IDENTIFYING WESTERN OREGON CROPS BY SATELLITE IMAGERY IN THE ABSENCE CURRENT YEAR GROUND-TRUTH DATA

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Introduction

Few can argue the urgency of improving the sustainability of modern agricultural production. Controversy abounds, however, on the subject of how to best try to achieve sustainability due to a wide variety of factors, including both differences in perspective among individual protagonists in the discussions and complexity of the processes that must ultimately define the long-term limits to humankind's ability to provision itself with adequate food, fiber, and other natural resources. Perhaps the most important question that should be asked in the search for agricultural sustainability is simply how robust/stable our current production systems truly are. Central to any attempts to begin to answer such questions is detailed knowledge of which crops are currently being grown, what inputs they receive/require, and what offsite impacts occur in their production. Successful acquisition of such information for the present and recent past would allow us to measure the slope/change and the acceleration (change in change) of factors ranging from economic viability to water quality to availability of high quality wildlife habitat. Unfortunately, such information is seldom collected for minor crops and only partially tracked even for major ones such as wheat, corn, and soybeans. A useful step forward in evaluating the sustainability of western Oregon crop production systems would be development of a detailed historical record of which crops have been grown at what locations over a period of several decades. Combining this information with models such as the Soil Water Assessment Tool (SWAT) and data such as synoptic water quality samples, wildlife diversity/abundance surveys, and USDA Census of Agriculture summary production statistics should help elevate the discussion of agricultural sustainability to more of an outcome-based approach and less of a debate of lofty principles and general philosophies, i.e., organic versus conventional agriculture, prohibition versus embracing of GMOs, locally grown food versus lowest-cost-no-matter-where production, etc.

Methods

Starting with the 2004-05 growing season, we systematically collected information on crops produced on several thousand western Oregon fields visible from public roads in a series of fall and spring drive-by surveys, including annual and perennial agricultural and horticultural crops, stand establishment status, planting methods, and post-harvest residue management of grass seed crops. Information for the first three harvest years has already been used as ground-truth data for successful remote sensing classification of Landsat and MODIS satellite imagery for 16 major agricultural crops in western Oregon. We have now elaborated on these methods to cover seven years and 57 landuses, including 19 classes of annually disturbed agriculture, 20 classes of perennial crops, 13 classes of forests and other natural landscape components, and five categories of urban development (Tables 1a, 1b, 1c). Data from the National Land Cover Dataset were used to define most of the forest and urban development landuse classes, though we also directly identified several such classes in our drive-by surveys.

Results and Discussion

The four broad categories of landuse (annual agriculture, perennial agriculture, forest, urban) were separated from each other at 97 to 98% overall accuracy, with most of the 2 to 3% error involving misclassification of some of the perennial agriculture classes. Not unexpectedly, forests were the most reliably identified landuse. The 39 classes of annual or perennial agriculture defined by our ground-truth data represented 99% of all field area surveyed. While the results satisfied our goal of being able to accurately define nearly all landuse across western Oregon, they can really only cover the time period of our ground-truth, drive-by survey, i.e., the 2004-05 cropping year on up until whenever we decide to quit expending the labor needed to conduct the survey for yet another year. The lack of ground-truth data prior to the 2005 harvest year along with the potential future termination of the survey led us to question whether it might be possible to extend our remote sensing classification results backward or forward in time through creation of synthetic ground-truth data from the period for which we have conducted drive-by surveys and successfully classified landuse in western Oregon. To test this idea, we first conducted a series of remote sensing classifications in which the ground-truth data actually came either from the year prior to or the year following the satellite images and production of the crops we wished to classify. Because we had already conducted a normal remote sensing classification using actual current-year ground-truth data, we were able to test the validity of our shift-year results against several alternatives. For annual crops such as Italian ryegrass, the shift-year method should work well since the vast majority of Italian ryegrass crops are actually grown year-after-year on the very same fields. The other extreme would be fields of fall- or spring-planted new grass seed stands, which would generally transition into a status of established perennial grass seed crops by the following year and only rarely represent a second year's replanting when the first year's planting had failed to establish.

Using subsequent-year ground-truth data to classify the previous year's landuse was about as successful as normal, same-year classification methods in two out of six cases (2006 and 2009 harvest years), moderately successful in one other case (2011 harvest year), and less successful in the remaining three cases (Table 2). Using prior-year ground-truth data to classify the subsequent year's landuse was more successful than normal, same-year classification in two out of six cases (2006 and 2008 harvest years), about as successful in three cases (2007, 2010, and 2011 harvest years), and less successful in the final case (Table 3). The most successful use of subsequent year ground-truth data to classify prior year landuse occurred for the combination of 2009 harvest year images with 2010 ground-truth. This classification had an overall accuracy of 93.4% relative to pixels where both the original (normal method) classification and the shift-year ground-truth data matched. This accuracy was achieved despite omission of 10 entire classes, four of which were also absent from the normal same-year classification. Accuracy of this shift-year classification was 96.5% when measured relative to the four large groups (annual agriculture, perennial agriculture, forests, urban development). All six of the additional landuse classes lost during shift-year classification were annually disturbed crops grown on relatively few fields.

For the five cases in which subsequent and previous year ground-truth methods can be directly compared, subsequent year ground-truth produced more accurate classifications in two cases while previous year ground-truth produced more accurate classifications in three cases (Tables 2 and 3). Based on our fairly successful results of using shift-year ground-truth data to classify individual images for years in which we also had current year ground-truth data, we conducted a full series of classifications over all available images for the 2003-2004 cropping year, one for which we did not have comprehensive ground-truth data. Our first step was to create a synthetic ground-truth dataset from the classified rasters of the following seven years. The method we chose to create the synthetic ground-truth data started with selection of all pixels that had been identically classified in all seven years, a method which gave us an adequately sized sample for 19 of the 57 desired classes. We then added five more classes from pixels that had been identical over the first 5 growing seasons of our ground-truth survey. The next groups of 11 and 5 classes came from pixels that were identical for the first three or two years of the survey, respectively. We obtained six more classes based solely on the 2004-05 cropping year. This left 11 classes that could not be added to the synthetic ground-truth data because they either were entirely absent from the original 2004-05 cropping year classification or were present at too small a number to provide satisfactory training sets. Our general cut-off was to view 1000 pixels as the minimum number required to include a given category in remote sensing classifications. This 46-class synthetic ground-truth data combined with 66 remote sensing image bands to produce training and test validation 57-category accuracies of 87.6 and 93.5% for the 2003-04 cropping year, better than that achieved in any of the normal, same year classifications. The 11 classes of annually disturbed agriculture missing from our 2003-04 cropping year remote sensing classification using synthetic ground-truth data were replaced by increases in area classified in three of the remaining annual crops: (1)

bare ground in the fall not otherwise classified as a specific crop, (2) fallow, and (3) *Brassicaceae* seed crops. Before unambiguously declaring success for our shift-year classification procedure using synthetic ground-truth data from subsequent years, we still need to validate our results using other resources such as county-wide crop production estimates. However, these initial results give us reason to believe that we will be able to eventually define where most of the crops grown in the past 20 to 30 years in western Oregon have been grown.

Table 1a. Landuse category descriptions for 19 classes of annually disturbed agriculture along with corresponding areas of remotely sensed classifications in each of eight cropping years.

No.	Description	2003-2004†	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	7-year mean§
						(mile^2)				
19 classes annually disturbed agriculture										
1	Bare ground in fall not any other class	415	241	234	219	317	3	78	86	168
2	Full straw Italian ryegrass	14	73	65	86	52	18	112	31	63
3	Spring-plant new grass seed stands	NA‡	45	36	40	43	57	12	2	34
12	Fall-plant Italian ryegrass	191	116	146	147	156	354	208	273	200
13	Fall-plant perennial ryegrass	80	75	58	83	49	3	4	3	39
14	Fall-plant tall fescue	NA	2213	7	8	6	0	0	0	319
15	Fall-plant clover	NA	3	23	14	17	9	5	2	10
16	Wheat and oats	19	189	46	56	152	436	261	325	209
17	Meadowfoam	2	3	9	9	3	2	7	6	5
27	Corn and sudangrass	NA	0	NA	NA	0	NA	NA	8	1
30	Fallow	212	49	40	32	47	0	21	9	28
35	Beans	NA	1	20	162	5	NA	6	0	28
36	Flowers	NA	1	2	2	1	0	0	0	1
40	Other fall-plant/no-till grass seed crops	NA	2	2	2	1	2	6	1	2
41	Spring-plant peas or other unidentified	NA	NA	46	22	2	10	4	3	12
42	New planting hops, filberts, blueberries	NA	238	0	0	0	0	1	0	34
43	New planting alfalfa or vetch	NA	1	0	2	1	0	1	7	2
44	Volunteer Italian ryegrass as pasture	NA	2	11	28	0	NA	0	11	7
55	Brassicaceae	292	23	14	6	0	0	3	4	7
Group totals		1225	3275	761	919	852	894	729	771	1171

†Classification based on synthetic ground-truth data developed from most common landuse classes over the next 7 years.
‡ NA denotes classes with no members in a given year's remote sensing classification. Values of 0 simply denote classes with total areas of greater than 0 and less than 0.5 square miles.
§Means cover 2005, 2006, 2007, 2008, 2009, 2010, and 2011 harvest years, the period over which full ground-truth data existed.

Table 1b. Landuse category descriptions for 20 classes of established perennial agriculture along with corresponding areas of remotely sensed classifications in each of eight cropping years.

No.	Description	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	7-year mean
		(mile^2)								
20 classes established perennial agriculture										
4	Established perennial ryegrass	12	149	167	137	152	41	78	91	116
5	Established orchardgrass	27	25	39	47	27	53	26	28	35
6	Established tall fescue	83	96	183	215	220	154	124	112	158
7	Pasture	608	422	415	340	856	854	880	1185	707
8	Established clover	53	14	11	25	17	33	35	11	21
9	Established mint	10	13	14	3	1	1	3	2	5
10	Haycrop	303	312	261	235	129	63	58	51	158
18	Established bentgrass	53	50	17	26	8	0	0	0	15
19	Established fine fescue	73	55	47	148	67	31	95	41	69
21	Wildrice lagoons	0	0	0	0	1	3	22	18	6
22	Wetland restoration	0	0	0	0	3	4	27	3	5
23	Established alfalfa	20	3	6	0	0	NA	5	5	3
24	Established blueberries	3	0	2	1	2	0	0	3	1
25	Filbert orchards	85	17	81	38	88	73	234	118	93
26	Caneberry	149	26	36	25	39	0	3	1	19
28	Nursery crops	1	91	164	117	125	1	3	2	72
29	Apple and cherry orchards	27	10	27	12	25	1	58	33	24
32	Vineyards	47	283	112	81	61	12	41	53	92
38	Hops	2	10	17	7	5	7	23	29	14
56	Strawberry	1	0	0	0	0	0	0	1	0
Group totals		1557	1576	1598	1457	1826	1332	1714	1788	1613

Table 1c. Landuse category descriptions for 13 classes of forests and other natural landscapes and 5 classes of urban development, along with corresponding areas of remotely sensed classifications in each of eight cropping years.

No.	Description	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	7-year mean
						($mile^2$)				
13 classes forests/other natural landscapes										
11	Poplars	2	0	11	2	1	0	2	0	2
20	Christmas tree plantations	364	1669	681	506	818	14	661	258	658
33	Reforestation projects	165	3	3056	1840	1807	0	27	20	965
34	Assorted other lowland forest	1957	851	946	749	479	0	0	4	433
37	Oaks	1	0	22	21	27	42	279	214	86
39	Shrubs and wildlife refuges	2	1	17	15	8	0	1	0	6
45	NLCD 11 open water	36	31	49	44	33	64	83	83	55
46	NLCD 90 woody wetlands	73	61	97	66	85	242	125	147	117
47	NLCD 95 herbaceous wetlands	10	10	13	14	11	70	85	63	38
51	NLCD 41 deciduous forest	441	870	309	497	356	108	148	173	351
52	NLCD 43 evergreen forest	2204	587	653	2185	1070	1743	2739	2863	1692
53	NLCD 44 mixed forest	251	136	676	378	1217	2611	271	274	795
54	NLCD 53 scrub/shrub	512	37	58	154	195	914	1639	1789	684
Group totals		6020	4257	6588	6470	6107	5809	6059	5888	5883
5 classes urban development										
31	Mixed grass and buildings	276	134	84	125	144	0	0	0	69
48	Developed open space (NLC 21)	23	4	5	228	90	855	316	337	262
49	Developed low intensity (NLC 22)	356	256	415	159	374	429	496	641	396
50	Developed medium intensity (NLC 23)	244	214	260	317	273	374	378	250	295
57	Developed high intensity (NLC 24)	68	55	58	96	103	76	76	94	80
Group totals		966	663	823	925	984	1734	1268	1322	1103
Totals for all 57 classes		9770	9770	9770	9770	9770	9770	9770	9770	9770

Table 2. Classification accuracies, kappa statistics, and omitted classes when subsequent year ground-truth was used on the best set of previous year image bands. Shift year accuracy was measured relative to all classified pixels for subsequent year rather than training/validation sets.

Ground-truth source cropping year	Image raster properties		Number missing classes and identification of the omitted classes from the original 57 categories	Normal same year training set best single-run results		Shift year classification tested with original classified rasters matching in both years	
	Cropping year	Bands present		Accuracy	Kappa	Accuracy	Kappa
		(No.)		(%)	(Fraction)	(%)	(Fraction)
2005-2006	2004-2005	62	6 (# 21, 27, 40-43)	52.4	0.505	39.6	0.371
2006-2007	2005-2006	42	3 (# 27, 40, 42)	57.9	0.560	89.3	0.876
2007-2008	2006-2007	68	18 (# 20-23, 33, 35-38, 40-42, 44-45, 47, 54-56)	66.4	0.640	48.4	0.437
2008-2009	2007-2008	58	10 (# 14, 23, 27, 30, 34, 35, 40, 42-44)	69.1	0.675	49.5	0.463
2009-2010	2008-2009	52	10 (# 14, 23, 27, 30, 35, 41-44, 55)	72.4	0.707	93.4	0.924
2010-2011	2009-2010	47	22 (# 3, 5, 11, 13-15, 18-20, 27, 28, 31, 35, 36, 39-44, 47, 55)	76.5	0.752	69.5	0.663
NA†	2010-2011	44	NA	80.2	0.788	NA	NA

†NA indicates that shift year classification was not run due to the absence of subsequent year ground-truth data.

Table 3. Classification accuracies, kappa statistics, and omitted classes when previous year ground-truth was used on the best set of subsequent year image bands. Shift year accuracy was measured relative to all classified pixels for previous year rather than training/validation sets.

Ground-truth source cropping year	Image raster properties		Number missing classes and identification of the omitted classes from the original 57 categories	Normal same year training set best single-run results		Shift year classification tested with original classified rasters matching in both years	
	Cropping year	Bands present		Accuracy	Kappa	Accuracy	Kappa
		(No.)		(%)	(Fraction)	(%)	(Fraction)
2004-2005	2005-2006	42	2 (# 41, 42)	57.9	0.560	72.3	0.700
2005-2006	2006-2007	68	10 (# 22, 23, 27, 29, 36, 38, 42, 46, 47, 56)	66.4	0.640	59.8	0.570
2006-2007	2007-2008	58	0	69.1	0.675	88.1	0.867
2007-2008	2008-2009	52	0	72.4	0.707	46.3	0.431
2008-2009	2009-2010	47	5 (# 23, 27, 35, 44, 47)	76.5	0.752	82.8	0.806
2009-2010	2010-2011	44	3 (# 27, 28, 36)	80.2	0.788	80.5	0.780