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Remote sensing classification of grass seed cropping practices in western Oregon

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Our primary objective was extending knowledge of major crop rotations and stand establishment conditions present in 4800 grass seed fields surveyed over three years in western Oregon to the entire Willamette Valley through classification of multi-band Landsat images and multi-temporal Moderate Resolution Imaging Spectroradiometer (MODIS) 16-day composite Normalized Difference Vegetation Index (NDVI). Mismatch in resolution between MODIS and Landsat data was resolved by edging of training and test validation areas using 3 by 3 neighbourhood tests for class uniformity, resampling of MODIS data to 50-m resolution followed by 3 by 3 neighbourhood smoothing to artificially enhance resolution, and resampling to 30 m for stacking data in groups of up to 64, 55 and 81 bands in 2004–2005, 2005–2006 and 2006–2007. Imposing several object-based rules raised final classification accuracies to 84.7, 77.1 and 87.6% for 16 categories of cropping practices in 2005, 2006 and 2007. Total grass seed area was under-predicted by 3.9, 5.4 and 1.8% compared to yearly Cooperative Extension Service estimates, with Italian ryegrass overestimated by an average of 8.4% and perennial ryegrass, orchardgrass and tall fescue underestimated by 10.4, 3.3 and 2.1%. Knowledge of field disturbance patterns will be crucial in future landscape-level analyses of relationships among ecosystem services.

1. Introduction

The USDA Conservation Effects Assessment Project (CEAP) aims to 'quantify the environmental effects of conservation practices applied to agricultural land' (Schnepf and Cox 2007, p. viii) through national assessments and basic research conducted within individual watersheds (Mausbach and Dedrick 2004, Schnepf and Cox 2007,

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USDA 2009). While substantial crop management information exists within government databases for traditional US farm programme crops such as wheat and corn, information for speciality crops such grasses grown for seed are largely absent from such records. Certain innate aspects of grass seed production systems, such as the fibrous-rooted nature of the crops and the multiple years that pass on average between tillage events, represent crop management practices that are considered to have a more conservation-friendly orientation than most of the officially sanctioned conservation practices used in major farm programme crops (Kennedy and Smith 1995, Nelson 2005). Consequently, the grass seed industry in western Oregon could serve as a model system for studying environmental benefits of reduced soil erosion, decreased nitrogen export to streams and rivers, and large-scale shifts from annual to perennial crops, concepts often touted as long-term goals for modern agriculture whose attainability is questioned and whose value measured only in computer simulations (Wentz *et al.* 1998, Steiner *et al.* 2004, Nelson 2005, Nelson *et al.* 2006). Key information needed for landscape-level analyses of the ecosystem benefits of established perennial grasses grown for seed includes when and where tillage for stand removal and seedbed preparation occurs to temporarily disrupt the otherwise ongoing benefits of conservation practices (Isaaks and Srivastava 1989, Ott and Swiaczny 2001, Titi 2003).

Grass seed agriculture constitutes a significant portion of the cultivated landscape in the Pacific Northwest, but limited public data exist on specific crops grown and management practices used in their production in individual fields. Reports from the Cooperative Extension Service, for example, summarize production area and yield by crop on a per county basis, shielding individual growers and fields from recognition (Young 2008). Similarly, data collected by the Oregon Seed Certification Service is viewed as confidential business information and no geographical information system (GIS) or other user-identifiable data are publicly released (Mueller-Warrant *et al.* 2008). The National Land Cover Database (NLCD) includes 29 class definitions, but only two represent agriculture, class 81 pasture/hay and class 82 cultivated crops (Homer *et al.* 2004). While the definition for class 81 includes grasses planted for production of seed, the definition for class 82 includes all land currently being tilled, with the result that classification of pixels within individual grass seed fields in western Oregon in the NLCD depended primarily on whether fields were in established perennial stands in 2001 or had just undergone tillage and seedbed preparation for planting of new stands. More agronomically detailed classification of crops exists in the USDA-National Agricultural Statistics Service (NASS) Cropland Data Layers, but those products are only produced approximately once every 3 years for the Pacific Northwest, and they lump all grass seed crops together in a single category, class 59 (USDA 2007).

Remotely sensed data from satellite and airborne platforms are widely available and potentially useful for identifying crops and monitoring the use of conservation practices like retention of crop residues on the soil surface (Thoma *et al.* 2004). Most remote sensing crop classification efforts over the past three decades have relied on Multispectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data from the Landsat series of satellites, with the 30-m resolution present in the majority of those data adequate for potentially identifying crops grown on fields as small as 1 ha (Vogelmann *et al.* 1998, Homer *et al.* 2004, Lillesand *et al.* 2004, Mather 2004). More recently, USDA-Foreign Agricultural Service (FAS) and NASS have replaced Landsat with Advanced Wide Field Sensor

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(AWiFS) data for crop monitoring in the USA and worldwide (USDA 2007). The better temporal coverage of the AWiFS data is generally viewed as outweighing its coarser spatial resolution (56 m), but because it is a collect-on-demand system rather than a programmed shoot-and-archive system like Landsat, archived AWiFS data for areas of interest oftentimes do not exist. Moderate Resolution Imaging Spectroradiometer (MODIS) data are acquired over most of the Earth's land surface on an almost daily basis due to the large swath width of its sensor, but only the nadir views recurring once every 16 days for a given satellite truly achieve the 250-m resolution used in 16-day composite products like the normalized differential vegetation index (NDVI). The high temporal frequency of MODIS data has allowed its use in detecting changes in land-cover and vegetation phenology despite relatively coarse spatial resolution compared to Landsat or AWiFS (Lunetta *et al.* 2006, Zhang *et al.* 2009).

Using a GIS along with remotely sensed data has several advantages when trying to develop a land use classification system (Aplin *et al.* 1999, Walter 2004). First, the classification training area can be derived from data within the GIS, potentially reducing the need for manual acquisition of ground-truth data. Second, information generated by a remote sensing classification can be incorporated into revisions of the GIS, facilitating future cycles of classification and revision. Third, conversion from pixel-based to object-based classification methods can improve classification accuracy by eliminating outlying classes within fields dominated by a single category. Single imaging dates are obviously unable to detect subsequent field disturbance, and prior field disturbance may be masked by intervening plant growth. In contrast, data gathered on multiple dates increase the chance of detecting field disturbance if procedures combine classifications over time (Lillesand *et al.* 2004). Lastly, using GIS data structures in ecological studies provides the option to conduct post-classification analyses at arbitrary spatial scales across the landscape, matching resolution of variables and pooling finer-scale results into broader-scale summaries (Lee and Wong 2001, Mitchell 2005).

In this study, we develop remote sensing classification of the major crops and crop production practices in western Oregon. Our approach was to use ground-truth data from the Calapooia River watershed and neighbouring counties to train and validate remotely sensed classification of the entire Willamette River basin. We focus on 16 major categories of agronomic cropping practices that comprise the vast majority of agricultural landuse in the lower elevations of the Willamette River Basin. The methods we developed for combining images of varying spatial resolution, cloud cover, and data coverage gaps may encourage other researchers to tackle similar challenges in identifying crop production practices used across other agricultural regions.

2. Study area

This research was conducted across the 29 800-km^2 Willamette River basin in western Oregon, with remote sensing classification restricted to the agricultural cropping area of the Willamette Valley as defined by NLCD (Homer *et al.* 2004) classes 81 (pasture/hay) and 82 (row crops) falling within 2002 or 2003 USDA-Farm Service Administration Common Land Unit (CLU) polygons or other known grass seed fields (figure 1). Agricultural field areas in Benton, Clackamas, Lane, Linn, Marion, Polk, Washington and Yamhill Counties in western Oregon totalled 5020 km^2, but

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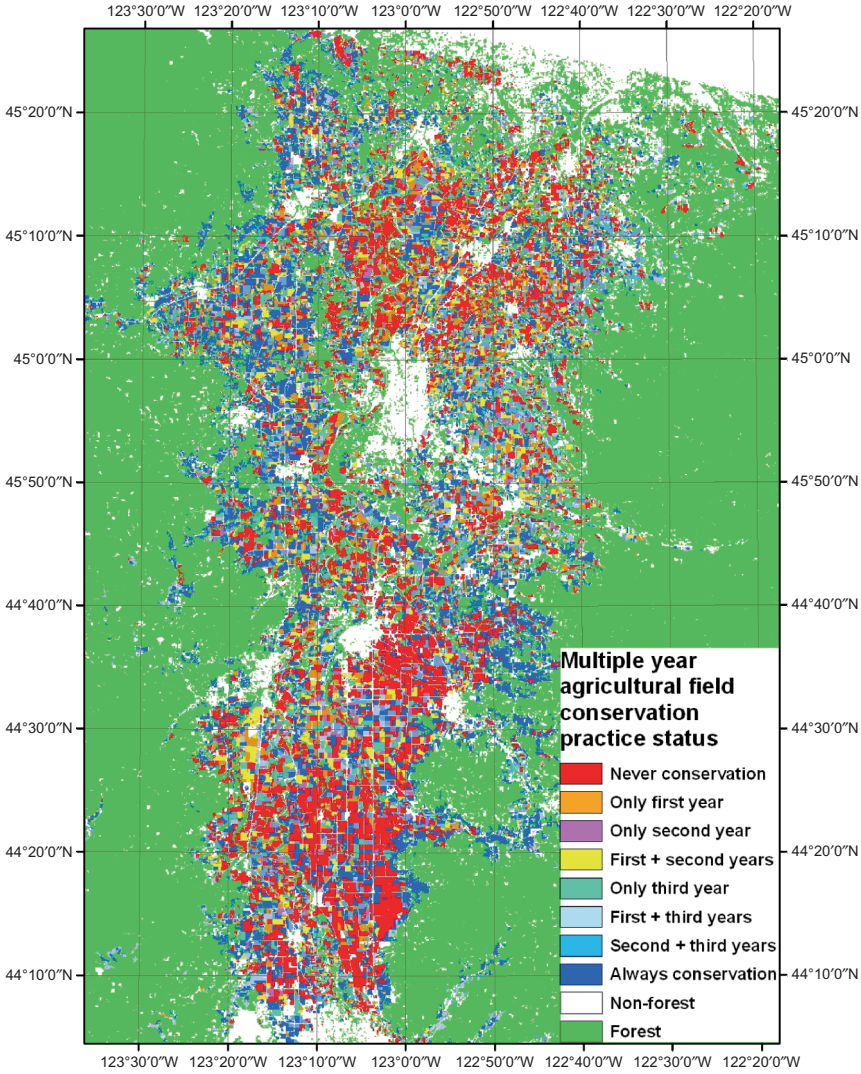

Figure 1. Multiple year agricultural field conservation status values at 1:600 000 scale. Agricultural field conservation was defined as true for previously established perennial crops (remote sensing classification categories 4–10), and otherwise false. Red denotes fields never using conservation practices, orange denotes use only in 2004–2005, purple denotes use only in 2005–2006, yellow denotes use only in first two years, tourmaline green denotes use only in 2006–2007, sodalite blue denotes use only in the first and third years, big sky blue denotes use only in second and third years, and Cretean blue denotes use in all three years. White represents non-forested, non-agricultural land, water, and urban areas, and quetzel green is forest.

Landsat scene boundaries on the north and south further restricted remote sensing classification efforts to 4423 km^2. Our ground surveys disproportionately emphasized the Calapooia River watershed in Linn County as it is the subject of a larger cooperative study on the conservation value of agricultural practices in western Oregon.

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3. Methods

3.1 *Data sources and analytical procedures*

We used ground-based surveys of agricultural fields in the Calapooia River watershed and surrounding counties during 2004–2005, 2005–2006 and 2006–2007 growing seasons to develop a list of crops being grown, stand establishment practices used, and post-harvest residue management practices (Mueller-Warrant *et al.*, unpublished data). We surveyed approximately 3000 fields in the Calapooia River watershed and an additional 1800 fields in neighbouring counties each growing season and documented 47 crop types, 15 stand establishment conditions, seven post harvest residue management practices, and 16 other management practices/field conditions. From that list, we created 20 combinations of crop type/stand establishment condition/residual vegetation management that accounted for over 96% of all agricultural fields in the Calapooia River watershed and 65% of fields in the neighbouring counties. This set of combinations was the focus of our remote sensing effort. Four of the 20 practices in initial remote sensing classifications were dropped from final efforts because of low accuracy due to high heterogeneity within the classes or extremely small sample sizes.

The 16 remaining classes comprised the core production practices utilized by Willamette Valley grass seed growers. Class number 1 was bare/disturbed ground in crops other than fall plantings of Italian ryegrass (*Lolium multiflorum* Lam.), perennial ryegrass (*Lolium perenne* L.), tall fescue (*Festuca arundinacea* Schreb.) and clover (*Trifolium* spp.). Class number 2 was full straw load chop, fall-germinated, volunteer Italian ryegrass. Class number 3 was spring planting of all grass seed crops. Classes number 4, 5 and 6 were established stands of perennial ryegrass, orchardgrass (*Dactylis glomerata* L.), and tall fescue, respectively. Class number 7 was mixed grass pasture. Class number 8 was established clover. Class number 9 was established peppermint (*Mentha* x *piperita* L.). Class number 10 was mixed grass hay crop. Classes number 11, 12, 13 and 14 were bare/disturbed ground fall-planted to Italian ryegrass, perennial ryegrass, tall fescue and clover, respectively. Class number 15 was cereal crops, primarily winter wheat (*Triticum aestivum* L.). Class number 16 was meadowfoam (*Limnanthes alba* L.).

We randomly assigned half of the fields to training sets and half to validation sets. Assignment of fields to training and validation datasets was conducted separately for years and ground-truth classes. Classes with odd numbers of fields had one more field assigned to the training set than to the test validation set. Field boundaries were modified from the original CLU polygons to match visual observation of fields and information provided by growers.

All available Landsat 5 TM and Landsat 7 ETM+ daytime images from 1993 through 2005 for Path 46 Row 29 processed to the Level 1G standard (radiometrically and geometrically corrected) were obtained from the USDA Imagery Archive, USDA-FAS. Other Level 1G Landsat 5 and Landsat 7 images for dates of interest were purchased from USGS-Earth Resources Observation System Data Center and Michigan State University Center for Global Change and Earth Observations. Additional Landsat images have been acquired from USGS subsequent to their decisions to freely release all Landsat 7 ETM+ data on 1 October 2008 and all Landsat 1–5 data on 9 January 2009. All Landsat images used in classifications were at resolutions of 30 m or finer. CLU shapefiles and Multi-Resolution Seamless Image Database (MrSID) format orthorectified high resolution (1 m pixels) National Agricultural Imagery Program (NAIP) black and white aerial photos for grass seed producing counties of Oregon were obtained from the USDA-Farm Service Administration field office in Tangent, OR.

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Pre-processing of the Landsat images included calculation of NDVI:

$$\mathrm{NDVI} = [(\mathrm{Band}_4 - \mathrm{Band}_3)/(\mathrm{Band}_4 + \mathrm{Band}_3)] \quad (1)$$

where Band_3 and Band_4 represent image spectral intensity in the red and near-infrared ranges (0.63–0.69 and 0.76–0.90 μm), scaled to an 8-bit, 0–255 value scale, and visual inspection for clouds, striping, and accuracy of the georeferencing provided with the images. Cloud masks were manually generated by setting limits within useful individual bands and merging those masks using the ArcGIS Raster Calculator (ESRI, Inc., Redlands, CA, USA). Masks were used to exclude cloudy pixels from further analysis for all bands from individual image dates. All Landsat 7 images collected after Scan Line Corrector (SLC) failure on 31 May 2003 contained data gaps in the eastern and western periphery of the Calapooia and multi-county GIS area, in addition to possible cloudy pixels. All images were georeferenced to sub-pixel agreement between patterns in the NDVI and locations of runways at the Corvallis Municipal Airport and a horseshoe bend in the Willamette River 13 km north-northeast of the airport in the 1994 NAIP orthophoto. No attempt was made to independently verify the accuracy of spatial referencing of the 1994 USDA-Farm Service Administration high resolution orthophoto. Where striping was apparent in the NDVI, a general mask of eight-pixel wide alternating bands was shifted north–south into alignment with the NDVI stripes, and this mask was used to subdivide all image bands for the date in question into two separate rasters. Values in one of the sets of rasters were manually adjusted up or down several digital numbers to remove visual differences within grass seed fields, following which the alternating bands were merged back together. Several images displayed one to two pixel-wide east–west offsets between stripes at major highways, and we therefore adjusted false easting and northing of each raster stripe to minimize east–west and north–south zigzag effects. Python 2.5 scripts and Turbo Pascal 5.5 programs written to conduct some of the image pre-processing steps are available by request from the corresponding author and online at http://www.ars.usda.gov/pandp/people/people.htm?personid=4006.

We also obtained MODIS NDVI 16-day composites for the three growing seasons defined as day 193 of the year before harvest through day 177 of the harvest year. MODIS Collection 4 NDVI and cloudiness data for calendar years 2004, 2005 and 2006 were obtained from archives of the Global Land Cover Facility (GLCF), College Park, MD, while MODIS Collection 5 data (MOD13Q1) for calendar year 2007 were obtained from NASA Land Processes Distributed Active Archive Center (LP-DAAC). The 250-m resolution MODIS data were resampled to 50-m pixels, which in turn were subjected to 3 by 3 neighbourhood averaging to smooth edges of the original 6.25 ha pixels and reduce overlap with field edges. For the MOD13Q1 Collection 5 data, the first two values of the data reliability raster were used to define cloud-free areas of the NDVI. Only the single most cloud-free value was used for the GLCF Collection 4 data. The 50-m pixels were resampled to 30-m pixels when merged with Landsat data in signature file creation and maximum likelihood (ML) classification.

Image signature files, class probability rasters, and ML classification rasters were initially generated using tools in the Multivariate Toolset of the ArcGIS Spatial Analyst Toolbox. Software limitations in ArcGIS Desktop versions 9.3 and earlier restricted analyses to a maximum of 20 classification categories (classes) and 20 raster image bands. Six useful Landsat images existed for the 2004–2005 growing season, five images for 2005–2006, and nine images for 2006–2007. In the first growing season, four images were cloud-free, with partial cloud cover in 28 September 2004 and

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7 March 2005 images. In the second growing season, three images were cloud-free, with partial cloud cover in 30 August 2005 and 13 May 2006 images. In the third growing season, two images were cloud-free, with partial cloud cover and/or SLC failure gaps in 1 August 2006, 17 August 2006, 2 September 2006, 20 October 2006, 8 May 2007, 24 May 2007 and 25 June 2007 images. There were 16, 15 and 17 useful MODIS NDVI images for the first, second, and third growing seasons, and data were entirely cloud-free for grass seed fields in the Calapooia and multi-county GIS in 13, 12 and 15 cases. Less than 0.3% of the data in areas of grass seed fields were lost due to clouds in the other three cases in the first growing season and the other two cases in the second and third growing seasons. Class probability and ML classification rasters were generated for each individual image date using a combination of the seven Landsat bands plus the NDVI transformation with the 'sample' *a priori* probability weighting option to adjust class sizes relative to the number of cells in the signature file. ML classification rasters were similarly generated for MODIS NDVI pooled over all usable dates within each of the three growing seasons. Because of concern over coarseness of the MODIS data, training and test validation classes were restricted to the more central areas of each individual field by testing whether all training or test validation pixels within 3 by 3 (or 5 by 5, 7 by 7 and 9 by 9) neighbourhoods possessed the same value. The general effect of these procedures was to remove pixels from the outer edges of individual fields except where they directly abutted other fields in the same ground-truth class.

Because of the 20-band software limitation, we could not perform ML classification within ArcGIS on composite Landsat multiband plus MODIS NDVI raster datasets for the entire growing season. There were 64 bands in the most fully cloud-free areas the first year, 55 bands the second year, and 81 bands the third year. Data were imported into ERDAS Imagine version 9.3 (ERDAS, Inc., Norcross, GA, USA) and subjected to a series of ML classifications trained with shapefiles matching those used for the 16 classes analysed in ArcGIS. *A priori* class probability levels were assigned based on class frequency in the training set, and ML classification in ERDAS Imagine was conducted both with and without use of the *a priori* class probability values. These ML classifications were conducted for the five cloud-free raster groups the first year (four Landsat plus MODIS), the four cloud-free raster groups the second year, the three cloud-free raster groups the third year, and for the series of rasters obtained by progressively adding the least cloudy remaining Landsat dataset to all other previously pooled rasters in each year (tables 1–3). A composite classification for each year was generated by assigning each pixel the class associated with the 'all rasters group' iterative result if the pixel was cloud-free for all dates. Otherwise, the cloud-free plus partly cloudy combination rasters that included the most image dates at a given pixel location were used.

Raster algebra calculations in the ArcGIS Raster Calculator were used to determine whether individual pixels were correctly classified, and if not, to characterize the nature of their misclassification. Value attribute tables from these classification correctness/misclassification rasters were imported into Microsoft Excel for further analysis. In particular, we tested for year-to-year consistency in pixel classification, in recognition of the fact that certain crop status transitions were illogical, with at least one of the three years necessarily being incorrectly classified. For example, crop status cannot change from established tall fescue in one year to established orchardgrass in a second year and back to established tall fescue in a third year. We assumed that the second-year classification of established orchardgrass was more likely in error than the other two classifications. A matrix of forbidden transitions was created identifying

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Table 1. Accuracy and Kappa on a per-pixel basis for maximum likelihood classifications using seven bands plus NDVI for each of six Landsat image dates and using 16 MODIS 16-day composite NDVI for 16 categories of agricultural practices in the 2004–2005 cropping year in western Oregon.

		Training set		Test validation set	
Landsat multiband plus MODIS NDVI image groups†	Cloud-free and image defect-free agricultural field raster area (30-m pixels)	Accuracy (%)	Kappa	Accuracy (%)	Kappa
Five groups pooled fewer MODIS‡	5 036 942	81.2	0.774	71.8	0.659
Five groups pooled all MODIS‡	4 937 509	81.6	0.779	71.7	0.656
Six groups pooled‡	4 415 354	84.4	0.812	73.0	0.672
Seven groups pooled‡	3 791 412	86.0	0.832	73.0	0.673
Final merge§	5 036 942	84.7	0.815	72.2	0.663
Transition consistency of 2005 class in final merge raster	5 036 869	98.3¶			
Replace year-to-year inconsistent pixels	5 036 869	85.1	0.820	73.3	0.676
Majority rule polygons	–	80.8	0.776	69.1	0.636
Majority rule raster	5 020 374	88.6	0.861	76.6	0.714
Transition consistency of 2005 class in majority rule raster	5 020 374	99.7¶			

†Coverage of Landsat images was reduced by partial cloud cover in western Oregon agricultural field areas on 28 September 2004 and 7 March 2005. Images were fully cloud-free on 26 July 2004, 11 August 2004, 14 October 2004 and 26 May 2005. MODIS data comprised all 16-day composite NDVI that were cloud-free for all western Oregon agricultural fields plus minimally cloud-impacted composites for day 241 in 2004 and days 97 and 113 in 2005. MODIS composites were assigned to cropping year from day 193 of 2004 through day 177 of 2005.

‡Image signature creation and maximum likelihood classification were conducted for all available cloud-free (and image defect-free) Landsat and MODIS raster bands, following which the least cloudy of the remaining images were successively added to the pooled raster collection until all data were included. The first partly cloudy data added to the fully cloud-free rasters were the three slightly cloudy MODIS NDVI which were added as a block of three bands, while the Landsat data were added as blocks of Bands 1–7 plus calculated NDVI one date at a time.

§Final merge raster assigned value from maximum likelihood classification of largest number of groups existing at each pixel.

¶Transition consistency tests identified which year out of three was logically inconsistent with classifications for the other two years, and footnoted value is percentage of consistent transitions in the entire raster.

33 cases for which single-year classifications of established tall fescue or orchardgrass were probably in error, 30 cases for established perennial ryegrass, 32 cases for full straw chop volunteer Italian ryegrass or established clover spp., eight cases for established pasture or hay crop, and 17 cases for Italian ryegrass not using the full straw chop volunteer stand method. Pixels identified using this forbidden transition

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Table 2. Accuracy and Kappa on a per-pixel basis for maximum likelihood classifications using seven bands plus NDVI for each of five Landsat image dates and using 15 MODIS 16-day composite NDVI for 16 categories of agricultural practices in the 2005–2006 cropping year in western Oregon.

		Training set		Test validation set	
Landsat multiband plus MODIS NDVI image groups†	Cloud-free and image defect-free agricultural field raster area (30-m pixels)	Accuracy (%)	Kappa	Accuracy (%)	Kappa
Four groups pooled fewer MODIS‡	5 038 558	69.2	0.640	60.0	0.527
Four groups pooled all MODIS‡	4 922 398	69.4	0.642	59.4	0.520
Five groups pooled‡	4 454 316	76.2	0.718	65.1	0.582
Six groups pooled‡	3 872 310	78.6	0.746	67.0	0.603
Final merge§	5 038 601	77.1	0.729	65.7	0.589
Transition consistency of 2006 class in final merge raster	5 036 869	98.1¶			
Replace inconsistent pixels	5 036 869	77.9	0.739	67.4	0.610
Majority rule polygons	–	75.2	0.713	66.8	0.613
Majority rule raster	5 020 374	82.2	0.787	72.8	0.671
Transition consistency of 2006 class in majority rule raster	5 020 374	99.6¶			

†Coverage of Landsat images was reduced by partial cloud cover in western Oregon agricultural field areas on 30 August 2005 and 13 May 2006. Images were fully cloud-free on 29 July 2005, 14 August 2005, and 27 April 2006. MODIS data comprised all 16-day composite NDVI that were cloud-free for all western Oregon agricultural fields plus minimally cloud-impacted composites for day 337 in 2005 and day 145 in 2006. MODIS composites were assigned to cropping year from day 193 of 2005 through day 177 of 2006.

‡Image signature creation and maximum likelihood classification were conducted for all available cloud-free (and image defect-free) Landsat and MODIS raster bands, following which the least cloudy of the remaining images were successively added to the pooled raster collection until all data were included. The first partly cloudy data added to the fully cloud-free rasters were the two slightly cloudy MODIS NDVI which were added as a block of two bands, while the Landsat data were added as blocks of Bands 1–7 plus calculated NDVI one date at a time.

§Final merge raster assigned value from maximum likelihood classification of largest number of groups existing at each pixel.

¶Transition consistency tests identified which year out of three was logically inconsistent with classifications for the other two years, and footnoted value is percentage of consistent transitions in the entire raster.

matrix were changed from their ML classification values into their second most likely probability class (fuzzy class two) prior to conversion of rasters to object-based classification. Majority-rule object-based classification was accomplished by generating unique identification numbers for each CLU polygon, converting the polygons to rasters with values of those unique IDs, intersecting those rasters with each of 16 rasters corresponding to the 16 possible pixel classes, and counting the number of

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Table 3. Accuracy and Kappa on a per-pixel basis for maximum likelihood classifications using seven bands plus NDVI for each of nine Landsat image dates and using 17 MODIS 16-day composite NDVI for 16 categories of agricultural practices in the 2006–2007 cropping year in western Oregon.

		Training set		Test validation set	
Landsat multiband plus MODIS NDVI image groups†	Cloud-free and image defect-free agricultural field raster area (30-m pixels)	Accuracy (%)	Kappa	Accuracy (%)	Kappa
Three groups pooled fewer MODIS‡	5 099 250	74.9	0.701	63.8	0.566
Three groups pooled all MODIS‡	5 039 120	75.5	0.708	63.8	0.567
Four groups pooled‡	4 730 368	78.9	0.750	66.5	0.600
Five groups pooled‡	4 403 193	80.3	0.765	67.7	0.612
Six groups pooled‡	3 822 915	83.8	0.807	69.9	0.638
Seven groups pooled‡	3 631 621	85.7	0.830	71.4	0.656
Eight groups pooled‡	3 294 858	86.3	0.837	70.9	0.651
Nine groups pooled‡	2 877 697	89.5	0.874	74.4	0.689
Ten groups pooled‡	2 246 360	91.5	0.897	76.0	0.705
Final merge§	5 099 250	87.6	0.854	72.7	0.675
Transition consistency of 2007 class in final merge raster	5 036 869	98.2¶			
Replace inconsistent pixels	5 036 869	87.5	0.852	73.7	0.688
Majority rule polygons	–	82.2	0.796	71.9	0.677
Majority rule raster	5 020 374	89.2	0.872	76.4	0.717
Transition consistency of 2007 class in majority rule raster	5 020 374	99.7¶			

†Coverage of Landsat images was reduced by partial cloud cover (and missing image areas in Landsat 7 data collected after Scan Line Corrector failure 31 May 2003) in western Oregon agricultural field areas on 1 August 2006, 17 August 2006, 2 September 2006, 20 October 2006, 8 May 2007, 24 May 2007 and 25 June 2007. Images were fully cloud-free and defect-free 16 July 2006 and 29 March 2007. MODIS data comprised all 16-day composite NDVI that were cloud-free for all western Oregon agricultural fields plus minimally cloud-impacted composites for days 33 and 97 in 2007. MODIS composites were assigned to cropping year from day 193 of 2006 through day 177 of 2007.

‡Image signature creation and maximum likelihood classification were conducted for all available cloud-free (and image defect-free) Landsat and MODIS raster bands, following which the least cloudy of the remaining images were successively added to the pooled raster collection until all data were included. The first partly cloudy data added to the fully cloud-free rasters were the two slightly cloudy MODIS NDVI which were added as a block of two bands, while the Landsat data were added as blocks of Bands 1–7 plus calculated NDVI one date at a time.

§Final merge raster assigned value from maximum likelihood classification of largest number of groups existing at each pixel.

¶Transition consistency tests identified which year out of three was logically inconsistent with classifications for the other two years, and footnoted value is percentage of consistent transitions in the entire raster.

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times each unique field ID occurred in each of the 16 cases. Python scripts automating these procedures are available online at http://www.ars.usda.gov/pandp/people/people.htm?personid=4006, and both majority-rule object-based classification values and second-place runner-up values were identified.

3.2 *Accuracy assessment and validation of remote sensing classification*

Reference data to support accuracy assessment and validation of remote sensing classification were half of the fields in the Calapooia GIS census plus half of the random survey fields in neighbouring counties. Prior to use of training and test validation sets for remote sensing classification and accuracy assessment, we examined the training and test validation sets for year-to-year consistency in crop status transitions. We removed totals of 50, 73 and 84 fields from the first, second and third years because of year-to-year inconsistency in crop identification or stand establishment status. User and producer classification accuracy and the Kappa statistic were calculated for all contingency (error) matrices using methods described by Mather (2004). Producer accuracy is an inverse indicator of the presence of errors of omission (underestimating a class) in the classification process, whereas user accuracy is an inverse indicator of the presence of errors of commission (overestimating a class). Both the Kappa statistic and the overall accuracy are single-valued summaries of classification error matrices. Potential values for the Kappa statistic range from ~0 to 1, with 0 corresponding to the level of agreement between ground truth and remotely sensed classifications likely to occur strictly by chance and 1 indicating complete agreement between remotely sensed classifications and ground-truth data.

Overall classification accuracy and Kappa from individual Landsat image acquisition dates for composites of Bands 1–7 plus NDVI were similar for training and test validation sets. Classification accuracy for the test validation set exceeded accuracy for the training set in two of six images the first year, three of five images the second year, and none of nine images the third year. Kappa for the test validation set exceeded Kappa for the training set in one of six images the first year, three of five images the second year, and none of nine images the third year. Averaged over all individual Landsat image acquisition date multiband rasters, accuracy from the training set to the test validation set only dropped from 50.1 to 49.0%, with Kappa dropping from 0.377 to 0.360.

Larger differences in classification accuracy and Kappa between training and test validation sets were noted when raster groups from multiple dates were pooled together to improve classification accuracy. Averaged over the three years, MODIS NDVI by themselves achieved 61.1% accuracy in the training sets but only 53.8% in the test validation sets, with Kappa averaging 0.526 and 0.434 for the training and validation sets (see §4.1 below for further details on use of MODIS data). When all available Landsat multiband and MODIS NDVI data were pooled, training set accuracy increased to maximums of 86.0, 78.6 and 91.5% for the 2005, 2006 and 2007 harvest years, with test validation accuracy increasing to 73.0, 67.0 and 76.0% for the same periods (tables 1–3). Relative differences in Kappa between training and test validation sets were somewhat greater than differences in simple accuracy. The improved classification accuracy achieved by using multiple image acquisition dates clearly came at some cost in terms of creating spectral signatures uniquely sensitive to the particular selection of fields present in the training and validation sets. Given that there are only minor differences in growth habit and visual appearance among many

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of the 16 categories we were attempting to classify, the increasing difference in accuracy between training and test validation sets as we improved overall accuracy of both sets comes as no surprise.

4. Results

4.1 *Enhancing MODIS resolution and adjusting edges of field boundaries*

Because of concern that the field of view of MODIS pixels near edges of grass seed fields often included crops from adjacent fields, along with trees, roads, and buildings between agricultural fields, training and test validation classes were restricted to the more central areas of each individual field. Tests were conducted to determine whether pooled rasters of all training and test validation pixels within 3 by 3 (or 5 by 5, 7 by 7 and 9 by 9) neighbourhoods possessed identical values. Our methods also required complete absence of any unclassified pixels within the N by N neighbourhoods. Removing 30-m pixels from increasingly larger areas around edges of individual training set fields increased classification accuracy within the smaller remaining central areas up through the case of 7 by 7 neighbourhoods in 2004–2005 (table 4). Similar effects occurred in the next two growing seasons. This increased accuracy occurred in both training set and test validation set areas, and was the anticipated outcome of removing mixed-category pixels from near field borders. Edging procedures, however, removed 26, 47, 61 and 72% of all data using 3 by 3, 5 by 5, 7 by 7 and 9 by 9 neighbourhoods, respectively. Indeed, several entire classes were lost from both training and test validation areas using the 9 by 9 method. Similar problems of lost classes occurred with use of simple 125-m buffers around all field edges. When accuracy was measured over the full original training or test validation areas rather than the remaining central zones, there was no drop in accuracy or Kappa for training or validation areas when 3 by 3 edging had been used on the training raster during signature file creation (3-year average increases of 0.2% in accuracy and 0.005 in Kappa). In contrast, accuracy measured within the original full coverage area decreased with 5 by 5 and 7 by 7 edging. Viewing the benefit of N by N edging from the perspective of improved validation accuracy within the smaller remaining core area, the first step (to 3 by 3 neighbourhoods) achieved 55% as much as the third step (to 7 by 7 neighbourhoods), while retaining 88% more training and test validation area. If our agricultural fields had been bigger, it would be easy to justify use of larger neighbourhoods for removing potentially mixed-category pixels near field borders. Given constraints in field sizes and our desire to use combinations of Landsat plus MODIS data in remote sensing classification, 3 by 3 neighbourhood edging was most effective in reducing the impact of mixed-category pixels and improving overall classification accuracy.

The second process we evaluated for reducing the impact of mismatch in pixel size between MODIS and Landsat data was to artificially enhance MODIS resolution by utilizing 3 by 3 neighbourhood averaging over 50-m pixel resampled versions of the original MODIS data. Our assumption was that for 50-m pixels near corners of an original 250-m pixel zone, the NDVI that would have been measured by a higher resolution sensor was likely to be closer to the average of the four nearest MODIS pixels than to the single value present at the closest pixel centre. Enhancement and smoothing of MODIS data increased training set classification accuracy from 54.6 to 57.3%, 52.0 to 55.2% and 52.9 to 56.6% over the three years when applied to full coverage of training and validation areas (i.e. no 3 by 3 neighbourhood edge removal). Validation accuracy for the same comparisons increased from 48.9 to 50.6%, 48.2 to

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Table 4. Effects of adjusting training and validation area field boundaries and artificially enhancing MODIS image resolution on accuracy of remote sensing classification in the 2004–2005, 2005–2006 and 2006–2007 growing seasons.

	Image signature creation methods				Training set		Validation set	
Crop year	Training raster	MODIS raster	ML classifying raster	Accuracy measurement basis	Accuracy (%)	Kappa	Accuracy (%)	Kappa
2004–2005	Full coverage	original	original	full coverage	54.6	0.452	48.9	0.379
2004–2005	3 by 3 edging	original	original	full coverage	54.8	0.456	48.9	0.380
2004–2005	3 by 3 edging	original	original	3 by 3 edging	59.2	0.503	52.6	0.417
2004–2005	5 by 5 edging	original	original	full coverage	54.4	0.452	48.3	0.375
2004–2005	5 by 5 edging	original	original	5 by 5 edging	63.0	0.545	55.0	0.442
2004–2005	7 by 7 edging	original	original	full coverage	52.7	0.434	46.9	0.361
2004–2005	7 by 7 edging	original	original	7 by 7 edging	64.7	0.565	55.6	0.450
2004–2005	Full coverage	enhanced	enhanced	full coverage	57.3	0.486	50.6	0.402
2004–2005	3 by 3 edging	enhanced	enhanced	3 by 3 edging	61.8	0.536	54.5	0.442
2004–2005	3 by 3 edging	enhanced	original	3 by 3 edging	58.8	0.502	51.6	0.411
2004–2005	3 by 3 edging	original	enhanced	3 by 3 edging	61.8	0.532	54.4	0.438
2005–2006	full coverage	original	original	full coverage	52.0	0.411	48.2	0.362
2005–2006	3 by 3 edging	original	original	full coverage	52.6	0.421	48.3	0.368
2005–2006	3 by 3 edging	original	original	3 by 3 edging	56.2	0.459	51.8	0.402
2005–2006	full coverage	enhanced	enhanced	full coverage	55.2	0.452	50.1	0.388
2005–2006	3 by 3 edging	enhanced	enhanced	3 by 3 edging	59.5	0.501	54.0	0.431
2005–2006	3 by 3 edging	enhanced	original	3 by 3 edging	52.2	0.423	48.7	0.379
2005–2006	3 by 3 edging	original	enhanced	3 by 3 edging	55.7	0.449	52.3	0.405
2006–2007	full coverage	original	original	full coverage	52.9	0.434	47.2	0.362
2006–2007	3 by 3 edging	original	original	full coverage	53.2	0.440	47.0	0.363
2006–2007	3 by 3 edging	original	original	3 by 3 edging	57.8	0.489	50.7	0.399
2006–2007	full coverage	enhanced	enhanced	full coverage	56.6	0.484	49.1	0.391
2006–2007	3 by 3 edging	enhanced	enhanced	3 by 3 edging	61.8	0.540	53.0	0.430
2006–2007	3 by 3 edging	enhanced	original	3 by 3 edging	56.8	0.485	48.8	0.386
2006–2007	3 by 3 edging	original	enhanced	3 by 3 edging	59.8	0.508	53.3	0.425

50.1% and 47.2 to 49.1%. When used in conjunction with 3 by 3 neighbourhood edging of training and validation sets, enhancement of MODIS increased training set accuracy from 59.2 to 61.8%, 56.2 to 59.5% and 57.8 to 61.8% over the three years. Validation accuracy for the same comparisons increased from 52.6 to 54.5%, 51.8 to 54.0% and 50.7 to 53.0%. Because increases in validation accuracy from MODIS enhancement were somewhat smaller than increases in training set accuracy, we evaluated benefits of MODIS enhancement on image signatures separately from benefits on ML classification. When enhanced MODIS data were classified using signature files based on the original MODIS data, accuracy and Kappa were nearly the same as when enhanced MODIS data were used for signature files in 2004–2005 for training and validation areas and in 2006–2007 for validation areas. In all other cases, MODIS enhancement improved the quality of the signature files for use with enhanced MODIS data in ML classification. When ML classification was conducted using the original MODIS data, image signatures from the original MODIS data outperformed those from the enhanced data. Because artificial enhancement of the MODIS data modestly but consistently improved accuracy and Kappa in both training and validation set areas over all three years, we conducted all Landsat plus MODIS multi-group classifications using the enhanced MODIS data, further resampling the enhanced MODIS data to 30-m pixels to match Landsat resolution. We also chose to use 3 by 3 neighbourhood edging of training and test validation sets in all multi-group classifications because that method consistently improved results with MODIS and had negligible effects with Landsat.

4.2 *Cropping practices in western Oregon*

The 20 most common cropping practices, defined primarily by crop grown and stand establishment status age, accounted for 96.7, 96.9 and 95.1% of all fields in the 2004–2005, 2005–2006 and 2006–2007 growing seasons in the Calapooia GIS but only 63.1, 60.9 and 70.4% in the neighbouring multicounty survey (Mueller-Warrant *et al.*, unpublished data). Seven of these practices involved the presence of bare or disturbed ground in late summer or Italian ryegrass production using a variety of residue management, tillage, and stand establishment techniques. The other 13 practices included production of a single crop, most often an established perennial grass, or wheat, meadowfoam, trees, and non-crop land. Four of the 20 practices were dropped from further analysis because of low accuracy caused by the presence of heterogeneous mixtures of management practices within a class or extremely small sample sizes. The largest omitted category was Italian ryegrass with unknown residue management and stand establishment methods. High degree of heterogeneity in this category was an indication that the fields in question likely belonged to either categories 2 or 11 rather than a separate unique category. Averaged over three years, there was 4.4 times as much training plus test validation area of Italian ryegrass planted into bare or disturbed ground (category 11) as there was using the full straw chop volunteer reseeding method (category 2). Remote sensing methods applied to Italian ryegrass fields with unknown residue management and stand establishment methods classified an average of 46% of them in category 11 and 14% in category 2 (table 5), with the 3.1-fold ratio of these two classes roughly approximating the ratio of these two classes in the ground-truth data. The remaining 40% of Italian ryegrass with unknown residue management and stand establishment methods classified into the other 14 categories.

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Table 5. Remote sensing classification matrix for the ill-defined GIS ground-truth categories of other Italian ryegrass and other fall plant perennial ryegrass in the 2004–2005, 2005–2006 and 2006–2007 growing seasons.

	GIS ground-truth category					
Remote sensing classification	Other Italian ryegrass not category 2 or 11 in 2004–2005 (% of pixels)	Other Italian ryegrass not category 2 or 11 in 2005–2006 (% of pixels)	Other Italian ryegrass not category 2 or 11 in 2006–2007 (% of pixels)	Other fall plant perennial ryegrass not category 4 or 12 in 2004–2005 (% of pixels)	Other fall plant perennial ryegrass not category 4 or 12 in 2005–2006 (% of pixels)	Other fall plant perennial ryegrass not category 4 or 12 in 2006–2007 (% of pixels)
2. Full straw Italian ryegrass	16.8	16.3	10.4	–	–	–
11. Bare/disturbed ground – Italian ryegrass	48.0	43.4	45.3	–	–	–
Remaining 14 classes	35.2	40.3	44.3	–	–	–
Total pixel count for other Italian ryegrass	58 172	31 577	33 588	–	–	–
4. Established perennial ryegrass	–	–	–	17.4	75.7	32.7
12. Bare/disturbed ground – perennial ryegrass	–	–	–	33.4	23.5	16.6
Remaining 14 classes	–	–	–	49.1	0.9	50.6
Total pixel count for other fall plant perennial ryegrass	–	–	–	12 762	1286	5073

The second omitted category was fall-planted perennial ryegrass on undisturbed ground. Heterogeneity in this category may indicate that some of the fields were partial failures of spring planting of grass seed crops being replanted in the fall using no-till methods, with the spring planting accounting for varying amounts of the total stand. Remote sensing classification methods applied to perennial ryegrass planted in the fall on undisturbed ground classified 51% in categories 4 or 12 the first year, 100% the second year and 49% the third year (table 5), with the remaining percentage in each year classified in the other 14 categories.

4.3 *Multiple image date classification accuracy*

Within individual cropping years, the most accurate classifications tended to be produced by Landsat images taken in July at the start of the cropping year and in May and June at the end of the cropping year. Multi-temporal MODIS data produced more accurate classifications than the single best Landsat image in all three years. The 'final merge' rasters reported in tables 1–3 merged the independent ML classifications for five through seven pooled image groups in 2004–2005, four through six pooled image groups in 2005–2006, and three through 10 pooled image groups in 2006–2007 using the highest number of images for pixels never masked by clouds. Progressively lower numbers of images were used for pixels masked in some images. In 2004–2005, this provided a 16-class training set accuracy of 84.7% with Kappa of 0.815 (table 1). In that same year, the seven-image group accuracy (on a smaller number of pixels) was 86.0% with Kappa of 0.832, the six-image group accuracy was 84.4% with Kappa of 0.812, and the five-image group accuracy (including all MODIS data) was 81.6% with Kappa of 0.779. In 2005–2006, our raster merging method provided a 16-class training set accuracy of 77.1% with Kappa of 0.729 (table 2). In that same year, the six-image group accuracy was 78.6% with Kappa of 0.746, the five-image group accuracy was 76.2% with Kappa of 0.718, and the four-image group accuracy (including all MODIS data) was 69.4% with Kappa of 0.640. In 2006–2007, our raster merging method provided a 16-class training set accuracy of 87.6% with Kappa of 0.854 (table 3). In that same year, accuracy and Kappa ranged from a high of 91.5% and 0.897 for the 10-image group to a low of 75.5% and 0.708 for the three-image group (including all MODIS data). Including the two or three MODIS dates with small but non-zero levels of cloudiness over the training and validation areas made little difference, with training set changes in accuracy of +0.4, +0.2 and +0.6% over the three years and test validation changes in accuracy of –0.1, –0.6 and 0.0% when the additional data were used. Similarity between accuracy of the highest number of merged images in each year (which only applied to pixels that were non-cloudy) with the accuracy after merging classifications of progressively lower numbers of images (which eventually included all pixels from the training set) suggested that the merging approach was robust for our purposes.

Replacing pixels that were inconsistent in year-to-year transitions in cropping practices with their second-most likely value (fuzzy class two) rather than their ML value in the conflicting year out of three increased training set accuracy by 0.4, 0.8 and –0.1% in the first, second and third years (tables 1–3). Kappa showed corresponding increases of 0.005, 0.010 and –0.002. Interestingly, much larger benefits from these replacements occurred in the test validation sets, with accuracy increasing by 1.1, 1.7 and 1.0% over the three years, and Kappa increasing by 0.013, 0.021 and 0.013. Unlike results from preliminary analyses that used methods less robust than ML in ERDAS Imagine to

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classify pooled raster datasets containing more than 20 bands, year-to-year transition consistency tests only identified 1.7, 1.9 and 1.8% of pixels in the 'final-merge' rasters over the three years as inconsistent.

Conversion from raster to object-based data using majority rule reclassification of all pixels within field polygons increased training set accuracy by an additional 3.5, 4.3 and 1.7% in the three years beyond that achieved by only replacing the inconsistent pixels (tables 1–3). Test validation set accuracy was similarly improved by majority rule reclassification, with increases of 3.3, 5.4 and 2.7%. Majority rule reclassification reduced pixels with inconsistent year-to-year classification to an average of only 0.3% of the data over the three years. Classification accuracy in the majority rule rasters was higher than in the majority rule polygons used to create those rasters, implying that larger fields were more accurately classified than smaller ones. A variety of alternate methods for imposing year-to-year transition consistency on classifications were also tested, but their accuracy was lower than the procedures just described. In particular, performing majority-rule object-based reclassification first and then replacing inconsistent polygon classes with the second-most likely value for the year conflicting with the other two slightly reduced accuracy in both training and validation sets in all three years.

The relationship between field size and classification accuracy was investigated further by plotting the percentage of pixels correctly classified versus field size for the 'final merge' rasters from all three years (figure 2). Accuracy was measured on the full-coverage of combined training plus test validation areas rather than the 3 by 3 neighbourhood edge removed version used in signature file creation. A log–log power curve fit to the data for 524 groups of 25 fields sequentially increasing in size ($R^2 = 0.41, p < 0.0001$) was relatively flat for medium to large size fields, with average accuracy only increasing from 69% at 20 ha to 76% at 50 ha. In contrast, accuracy

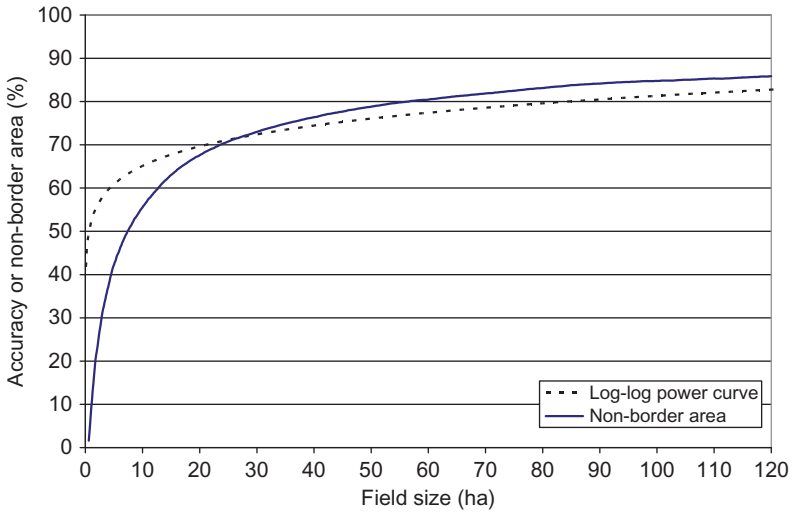

Figure 2. Relationships among field size, per-pixel classification accuracy for 'final merge' rasters from all three years, and average percentage of non-border 30-m pixels present within randomly shaped fields. Dotted line is log–log power curve regression calculated from averages of sequentially larger blocks of 25 fields, and averages 98.0% of non-border area for all fields larger than 16 ha.

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dropped to 56% at 2 ha and 48% at 0.4 ha. There was a close fit between increase in accuracy with increasing field size and increase in proportion of non-border pixels. Averaged over 49 Monte Carlo runs for random field shapes (rectangles whose ratios of width to length were random values >0 and ≤ 1), only 15% of 30-m pixels occurred at polygon borders for 80 ha fields, whereas 79% of pixels occurred at borders for 0.4 ha fields. For fields larger than 16 ha, pixel classification accuracy averaged 98.0% of the proportion of non-border pixels present in fields, closely matching the power curve regression. For fields smaller than 16 ha, pixel classification accuracy relative to the proportion of non-border pixels increased with decreasing field size, suggesting that smaller fields were more likely to have approximately square shapes (and thus higher than randomly expected proportions of non-border pixels) than larger fields.

4.4 *Detailed analysis of classification error matrices from majority rule rasters*

The dominant cropping practice in all three years, occurring on an average of 29.6% of the agricultural field area, was Italian ryegrass seed production on ground that was bare in late summer due to tillage or field burning. Identification of this practice was achieved at producer accuracies of 92.2, 78.8 and 93.6% in training set areas over the three years (tables 6–8). User accuracies for these identifications were 92.3, 89.7 and 92.8%. The next most common cropping practices were established tall fescue and established perennial ryegrass seed production, occurring on averages of 20.0 and 17.3% of the field area. Identification of established tall fescue grown for seed was achieved at producer accuracies of 85.8, 87.7 and 90.6% in training set areas over the three years. User accuracies for these identifications were 91.3, 85.3 and 90.2%. Identification of established perennial ryegrass grown for seed was achieved at producer accuracies of 86.5, 80.2 and 84.0% in training set areas over the three years. User accuracies for these identifications were 89.5, 89.9 and 92.0%. The fourth most common practice was bare or disturbed ground planted to crops other than Italian ryegrass, perennial ryegrass, tall fescue and clover, occurring on an average of 6.4% of the field area. The multiplicity of crops included in this category was likely responsible for the reduced success relative to the three most common cropping practices. Bare or disturbed ground planted to other crops was identified at producer accuracies of 86.5, 77.1 and 89.2%, with user accuracies of 73.2, 53.2 and 74.2%. The fifth most common practice was volunteer stand establishment of Italian ryegrass with full straw chop residue management, occurring on an average of 5.3% of the field area. This practice was identified at producer accuracies of 97.5, 93.1 and 85.7%, with user accuracies of 78.4, 47.3 and 90.1%. Given difficulties in the drive-by census of differentiating between this practice of producing Italian ryegrass and the more common one involving tillage, these accuracies are encouraging and indicate successful detection of chopped straw left on the soil surface in late summer. The low user accuracy in the second year may in part reflect possible ground-truth errors rather than remote sensing classification accuracy.

The sixth most common practice, occurring on an average of 3.6% of the field area, was fall seeding of new stands of perennial ryegrass grown for seed. This practice was identified at producer accuracies of 81.1, 69.4 and 84.2%, with user accuracies of 82.3, 80.6 and 87.0% (tables 6–8). The misclassifications that occurred primarily represented confusion of this practice with fall plantings of Italian ryegrass on bare or disturbed ground and established perennial ryegrass seed production fields. The seventh most common practice, occurring on an average of 3.5% of the field area,

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Table 6. Per-pixel classification error matrix for 16 categories of agricultural practices in western Oregon in the 2004–2005 growing season, using maximum likelihood pixel classification for six Landsat image dates of seven bands plus NDVI and 16 MODIS 16-day composite NDVI followed by per-polygon majority rule reclassification.

	Remote sensing classification†																	
Ground-truth field category†	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Producer's accuracy (%)	Omission errors (%)
1	**14 068**	36	21	187	20	0	154	0	0	0	913	140	0	0	99	0	86.5	13.5
2	101	**12 746**	0	519	0	18	6	0	0	0	302	0	0	0	0	0	97.5	2.5
3	26	0	**4057**	214	0	28	3	0	0	0	0	6	0	0	0	0	93.6	6.4
4	1890	344	1123	**50 461**	0	1835	172	3	0	0	1169	912	0	0	439	0	86.5	13.5
5	16	33	0	260	**7243**	41	44	0	0	0	443	201	0	0	8	0	87.4	12.6
6	1074	123	0	2037	194	**48 535**	869	5	191	4	2621	69	87	0	788	0	85.8	14.2
7	343	28	19	180	0	315	**8132**	0	0	105	142	0	0	0	18	0	87.6	12.4
8	19	0	0	39	0	0	0	**3303**	0	0	0	0	0	0	0	0	98.3	1.7
9	0	0	0	0	0	0	0	0	**2759**	0	17	0	0	0	0	0	99.4	0.6
10	5	0	0	14	0	0	36	0	0	**1382**	0	0	0	0	0	0	96.2	3.8
11	546	2270	322	1269	60	1535	14	0	0	0	**81 847**	746	108	0	28	0	92.2	7.8
12	332	668	0	580	0	2	0	0	0	0	783	**10 354**	0	0	53	0	81.1	18.9
13	21	0	0	108	0	565	0	0	0	0	52	0	**2321**	0	0	0	75.7	24.3
14	13	0	0	18	0	4	0	27	0	0	18	0	0	**2802**	0	0	97.2	2.8
15	762	0	0	464	120	305	26	0	0	99	408	160	0	0	**8969**	0	79.3	20.7
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**746**	100.0	0.0
User's accuracy (%)	73.2	78.4	73.2	89.5	94.8	91.3	86.0	99.0	93.5	86.9	92.3	82.3	92.2	100.0	86.2	100.0	88.6	11.4
Commission errors (%)	26.8	21.6	26.8	10.5	5.2	8.7	14.0	1.0	6.5	13.1	7.7	17.7	7.8	0.0	13.8	0.0	11.4	
																	$\kappa = 0.861$‡	

†Ground-truth and remote sensing classification categories were as follows: 1 – Bare/disturbed ground in crops other than fall plantings of Italian ryegrass, perennial ryegrass, tall fescue and clover spp.; 2 – Full straw volunteer Italian ryegrass; 3 – Spring plantings of any grass seed crop; 4 – Established perennial ryegrass; 5 – Established orchardgrass; 6 – Established tall fescue; 7 – Mixed grass spp. pasture; 8 – Established clover spp.; 9 – Established mint; 10 – Mixed grass spp. hay crop; 11 – Bare/disturbed ground fall planted to Italian ryegrass; 12 – Bare/disturbed ground fall planted to perennial ryegrass; 13 – Bare/disturbed ground fall planted to tall fescue; 14 – Bare/disturbed ground fall planted to clover spp.; 15 – Cereal crops, primarily winter wheat; 16 – Meadowfoam.
‡Tabular data calculated for training set derived from random half of all field polygons. Overall accuracy and Kappa for test validation set derived from the other half of all field polygons were 76.6% and 0.714.

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Table 7. Per-pixel classification error matrix for 16 categories of agricultural practices in western Oregon in the 2005–2006 growing season, using maximum likelihood pixel classification for five Landsat image dates of seven bands plus NDVI and 15 MODIS 16-day composite NDVI followed by per-polygon majority rule reclassification.

	Remote sensing classification†																	
Ground-truth field category†	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Producer's accuracy (%)	Omission errors (%)
1	**13 029**	49	0	719	12	547	214	0	0	24	1873	0	184	0	0	55	77.1	22.9
2	201	**15 557**	0	62	156	9	45	0	0	0	876	11	1	0	0	0	93.1	6.9
3	496	0	**6733**	152	9	1807	2	0	0	0	0	0	69	0	0	0	72.6	27.4
4	4399	200	23	**48 385**	0	3672	96	0	60	1	2354	1120	0	0	5	0	80.2	19.8
5	65	35	0	0	**8039**	190	6	0	0	0	430	0	0	0	2	0	91.7	8.3
6	2493	736	94	1566	186	**55 205**	509	2	45	9	1969	52	100	1	6	0	87.7	12.3
7	407	35	2	318	29	248	**8652**	5	0	627	255	0	1	0	0	0	81.8	18.2
8	10	1	0	19	0	245	11	**4665**	0	0	1	9	0	34	0	0	93.4	6.6
9	0	0	0	0	0	0	0	0	**1357**	0	0	0	0	0	0	0	100.0	0.0
10	264	0	0	56	0	13	146	0	0	**2185**	2	0	0	0	0	0	82.0	18.0
11	2319	16 254	269	1126	51	650	319	1	0	0	**78 491**	69	10	29	26	42	78.8	21.2
12	260	0	55	553	93	31	106	159	0	0	1196	**5669**	0	0	46	0	69.4	30.6
13	161	0	0	0	0	1656	0	0	0	7	44	100	**5860**	0	0	0	74.9	25.1
14	223	0	0	36	5	78	166	0	0	0	5	0	0	**6465**	0	0	92.6	7.4
15	157	0	0	757	0	367	23	0	0	0	19	0	0	0	**3926**	0	74.8	25.2
16	2	0	0	45	0	0	0	0	0	0	0	0	0	0	0	**4338**	98.9	1.1
User's accuracy (%)	53.2	47.3	93.8	89.9	93.7	85.3	84.0	96.5	92.8	76.6	89.7	80.6	94.1	99.0	97.9	97.8	82.2	17.8
Commission errors (%)	46.8	52.7	6.2	10.1	6.3	14.7	16.0	3.5	7.2	23.4	10.3	19.4	5.9	1.0	2.1	2.2	17.8	
																	$\kappa = 0.787$‡	

†Ground-truth and remote sensing classification categories were as follows: 1 – Bare/disturbed ground in crops other than fall plantings of Italian ryegrass, perennial ryegrass, tall fescue and clover spp.; 2 – Full straw volunteer Italian ryegrass; 3 – Spring plantings of any grass seed crop; 4 – Established perennial ryegrass; 5 – Established orchardgrass; 6 – Established tall fescue; 7 – Mixed grass spp. pasture; 8 – Established clover spp.; 9 – Established mint; 10 – Mixed grass spp. hay crop; 11 – Bare/disturbed ground fall planted to Italian ryegrass; 12 – Bare/disturbed ground fall planted to perennial ryegrass; 13 – Bare/disturbed ground fall planted to tall fescue; 14 – Bare/disturbed ground fall planted to clover spp.; 15 – Cereal crops, primarily winter wheat; 16 – Meadowfoam.
‡Tabular data calculated for training set derived from random half of all field polygons. Overall accuracy and Kappa for test validation set derived from the other half of all field polygons were 72.8% and 0.671.

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Table 8. Per-pixel classification error matrix for 16 categories of agricultural practices in western Oregon in the 2006–2007 growing season, using maximum likelihood pixel classification for nine Landsat image dates of seven bands plus NDVI and 17 MODIS 16-day composite NDVI followed by per-polygon majority rule reclassification.

	Remote sensing classification†																	
Ground-truth field category†	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Producer's accuracy (%)	Omission errors (%)
1	**25 110**	9	75	585	41	796	317	2	0	4	799	170	0	0	101	143	89.2	10.8
2	88	**18 108**	15	2	0	106	74	1	0	0	2538	0	2	0	0	189	85.7	14.3
3	186	120	**11 079**	14	11	1927	57	2	0	0	319	213	0	0	1	4	79.5	20.5
4	1966	526	350	**33 161**	6	1262	90	4	0	0	441	1037	0	0	77	542	84.0	16.0
5	11	396	0	0	**7385**	619	24	0	0	0	434	84	0	0	1	0	82.5	17.5
6	2025	1	1098	333	308	**67 485**	799	58	0	164	1988	146	1	0	40	3	90.6	9.4
7	272	155	11	41	0	342	**12 991**	0	0	155	175	18	0	6	3	0	91.7	8.3
8	191	0	1	4	0	986	26	**7638**	0	0	83	38	0	221	1	0	83.1	16.9
9	0	0	0	0	0	0	5	0	**1156**	0	0	0	0	0	0	0	99.6	0.4
10	37	4	0	7	0	202	279	0	0	**2982**	5	0	0	0	1	1	84.8	15.2
11	2664	677	62	336	188	792	518	416	0	78	**91 616**	204	0	13	89	271	93.6	6.4
12	477	0	0	1375	0	254	14	1	0	0	242	**12 764**	0	7	30	0	84.2	15.8
13	326	0	0	0	0	0	0	0	0	5	0	0	**1631**	0	1	0	83.1	16.9
14	38	0	113	31	0	0	1	161	0	0	3	0	0	**4644**	0	0	93.0	7.0
15	345	93	0	175	0	2	3	0	0	0	68	0	0	20	**7566**	0	91.5	8.5
16	103	0	145	0	4	67	141	0	0	0	0	0	0	0	0	**4734**	91.1	8.9
User's accuracy (%)	74.2	90.1	85.6	92.0	93.0	90.2	84.7	92.2	100.0	88.0	92.8	87.0	99.8	94.6	95.6	80.4	89.2	10.8
Commission errors (%)	25.8	9.9	14.4	8.0	7.0	9.8	15.3	7.8	0.0	12.0	7.2	13.0	0.2	5.4	4.4	19.6	10.8	
																	$\kappa = 0.872$‡	

†Ground-truth and remote sensing classification categories were as follows: 1 – Bare/disturbed ground in crops other than fall plantings of Italian ryegrass, perennial ryegrass, tall fescue and clover spp.; 2 – Full straw volunteer Italian ryegrass; 3 – Spring plantings of any grass seed crop; 4 – Established perennial ryegrass; 5 – Established orchardgrass; 6 – Established tall fescue; 7 – Mixed grass spp. pasture; 8 – Established clover spp.; 9 – Established mint; 10 – Mixed grass spp. hay crop; 11 – Bare/disturbed ground fall planted to Italian ryegrass; 12 – Bare/disturbed ground fall planted to perennial ryegrass; 13 – Bare/disturbed ground fall planted to tall fescue; 14 – Bare/disturbed ground fall planted to clover spp.; 15 – Cereal crops, primarily winter wheat; 16 – Meadowfoam.

‡Tabular data calculated for training set derived from random half of all field polygons. Overall accuracy and Kappa for test validation set derived from the other half of all field polygons were 76.4% and 0.717.

was mixed-grass pasture. This practice was identified at producer accuracies of 87.6, 81.8 and 91.7%, with user accuracies of 86.0, 84.0 and 84.7%. The eighth most common practice, occurring on an average of 2.8% of the field area, was spring planting of a variety of grass species, primarily tall fescue, orchardgrass, or perennial ryegrass. This practice was identified at producer accuracies of 93.6, 72.6 and 79.5%, with user accuracies of 73.2, 93.8 and 85.6%. The higher user than producer accuracy in two out of three years for this classification category suggests that fields classified as spring grass seed plantings usually were correct, and that many spring plantings were mistaken for other categories, especially established tall fescue. The ninth most common practice was cereal production, mainly fall-planted winter wheat, occurring on an average of 2.5% of the field area. This practice was identified at producer accuracies of 79.3, 74.8 and 91.5%, with user accuracies of 86.2, 97.9 and 95.6%. The higher user than producer accuracy suggests that winter wheat classifications usually truly were winter wheat, while many real wheat fields were mistaken for other categories such as established perennial ryegrass and bare/disturbed ground planted to Italian ryegrass. The tenth most common practice was established orchardgrass grown for seed, occurring on an average of 2.5% of the field area. This practice was identified at producer accuracies of 87.4, 91.7 and 82.5%, with user accuracies of 94.8, 93.7 and 93.0%. Producer and user accuracy for identifying established orchardgrass were generally higher than those for perennial ryegrass and tall fescue, with exception of producer accuracy the third year.

The remaining six classification categories only occurred on an average total of 6.5% of the field area. Among these remaining categories, established clover, established mint, bare/disturbed ground planted to clover, and meadowfoam were most reliably identified, with producer and user accuracies averaging 95.5% over all three years (tables 6–8). Mixed grass hay crop was identified at average producer and user accuracies of 87.7 and 83.8% over the three years. Mixed grass hay crop was most often mistaken for mixed grass pasture, although it was also often misclassified as bare/disturbed ground planted to other crops (second year) and as established orchardgrass (third year). Bare or disturbed ground fall planted to tall fescue had greater user than producer accuracy in all years, with producer accuracy averaging 77.9% and user accuracy averaging 95.4%. Bare or disturbed ground fall planted to tall fescue was most commonly mistaken for established tall fescue (first and second years) and bare/disturbed ground planted to other crops (third year).

Because majority rule test validation accuracy averaged 12.0, 9.4 and 12.8% lower than training set accuracy over the three years (tables 1–3), we compared error classification matrices for the training sets (tables 6–8) with those for the test validation sets to identify the main sources of decreased accuracy in test validation. Not unexpectedly, most increases in classification error going from training to test validation sets involved the most highly similar pairs of cropping practices. In all but a few cases, most of the additional classification errors during test validation occurred in one direction only from ground-truth class N to remote sensing class M within individual years, and not in the reciprocal direction from ground-truth class M to remote sensing class N. It was common, however, for the direction of the misclassification to switch among years. The most common error was confusion between the two Italian ryegrass production methods, classes 2 and 11. The second most common error was confusion between classes 4 and 12, established perennial ryegrass and fall plantings of new perennial ryegrass on bare or disturbed ground. Five of the next seven most common errors paired class 1 (bare or disturbed ground planted to other

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unidentified crops) with either bare or disturbed ground fall planted to perennial ryegrass, tall fescue, or clover (classes 12, 13 or 14), established perennial ryegrass (class 4), or wheat and other cereals (class 15). The fourth most common error was confusion between classes 4 and 6, established perennial ryegrass and established tall fescue. While average members of classes 4 and 6 differ substantially in their late-summer regrowth patterns, the most vigorous perennial ryegrass stands (e.g. fields of the variety 'Linn perennial') and the least vigorous tall fescue stands can be hard to distinguish even when standing in the fields. The final commonly occurring error was misclassification of ground-truth class 10 (mixed grass haycrop) as remote sensing class 7 (mixed grass pasture). Given that the ground-truth distinction between these two categories was often only the presence or absence of fences and livestock, small increases in this particular classification error going from training sets to test validation sets are not a source of concern. Out of 240 possible misclassifications each year between 16 ground-truth classes and 16 remote sensing classes, the nine most common errors involving pairs of hard-to-distinguish classes (present in an average of 10 cases each year, eight one-way cases and one two-way reciprocal case) represented an average of 48.6% of all increased errors in test validation over training set areas. The remaining 51.4% of the increased errors in test validation versus training areas comprised matches between pairs of ground-truth and remote sensing classes that stood out as unusually large only once in the three years.

When classification categories were regrouped into the nine that involved field disturbance (classes 1–3 and 11–16) and the seven that represented continuation of established perennial crop stands (classes 4–10), overall training set accuracy for the division into disturbed versus non-disturbed conservation condition was 93.8, 92.2 and 93.9% in the three years, while validation accuracy was 89.9, 88.3 and 88.3%. Disturbed ground was classified at an average producer accuracy of 93.3% whereas producer accuracy for maintenance of established perennial crop stands was 88.5%. Given that the yearly cropping cycle of established perennial grass seed stands often involves post-harvest removal of straw followed by a period of late summer moisture-stress induced dormancy with little or no crop regrowth, the most dormant established perennial crops and the least physically disturbed fallow ground or newly planted perennial crops will inherently be hard to distinguish. Over 63% of the remote sensing classification errors in distinguishing between conservation and non-conservation field condition involved misclassifying established perennial stands as fields undergoing disturbance. Because misclassification in the other direction only occurred on 6.7% of the truly disturbed field area (or 4.0% of total field area), we are confident that our agricultural field conservation status rasters accurately represent potential sources of nitrate and sediment across the landscape for use in ongoing analyses of the impact of soil disturbance on water quality and indicator species biology (figure 1).

We also tested the accuracy with which multi-year versions ground-truth and remote sensing classification of conservation versus disturbed field condition agreed. Pooling 3 by 3 neighbourhood edged training and validation sets together, 3-year conservation status for remote sensing and ground-truth data agreed in 83.2% of all cases. Within individual years, pooled accuracy was 92.6, 91.8 and 92.1%. Because the 3-year pooled accuracy was higher than the product of the accuracies in the three separate years (78.3%), classification errors of conservation versus disturbed field condition within individual years were not fully independent. In other words, conservation classification accuracy over the full 3-year period behaved as if average

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accuracy within individual years was 94.0% rather than the observed 92.2%, with the difference representing fields with relatively consistent disagreement between ground-truth and remote sensing classification conservation status across multiple years. The possibility that consistent disagreement in conservation status in some of these fields is indicative of errors in ground-truth data rather than remote sensing classification will be examined in future research.

4.5 *Similarity to Extension Service county-wide crop production estimate*

An independent method for assessing accuracy compared county-wide production area totals for grass seed crops published by Oregon State University Extension Service with results from our remote sensing classification procedures. Totalled over all crops and counties, our remote sensing classification after majority-rule object-based classification of pixels adjusted for inconsistent year-to-year transitions was lower than Extension Service estimates by 3.9, 5.4 and 1.8% in the first, second and third years (table 9). Most of the underestimation (93%) occurred in Linn County, the area of greatest concentration of grass seed fields. When totalled over all counties and averaged over all years, remote sensing appeared to overestimate Italian ryegrass by 8.4% and underestimate perennial ryegrass, orchardgrass and tall fescue by 10.4, 3.3 and 2.1%, respectively. Given methodological issues with the Extension Service crop production estimates and production adjustments in response to grass seed inventory carryover, it is likely that not all discrepancies between remote sensing classifications and Extension Service estimates represent errors in the remote sensing classification. Collection of several more years of census and survey data on agricultural production practices in western Oregon will permit future remote sensing classifications to better differentiate between Italian ryegrass and other crops using the assumption that growers are unlikely to switch back and forth between Italian ryegrass and other grass seed crops due to the difficulty in controlling Italian ryegrass as a weed.

5. Discussion

Success in remote sensing classification was clearly impacted by availability of useful data covering the entire growing season. Classification accuracy in the first year exceeded that in the second year by 6–7%, likely a consequence of having one more Landsat image to use in the first year. Although gaps in Landsat 7 data due to SLC failure complicated classification procedures, inclusion of data from May and June of 2007 were critical to achieving higher classification accuracy that year. Without those data, accuracy during the third year would have been lower than either of the previous years. Images in May and June provided data for the critical spring growth period during which crops differentiate in morphology, leaf colour and maturity. Despite coarser spatial resolution, time-series MODIS data were at least as useful in classifying western Oregon grass seed crops as multi-band data from the single best Landsat image acquisition date in any year.

Both object-based classification methods increased overall classification accuracy. Majority-rule reclassification methods are well known, and improve classification accuracy by eliminating rare classes inside of objects defined by independent vector data (such as the CLU layer) or other means. Year-to-year consistency tests we implemented require a minimum of three consecutive years of data, but can be imposed on either pixels, majority-rule polygons, or pixels first followed by majority-rule

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Table 9. Crop type area totals by county as reported by Oregon State University Extension Service and as identified by remote sensing classification procedures in the 2004–2005, 2005–2006 and 2006–2007 growing seasons.

	Area (ha)						
	Crop type						
County, crop year, and method	Italian ryegrass	Perennial ryegrass	Orchardgrass	Tall fescue	All other grass seed crops	Spring plant new grass seed	Total for all grass seed crops
Benton – 2004–2005 – Extension Service	4775	3642	1457	4047	263	–	14 184
Benton – 2004–2005 – remote sensing	3306	3364	2167	4225	–	6	13 068
Benton – 2005–2006 – Extension Service	5059	3318	1416	4249	263	–	14 306
Benton – 2005–2006 – remote sensing	3816	2952	1957	4104	–	302	13 130
Benton – 2006–2007 – Extension Service	5261	3035	1376	4504	263	–	14 439
Benton – 2006–2007 – remote sensing	5458	1283	1674	4273	–	703	13 391
Clackamas – 2004–2005 – Extension Service	0	1942	0	1133	405	–	3480
Clackamas – 2004–2005 – remote sensing	69	2717	22	704	–	16	3528
Clackamas – 2005–2006 – Extension Service	0	1942	0	1214	437	–	3594
Clackamas – 2005–2006 – remote sensing	125	2700	24	1505	–	37	4392
Clackamas – 2006–2007 – Extension Service	0	1740	0	1295	502	–	3537
Clackamas – 2006–2007 – remote sensing	0	2794	3	1082	–	289	4167
Lane – 2004–2005 – Extension Service	4006	3594	486	3339	202	–	11 627
Lane – 2004–2005 – remote sensing	8409	1881	706	3418	–	0	14 413
Lane – 2005–2006 – Extension Service	4087	3379	445	3521	182	–	11 614
Lane – 2005–2006 – remote sensing	7302	987	819	4006	–	106	13 220

(*Continued*)

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Table 9. (*Continued.*)

County, crop year, and method	Area (ha)						
	Crop type						
	Italian ryegrass	Perennial ryegrass	Orchardgrass	Tall fescue	All other grass seed crops	Spring plant new grass seed	Total for all grass seed crops
Lane – 2006–2007 – Extension Service	4128	3136	437	3723	182	–	11 606
Lane – 2006–2007 – remote sensing	8705	959	820	3462	–	475	14 420
Linn – 2004–2005 – Extension Service	36 948	25 374	1781	14 204	1716	–	80 023
Linn – 2004–2005 – remote sensing	40 291	16 526	1854	14 605	–	1056	74 332
Linn – 2005–2006 – Extension Service	37 393	22 986	1700	14 933	1538	–	78 549
Linn – 2005–2006 – remote sensing	40 732	12 408	1789	16 576	–	728	72 234
Linn – 2006–2007 – Extension Service	37 474	21 206	1683	15 075	1578	–	77 016
Linn – 2006–2007 – remote sensing	39 526	10 377	1545	15 494	–	3198	70 141
Marion – 2004–2005 – Extension Service	405	19 425	263	6070	4415	–	30 578
Marion – 2004–2005 – remote sensing	730	26 054	132	3597	–	142	30 655
Marion – 2005–2006 – Extension Service	1214	19 020	243	6475	5322	–	32 274
Marion – 2005–2006 – remote sensing	1453	22 590	104	5518	–	335	30 002
Marion – 2006–2007 – Extension Service	809	19 425	243	7284	6159	–	33 921
Marion – 2006–2007 – remote sensing	925	24 664	83	5248	–	1544	32 464
Polk – 2004–2005 – Extension Service	3399	8903	2145	10 360	0	–	24 807
Polk – 2004–2005 – remote sensing	1145	9323	1537	12 186	–	0	24 190
Polk – 2005–2006 – Extension Service	3966	6070	1902	11 331	121	–	23 391
Polk – 2005–2006 – remote sensing	2198	7115	1539	11 936	–	887	23 676
Polk – 2006–2007 – Extension Service	2833	5261	1781	11 129	0	–	21 003
Polk – 2006–2007 – remote sensing	2308	6454	1434	12 568	–	2127	24 891
Yamhill – 2004–2005 – Extension Service	1012	7972	728	10 724	0	–	20 437
Yamhill – 2004–2005 – remote sensing	102	7331	246	10 122	–	0	17 802
Yamhill – 2005–2006 – Extension Service	1214	7527	647	11 736	0	–	21 125

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Table 9. (*Continued.*)

County, crop year, and method	Area (ha)						
	Crop type						
	Italian ryegrass	Perennial ryegrass	Orchardgrass	Tall fescue	All other grass seed crops	Spring plant new grass seed	Total for all grass seed crops
Yamhill – 2005–2006 – remote sensing	675	6455	120	10 148	–	838	18 235
Yamhill – 2006–2007 – Extension Service	1012	6151	607	11 412	0	–	19 182
Yamhill – 2006–2007 – remote sensing	716	5874	134	9742	–	1551	18 017
Seven County Total – 2004–2005 – Extension Service†	50 545	70 852	6859	49 878	7001	–	185 136
Seven County Total – 2004–2005 – remote sensing†	54 052	67 196	6662	48 857	–	1221	177 989
Seven County Total – 2005–2006 – Extension Service†	52 933	64 244	6354	53 459	7863	–	184 852
Seven County Total – 2005–2006 – remote sensing†	56 302	55 208	6353	53 793	–	3233	174 889
Seven County Total – 2006–2007 – Extension Service†	51 516	59 954	6127	54 422	8685	–	180 704
Seven County Total – 2006–2007 – remote sensing†	57 639	52 404	5693	51 870	–	9886	177 493

†Washington County data excluded from Northwest District (western Oregon) totals because Landsat scenes only covered approximately 10% of county grass seed area.

polygons. Year-to-year consistency could be tested with our data because we included two or more categories for each perennial crop species, one representing production of previously established stands and another covering the stand establishment process. Large subsets of the 256 potential transitions between years for the 16 classes in each year were identified as being illogical, inconsistent with normal stand establishment procedures. Availability of two separate year-to-year transitions allowed us to tentatively identify the individual year most likely to have been misclassified. It will be possible to impose additional constraints on year-to-year transitions in cropping practices when data from fourth, fifth and sixth years becomes available.

While the proportion of agricultural field area in western Oregon employing conservation practices fluctuated slightly over time (50.6, 45.7 and 51.4% by remote sensing classification in first, second and third years), the turnover between conservation practices and the bare or disturbed ground condition associated with removing old stands, producing rotational crops, and establishing new grass seed stands was of interest. As measured by ground-truth training and test validation rasters, an average of 82.5% of the area in conservation practices in any year continued in conservation practice the next year, while the 17.4% did not. Commitment to conservation practices over all three years was only 0.9% higher than expected from multiplying the two separate year-to-year rates for remaining in conservation condition. As measured by remote sensing classification rasters covering only the area of the ground-truth data, an average of 81.1% of the area in conservation practices in one year continued in conservation practice the next year, while 18.9% did not. Commitment to conservation practices over all three years was 1.0% higher than expected from multiplying the two separate year-to-year rates. When remote sensing classification rasters were measured across the entire western Oregon agricultural field area, an average of 75.2% of the area in conservation practices in any year continued in conservation practice the next, while 24.8% did not. Commitment to conservation practices over all three years was 1.4% higher than expected from multiplying the two separate year-to-year rates. The lower values for conservation practices across the entire western Oregon agricultural field area relative to those estimated by ground-truth training and test validation fields is a consequence of the greater abundance of irrigated, summer annual crops in the northern sections of the Willamette Valley.

Because commitment to conservation practices over all three years differed only slightly from that expected as the product of continuity of conservation from 2005 to 2006 and 2006–2007, fraction of field area likely to be continuously in conservation condition over arbitrary periods of time can be reasonably well represented by simple power functions of the form in equations (2) and (3)

$$\text{Conservation (ground} - \text{truth fields only)} = 0.825^{Years} \tag{2}$$

$$\text{Conservation (entire remote sensing area)} = 0.752^{Years}. \tag{3}$$

Such functions imply that we can expect 90% of ground-truth fields to be disturbed by tillage, herbicides or fire within 12 years, and the same proportion of the entire agricultural landscape within 8 years. Less than one-half of all agricultural fields are likely to remain undisturbed for 3 years, and less than one-quarter for 5 years. While not as intensive as row-crop agriculture in the US corn belt, the moderate rate of stand turnover suggests that wildlife success within fields will be strongly dominated by field-to-field migration and ability to colonize newly available habitat.

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6. Conclusions

Crop production practices dominating agricultural landuse in western Oregon's Willamette Valley were successfully identified by remote sensing classification of combinations of 30-m Landsat and 250-m MODIS data. Limited availability of fully cloud-free Landsat scenes forced us to conduct multiple classifications within cloud-free and SLC failure gap-free areas of groups of rasters, and then merge the best available results into full-coverage composites. Classification accuracy was further improved by use of object-based methods, specifically majority-rule reclassification within field polygons and year-to-year consistency testing of cropping sequences. While our data agreed closely with independent estimates from the Cooperative Extension Service of grass seed production by crop totalled over counties, additional years of analysis should reduce classification errors and improve the tracking of crop history and management practices within individual fields. The ability to distinguish disturbed fields from those in which established perennial crops remain in production is of particular interest to the CEAP special grant project for the Calapooia River watershed that examines landscape-level effects of crop management practices, especially tillage, on water quality, indicator species biology, and ecosystem services.

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