Agricultural Classification of Multi-Temporal MODIS Imagery in Northwest Argentina Using Kansas Crop Phenologies

September 17, 2014

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Jarrett Keifer
Department of Geography

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RESEARCH QUESTIONS

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- develop a phenological classification toolset?
- extract crop signatures from Kansas data?
- classify an Argentina study area with the Kansas signatures?

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OUTLINE

1. Background
2. Study Areas
3. Data and Methods
4. Results and Discussion
5. Conclusion

BACKGROUND

DEFORESTATION IN ARGENTINA

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- 1998 to 2002: 940,000 ha deforested
- *Ley de Bosques* passed in November 2007
  - Classified red, yellow, and green areas through the *Ordenamiento Territorial de los Bosques Nativos* (Land Management Order for Native Forests, OTBN) passed in 2009

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DEFORESTATION IN ARGENTINA

Deforestation in Argentina, 2006 to 2011

Time Period	Hectares Deforested
2006 to *Ley de Bosques* (2007)	573,296
Ley de Bosques to OTBN (2009)	473,001
OTBN to 2011	459,108
Total	1,505,405

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- Deforestation has remained extremely high
- Questions the effectiveness of the *Ley de Bosques*

SOY AND ITS EFFECTS

- Argentina's soybean cultivation has continually increased
  - 5 million ha in 1993 to 19 million ha in 2011

SOY AND ITS EFFECTS

- Soy production highly mechanized
- Over 99 percent of Argentine soy is genetically modified
  - Resistance to glyphosate = heavy pesticide use
- Capital requirements cut out small producers

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- Better understanding of the dynamics of deforestation
- More effective land management policies

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  - Normalized Difference Vegetation Index (NDVI)

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- has issues with non-linearity and additive noise

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Questions

- What if two crops have similar VI values on a single date?
- How does one determine a crop's VI values?

Question

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Answer

Use imagery from multiple dates.

TIME SERIES IMAGES

NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Sensor

- Terra and Aqua satellites
- Each images the Earth once per day
- Composite 16-day NDVI imagery at 250-meter resolution

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Time Series Image (TSI)

- Each band is a 16-day VI composite
- Bands are sequential composites
- Contains enough bands to cover an entire growing season

Graphics/tsi_bands_2.pdf

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Key Points

- A TSI pixel shows VI values over time
- Each crop's phenology exhibits a unique temporal signature

CROP TEMPORAL SIGNATURES

Graphics/wardlowCropSignatures.png

(From Wardlow and Egbert 2005)

Question

How does one determine a crop's VI values?

PHENOLOGICAL CLASSIFICATION

Question

How does one determine a crop's VI values?

Answer

Existing approaches require training sites.

Problem

What if you don’t have training sites?

TIME SERIES IMAGES

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Sounds a lot like hyperspectral remote sensing...

TIME SERIES IMAGES

Idea

Could we use a hyperspectal-like method to fit known crop signatures to unknown pixels?

TIME SERIES IMAGES

Graphics/transformations.pdf

TSF METHOD

Two-Step Filter (TSF) method from Sakamoto et al. (2010)

- Two steps: (1) wavelet smoothing and (2) curve fitting
- Curve fitting can fit reference signature to unknown pixels

TSF METHOD

TSF Equation 1

$$RMSE = \left[\frac{1}{365/s} \sum_{x=j(0),\,j(1)\ldots}^{n} \big(f(x) - g(x)\big)^2\right]^{\frac{1}{2}}$$

where

- n is the number of dates in the TSI
- $f(x)$ is the temporal signature for a given pixel in a dataset
- x is the DOY, as defined by $j(y)$

TSF Equation 2

$$g(x) = \mathit{yscale} \times \; h\left(\mathit{xscale} \times (x + \mathit{tshift})\right)$$

where

- *yscale* and *xscale* are coefficients controlling the vertical and horizontal scaling of a reference signature $h(x)$
- *tshift* is a constant representing the horizontal shift, in days, of $h(x)$
- x is the DOY

TSF METHOD

Graphics/transformations.pdf

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Minimizing Equation 1 with appropriate constraints on *yscale*, *xscale*, and *tshift* will find the fit of a a reference signature to a pixel.

The signature with the lowest RMSE provides the most probable identification.

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Answer

The TSF equations allow the classification of unknown pixels using a library of crop signatures.

STUDY AREAS

KANSAS STUDY AREA

- 2012 Kansas top crops:
  - Winter wheat
  - Corn
  - Soy
- Ground truth: USDA Cropland Data Layer

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Kansas Study Site Planting Dates
(adapted from Shroyer et al. 1996)

Crop	Planting Date Range
Wheat	25 September to 20 October
Corn	1 April to 10 May
Sorghum	15 May to 20 June
Soybeans	5 May to 10 June

Graphics/argentinaOverview_landscape.pdf

Graphics/pellegrini75to14_landscape.pdf

Deforestation in Pellegrini, 2001 to 2011

Time Period	Hectares Cleared	Percent of Land Area	Hectares per Year
2001 to 2005	5,968	0.9	1,492
2006 to 2011	75,249	10.9	15,050

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Annual rate of clearing increased over 1000%!

Top crops in Pellegrini, 2001 to 2005

- Soy
- Corn
- Winter Wheat

(From Volante et al. 2005)

DATA AND METHODS

DATASETS

- 250-meter MODIS 16-day composite VI imagery
- 30-meter 2012 USDA Cropland Data Layer
- 30-meter Landsat 8 OLI satellite imagery
- Pellegrini boundary shapefile

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DATASETS

- 2014 Pellegrini Land Cover vector dataset

PELLEGRINI DATA COLLECTION

- Data collection in Pellegrini 12 March to 3 April
  - 400 random sample points
    - Direct observation
    - Interviews with farmers
    - Satellite image interpretation
  - Agricultural practices and planting/harvesting dates

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PROCESSING WORKFLOW

1. Reproject the MODIS composite VIs
2. Assemble composite VIs into TSIs
3. Extract crop signatures from the Kansas TSI
   - 3.1 Identify pure pixels (e.g. non-mixels)
   - 3.2 Use the CDL to isolate each crop
   - 3.3 Identify phenological groups using k-means clustering
   - 3.4 Extract pixel values for each group and average
4. Fit the Kansas signatures to the Kansas TSI using the TSF method
5. Classify the Kansas RMSE rasters and assess accuracy
6. Fit the Kansas signatures to the Argentina TSI
7. Classify the Argentina RMSE rasters and assess accuracy

1. REPROJECTION

- Land Processes Distributed Active Archive Center's (LPDAAC) MODIS Reprojection Tool

2. BUILDING THE TSIs

- Python command line tool (PCLT) to stack composites
- Kansas TSI covered 2012 DOY 97 to 2012 DOY 273
- Argentina TSI covered 2014 DOY -13 to 2014 DOY 161
  - Aqua DOY 105 composite used in place of DOY 113 composite
  - DOY 129 interpolated from DOY 105 and DOY 145 composites

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- Resampled CDL to MODIS grid by majority
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  - Corn
  - Soy
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Now we have crop signatures!

FITTING SIGNATURES

4, 6. Fit Kansas signatures to `<insert study area here>` TSI using TSF method

- Not using the TSF's wavelet filtering
- PCLT to fit reference signatures to a TSI using TSF equations
  - Creates a RMSE raster for each signature
  - *xscale* and *yscale* bounds: 0.6 to 1.4
  - *tshift* bounds: ±10 days Kansas, 120 to 140 days Argentina

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CLASSIFYING RMSE RASTERS

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Brute force through different threshold combinations, classifying and assessing the accuracy to find the best result.

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RESULTS AND DISCUSSION

RESULTS

- Summer 2014 Pellegrini ground truth
- Pellegrini agricultural practices
- Kansas crop signatures
- Kansas classification
- Pellegrini classification

PELLEGRINI GROUND TRUTH

- 378 of 400 sample points were identified
- Many additional fields were collected

Graphics/collecteddata.pdf

PELLEGRINI GROUND TRUTH

Summer 2014 Pellegrini Land Cover Classes

Cover Type	Hectares	Sample Points
Forested	389,541	247
Other	42,229	22
Corn	41,488	36
Pasture	35,057	37
Soy	27,498	24
Poroto	9,539	7
Nothing	3,057	3
Sorghum	1,646	2
Unknown	92,248	17
Omitted	52,052	5
Total	694,346	400

Key Dates for Pellegrini Summer Crops

Crop	Ideal Planting Range	Harvesting Begins
Soy	15 December to 15 January	1 May
Corn	15 January to 15 February	1 June
Sorghum	15 January to 15 February	1 June
Poroto	15 January to 20 February	10 May

KANSAS CROP SIGNATURES

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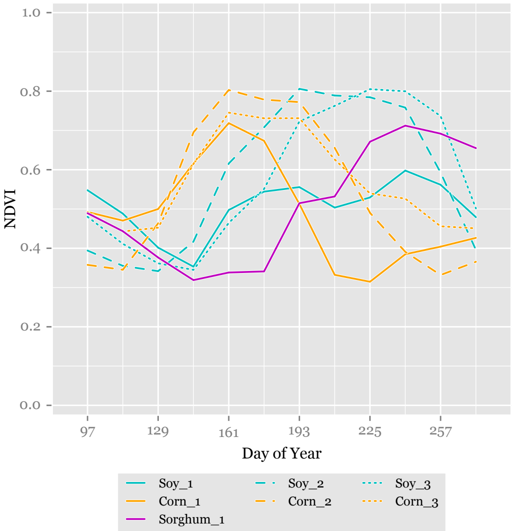
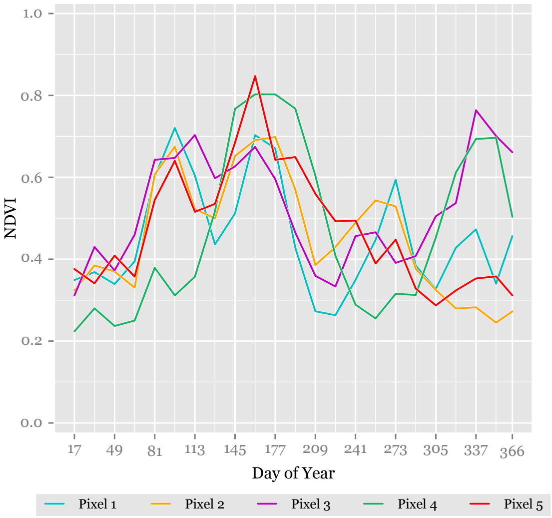
KANSAS CROP SIGNATURES



STRANGE KANSAS CORN SIGNATURES



KANSAS VERIFICATION CLASSIFICATION

Graphics/KSclass.pdf

KANSAS VERIFICATION CLASSIFICATION

Summer 2012 Kansas Classification Accuracy

		Reference Data					
		Corn	Soy	Sorghum	Other	Total	User Acc.
Classified	Corn	369	65	5	17	456	80.92%
	Soy	32	273	10	47	362	75.41%
	Sorghum	0	0	2	6	8	25.00%
	Other	13	16	1	503	533	94.37%
	Total	414	354	18	573	1359	
	Producer Acc.	89.13%	77.12%	11.11%	87.78%		

Overall Accuracy: 84.40%
Kappa: 0.76

KANSAS VERIFICATION CLASSIFICATION

Kansas Classification
RMSE Thresholds

Signature	Threshold Value
Corn_1	1000
Corn_2	750
Corn_3	500
Soy_1	750
Soy_2	1300
Soy_3	500
Sorghum	450

KANSAS VERIFICATION CLASSIFICATION

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PELLEGRINI CLASSIFICATION

Summer 2014 Pellegrini Classification Accuracy

		Reference Data					
		Corn	Soy	Sorghum	Other	Total	User Acc.
Classified	Corn	24	13	0	8	45	53.33%
	Soy	0	2	1	2	5	40.00%
	Sorghum	0	0	0	0	0	0.00%
	Other	12	9	1	306	328	93.29%
	Total	36	24	2	316	378	
	Producer Acc.	66.67%	8.33%	0.00%	96.84%		

Overall Accuracy: 87.83%

Kappa: 0.54

PELLEGRINI CLASSIFICATION

Pellegrini Best Classification RMSE Thresholds

Signature	Threshold Value
Corn_1	550
Corn_2	850
Corn_3	0
Soy_1	0
Soy_2	600
Soy_3	950
Sorghum_1	0

PELLEGRINI CLASSIFICATION

Pellegrini Best Classification RMSE Thresholds

Signature	Threshold Value
Corn_1	550
Corn_2	850
Corn_3	0
Soy_1	0
Soy_2	600
Soy_3	950
Sorghum_1	0

PELLEGRINI CLASSIFICATION

Graphics/ARclassed.pdf

PELLEGRINI CLASSIFICATION

Pellegrini Classification Checked Against All Pure Pixels

		Reference Data					
		Corn	Soy	Sorghum	Other	Total	User Acc.
Classified	Corn	3283	2076	61	1201	6621	49.58%
	Soy	189	313	36	458	996	31.43%
	Sorghum	0	0	0	0	0	0.00%
	Other	2234	1523	60	74387	78204	95.12%
	Total	5706	3912	157	76046	85821	
	Producer Acc.	57.54%	8.00%	0.00%	97.82%		

Overall Accuracy: 90.87%
Kappa: 0.51

PELLEGRINI CLASSIFICATION

Pellegrini Corn and Soy Confusion with Other Land Cover Classes

Land Cover	Total Pixels	Confused as Corn	Percent of Total	Confused as Soy	Percent of Total
Forested	63,978	194	0.30	26	0.04
Other	5,393	306	5.67	322	5.97
Pasture	5,252	396	7.54	50	0.95
Poroto	1,369	303	22.13	59	4.31
Nothing	485	2	0.41	1	0.21

CONCLUSION