wv2	cTree	comClass	87.68	84.76	-	-	81.27	63.64	84.10	84.91	69.55	87.68
WE3A	wv2	cTree	comStruc	94.61	90.81	-	-	90.96	85.24	93.16	91.60	89.34	94.61
WE3A	wv2	rndFor	comClass	90.87	88.69	-	-	81.36	64.67	86.99	86.66	73.10	90.87
WE3A	wv2	rndFor	comStruc	96.05	93.30	88.89	85.56	91.27	86.81	94.04	93.77	90.51	96.05
WE3A	wv2	rndFor	classAggStruc	96.51	94.09	-	-	-	-	-	-	-	-
WE3A	ls	rndFor	comClass	93.07	91.22	73.56	61.06	90.10	79.46	93.07	-	-	-
WE3A	ls	rndFor	classAggStruc	96.29	94.70	85.13	73.48	-	-	-	-	-	-

evaluation: overall and class-specific accuracies and Kappa statistic estimates

1) model-based - cross-validated results (oaMod; kaMod)

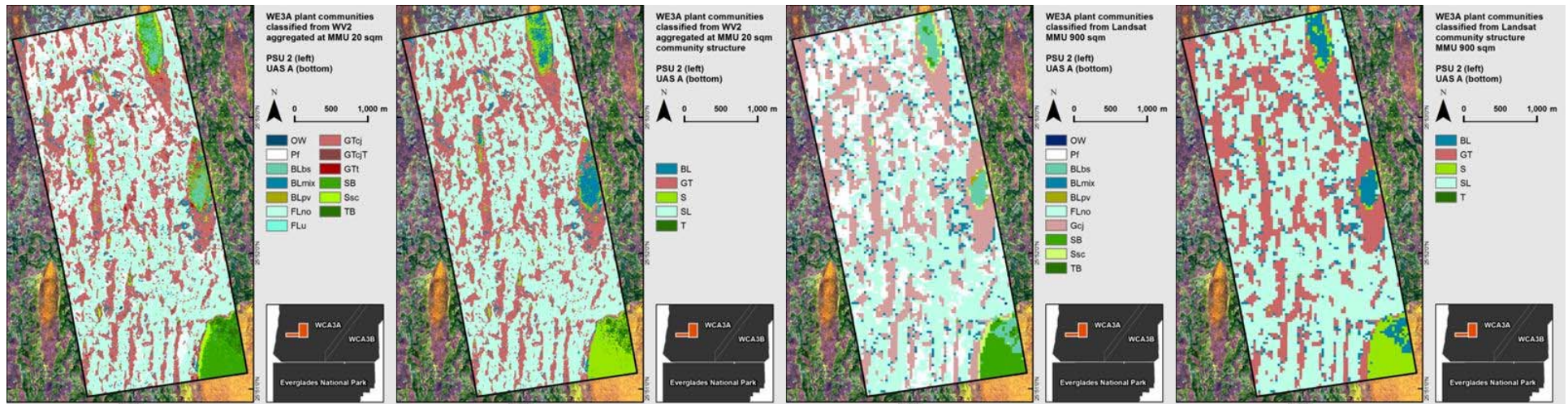




models				accuracy				model based overall accuracy by variable set					
roi	img	clf	predLevel	oaMod	kaMod	oaDes	kaDes	wet	dry	bi	wetTxt	dryTxt	biTxt
WE3A	wv2	cTree	comClass	87.68	84.76	-	-	81.27	63.64	84.10	84.91	69.55	87.68
WE3A	wv2	cTree	comStruc	94.61	90.81	-	-	90.96	85.24	93.16	91.60	89.34	94.61
WE3A	wv2	rndFor	comClass	90.87	88.69	-	-	81.36	64.67	86.99	86.66	73.10	90.87
WE3A	wv2	rndFor	comStruc	96.05	93.30	88.89	85.56	91.27	86.81	94.04	93.77	90.51	96.05
WE3A	wv2	rndFor	classAggStruc	96.51	94.09	-	-	-	-	-	-	-	-
WE3A	ls	rndFor	comClass	93.07	91.22	73.56	61.06	90.10	79.46	93.07	-	-	-
WE3A	ls	rndFor	classAggStruc	96.29	94.70	85.13	73.48	-	-	-	-	-	-

evaluation: overall and class-specific accuracies and Kappa statistic estimates

1) model-based - cross-validated results (oaMod; kaMod)



models				accuracy				model based overall accuracy by variable set					
roi	img	clf	predLevel	oaMod	kaMod	oaDes	kaDes	wet	dry	bi	wetTxt	dryTxt	biTxt
WE3A	wv2	cTree	comClass	87.68	84.76	-	-	81.27	63.64	84.10	84.91	69.55	87.68
WE3A	wv2	cTree	comStruc	94.61	90.81	-	-	90.96	85.24	93.16	91.60	89.34	94.61
WE3A	wv2	rndFor	comClass	90.87	88.69	-	-	81.36	64.67	86.99	86.66	73.10	90.87
WE3A	wv2	rndFor	comStruc	96.05	93.30	88.89	85.56	91.27	86.81	94.04	93.77	90.51	96.05
WE3A	wv2	rndFor	classAggStruc	96.51	94.09	-	-	-	-	-	-	-	-
WE3A	ls	rndFor	comClass	93.07	91.22	73.56	61.06	90.10	79.46	93.07	-	-	-
WE3A	ls	rndFor	classAggStruc	96.29	94.70	85.13	73.48	-	-	-	-	-	-

evaluation: overall and class-specific accuracies and Kappa statistic estimates

- 1) model-based - cross-validated results (oaMod; kaMod)
- 2) design-based - post-classification stratified random samples (oaDes; kaDes)

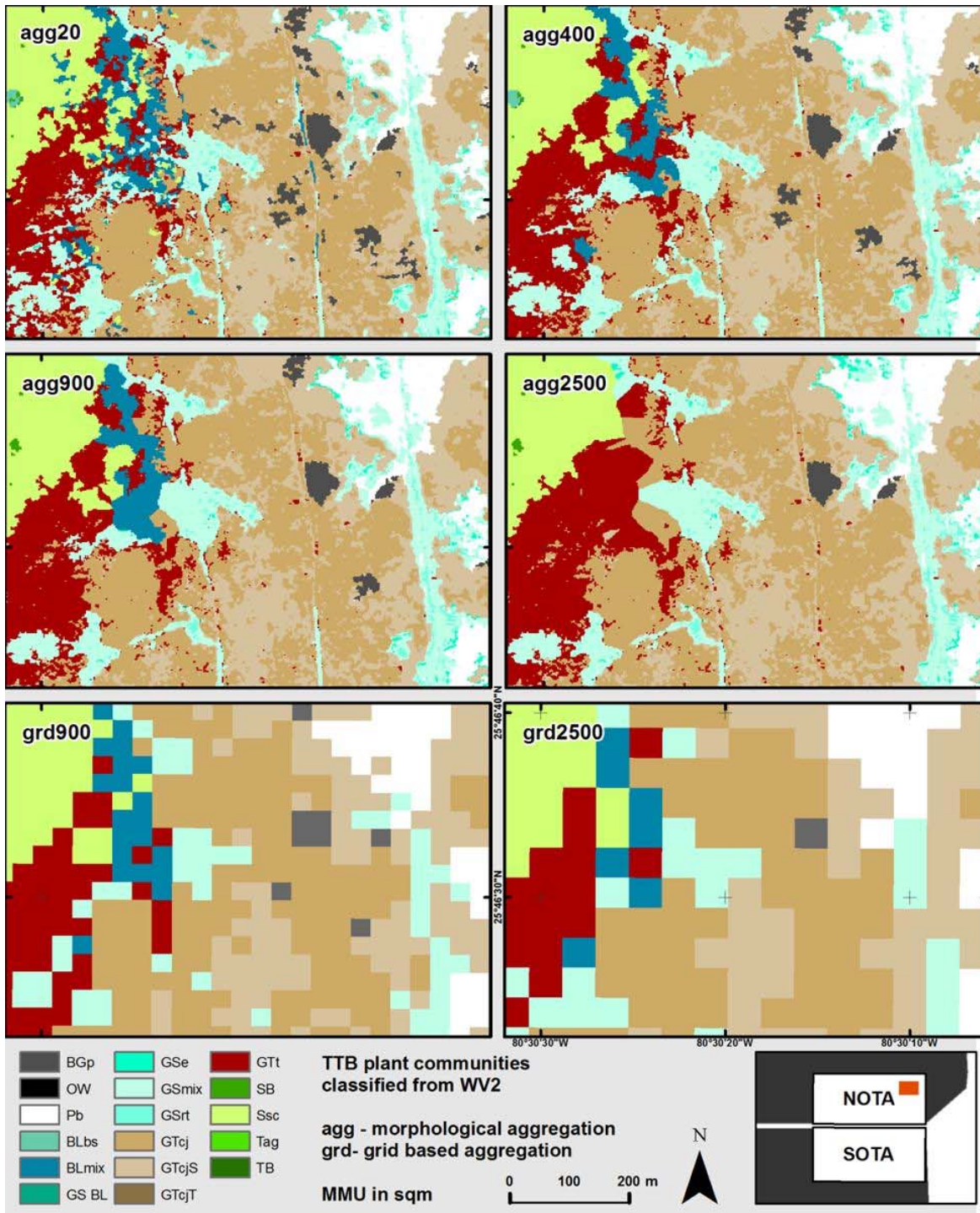








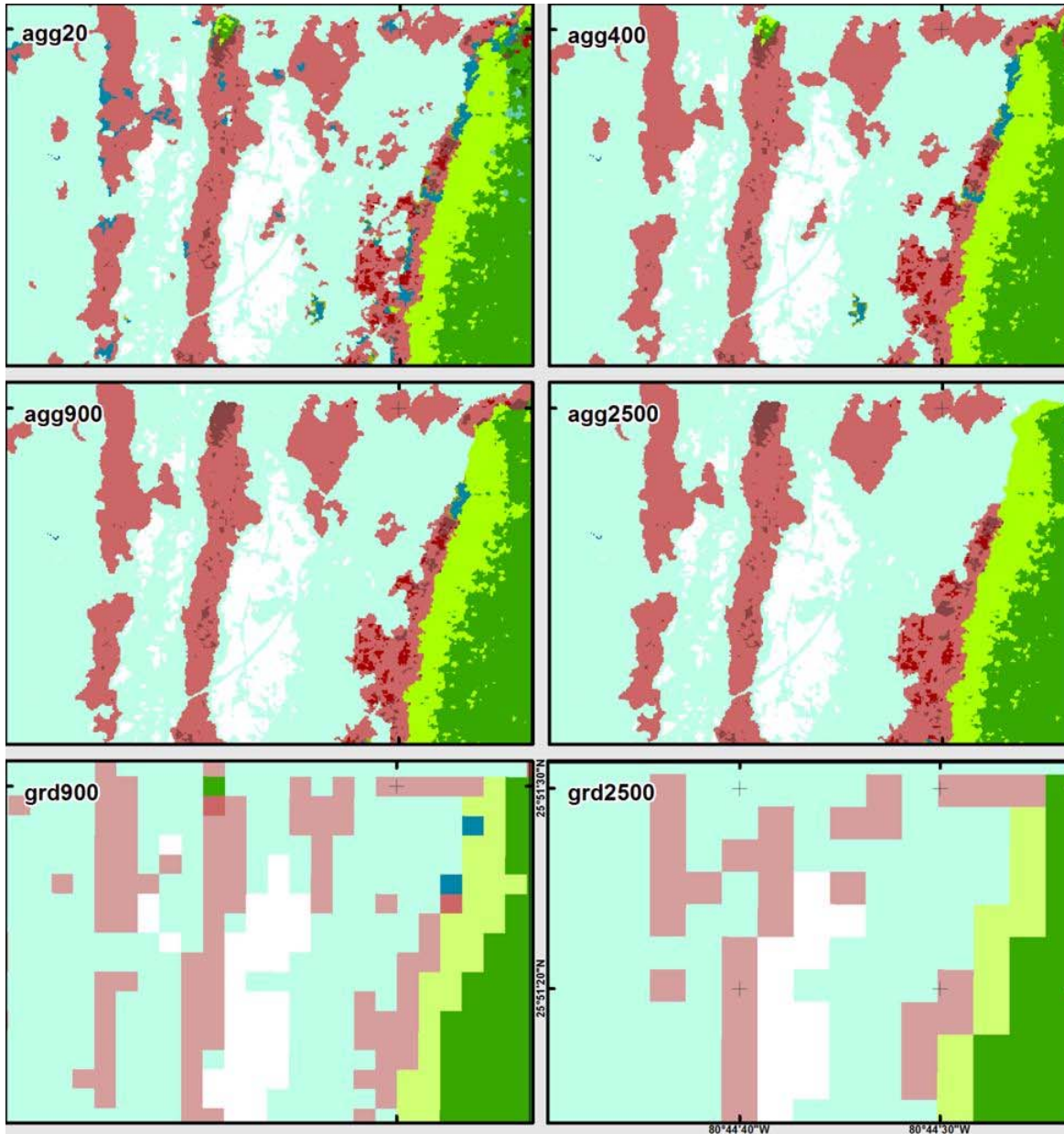




# Results : Scaling

TTB - NOTA

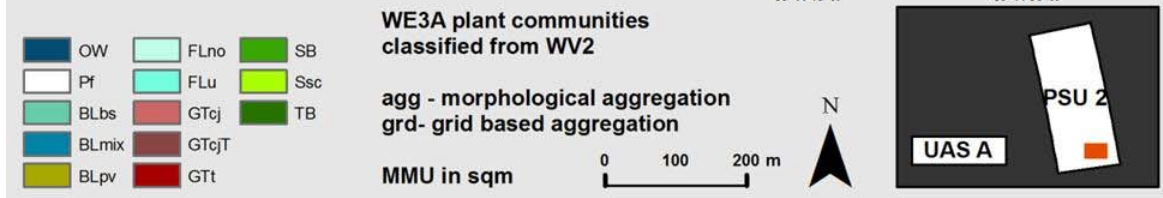
- 1) grid-based spatial aggregation (grd)
- 2) morphological spatial aggregation (agg)



# Results : Scaling

WE3A - PSU 2

- 1) grid-based spatial aggregation (grd)
- 2) morphological spatial aggregation (agg)







# Results Scaling WE3A

comClass	wv2	mmu20	mmu40	mmu400	mmu900	grd900	ls	mmu2500	grd2500
_OW	0.9	0.9	0.9	0.9	0.9	0.4	0.4	0.9	0.3
_Pf	9.4	9.4	9.4	9.6	9.7	7.2	16.7	10.0	6.0
BLbs	1.3	1.3	1.3	1.4	1.4	1.3	2.4	1.3	1.4
BLmix	3.7	3.3	3.0	1.6	1.2	1.2	5.1	0.9	0.7
BLpv	0.8	0.8	0.8	0.7	0.7	0.6	0.2	0.7	0.6
FLno	46.6	46.6	46.6	47.2	47.6	50.1	39.4	48.8	51.8
FLu	0.0	0.0	0.0	0.0	0.0	-	-	0.0	-
GTcj	31.1	31.5	31.8	32.8	32.7	34.1	32.5	31.7	34.7
GTcjT	1.0	1.0	1.0	1.0	1.0	0.2	-	1.1	0.0
GTt	0.3	0.3	0.3	0.3	0.3	0.1	-	0.3	0.0
SB	2.9	2.9	3.0	3.0	2.9	3.0	2.4	2.9	2.9
Ssc	1.5	1.5	1.5	1.2	1.1	1.3	1.1	0.9	1.1
TB	0.5	0.5	0.5	0.5	0.4	0.5	0.0	0.5	0.5
total	100	100	100	100	100	100	100	100	100
diversity	13	13	13	13	13	12	10	13	12
comClass	wv2	mmu20	mmu40	mmu400	mmu900	grd900	ls	mmu2500	grd2500
_OW	0.9	0.0	0.0	0.0	0.0	-55.3	-55.6	0.0	-70.1
_Pf	9.4	0.0	0.0	2.1	3.2	-23.5	77.7	6.4	-36.6
BLbs	1.3	0.0	0.0	7.7	7.7	3.5	84.6	0.0	9.4
BLmix	3.7	-10.8	-18.9	-56.8	-67.6	-68.6	37.8	-75.7	-80.4
BLpv	0.8	0.0	0.0	-12.5	-12.5	-30.5	-75.0	-12.5	-27.3
FLno	46.6	0.0	0.0	1.3	2.1	7.6	-15.5	4.7	11.2
FLu	0.0	0.0	0.0	0.0	0.0	-	-	0.0	-
GTcj	31.1	1.3	2.3	5.5	5.1	9.7	4.5	1.9	11.5
GTcjT	1.0	0.0	0.0	0.0	0.0	-77.7	-	10.0	-96.2
GTt	0.3	0.0	0.0	0.0	0.0	-79.9	-	0.0	-86.8
SB	2.9	0.0	3.4	3.4	0.0	4.5	-17.2	0.0	1.1
Ssc	1.5	0.0	0.0	-20.0	-26.7	-12.0	-26.7	-40.0	-28.3
TB	0.5	0.0	0.0	0.0	-20.0	-6.6	-100.0	0.0	-5.5
total	100	0.0	0.1	0.2	-0.1	0.0	0.2	0.0	0.0
diversity	13	0.0	0.0	0.0	0.0	-7.7	-23.1	0.0	-7.7

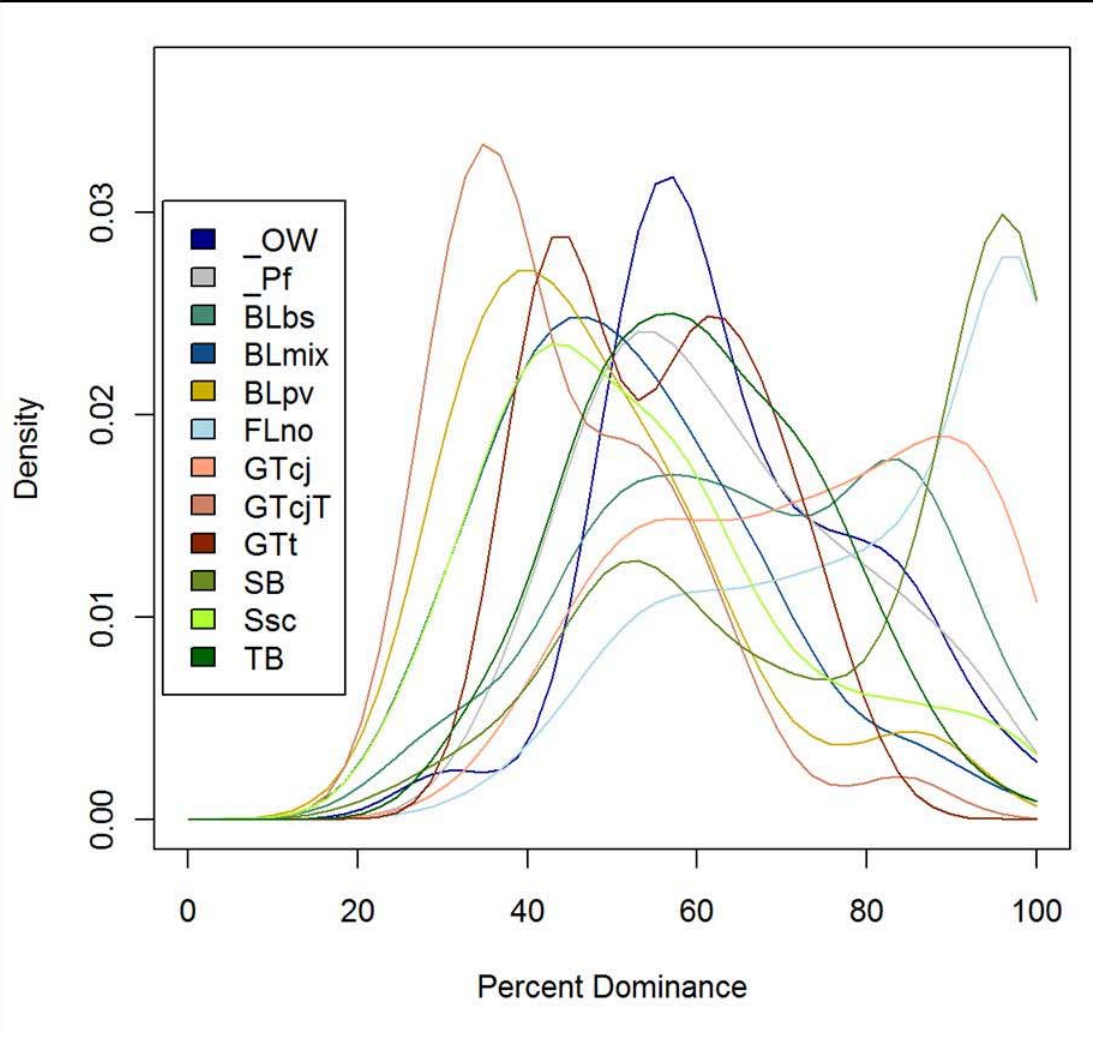


# Summary

- WV2 - achieved high levels of detection accuracies for plant communities
- most accurate models: bi-seasonal spectral reflectance + texture
- predicting structural class performed slightly better than community class
- post-classification hierarchical aggregation resulted in significantly better results than classification at structural level
- morphological aggregation preserved general community boundaries at much higher precision than grid-based aggregation methods
  - more reliable assessment of landscape configuration and detection of expansion and contraction of communities

[ftp://gisrsftp.fiu.edu/Share/gann/4500058664\\_synthesisReport.pdf](ftp://gisrsftp.fiu.edu/Share/gann/4500058664_synthesisReport.pdf)

# Current Work



Class distribution for 30x30 m grid when dominant

→ what effects have sampling scale and method on classification of plant communities?

→ how do they affect detection and mapping of communities across spatial scales using RS

- determine how class definitions **vary across spatial scales**
- determine how definition stability affects **mapping consistency**
- estimate **validity** of class descriptors and detection probabilities beyond survey areas as a function of spatial distance