Analyst Variability in Labeling of Unsupervised Classifications

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ABSTRACT: Analyst variability in the labeling of unsupervised classifications is tested for Landsat 5 Thematic Mapper image products covering two test sites in southern California. The accuracy of results are tested using samples from a photo interpreted base map of the area. The significance of differences between analysts is indicated by comparing Kappa statistics derived from error matrices. Analyst variability is found to be statistically significant in most cases. Certain analysts provided consistently better results for a given study area, with the degree of success not being predictably related to greater knowledge of the study area or degree of training. This work demonstrates the potential influence of analyst bias on what would otherwise seem to be a fairly objective method and suggests that controls for this subjectivity should be factored into experimental designs.

THIS REPORT EXAMINES THE IMPACT of analyst variability in the labeling of clustered data products on classification accuracy for two test sites in southern California. Analyst variability is shown to have consistent, significant effects on selected unsupervised classification strategies. Analyst variability may threaten the accuracy, objectivity, and extensibility of unsupervised classifications.

In this study Thematic Mapper image data are classified by three analysts using unsupervised techniques. Accuracy statistics are developed for each classification by comparison with random samples from photo interpreted base maps. Analyst variability in the labeling of spectral clusters is assessed using both percent correctly classified and Kappa statistics (Congalton and Mead, 1983).

This effort was completed as part of an ongoing research effort to examine the potential of new classification methods, focusing on the integration of remote sensing and GIS technologies. These results provide part of a baseline to describe the capabilities and characteristics of traditional methods.

STUDY SITES

The test sites for this study correspond to the U.S. Geological Survey (USGS) 7.5-minute Goleta and Lompoc quadrangles for Santa Barbara County, California. The locations of these two sites are presented in Figure 1. Topographic relief in the test sites is dominated by faulting associated with the California Transverse Range, which has a predominately east/west trend in this area. Vegetation is characteristic of the Mediterranean climate. Areas of higher moisture stress support chaparral communities (ceanothus/manzanita/scrub oak/chemise) with zeromorphic adaptations such as small leaves and waxy epidermal deposits. Grassland areas are dominated by annual herbs and forbs. Coast live oak (Quercus agrifolia) and valley oak (Quercus lobata) may range from sparse density in savanna like areas to relatively dense stands. Riparian zones may support closed canopies of willow (Salix sp.), sycamore (Platinus racemosa), and alder (Alnus rhombifolia).

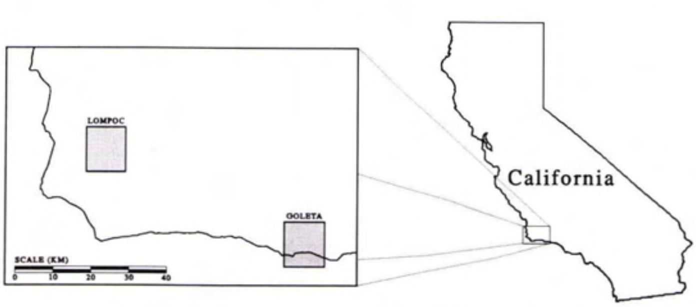

FIG. 1. Location of the Goleta and Lompoc quadrangles.

The Goleta quadrangle contains commercial, industrial, and residential areas intermixed with small agricultural plots and areas of natural vegetation. Orchards are found on the foothills. Upland areas are dominated by chaparral, broken by large outcrops of sandstone. In the Lompoc quadrangle, lowland areas are mostly under commercial, residential, light industrial, and agricultural development. Hill slopes contain both orchards and natural vegetation. Herbaceous and chaparral cover are common. Forested stands of Bishop pine (Pinus muricata) and Douglas Fir (Pseudotsuga menziesii) can be found in canyons of the northern portion of the quadrangle.

IMAGE DATA

Multispectral data were acquired for both study areas by the Landsat 5 Thematic Mapper (TM) sensor on 29 February 1989 and 9 September 1988. The TM thermal channel (10.4 to 12.5 μm) was not used in this study. Image data were registered to the projection and extent of the USGS quadrangles at a 30-metre resolution using a first-order polynomial and nearest neighbor resampling. All images were corrected for atmospheric path radiance in a manner similar to that described by Crippen (1989). In order to reduce data volumes, the southern boundary of the Goleta quadrangle was moved northwards to eliminate an area which is entirely ocean. Sufficient ocean area was preserved within the study site to ensure that classification accuracy for water bodies could be adequately estimated.

In order to test the data dependency of observed patterns, three image data products were used for each test site. These three images were

- TM bands 1, 2, 3, 4, 5, and 7 for the February acquisition;
- TM bands 1, 2, 3, 4, 5, and 7 for the September acquisition; and
- a composite image of original bands and spectral transformations of bands from both dates.

Band selection for the composite image was accomplished using discriminant analysis on all original channels, as well as tasseled cap, ratio, texture, and low pass filter transformations. The band selection method is described in detail in McGwire and Estes (1991). This composite image is included to identify whether additional information from temporal dynamics or spectral transformations may help standardize classification results. Those spectral variables which were used in the composite image for each test site are provided in Table 1.

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TABLE 1. SPECTRAL VARIABLES IN COMPOSITE IMAGES

GOLETA		LOMPOC	
September	NDVI	September	TM3
September	Greenness*	February	TM4
February	TM3	September	NDVI
February	TM4	February	TM7
February	TM5	February	NDVI
February	Wetness*	February	TM5
February	TM1	September	TM1
September	TM1	February	TM1
September	Brightness*	September	Brightness*
September	TM7	September	Texture TM7

* Tasseled Cap

TABLE 2. CLASSIFICATION SCHEME FOR TEST SITES

1) forest	tree cover > 60%
2) woodland/shrub	20% < tree cover < 60%
3) herbaceous	tree cover < 20%
4) wetland	
5) water	
6) barren	
7) agriculture	
8) urban/built up	

BASE MAP

In order to test classification results, land-cover maps were generated for the two quadrangles by photographic interpretation of 1:24,000-scale natural color aerial photography. Photography was acquired in September of 1989. Two trained photo interpreters developed the land-cover maps using magnification, stereo viewing, and extensive knowledge of the area being surveyed. The land-cover classification scheme used in this effort is outlined in Table 2. Vegetation classes in this classification scheme are derived from the U.S. Forest Service's vegetation classification system for Southern California. Interpreters were provided with transparent test patterns of density levels corresponding with the percent cover values used to delineate forest, woodland/shrub, and grassland categories. Prior to implementation of the actual mapping effort, the two interpreters each produced an acetate overlay for a specified test photo. The two independently derived products were examined in a meeting between interpreters to facilitate the standardization of mapping criteria. Subsequently, overlays were cross-checked between interpreters with line work and class membership requiring full agreement.

Linework was transferred to original USGS topographic quadrangle maps using Bausch and Lomb zoom transfer scopes. Some difficulty was encountered in enforcing geometric control in areas of significant relief. This situation was especially apparent in the northern portion of the Goleta quadrangle where steep slopes were combined with a lack of adequate reference points. Line work in these areas was transferred to the base map using the best possible procedures. Detail was digitized and cleaned using Arc/Info GIS software. Complete map coverages were then rasterized into a grid coinciding with the image data.

In order to reduce errors of misregistration between photo interpreted and digital data products, pixels on either side of class boundaries in the photo interpreted product were masked out. In addition, the resulting masked map was overlain on a color composite of original TM imagery and remaining misregistered areas were manually removed. The process of masking borders removed the majority of the "forest" and "bare" classes in the Goleta study area. In order to compensate for this, original polygons for these classes were restored and misregistered areas were removed manually. The deletion of border areas in this study reduces ambiguity in actual class membership but will also create a bias in the reported accuracy for map products. This bias will almost certainly make results appear somewhat better than they actually are.

Accuracy of the masked base map was tested by generating 150 randomly located points within the unmasked areas. Class membership for the sample locations was assigned based on majority membership within the single, chosen pixel. This approach allowed the generalizing effects of the 2-mm minimum mapping unit (MMU: approx. 1.5 pixels) used in map compilation to be directly assessed. A combination of detailed re-inspection of aerial photography and field inspection was used to determine actual land cover. Map accuracy derived in this manner for the two study sites is presented below. Confidence intervals are taken from Hord and Brooner (1976).

	Goleta	Lompoc
Estimated Accuracy	90%	97%
95% Confidence	84% - 94%	93% - 99%

The lower map accuracy for the Goleta area was due to two general types of confusion. Some pixels which were actually urban were mapped as forest, woodland/shrub, or grass. This confusion may easily be due to inclusions within land-cover polygons which were smaller than the MMU of compilation. Urban areas in the Lompoc study site were generally more compact and uniform so this effect would not be as strong. In addition, some pixels which were actually the woodland/shrub class were labeled as forest. The MMU problem may contribute to this confusion to some degree. However, it is likely that the confusion is primarily due to the difficulty of delineating a boundary between the woodland/shrub and forest classes on the continuous gradient of tree cover. This confusion was more likely to occur in the Goleta site where the woodland/shrub class is dominated by so-called "hard chaparral" species such as manzanita (Arctostaphylos sp.), scrub oak (Quercus dumosa), and Ceanothus sp. These woody species are larger and less distinct from the forest class than the soft chaparral species such as sage (Salvia spp.), buckwheat (Eriogonum Fasciculatum), and Artemisia californica which dominate the woodland/shrub class of the Lompoc site. Error in the Goleta photo interpreted land-cover map will affect the validity of interpretations drawn from error matrices. It will be assumed that the accuracy of the masked photo interpreted product is sufficiently higher than that of the digital classifications that the derived error statistics will be representative.

METHOD

The method used in this study tests the variability of unsupervised classifications generated by three analysts. All analysts were trained in photo interpretation and digital image processing, though analyst #3 had several years more experience with these techniques than analysts #1 and #2. Analysts #1 and #2 were most familiar with the specific distribution of land covers in both test sites through their experience in creating the air photo base maps. All analysts had lived in the Goleta test area for a number of years. Analyst #1 had lived in the region of the Lompoc test site for some time and performed the field inspection in that area for base map accuracy assessment. Analysts #2 and #3 had very limited field experience in the Lompoc area. Analyst #3's knowledge of the Lompoc site was primarily based on brief inspection of aerial photography.

Two unsupervised classification approaches were tested on each of the aforementioned image products. The unsupervised classification algorithm used in this study was the ISODATA algorithm of the ERDAS image processing software package. The

ISODATA algorithm generates a user specified number of clusters in one pass through the image data and then iteratively goes through the image, modifying cluster characteristics until results converge on stable cluster characteristics.

The two TM images and the composite image for each site were classified by the ISODATA algorithm with a user specified value of 50 clusters. These 50 clusters were then individually assigned into one of the land-cover classes in Table 2 and noted as to whether the cluster was relatively pure or mixed. Cluster labeling was accomplished by graphically superimposing the spatial distributions of pixels classified into a particular cluster over image data for the area. Analysts labeled each spectral class based on the majority of pixels falling into a particular land cover. In this first unsupervised classification approach, each of the analysts independently labeled identical clustered products.

A second clustering was performed by each analyst on each image to better subdivide clusters which had mixed membership. Those original spectral clusters indicated by an analyst to be relatively pure were masked from the image and remaining areas were reclassified using ISODATA. The logic of this approach is that a second iteration of the clustering algorithm may partition finer patterns in the variance of remaining data. The number of clusters specified for the second pass was set at 20. Clusters were labeled as described above, and classified data files for the two study areas were created containing acceptable classes from the first pass and relabeled areas from the second pass. Differences in analysts' choice of which clusters to reclassify resulted in different data products for labeling. It was unknown if this would increase analyst variability or whether convergence towards a maximum potential accuracy might decrease variability.

Accuracies of the various classifications were assessed relative to the photo interpreted base map developed for each study site. Land-cover classifications were analyzed using conventional matrices for predicted versus actual class membership at test locations. Two summary statistics—percent correctly classified (PCC) and the Kappa statistic (Congalton and Mead, 1983; Rosenfield and Fitzpatrick-Linz, 1986)—were generated from each matrix for comparing the performance of various methods and analysts. PCC provides an intuitive measure of classification accuracy. The Kappa statistic is a measure of overall agreement based on discrete multivariate analysis as described by Bishop *et al.* (1975). The Kappa statistic theoretically deflates accuracy statistics based on chance occurrence of correct classification. By using the approximate large sample variance, confidence intervals can be generated for the Kappa statistic. Given the asymptotic normality of the Kappa statistic, the significance of differences between classifications can be tested by using the normal curve deviate (Congalton and Mead, 1983; Congalton *et al.*, 1983), hereafter referred to as the Z value. The Kappa and associated Z statistics were generated by a program written by Congalton (1979).

Photo interpreted base maps for the two study areas were randomly sampled within unmasked areas for comparison with classification results. An exhaustive overlay of the data sets was not used because spatial autocorrelation and MMU affect proximate pixels, violating the requirement for sample independence (Congalton, 1988; McGwire *et al.*, 1992). In selecting a sampling frame, Congalton (1988) showed that random sampling may provide more efficient characterization of error than systematic sampling when there is spatial autocorrelation in classification errors. Over 7,000 samples were generated randomly for each of the two study areas. This large number allowed reasonable area weighted representation despite the great differences in area covered by each class. It is assumed in this study that the area of coverage for land-cover classes is approximately the same for the masked product as the original map. The area covered by water and wetland classes in the Lompoc study area was too small to allow for significant testing.

Modification of digital classifications was necessary in order to maintain agreement in scale with the MMU of the photo interpreted map. Prior to error analysis, digital classifications were transformed using majority filtering. This transformation reassigned pixel values based on the most prevalent class membership within a 3 by 3 moving window. In addition to reconciling the scale of digital processing to the MMU used in manual mapping, majority filtering has been found to increase classification accuracy by reducing "random" noise in classification results (Scarpace et al., 1981).

RESULTS

Summary statistics for error matrices derived from the various unsupervised approaches are presented in Table 3. Table 3 provides the percent correctly classified (PCC) and Kappa statistics for each image data product, unsupervised classification technique, and analyst. The significance of differences between various methods and analysts is provided using the aforementioned Z statistic (Congalton and Mead, 1983). Assuming the asymptotic relationship between Z and the standard normal deviate is valid, Z values greater than ± 1.96 should indicate significant differences at a 95 percent confidence level.

Differences in overall accuracy between the single- and two-stage unsupervised approaches were generally small for a given interpreter and image. Less than half of these differences were indicated as significant by the Z test statistic. Among the significant differences, results of the two-stage clustering are actually poorer than for the single-stage classification except for the September image of Lompoc. It is expected that this occurred as a result of specifying too few clusters for the second iteration. The abnormally low accuracy (59 percent) of the second clustering of February imagery for Lompoc by interpreter #1 is suspected to be the result of a data entry error rather than being entirely due to differences in analyst interpretation. Because of the generally poorer results of the two-stage method, the remaining analyses use only the first iteration clustering for comparison.

Significant and consistent differences were found between results of cluster labeling by the three analysts. Analyst #1 regularly produced maps with as much as 12 percent lower PCC than the other two analysts. Cluster labeling by analyst #3 consistently produced the highest accuracies for the Goleta study area while analyst #2 produced the most accurate maps for the Lompoc site. The only case where differences between analysts #2 and #3 were not significant was with the composite image for Goleta. The relative success of analysts was not predictably related to the relative degree of knowledge of the study areas, participation in photo base map generation, or years of experience in image processing and interpretive techniques.

Among the three images for each study area, the relative performance between classified products agreed for the two more successful interpreters. In Goleta, the September image provided the highest classification accuracy, followed by the composite and February images. The best result for the Lompoc site was obtained using the composite image, with the February and September images following in descending order. Relative accuracies among images for analyst #1 run counter to the two more successful analysts, with the order in Lompoc being directly reversed. In this case perception, or preconception, is as influential to classification accuracy as phenological changes or spectral transformations.

CONCLUSION

The labeling of unsupervised classifications by image overlay is not unambiguous. A number of factors may contribute to

TABLE 3. PCC, KAPPA, AND Z STATISTICS FOR UNSUPERVISED METHODS

Image	Analyst/ Iteration	PCC	Kappa	*Z statistic*				
				B	C	D	E	F
Goleta February	A	71%	0.623	−1.90	−9.86	−6.29	−12.28	−10.79
	B	72%	0.639		−7.87	−4.36	−10.24	−8.78
	C	78%	0.705			3.42	−2.29	−0.86
	D	76%	0.676				−5.72	−4.29
	E	79%	0.724					1.43
	F	78%	0.712					
Goleta September	A	75%	0.684	3.78	−10.55	−10.76	−14.09	−13.36
	B	73%	0.652		−14.35	−14.56	−17.91	−17.18
	C	82%	0.768			−0.20	−3.46	−2.73
	D	83%	0.769				−3.26	−2.53
	E	84%	0.793					0.74
	F	84%	0.788					
Goleta Composite	A	77%	0.705	5.50	−4.69	−4.69	−5.18	−3.75
	B	75%	0.659		−10.14	−10.14	−10.63	−9.20
	C	80%	0.743			0.00	−0.49	0.92
	D	80%	0.743				−0.49	0.92
	E	81%	0.747					1.41
	F	80%	0.736					
Lompoc February	A	77%	0.625	22.37	−13.36	−13.72	−10.57	−12.41
	B	59%	0.398		−37.07	−37.47	−34.15	−36.13
	C	86%	0.757			−0.37	2.88	1.00
	D	86%	0.761				3.25	1.38
	E	83%	0.730					−1.88
	F	84%	0.748					
Lompoc September	A	78%	0.656	−3.56	−8.97	−7.43	−1.99	−3.96
	B	82%	0.691		−5.32	−3.82	1.62	−0.34
	C	85%	0.743			1.47	7.06	5.06
	D	84%	0.729				5.51	3.54
	E	79%	0.675					−2.00
	F	80%	0.695					
Lompoc Composite	A	74%	0.607	3.46	−16.42	−16.42	−13.56	−5.33
	B	70%	0.572		−20.38	−20.38	−17.42	−8.96
	C	86%	0.767			0.00	2.84	11.18
	D	86%	0.767				2.84	11.18
	E	84%	0.741					8.31
	F	78%	0.661					

A) Analyst #1–1st cluster
B) Analyst #1–2nd cluster
C) Analyst #2–1st cluster
D) Analyst #2–2nd cluster
E) Analyst #3–1st cluster
F) Analyst #3–2nd cluster

variability in the perception of area covered by clusters in image overlays. Examples include

- analyst expectation of the appearance of land covers in images,
- relative contrast between graphic overlays and background images,
- location of clusters in the image area, and
- spatial texture or granularity in clusters.

The variability among analysts in this study was found to be systematic in some respects. However, the reader is cautioned that these results are derived from the limited sample of three images of two study sites. Results of this study suggest that

- simple reclassification of mixed clusters does not necessarily increase classification accuracy or provide more consistent results,
- performance of analysts may be consistently better or worse at a given location regardless of image data product selection,
- success among analysts with some level of training and site knowledge might not be predictably related to the degree of that experience, and
- those image products which provide the best results for one interpreter might not be the best for another.

Analyst variability, as demonstrated in this study, suggests that experimental designs using classified remotely sensed data should provide some control for this effect. Methods relying solely on human interpretation may be subject to unpredictable accuracy and bias. This may be of increased concern when the costs of misclassification varies among classes, compounding perception of area covered with variable prioritization. Aronoff (1984) describes a method to optimally label clusters, given user defined fields of known cover types and cost estimates for each class. However, care must also be exercised with Aronoff's method as it may be equally sensitive to analyst variability and bias if the placement of ground truth samples is not randomized.

Given that significant variability was found among analysts in labeling identical clustered data products, it may be safe to assume that the increased analyst dependence of supervised methods would result in at least a similar, if not greater, degree of variability.

In addition to assessing the influence of analyst variability on experimental design, it may be useful to incorporate an exercise which is similar to this study into educational programs. This would provide feedback to students which may increase awareness of an individual's perceptual biases in classification.

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