ACCURACY COMPARISON OF TREE MAPPING METHODS IN EASTERN OREGON

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This accuracy assessment report is divided into two sections. The first compares the accuracies achieved by several methods in mapping canopy cover of tree-sized vegetation (of which western juniper is the most significant species in the project area). These methods could be used to produce maps allowing a wide variety of ecological and management alternative analyses. The second section compares the accuracies of map products that are currently available over the entire range of western juniper in Oregon, or could be feasibly produced during the near future (calendar year 2014). Because an additional map product is considered in the second analysis which is based on a thematic vegetation classification, that analysis treats only the relative success of the methods in mapping juniper presence and absence.

All accuracy estimates in both analyses are derived from comparison of the map products with reference data generated by Poznanovic (2013) and Poznanovic *et al.* (in press).

SECTION A. COMPARISON OF CANOPY COVER MAP PRODUCTS

1. SUMMARY

We compared the accuracies of seven alternatives for mapping canopy cover of tree-sized vegetation (7’ or greater height) in eastern Oregon. The only species achieving that height with significant presence in the assessment area is western juniper (*Juniperus occidentalis*). Two of the products—a new Nested Texture Mapping (NTM) tree cover map and the Integrated Landscape Assessment Project (ILAP) tree cover product—are at 30-meter resolution and are available across the range of the greater sage-grouse in Oregon. The five additional methods assessed—Spatial Wavelet Analysis (SWA), image segmentation and classification (SEG), ISODATA clustering, supervised Maximum Likelihood Classification (MLC), and a single-pixel Random Forests method (SPRF)—are meant to be run at fine resolutions (nominally 1-meter) and present greater logistical challenges over large project areas. Map accuracies were computed with reference to 498 50-meter diameter circular plots located in three distinct portions of eastern Oregon. The reference data (“ground truth”) were created by on-screen digitizing of juniper crowns for each of the plots, based on 0.5-meter resolution color-infrared aerial photography collected in 2009.

The NTM product achieved higher accuracies than all other methods in mapping tree canopy cover class; the differences were statistically significant at the 95% confidence level except for the comparison to the SEG product. It achieved this despite an inherent disadvantage to the 30-meter resolution products in the comparison, as the reference plots were not ideally sized for assessing 30-meter data. In addition, because all fine resolution products other than SWA were trained and tuned specifically on the test areas, they are less likely to provide repeatable results when extended to other areas without recalibration. Furthermore, all the fine resolution products (including SWA) were produced from the same 2009 imagery as the reference data, eliminating a wide range of potential confounding factors, including variation in air photo collection characteristics, crown/shadow confusion, change over time, and the possibility of spatial misregistration error. The NTM product, based on 2012 aerial photography and 2011 Landsat TM data, is susceptible to these factors, so the analysis gives a more realistic evaluation of its likely operational performance. The ILAP product used only 2006 TM data.

The apparent strong accuracy advantage of the NTM method, coupled with its repeatability and scalability to large mapping areas, argues for its adoption in applications—such as sage-grouse conservation efforts—for which the spatial distribution and density of western juniper are important considerations.

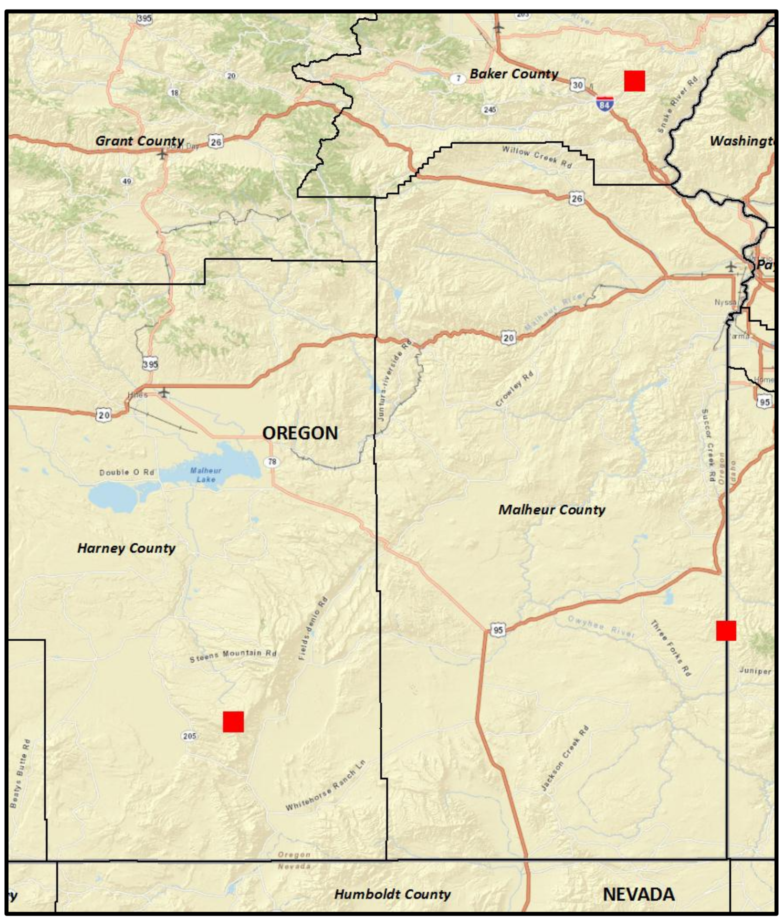

Figure 1. Red squares indicate the three test areas.

2. METHODS

2.1. Data Summarization

2.1.1. Study Area & Reference Data

Reference data were generated for 498 plots located in three distinct areas of eastern Oregon (Figure 1). A numeric tree canopy cover estimate was generated for each 50-meter diameter plot by digitizing tree crowns on 2009 0.5-m resolution color-infrared aerial photography. The plots were randomly sampled from strata defined by tree canopy cover estimates across the range of possible values. The plot selection and cover estimation procedures are detailed in Poznanovic (2013) and Poznanovic *et al.* (in press).

The plots were located in areas where few trees other than western juniper are found. However, we refer here to tree cover rather than juniper cover specifically because none of the methods tested distinguish between juniper and other tree species without additional post-processing (note that ILAP provides a juniper cover product in addition to a tree cover product, but its accuracy was found to be considerably lower than the tree cover product and it is omitted here, enabling a comparison on more equal footing with the other methods). In addition, none of the methods can reliably identify trees below some minimum size threshold (perhaps 2-3 square meters of horizontal crown area).

2.1.2. Fine Resolution Map Product Summaries

Numeric predictions of tree canopy cover for the fine resolution methods (SWA, SEG, ISODATA, MLC, and SPRF) were summarized by simply computing the fraction of the 1-meter pixels within each plot classified as tree crown (Poznanovic 2013).

2.1.3. Medium Resolution Map Product Summaries

Although the pixel predictions of the fine resolution map products could be unambiguously assigned as laying either inside or outside a particular reference plot, the medium resolution products overlapped the reference plots less cleanly (see Figure 3). Numeric predictions of tree canopy cover for the ILAP and unfiltered NTM products were summarized for the reference plots by averaging the 30-meter resolution predictions for the pixels intersecting each plot, linearly weighting each pixel's contribution by the proportion of the 50-meter diameter plot area intersected by it. The NTM product represents cover class thematically, and so before summarizing into the plots we first converted each pixel's predicted cover class to a quantitative cover, assumed to be the midpoint of the predicted cover class.

2.2. Accuracy Assessment

2.2.1. Exact Class-Based Assessment

All quantitative cover predictions, including the reference plot data and the seven map products, were binned into six classes corresponding to tree absence (class C0), presence at less than 4% cover (C1), 4 – 10% cover (C2), 10 – 20% cover (C3), 20 – 50% cover (C4), and over 50% cover (C5). Our choice of cover classes was guided by recent research suggesting that 4% juniper cover is a key threshold impacting sage-grouse reproductive success (Baruch-Mordo 2013) and by selecting other reasonable thresholds of canopy density corresponding to distinct management implications. The classes chosen are similar to those used by Falkowski and Evans (2012).

We assessed each method against the reference data via a confusion matrix, and calculated overall accuracy and class-specific user's and producer's accuracies. We followed the recommendation of Foody (2009) and used confidence intervals to test for significant differences in classification accuracy between the methods. For each proportion estimate (overall accuracy and class-specific user's and producer's accuracies) with $n \geq 20$, we calculated the 95% confidence interval of the estimate assuming normality. We included the continuity correction to allow approximation of the binomial distribution with the normal distribution. Thus the 95% CI for each proportion estimate p was calculated via:

$$p \pm \left(z_{\alpha/2}\,(SE) + \frac{1}{2n}\right) = p \pm \left(1.96\sqrt{\frac{p(1-p)}{n}} + \frac{1}{2n}\right)$$

Note that because we compared the accuracies of many methodologies, we did not calculate confidence intervals for each pairwise accuracy difference estimate, but simply assessed whether there was overlap of the confidence intervals for the accuracy estimates themselves. This is a conservative method for testing for accuracy differences among the methods.

2.2.2. Fuzzy Class-Based Assessment

To distinguish between minor and major mapping errors, the total accuracy, user's and producer's accuracies, and 95% confidence intervals for estimates were also calculated in a fuzzy context, in which one cover class to either side of the reference class was considered correct (e.g., for a plot with reference class C2, map answers of C1, C2, and C3 were treated as correct). The numerator of each accuracy measure calculated from the confusion matrix was modified accordingly. Confidence intervals were determined as before for the revised accuracy assessments.

2.2.3. Class Proportions Assessment

In addition to the confusion matrices, we made another assessment of prediction bias in each of the map products by accumulating histograms representing the abundance of each cover class across the test areas. The degree to which each method correctly estimated the cover class proportions and the shape of the cover class distribution in the reference data was assessed graphically.

3. RESULTS

3.1. Exact Class-Based Assessment

Tables 1 – 7 show the confusion matrices, overall, user's and producer's accuracies, and all 95% confidence intervals for each of the map products in the exact class-based assessment. The tables are presented in decreasing order of overall accuracy. The NTM product was found to have the highest overall accuracy, at 57.8%, followed by the SEG product at 53.8%. ISODATA and SWA had significantly lower (95% CI's non-overlapping) and similar overall accuracies. The ILAP tree product, SPRF, and MLC methods had substantially lower accuracies than the other methods.

The results among the fine resolution methods generally match the findings in Poznanovic (2013), who found SWA and SEG to have the highest accuracies, followed closely by ISODATA, with SPRF and finally MLC substantially lower. Here, the results differ somewhat due to the different canopy cover classes used. For instance, Poznanovic (2013) used classes composed of even 20% intervals of canopy cover and so did not compare the ability of the methods to distinguish differing amounts of cover below 20%. Also, only the northern three of the five study areas from Poznanovic (2013) are used here because the others fell outside the NTM and ILAP map extents.

Table 1. NTM map product confusion matrix, against reference cover classes.

- Mapped Class -		---------------------- Observed Class ----------------------									
Class	**Cover**	C0	C1	C2	C3	C4	C5	**Total**	**Correct**	**User Acc**	**95% CI**
C0	Absent	110	8					118	110	**93.2%**	88.3% - 98.2%
C1	< 4%	29	28	5	1			63	28	**44.4%**	31.4% - 57.5%
C2	4 - 10%	14	13	16	15	3	1	62	16	**25.8%**	14.1% - 37.5%
C3	10 - 20%	5	3	12	31	29	2	82	31	**37.8%**	26.7% - 48.9%
C4	20 - 50%	3	1	3	15	78	35	135	78	**57.8%**	49.1% - 66.5%
C5	>= 50%					13	25	38	25	**65.8%**	49.4% - 82.2%
	Total	161	53	36	62	123	63	**498**			
	Correct	110	28	16	31	78	25		**288**		
	Prod Acc	**68.3%**	**52.8%**	**44.4%**	**50.0%**	**63.4%**	**39.7%**	**Overall Acc =**		**57.8%**	**53.4% - 62.3%**
	95% CI	60.8% - 75.8%	38.4% - 67.2%	26.8% - 62.1%	36.7% - 63.3%	54.5% - 72.3%	26.8% - 52.6%				

Table 2. SEG map product confusion matrix, against reference cover classes.

- Mapped Class -		---------------------- Observed Class ----------------------									
Class	**Cover**	C0	C1	C2	C3	C4	C5	**Total**	**Correct**	**User Acc**	**95% CI**
C0	Absent	99	14	1				114	99	**86.8%**	80.2% - 93.5%
C1	< 4%	34	15	5	2	2		58	15	**25.9%**	13.7% - 38.0%
C2	4 - 10%	9	8	14	13	5	1	50	14	**28.0%**	14.6% - 41.4%
C3	10 - 20%	6	10	10	31	22	1	80	31	**38.8%**	27.4% - 50.1%
C4	20 - 50%	9	6	5	14	76	28	138	76	**55.1%**	46.4% - 63.7%
C5	>= 50%	4		1	2	18	33	58	33	**56.9%**	43.3% - 70.5%
	Total	161	53	36	62	123	63	**498**			
	Correct	99	15	14	31	76	33		**268**		
	Prod Acc	**61.5%**	**28.3%**	**38.9%**	**50.0%**	**61.8%**	**52.4%**	**Overall Acc =**		**53.8%**	**49.3% - 58.3%**
	95% CI	53.7% - 69.3%	15.2% - 41.4%	21.6% - 56.2%	36.7% - 63.3%	52.8% - 70.8%	39.3% - 65.5%				

Table 3. ISODATA map product confusion matrix, against reference cover classes.

- Mapped Class -		---------------------- Observed Class ----------------------									
Class	**Cover**	C0	C1	C2	C3	C4	C5	**Total**	**Correct**	**User Acc**	**95% CI**
C0	Absent	49						49	49	**100.0%**	99.0% - 100.0%
C1	< 4%	60	29	6	2			97	29	**29.9%**	20.3% - 39.5%
C2	4 - 10%	15	7	9	11	5		47	9	**19.1%**	6.8% - 31.5%
C3	10 - 20%	11	7	9	27	35	1	90	27	**30.0%**	20.0% - 40.0%
C4	20 - 50%	17	5	12	19	76	32	161	76	**47.2%**	39.2% - 55.2%
C5	>= 50%	9	5		3	7	30	54	30	**55.6%**	41.4% - 69.7%
	Total	161	53	36	62	123	63	**498**			
	Correct	49	29	9	27	76	30		**220**		
	Prod Acc	**30.4%**	**54.7%**	**25.0%**	**43.5%**	**61.8%**	**47.6%**	**Overall Acc =**		**44.2%**	**39.7% - 48.6%**
	95% CI	23.0% - 37.9%	40.4% - 69.1%	9.5% - 40.5%	30.4% - 56.7%	52.8% - 70.8%	34.5% - 60.7%				

Table 4. SWA map product confusion matrix, against reference cover classes.

- Mapped Class -		---------------------- Observed Class ----------------------									
Class	**Cover**	C0	C1	C2	C3	C4	C5	**Total**	**Correct**	**User Acc**	**95% CI**
C0	Absent	79	3			2		84	79	**94.0%**	88.4% - 99.7%
C1	< 4%	40	21	3	2		1	67	21	**31.3%**	19.5% - 43.2%
C2	4 - 10%	10	12	11	14	12		59	11	**18.6%**	7.9% - 29.4%
C3	10 - 20%	30	17	18	38	46	10	159	38	**23.9%**	17.0% - 30.8%
C4	20 - 50%	2		4	8	63	50	127	63	**49.6%**	40.5% - 58.7%
C5	>= 50%						2	2	2	**100.0%**	---
	Total	161	53	36	62	123	63	**498**			
	Correct	79	21	11	38	63	2		**214**		
	Prod Acc	**49.1%**	**39.6%**	**30.6%**	**61.3%**	**51.2%**	**3.2%**	**Overall Acc =**		**43.0%**	**38.5% - 47.4%**
	95% CI	41.0% - 57.1%	25.5% - 53.7%	14.1% - 47.0%	48.4% - 74.2%	42.0% - 60.5%	0.0% - 8.3%				

Table 5. ILAP tree cover map product confusion matrix, against reference cover classes.

- Mapped Class -		---------------------- Observed Class ----------------------									
Class	**Cover**	C0	C1	C2	C3	C4	C5	**Total**	**Correct**	**User Acc**	**95% CI**
C0	Absent	106	23	21	31	33	8	222	106	**47.7%**	41.0% - 54.5%
C1	< 4%	19	5	3	4	8	2	41	5	**12.2%**	1.0% - 23.4%
C2	4 - 10%	5	8	6	11	13	1	44	6	**13.6%**	2.4% - 24.9%
C3	10 - 20%	3	4	2	6	29	24	68	6	**8.8%**	1.3% - 16.3%
C4	20 - 50%	8	3	2	6	34	27	80	34	**42.5%**	31.0% - 54.0%
C5	>= 50%	1				2		3	0	**0.0%**	---
	Total	142	43	34	58	119	62	**458**			
	Correct	106	5	6	6	34	0		**157**		
	Prod Acc	**74.6%**	**11.6%**	**17.6%**	**10.3%**	**28.6%**	**0.0%**	**Overall Acc =**		**34.3%**	**29.8% - 38.7%**
	95% CI	67.1% - 82.2%	0.9% - 22.4%	3.4% - 31.9%	1.6% - 19.0%	20.0% - 37.1%	0.0% - 0.8%				

Table 6. SPRF map product confusion matrix, against reference cover classes.

- Mapped Class -		---------------------- Observed Class ----------------------									
Class	**Cover**	C0	C1	C2	C3	C4	C5	**Total**	**Correct**	**User Acc**	**95% CI**
C0	Absent	26						26	26	**100.0%**	98.1% - 100.0%
C1	< 4%	51	22	1	3			77	22	**28.6%**	17.8% - 39.3%
C2	4 - 10%	17	10	14	16	4		61	14	**23.0%**	11.6% - 34.3%
C3	10 - 20%	24	8	10	15	39	6	102	15	**14.7%**	7.3% - 22.1%
C4	20 - 50%	33	10	7	26	76	53	205	76	**37.1%**	30.2% - 43.9%
C5	>= 50%	10	3	4	2	4	4	27	4	**14.8%**	0.0% - 30.1%
	Total	161	53	36	62	123	63	**498**			
	Correct	26	22	14	15	76	4		**157**		
	Prod Acc	**16.1%**	**41.5%**	**38.9%**	**24.2%**	**61.8%**	**6.3%**	**Overall Acc =**		**31.5%**	**27.3% - 35.7%**
	95% CI	10.2% - 22.1%	27.3% - 55.7%	21.6% - 56.2%	12.7% - 35.7%	52.8% - 70.8%	0.0% - 13.2%				

Table 7. MLC map product confusion matrix, against reference cover classes.

- Mapped Class -		---------------------- Observed Class ----------------------									
Class	**Cover**	C0	C1	C2	C3	C4	C5	**Total**	**Correct**	**User Acc**	**95% CI**
C0	Absent	2						2	2	**100.0%**	---
C1	< 4%	24	11	1				36	11	**30.6%**	14.1% - 47.0%
C2	4 - 10%	23	9	5				37	5	**13.5%**	1.1% - 25.9%
C3	10 - 20%	29	6	6	10	11		62	10	**16.1%**	6.2% - 26.1%
C4	20 - 50%	32	11	9	20	58	18	148	58	**39.2%**	31.0% - 47.4%
C5	>= 50%	51	16	15	32	54	45	213	45	**21.1%**	15.4% - 26.8%
	Total	161	53	36	62	123	63	**498**			
	Correct	2	11	5	10	58	45		**131**		
	Prod Acc	**1.2%**	**20.8%**	**13.9%**	**16.1%**	**47.2%**	**71.4%**	**Overall Acc =**		**26.3%**	**22.3% - 30.3%**
	95% CI	0.0% - 3.3%	8.9% - 32.6%	1.2% - 26.6%	6.2% - 26.1%	37.9% - 56.4%	59.5% - 83.4%				

3.2. Fuzzy Class-Based Assessment

Table 8 gives the overall accuracies with 95% confidence intervals for each of the map products in the fuzzy class-based assessment. The NTM product's fuzzy accuracy of 92.8% was found to be significantly higher than that of all other methods. Again, the SEG product was found to be second best. The ILAP tree cover product performed relatively poorly in this test, with significantly lower accuracy than all methods other than the MLC method.

Table 8. Overall accuracy for all methods in the fuzzy class-based assessment, with 95% confidence interval.

Method	Fuzzy Overall Accuracy (95% CI)
NTM	92.8% (90.4% - 95.1%)
SEG	87.1% (84.1% - 90.2%)
SWA	81.9% (78.4% - 85.4%)
ISODATA	81.5% (78.0%-85.0%)
SPRF	73.7% (69.7% - 77.7%)
ILAP (tree cover)	62.7% (58.1% - 67.2%)
MLC	55.0% (50.6% - 59.5%)

3.3. Class Proportions Assessment

Figure 2 graphically illustrates the cover class proportions in the reference data and in three of the map products. All three of these methods generally approximate the reference cover class distribution, but NTM appears to come closest to matching its shape. Both ILAP tree cover and SWA greatly underestimate the frequency of C5 (over 50% juniper cover), while ILAP tree cover substantially overestimates the frequency of C0 (juniper absent). However, none of the methods are perfect. Only ILAP correctly finds C0 to be the most common class; NTM finds slightly more C4 (20-50% cover), and SWA finds C3 (10-20% cover) to be most abundant.

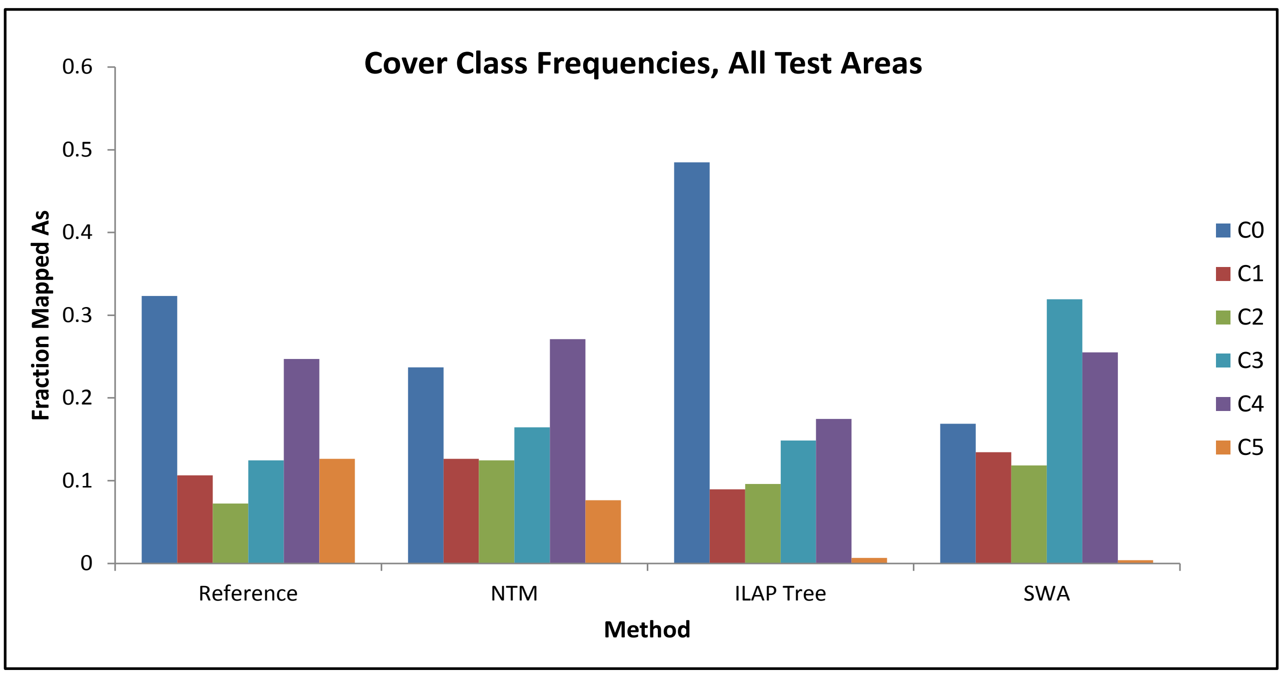

Figure 2. Cover class proportions across the test areas for the reference data compared to three of the map products.

4. DISCUSSION

The fine resolution mapping methods had several advantages in the accuracy comparison. All were produced from the same imagery used to create the test data, eliminating a wide range of potential confounding factors, including variation in air photo collection characteristics, crown/shadow confusion associated with collection time of day, change over time, and the possibility of spatial misregistration error. With the exception of the SWA product, all were built and tuned on the test areas themselves. It was possible to create precise spatial summaries of their outputs in the test plots, because the 1-meter pixels could be unambiguously associated with a particular plot.

The NTM and ILAP products were created for use over their entire extent and not specifically tuned to any particular subregions, and were based on imagery sources collected in other years (e.g., NTM was created from 2012 aerial photography and 2011 Landsat TM imagery). Because their 30-meter pixels were not much smaller than the test plots, substantial overlap occurred and pixels could not be unambiguously assigned as inside or outside the plot boundary (see Figure 3). Any method of summarizing these pixels into a plot either omits cover data predicted within the plot, or is influenced by cover predictions from outside the plot. Using a weighted average reduced this problem, but it remains a significant comparison disadvantage to the medium resolution methods. In addition, since the test areas are heterogeneous at a fine scale, minor spatial misregistration between the 30-meter pixels and the fine resolution reference data can result in apparent inaccuracies that are due only to spatial offsets.

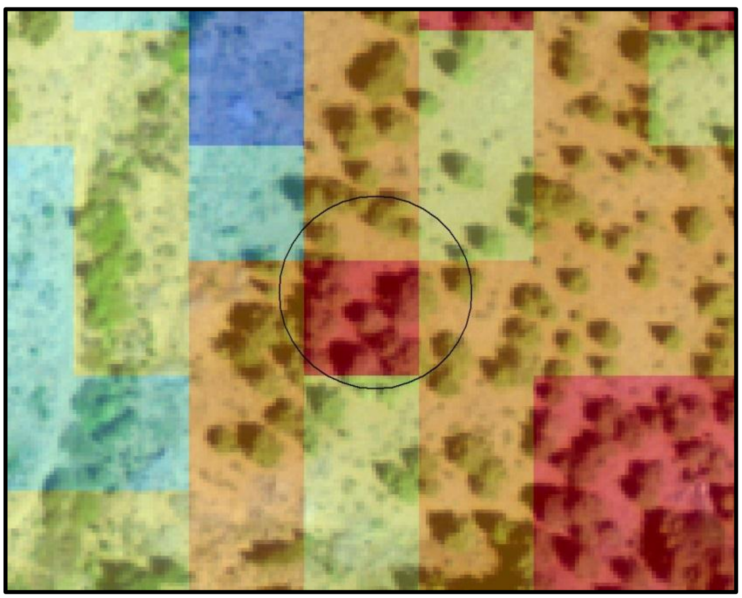

Figure 3. Irregular overlapping of 30-meter resolution predicted juniper cover pixels with 50-meter diameter plot.

Despite these disadvantages in the comparison, the NTM tree product achieved higher accuracies than all other methods in the tests performed here. Its accuracy advantages in mapping tree canopy cover class were statistically significant at the 95% confidence level except when compared to the SEG product. When assessed in a fuzzy context, in which minor mapping errors are discounted, its accuracy level was significantly higher than all other methods, including SEG. It also achieved a better balance of class mapping errors than the other methods, as evidenced by lower relative standard deviations of the user's and producer's accuracies.

The NTM method's performance is primarily due to its use of fine resolution texture information calculated at a range of spatial grain sizes based on image metrics in which juniper crowns are strongly set off from image backgrounds. It exploits much of the same image information as SWA, but in a more computationally efficient manner, because coarser scale texture information (corresponding to larger spatial wavelet window sizes) is computed from reduced resolution versions of the input imagery. A Random Forests predictive modeling approach is applied to a large collection of texture metrics and other image derivatives, allowing its use in a wide variety of mapping tasks parameterized by training data. It is scalable to large mapping areas because the fine resolution information is aggregated to coarser, more manageable resolutions prior to the predictive modeling process. Nielsen and Noone (2014) contains methodological details about the technique.

The SEG approach was found to be the second most accurate method. However, this technique requires developing complex rulesets and is overly subjective and not repeatable (Poznanovic 2013). The procedure is also not scalable to regional applications; segmentation over even small areas is a resource-intensive process. The most promising of the fine resolution methods is the SWA approach (Falkowski *et al.* 2006). Its ability to detect individual objects allows attribute prediction at the individual tree level (e.g., crown diameter, basal area) that no other method tested here can currently achieve, and it has reasonable accuracy levels and repeatability. However, Falkowski and Evans (2012) recommend other feature detection techniques as more computationally efficient methods for mapping juniper canopy cover. Those alternatives were not tested here.

The ILAP product performed relatively poorly compared to other methods in mapping canopy cover classes. The ILAP methodology was not designed for use at scales approximating the pixel resolution of its products, but rather was designed for summarizing over broader areas (Emilie Henderson, pers. comm.). Indeed, its performance at estimating land cover proportions is seen to be improved at those scales (Henderson *et al.* in press). The cover class proportions illustrated in Figure 2 bear this out, as the ILAP tree cover product is seen to generally approximate the patterns found in the reference data.

Table 9 contains a summary for each of the methods of the key accuracy metrics and additional information pertinent to producing broad scale consistent maps of juniper canopy cover. Maps of tree cover produced by all methods documented here must be post-processed if western juniper is to be separated from other tree species.

Table 9. Comparison of methods for mapping tree canopy cover, listed in order of decreasing exact class overall accuracy. Additional characteristics are given for each method that relate to its appropriateness for applying to very large mapping areas.

Method	Exact Overall Accuracy (95% CI)	Fuzzy Overall Accuracy (95% CI)	Res (m)	Repeatable?	Logistical Challenge
NTM	57.8% (53.4%-62.3%)	92.8% (90.4%-95.1%)	30	yes	reasonable
SEG	53.8% (49.3%-58.3%)	87.1% (84.1%-90.2%)	1	no	very difficult
ISODATA	44.2% (39.7%-48.6%)	81.5% (78.0%-85.0%)	1	no	difficult
SWA	43.0% (38.5%-47.4%)	81.9% (78.4%-85.4%)	1	yes	difficult
ILAP (tree cover)	34.3% (29.8%-38.7%)	62.7% (58.1%-67.2%)	30	yes	reasonable
SPRF	31.5% (27.3%-35.7%)	73.7% (69.7%-77.7%)	1	possibly	difficult
MLC	26.3% (22.3%-30.3%)	55.0% (50.6%-59.5%)	1	probably not	difficult

SECTION B. COMPARISON OF STATEWIDE PRESENCE/ABSENCE MAP PRODUCTS

1. SUMMARY

We compared the accuracy of three map products that are available over the entire range of western juniper in Oregon, or could be feasibly produced during the near future (calendar year 2014). NTM and ILAP, which can be used to map juniper cover class, were also considered in the analysis in section A. The additional product considered here is the Northwest Regional Gap Analysis Project (NWGAP). Both ILAP and NWGAP are available across the full range of western juniper in Oregon. NTM is currently available throughout the range of the greater sage-grouse in Oregon, and approximately 80% of the full range of western juniper in the state.

Because NWGAP is based on a thematic vegetation classification, it can only be used to map juniper presence and absence. Thus, this analysis only compares the relative abilities of these three products to map juniper presence. LANDFIRE represents another dataset that could be used to map juniper presence, but it was not evaluated here.

The map accuracies were compared using the same plot data described in section A. For mapping tree presence and absence, the NTM product performed significantly better than the ILAP and NWGAP products at all values of the canopy cover threshold value used to define presence. No statistically significant differences were found between the ILAP and NWGAP products, although in both cases the tree cover products had significantly higher accuracies than the juniper cover products. However, the tree products would first need to be restricted to juniper alone in order to compare their accuracies for mapping juniper. It is not clear which approach would be preferable based on this analysis.

2. METHODS

2.1. Data Summarization

The same study area and reference data were used as described in section A. Numeric predictions of tree canopy cover for the ILAP and NTM maps were summarized over the reference plots similarly. The NWGAP data, which mapped to a vegetation classification rather than making canopy cover estimates, were handled differently. The proportion of each 50-meter reference plot mapped as juniper was determined from the 30-meter pixels, using weighted averages proportional to each pixel’s overlap with the plot. Juniper was considered present on plots with mapped juniper proportions of 50% or higher.

Although NTM and the fine resolution products described in section A did not distinguish juniper cover from overall tree cover, both ILAP and NWGAP can be used to map either the presence of trees in general or of western juniper specifically. Although evaluating tree presence maps from these products allows a more equitable comparison with NTM, juniper presence is considered here also, as no additional post-processing would be required to convert these into juniper presence maps across the state. Thus, two summaries were done for the ILAP data, one based on the predicted juniper cover, and one based on total tree cover. Similarly, the NWGAP product was used to determine presence of juniper and of trees in general, corresponding to its mapped juniper classes and to all mapped forest and woodland classes, respectively.

2.2. Presence/Absence Accuracy Assessment

Five presence/absence maps were compared, based on the NTM product, the ILAP juniper and tree cover products, and the NWGAP juniper and forest and woodland class products. A range of different cover thresholds defining the boundary between presence and absence were applied to the reference plot data and to the numeric cover predictions of the NTM and ILAP products. At each threshold level, the NTM and ILAP products were compared to the two NWGAP-based products using a simple 2-class confusion matrix.

3. RESULTS AND DISCUSSION

3.1. Presence/Absence Assessment

Table 10 gives the accuracy in mapping juniper presence and absence for a range of thresholds of cover used to define "presence." The NWGAP juniper map reached its highest accuracy (69.9%) at a threshold of 21%. However, this may be too high a threshold for producing maps that would be very useful for management purposes. The results are shown here for a range of thresholds that would likely be useful for different applications.

Presence/absence from NTM was found to be significantly more accurate (non-overlapping 95% confidence intervals) than all other products at all levels of the presence threshold. The ILAP and NWGAP tree cover products were found to be significantly more accurate than either of the juniper cover products at all levels of the threshold. However, these products (like NTM) would require additional filtering to map juniper separately from other tree cover. Although the NWGAP products tended to have higher accuracies (especially for the tree cover product), the differences between the ILAP and NWGAP tree cover products or the ILAP and NWGAP juniper cover products did not rise to the level of statistical significance.

Table 10. Overall accuracy for five map products at predicting juniper presence and absence, at a variety of thresholds used to define presence.

	---------------OVERALL ACCURACY---------------				
Presence Threshold	**NTM**	**ILAP Tree**	**NWGAP Tree**	**ILAP Juniper**	**NWGAP Juniper**
0.1%	82.3%	65.5%	67.5%	52.2%	48.5%
0.2%	83.3%	64.6%	67.7%	50.9%	48.7%
0.5%	84.3%	65.7%	69.2%	51.5%	50.2%
1.0%	84.9%	65.1%	71.2%	50.9%	52.2%
2.0%	88.6%	67.2%	72.6%	54.4%	53.5%
4.0%	91.0%	69.0%	72.6%	54.8%	54.4%
10.0%	90.6%	70.7%	76.5%	57.6%	60.2%
20.0%	88.6%	69.9%	81.2%	60.9%	69.2%

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