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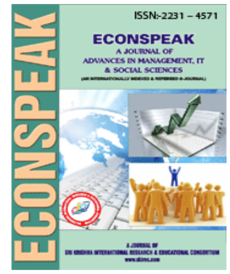

DISCRIMINATION OF VARIOUS SUGARCANE VARIETIES USING HYPERSPECTRAL DATA/ EO-1 HYPERION DATA

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ABSTRACT

In the remote sensing for precision agriculture applications, the utility of space-borne hyperspectral imaging for the development of vegetation-specific spectral library and automatic identification and classification of sugarcane varieties(COJ-64, CO-238, CO-1148, COH-119) have been studied. High spectral resolution data collected by the Hyperion/EO-1 instrument is converted into surface reflectance images and evaluated for the discrimination of five Indian sugarcane varieties.

Using an atmospherically corrected EO-1 Hyperion image acquired over Northern part of India, the utility of space-borne hyperspectral imaging for the development of a crop-specific spectral library and automatic identification and classification of five sugarcane varieties have been investigated in this study. The variety CO-1148 presented lower reflectance values, deeper lignin-cellulose absorption bands at 2103 nm and 2304 nm, shallower leaf liquid water absorption bands at 983 nm and 1205 nm, and lower leaf liquid water content than the other sugarcane varieties. To discriminate this di, a single near-infrared (NIR) band threshold was used. To discriminate the other four sugarcane varieties with similar reflectance values, MDA was used producing a classification accuracy of 89.5% for a hold-out set of pixels. The comparison between the ground truth data and the MDA-derived classification image confirmed the model capacity to differentiate the varieties accurately. The best results were obtained for the cultivar COH-119 that presented the lowest spectral variability in the discriminant space. Some misclassified areas were *associated with the cultivars CO-238 and CO-108 that showed the highest spectral variability.*

The comparison of ground truth data with the classification image confirmed the potential of the Hyperion data and of the proposed approach to differentiate sugarcane varieties in Northern India.

INTRODUCTION

India is the second largest world producer of sugarcane with more than 4.41 million hectares planted in the country (Sugarcane Technology Report, 2009). The state of Uttar Pardesh and Uttarakhand , located in north part of the country and responsible for 40% of the Indian production in 2008/2009 (Sugarcane Technology Report, 2009). In India, sugarcane is used to obtain sugar, anhydrous alcohol (gasoline additive) and hydrated alcohol (natural, clean and renewable pure fuel for vehicles) for the internal and external markets (Oliveira, 2002). Steam, derived from sugarcane burning biogas, is also employed to generate electrical power. To improve the efficiency of the Indian industry, new sugarcane varieties with higher yields are continuously developed and tested. An ideal sugarcane variety should be well adapted to local variations in climate, soil type and cutting system (manual or mechanized) or rationing (Badaloo et al.1999). It should be resistant to pests, diseases and water stress, and it should have high concentrations of sucrose in the storage tissue (Raizer & Vencovsky, 1999). Sugarcane farmers often replace old sugarcane varieties for newer varieties. Thus, the mapping of the sugarcane varieties is very important for yield prediction and crop damage risk assessment.

Remote sensing investigations in sugarcane plantations are usually related to classification and mapping (Tardin et al., 1992), crop managemen, and yield estimation . However, most of the remote sensing studies to discriminate varieties were performed with other crops (Daughtry & Walthall, 1998; Hansen & Schjoerring, 2003;). Hyperspectral instruments, such as the Hyperion (242 bands) on board the Earth Observing-1 (EO-1) spacecraft, allow the identification of vegetation absorption features that are not identified by multispectral sensors (Huete et al., 2003; Roberts et al., 2003). Furthermore, in relation to multispectral sensors, they provide an enhanced level of information for atmospheric correction (Datt et al., 2003). By collecting data from an orbital level, potential applications derived from the use of airborne imaging spectrometers can also be tested over a wide range of environmental conditions (Asner & Heidebrecht, 2003). Although there are several examples of the study of crops with different hyperspectral instruments (2003; Goel et al., 2003; Haboudane et al., 2002), only a few investigations are related to sugarcane plantations.

The objectives of this research were (1) development of cultivar based spectral library for different sugarcane varieties at growth phase using data from Hyperion image and in-situ hyperspectral measurements and (2) to test the potential of the developed spectral library for identification and classification of some important crop cultivars of sugarcane varieties in Uttarhkand state, India. Further, this study to provide a correlation of field based crop spectra to a set reference crop spectra collected from Hyperion data.

2. STUDY AREA

The study area "Village Sultanpur, district Haridwar" is located in Uttarkhand, India. The study area is lying between 29°45′32.72″E, 78°7′16.86″N and 29°44′54.47″E, 78°8′12.09″N with area of 11,9210 ha. Uttarkhand is an agrarian state. About 80% of the population of the state is dependent on agriculture for its livelihood. 60% of the available land is irrigated.

3. METHODOLOGY

3.1. HYPERION DATA

The data used in this study have been collected from Hyperion instrument on April 10,2005 at 05:09:24 GMT and other ancillary data like crop type, cultivar, date of sown/transplant, plant height, soil type etc. The Hyperion instrument on the Earth Observing-1 (EO-1) satellite of NASA records visible light and other reflected electromagnetic energy ranging from 0.4 to 2.5 mm in 220 channels that are 10-nm wide. Its spatial resolution of 30 m and the orbit of the satellite complement those of Landsat.(see in fig.1)

3.2. PRE-PROCESSING OF HYPERION DATA

The Hyperion image has been georeferenced with the help of Survey of India toposheets

(Scale 1: 250,000) and resampled to 30 m-pixel size using nearest neighbourhood method.The image processing has been done using ENVI +IDL 4.5 software. Since Hyperion operates from a space platform with consequently modest surface signal levels and full-column atmospheric effects, its data require careful processing. The striping has been minimized using the Fast Fourier Transform technique using ENVI image processing software. The destriped Hyperion image is subjected to further processing for standard atmospheric corrections using FLAASH atmospheric correction software module. All the pixels of Hyperion image belonging to non-vegetation, shrubs and grasses classes, which are not part of classes of interest in the present study, have been eliminated from the image by creating a mask using a threshold value of 0.23 for Normalized Difference Vegetation Index (NDVI) image generated from Hyperion

3.3 DATA ANALYSIS

Detailed ground information was provided by local sugarcane farmer and plotted over a geo-referenced image (nearest-neighbor resampling). The information included: sugarcane types, date of planting, cutting and soil type. The five type of sugarcane under study are: COJ-64, CO-238, CO-1148, CO-108, and COH-119. The spectral reflectance of the five types are determined by selecting 225 pixels (45 per variety) in the Hyperion image (table 1).

To discriminate varieties with similar reflectance values, multiple discriminant analysis (MDA), also termed canonical discriminant analysis, was applied over the data. This technique was selected in this study to deal simultaneously with three important needs: multigroup maximal separability, classification, and dimensionality reduction. This approach adopts a similar perspective to principal components analysis; that is, the rows of the data matrix constitute points in a multidimensional space. Based on linear combinations of the predictor variables, discriminating functions are determined in this space to obtain the best separation of the groups (Murtagh & Heck, 1987).

In the present study, the variables considered in the MDA approach included:

(a) the surface reflectance values of the following Hyperion bands: bands 10 (447 nm) to 57 (925 nm), 79 (932 nm) to 115 (1296 nm), 135 (1498 nm) to 163 (1780 nm), and 185 (2002 nm) to 224 (2395 nm), thus, excluding bands positioned around the strong atmospheric 524 L.S. Galva˜o et al. / Remote Sensing of Environment 94 (2005) 523–534 water vapor intervals at 1400 nm and 1900 nm;

(b) all ratios of reflectance between the selected bands; and

(c) a set of spectral indices or parameters potentially sensitive to changes in chlorophyll, leaf liquid water, and lignincellulose (Table 1). By performing band rationing, several other spectral indices reported in the literature and not listed in Table 1 were indirectly considered in the analysis such as the Pigment Specific Simple Ratio indices (PSSRa=q803 nm/ q681 nm; PSSRb=q803 nm/q630 nm; PSSRc=q803 nm/q467 nm) from Blackburn (1998). The Leaf Water Vegetation Indices (LWVI-1 and LWVI-2) were calculated from bands placedat the edge and centre of the 983 nm and 1205 nm liquid water spectral features, respectively. They were introduced in this study as variants of the Normalized Difference Water Index (NDWI) from Gao (1996).

To characterize variations in depth of the major absorption bands present in sugarcane spectra on a per pixel basis, the continuum removal method was applied to normalize the curves, to isolate the features, and to allow their comparison from a common baseline. Straight lines segments connecting the edges (wavelengths of reflectance maxima listed in Table 2) of the absorption bands centred at 671 nm (chlorophyll), 983 nm and 1205 nm (leaf liquid water), and 2103 nm and 2304 nm (lignin-cellulose) were used to define the continuum. A detailed description of the continuum removal method is given by Clark & Roush(1984).

To identify differences in the rate of change (slope) of the Hyperion sugarcane spectra, the first-order derivative curves were calculated in the transition from the red to the nearinfrared interval (691 nm to 763 nm). The Savitzky-Golay smoothing method, which provided a local polynomial regression around each point, was used in the derivative computation (Tsai & Philpot, 1998). A wavelength position equivalent to the maximum slope was used to represent the red edge inflection point, a potential indicator of changes in chlorophyll. The maximum derivative value was also selected as a potential variable for MDA. A stepwise method was applied to select the best variables among the surface reflectance values, ratios of reflectance and the spectral indices. The objective was to look for the optimum discriminant function to differentiate the varieties, thus trying to maximize the Mahalanobis distance for the two most similar groups. The probability of

F was used as a criterion to include (0.05) and to remove (0.10) variables in forward and backward steps.

4. RESULTS

4.1. SPECTRAL RESPONSE OF SUGARCANE VARIETIES

Fig. 1 shows a true color composite of the study area with the Hyperion bands centred at 671 nm (red), 569 nm (green) and 478 nm (blue). Fig. 2 shows a false color composite (bands at 1073 nm, 16448 nm and 2193 nm in red, green and blue colors, respectively) with an indication of the areas representative of the five sugarcane varieties under study. Sugarcane varieties appear in reddish colors. The discrimination of the variety CO-1148 (dark red color) from the other varieties (light red colors) is evident.

Fig. 3 shows the average Hyperion reflectance spectra of the five sugarcane varieties. As shown in fig.2 , the transition from the low (CO-1148) to the high reflectance (CO-108) varieties represents the change from CO-1148 to CO-108, or from erect to medium arch foliage.

In comparison with the other sugarcane varieties, CO-1148 presented also deeper lignin-cellulose absorption bands at 2103 nm and 2304 nm, shallower leaf liquid water absorption bands at 983 nm and 1205 nm, and lower values of ACORN-derived liquid water content. A negative relationship (r=_0.80) between LWVI-2 and the 2304 nm absorption band depth was observed in the present study. The transition from the variety CO-1148 to the cultivar CO-108 is characterized by an increase in the Leaf Water Vegetation Index values (LWVI-2) and by a decrease in the depth of the 2304 nm absorption band, both due to the larger amounts of non-photosynthetically-active constituents within the canopy viewed by the sensor in the CO-1148 variety. In comparison to the cultivar CO-108, the sugarcane variety CO-1148 showed shallower leaf liquid water absorption bands at 1205 nm and a lower rate of change in the red edge domain (r=+0.93), as expressed by lower first-order derivative values observed for CO-1148. The wavelength equivalent to the highest rate of change (average red edge position) for the cultivar CO-1148 is located at slightly shorter wavelengths (713F3.35 nm for CO-1148; 717F5.06 nm for CO-108).

Table 3 presents the average surface reflectance of the five sugarcane varieties under study for some Hyperion bands located in the blue, green, red, near-infrared (NIR) and shortwave infrared (SWIR) spectral intervals. To provide a better idea of the spectral variability and reflectance differences between the groups, standard deviation and confidence intervals for the means are indicated. The smallest standard deviation values were observed for the varieties CO-1148 and COH-119. On the other hand, the highest degree of variability was verified for the cultivars CO-108 and CO-238. Results of Table 3 confirmed the strong reflectance differences between the cultivar SP80-1842 and the other varieties, especially in the NIR interval.

In the present study, the influence of a single factor (e.g., sugarcane age, cutting or soil type) to explain differences in standard deviation values between the varieties (Table 3) was not observed. In general, such differences are the result of the combined influence of the agronomical characteristics of the sugarcane cultivars, which may include: canopy closure, degree of dead leaf retention, leaf width and size, erectness or canopy architecture, degree of lodging, and soil preference. Local water stress, pests and diseases may also be important factors.

4.2. DISCRIMINATION OF THE SUGARCANE VARIETIES

In Figs. 2 and 3, the variety CO-1148 is easily discriminated from the other four varieties due to its lower NIR reflectance response. Thus, the simplest way to perform such discrimination was to use a band threshold in the NIR interval (e.g., pixels with reflectance values lower than 30% at 864 nm; not shown). Furthermore, as previously mentioned, the CO-1148 presented deeper lignin-cellulose absorption bands at 2103 nm and 2304 nm, shallower leaf liquid water absorption bands at 983 nm and 1205 nm, and lower values of ACORN-derived leaf liquid water content than the other varieties.

Discrimination between the remaining four varieties (COJ-64, CO-238, CO-108, and CO-119) was much more difficult due to the similarity of their average reflectance spectra (Fig. 3). Such discrimination required the use of multiple or canonical discriminant analysis to enhance small spectral differences between the cultivars.

The predictive power of the reflectance values of the Hyperion bands, the ratios of reflectance, and of some spectral variables (Table 2) to discriminate the four sugarcane varieties, the reflectance values of the Hyperion bands were considered individually for the subsequent calculation of the average classification accuracy of the discriminant functions at different spectral intervals.

The best spectral intervals to discriminate the four Indian sugarcane varieties were: the SWIR-1 (1498–1780 nm), the NIR-2 (915–1296 nm), and the green (508–600 nm).

The best results (36–40% of correct classification of the pixels) were obtained with the following ratios of reflectance of the Hyperion bands: (a) SWIR-1/ green andSWIR-2/green ratios; (b) SWIR-1/NIR-1 and SWIR-1/NIR-2 ratios; and (c) NIR-2/NIR-1 and NIR-2/ NIR-2 ratios. The spectral indices that exhibited the best discriminatory power were associated with the leaf liquid water (LWVI-2 and depth of the 1205 nm and 983 nm absorption bands) and lignin-cellulose (depth of the 2304 nm absorption band) spectral features. Using a stepwise method, the following set of variables were selected to compose the final three-function canonical discriminant model: (a) the reflectance values of the Hyperion bands placed at 651 nm, 722 nm, 813 nm, 1084 nm, 1124 nm, 1649 nm, and 2002 nm; (b) the ratios of reflectance 2355/2052 nm, 1750/478 nm, 1750/569 nm, and 1255/478 nm; and (c) the depth of the absorption bands centred at 671 nm (chlorophyll), 983 nm (leaf liquid water), and at 2304 nm (lignin-cellulose); the NDWI, and the DSWI. This discriminant model was responsible for 86% of the correct classification of the pixels used to obtain the functions (training pixels). The first three canonical discriminant functions accounted for 55%, 30% and 15% of the data variance, respectively, as indicated by their eigenvalues (not shown). The functions presented canonical correlation values of 0.84, 0.75 and 0.63, respectively, which indicated the good discriminatory power of the model.

The first discriminant function is especially useful to differentiate the sugarcane varieties CJ-8486 and COJ-64 from the cultivars CO-1148 and CO-108 . On the other hand, the second canonical axis enhanced sugarcane separation of the varieties COJ-65 and CO-108 from the two other cultivars. Finally, the third canonical function enhanced the discrimination of the variety CJ-8486 from the remaining cultivars.

4.3. VALIDATION OF THE DISCRIMINATORY POWER OF THE CANONICAL FUNCTIONS

Table 4 shows the classification results derived from the three canonical discriminant functions for a hold-out set of 75 pixels (25 per variety). Overall a classification accuracy of 89.5% was reached, which demonstrated the good discriminatory power of the canonical functions to differentiate the four varieties. The three discriminant functions were able to classify 90% of the pixels correctly for the varieties COJ-64, CO-108 and COH-119, and 80% for the variety CO-238. The comparison between the ground truth data (and the MDA-derived classified image in the study area that contains most of the sugarcane plantations. The variety CO-1148, easily discriminated by an NIR band threshold at 864 nm, were also shown for reference. In general, the good performance of the canonical discriminant analysis to discriminate the four sugarcane varieties with strong similarity in reflectance values. The best results were obtained for the cultivars COH-119 and COJ-64. Most of the misclassified areas were associated with the varieties with high spectral variability in the discriminant space. Although most pixels of cultivar CO-238 were correctly classified, on three fields , a number of pixels were classified as COJ-64, CO-108, and COH-119 probably due to local variations in management practices. On one field of cultivar CO-108 , some pixels were erroneously classified as COH-119. In the study area, the varieties COH-119, CO-64, CO-238 and CO-108 presented correct pixel classification of 96%, 86%, 76% and 73%, respectively. In spite of the good results that demonstrate the applicability of the present approach, further study is necessary to confirm sugarcane variety discrimination under other environmental conditions.

4. CONCLUSONS

The five Indian sugarcane varieties under study were discriminated with EO-1 Hyperion data using reflectance values, ratios of reflectance and several spectral indices sensitive to changes in chlorophyll content, leaf water and lignin-cellulose. Differences in canopy architecture affected sunlight penetration and reflectance, resulting in a higher reflectance for CO-108 than CO-1148 plants. The cultivar CO-1148 is the most easily identified, presenting lower reflectance values, deeper lignin-cellulose absorption bands at 2103 nm and 2304 nm, shallower leaf liquid water absorption bands at 983 nm and 1205 nm, and lower leaf liquid water content than the other sugarcane varieties.

In the study area, the variety CO-1148 is discriminated by using a band threshold in the NIR interval. The remaining varieties with similar reflectance values were discriminated by using multiple discriminant analysis with: (a) the reflectance values of the Hyperion bands placed at 651 nm, 722 nm, 813 nm, 1084 nm, 1124 nm, 1649 nm, and 2002 nm; (b) the ratios of reflectance 2355/2052 nm, 1750/478 nm, 1750/569 nm, and 1255/478 nm; and (c) the depth of the absorption bands centred at 671 nm (chlorophyll), 983 nm (leaf liquid water), and at 2304 nm (lignincellulose); the NDWI, and the DSWI. The classification accuracy with a separate set of pixels reached a value of 89.5%, which demonstrated the good discriminatory power of the canonical functions to differentiate the sugarcane varieties with similar reflectance. The comparison of the ground truth data with the classification image derived from the discriminant analysis confirmed the good performance of the discriminatory model. The best results were obtained for the cultivar COH-119 that presented the lowest spectral variability in the discriminant space. On the other hand, some misclassified areas were associated with the cultivars CO-238 and CO-108 that presented the highest spectral variability. Further research must be carried out in other areas to confirm these results.

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Fig. 1:True color composite of the study area with the hyperion bands centred at 671 nm (red), 569 nm (green) and 478 nm (blue).

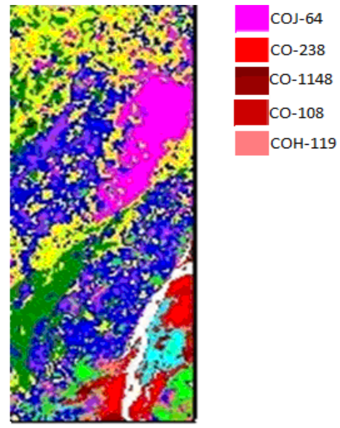

Fig. 2: False color composite with the bands centred at 864 nm, 1649 nm and 2204 nm in red, green and blue colors, respectively.

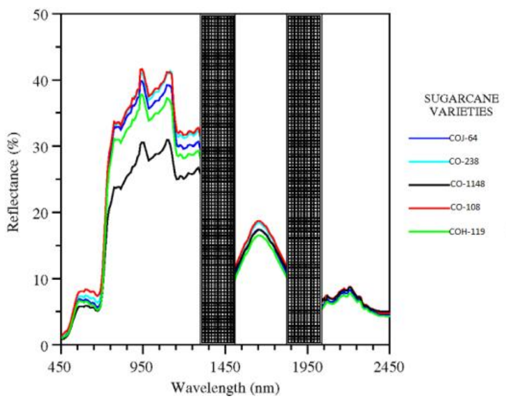

Fig. 3. Average Hyperion surface reflectance spectra of the five sugarcane varieties (45 pixels per variety) under study. The shaded columns around 1400 nm and 1900 nm indicate the two major atmospheric absorption intervals due to water vapor.

Table 1: Training Classes and testing pixels

S.NO.	Class Type	No. of pixelst Training Site
1.	**Sugarcane(COJ-64)**	45
2.	**Sugarcane(CO-238)**	45
3.	**Sugarcane(CO-1148)**	45
4.	**Sugarcane(CO-108)**	45
5.	**Sugarcane(COH-119)**	45

Table 2:Spectral indices used in this study

S. No.	Variables	Equation/method	Reference
1	Depth of the 671 nm absorption band (chlorophyll)	Continuum removal method (edges at 569 nm and 763 nm)	Clark & Roush (1984
2	Depth of the 983 nm and 1205 nm absorption bands (leaf liquid water)	Continuum removal method (edges at 933 nm and 1094 nm; 1094 nm and 1286 nm)	Clark & Roush (1984
3	Depth of the 2103 nm and 2304 nm absorption bands (lignin-cellulose)	Continuum removal method (edges at 2052 nm and 2214 nm; 2214 nm and 2385 nm)	Clark & Roush (1984
4	Disease Water Stress Index (DSWI)	$(q_{803nm}+q_{549nm})/(q_{1659nm}+q_{681nm})$	Apan et al. (2004)
5	First derivative and red edge position	Savitzky-Golay smoothing method (691 nm to 763 nm	Tsai & Philpot (1998)
6	Liquid water content	ACORN-derived method	Imspec (2001
7	Modified Chlorophyll Absorption in Reflectance Index (MCARI)	$[(q_{701nm}-q_{671nm})-0.2(q_{701nm}-q_{549nm})](q_{701nm}/q_{671nm})$	Daughtry et al. (2000)
8	Normalized Difference Vegetation Index (NDVI)	$(q_{864nm}-q_{671nm})/(q_{864nm}+q_{671nm})$	Rouse et al. (1973)
9	Normalized Difference Water Index (NDWI)	$(q_{864nm}-q_{1245nm})/(q_{864nm}+q_{1245nm})$	Gao (1996)
10	Leaf Water Vegetation Index (LWVI-1)	$(q_{1094nm}-q_{893nm})/(q_{1094nm}+q_{983nm})$	This study, an NDWI variant
11	Leaf Water Vegetation Index (LWVI-2)	$(q_{1094nm}-q_{1205nm})/(q_{1094nm}+q_{1205nm})$	This study, an NDWI variant
12	Photochemical Reflectance Index (PRI)	$(q_{529nm}-q_{569nm})/(q_{529nm}+q_{569nm})$	Gamon et al. (1992)
13	Red-Edge Vegetation Stress Index (RVSI)	$((q_{712nm}+q_{752nm})/2)-q_{732nm}$	Merton & Huntington (1999)

q is the reflectance. In the equations, the wavelengths indicated are from Hyperion bands

Table 3: Average surface reflectance of the five studied sugarcane varieties for some Hyperion bands

Sugarcane types	Blue(478 nm %	Green (569 nm %)	Red (671 nm %)	NIR	SWIR	SWIR	N
COJ-64	1.30, 1.36	6.55, 7.09	5.24, 6.02	33.83, 35.91	17.02,17.78	7.98, 8.48	45
CO-238	1.31, 1.57	7.03, 7.59	5.86, 6.86	34.57, 36.77	17.76, 19.08	8.13,9.03	45
CO-1148	1.03, 1.17	5.64, 5.92	4.90, 5.30	25.39, 26.21	16.94, 17.68	8.41, 8.95	45
CO-108	1.82, 2.18	7.65, 8.43	6.71, 7.97	35.18, 36.54	18.25, 19.23	8.47, 8.97	45
COH-119	1.29, 1.31	6.46, 6.74	4.96, 5.52	32.37, 33.29	16.14, 16.88	7.32, 8.16	45

N is the number of pixels used in the calculation

Table 4: Classification results derived from the three canonical discriminant functions for a separate set of pixels

Actual group	Predicted group membership				
	COJ-64	**CO-238**	**CO-108**	**COH-119**	N
COJ-64	18(90%)	0(0%)	1(5%)	1(5%)	45
CO-238	2(10%)	16(80%)	2(10%)	0(0%)	45
CO-108	2(10%)	0(0%)	18(90%)	0(0%)	45
COH-119	1(5%)	1(5%)	0(0%)	18(90%)	45

N is the number of pixels used in the calculation.