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Segmentation based clustering of Hyperspectral Images

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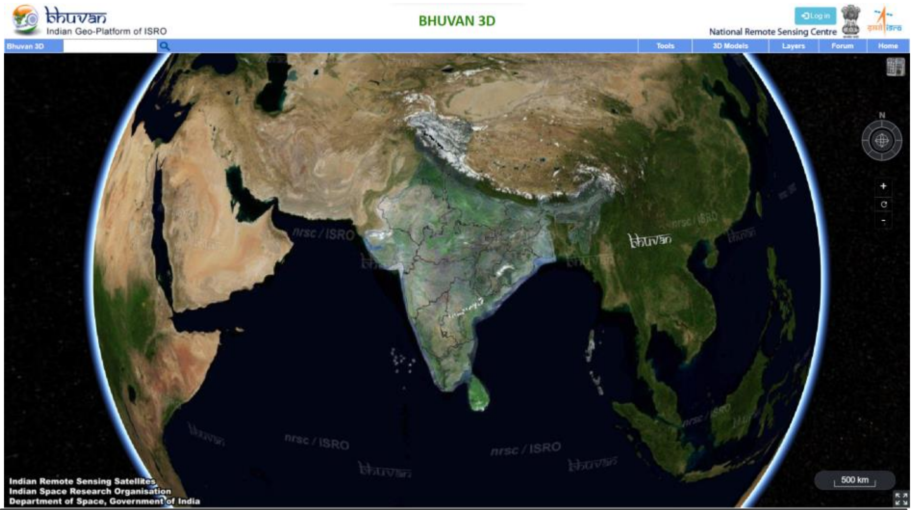
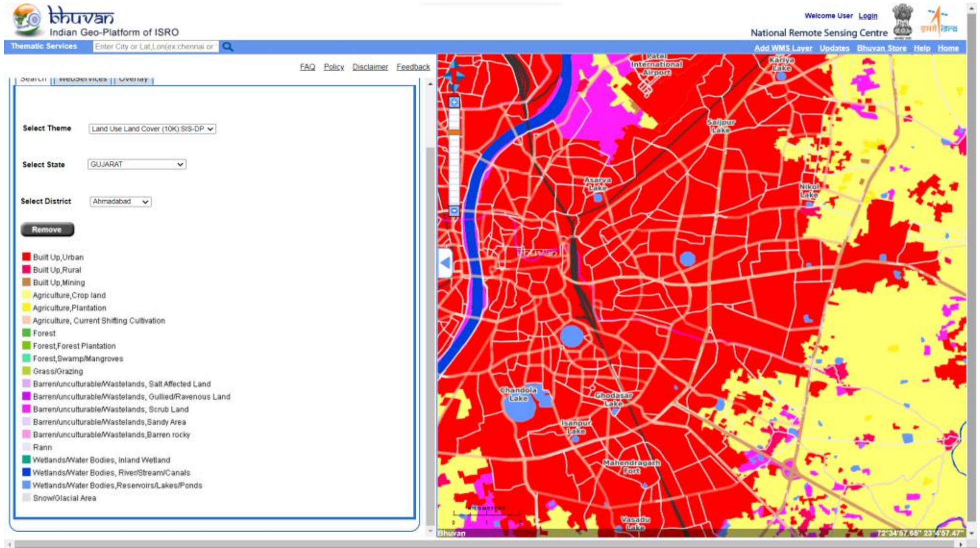
Introduction

Remote sensing refers to obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation.

- Remote sensing systems are a very important source of information for GIS, as they provide access to spatio-temporal information on surface processes on scales ranging from regional to global.
- The spatial data generally is in the form of maps, which could be showing topography, geology, soil types, forest and vegetation, land use, water resource availability etc., stored as layers in a digital form.
- Integrating many layers of data in a computer can easily generate new thematic maps.



Bhuvan, is an Indian web based utility provides a set of map based content prepared by ISRO



Land Use Land Cover data of the Ahmedabad city

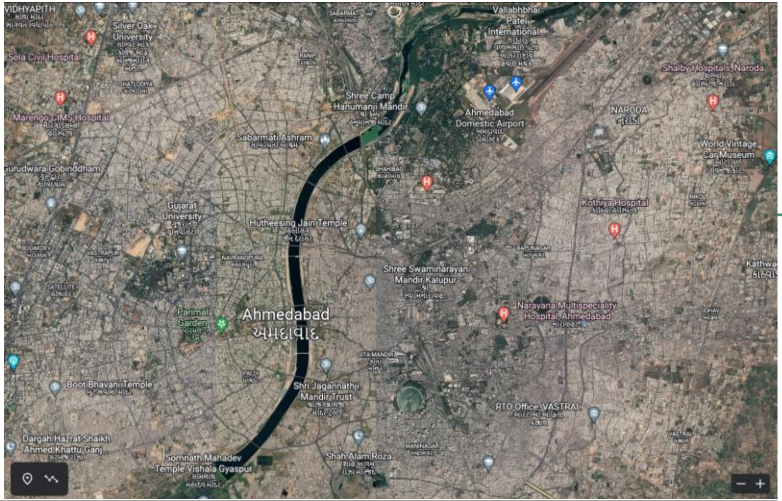
Digital Image

An image is represented by its dimensions (height and width) based on the number of pixels. This pixel is a point on the image that takes on a specific shade, opacity or color. It usually represented in Grayscale, RGB. Digital Image may consists of

- **Spatial component** describes the quality of an image and how detailed objects are in an image. If the grid cells are smaller, this means the spatial resolution has more detail with more pixels.
- **Spectral Component** describes the amount of spectral detail in a band. High spectral resolution means its bands are more narrow.
- **Radiometric Component** corresponds to the sensitivity of a sensor, i.e. its ability to measure and to enable distinction within the same spectral band of differences in the electromagnetic energy reflected by the elementary ground surfaces.
- **Temporal Component** corresponds a series of images taken at different time to monitor the dynamic changes of the objects

Temporal data showing wildfire in 2010, 2017, and 2020.

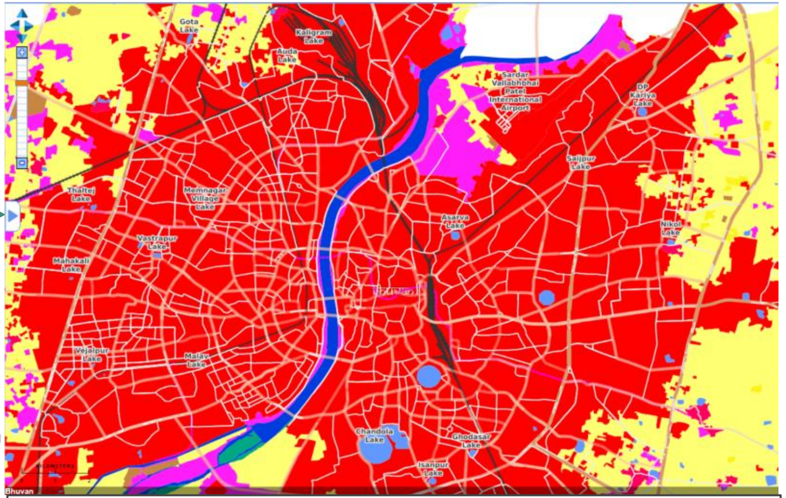
Information Conversion



Unclassified image of Ahmedabad City downloaded from Google Earth

Classification

- Built Up,Urban
- Built Up,Rural
- Built Up,Mining
- Agriculture,Crop land
- Agriculture,Plantation
- Agriculture, Current Shifting Cultivation
- Forest
- Forest,Forest Plantation
- Forest,Swamp/Mangroves
- Grass/Grazing
- Barren/unculturable/Wastelands, Salt Affected Land
- Barren/unculturable/Wastelands, Gullied/Ravenous Land
- Barren/unculturable/Wastelands, Scrub Land
- Barren/unculturable/Wastelands,Sandy Area
- Barren/unculturable/Wastelands,Barren rocky
- Rann
- Wetlands/Water Bodies, Inland Wetland
- Wetlands/Water Bodies, River/Stream/Canals
- Wetlands/Water Bodies,Reservoirs/Lakes/Ponds
- Snow/Glacial Area



Classified LULC data of Ahmedabad City downloaded from Bhuvan NRSC

Need of Land Use Land Cover Data:

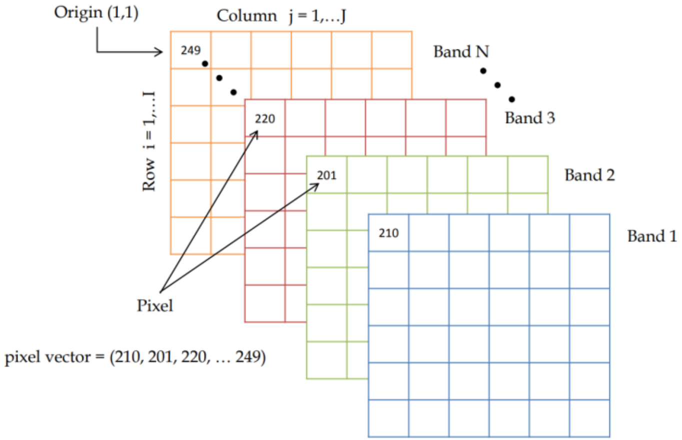
- Provides a better understanding of land utilization aspects,
- Land cover and use information may be used for planning, monitoring, and evaluation of development, industrial activity, or reclamation.

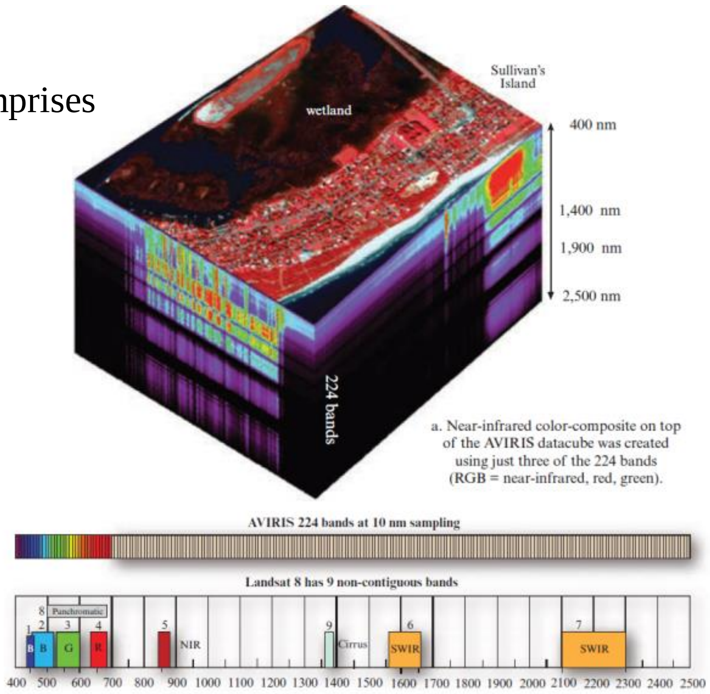
Objective

To propose a novel segmentation-based clustering methodology for classification of hyperspectral image. To improve classification accuracy of the input dataset.

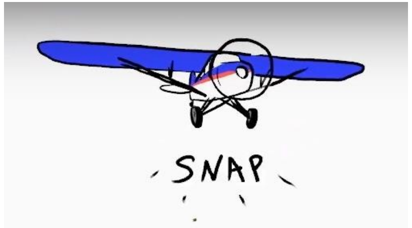
Hyperspectral image is considered in the form of a matrix which comprises information in rows and columns with number of pixels and bands.

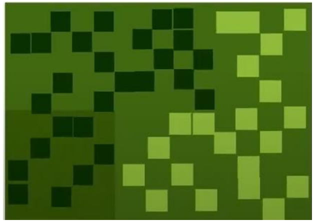
- Bands are continuous and regularly spaced.
- Higher spectral resolution, thus giving the opportunity to push further the information extraction capability

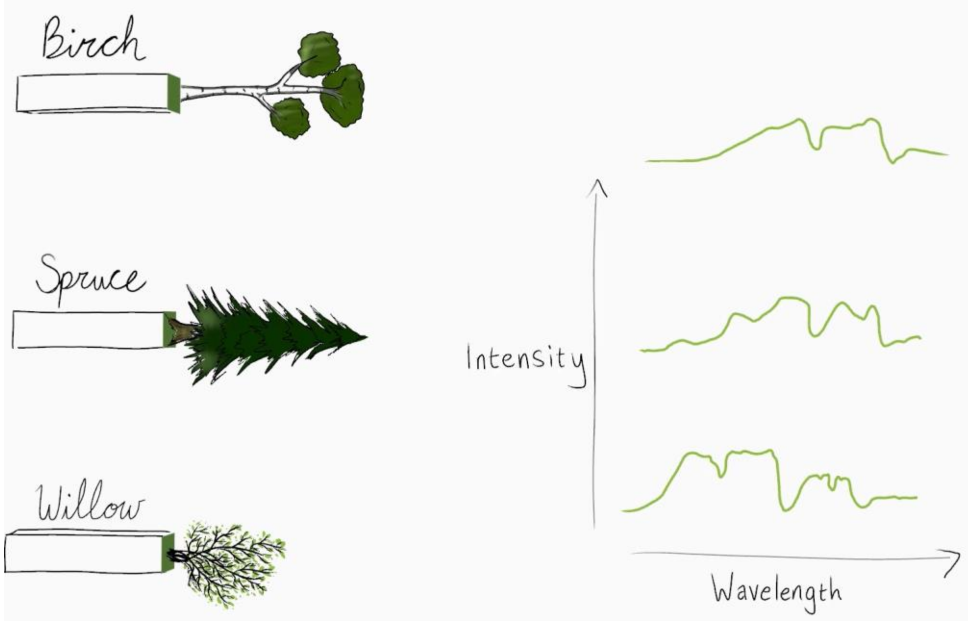


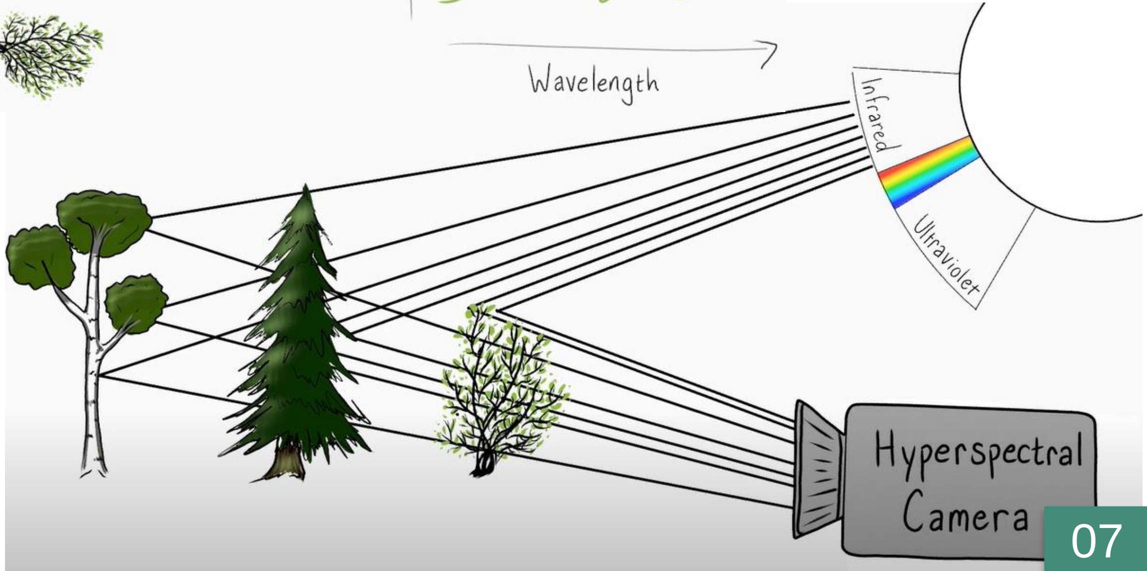


Source: Remote Sensing of the Environment – An Earth Resource Perspective, by John R. Jensen


SNAP




Birch
Spruce
Willow
Intensity
Wavelength


Infrared
Ultraviolet
Hyperspectral Camera

Literature Review

Sr No.	Year of Publication	Paper/Book	Remarks
1	August, 2022	Yao Ding; Zhili Zhang; Xiaofeng Zhao; Yaoming Cai; Siye Li; Biao Deng; Weiwei Cai, "Self-Supervised Locality Preserving Low-Pass Graph Convolutional Embedding for Large-Scale Hyperspectral Image Clustering“, IEEE Transactions on Geoscience and Remote Sensing.	Compared with supervised or semi-supervised methods, HSI clustering is often a fundamental but challenging task, due to prior knowledge deficiency, large spectral variability, and high dimension of HSI.
2	February, 2022	Sen Jia; Yue Yuan; Nanying Li; Jianhui Liao; Qiang Huang; Xiuping Jia; Meng Xu, "A Multiscale Superpixel-Level Group Clustering Framework for Hyperspectral Band Selection", IEEE Transactions on Geoscience and Remote Sensing.	Principal Component Analysis (PCA) was introduced as a linear dimensionality reduction technique for HSI which projects the high-dimensional data to a low-dimensional subspace with principal components maximizing the variance of the projected data.
3	April, 2020	J. Chang, G. Meng, L. Wang, S. Xiang and C. Pan, "Deep self-evolution clustering", IEEE Trans. Pattern Anal. Mach. Intel.	The key to the HSI clustering is to measure the similarity between data points.
4	July, 2017	Y. Li, L. Zhang, C. Tian, C. Ding, Y. Zhang and W. Wei, "Hyperspectral image super-resolution extending: An effective fusion based method without knowing the spatial transformation matrix", Proc. IEEE Int. Conf. Multimedia Expo (ICME)	The abundant spectral information of HSIs comes at the cost of greatly reducing spatial resolution which hinders the widespread applications of HSIs.

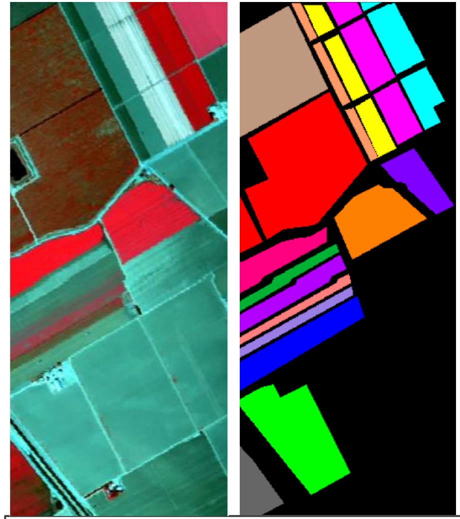
Literature Review

Sr No.	Year of Publication	Paper/Book	Remarks
5	January, 2013	B. Luo, C. Yang, J. Chanussot and L. Zhang, "Crop yield estimation based on unsupervised linear unmixing of multidate hyperspectral imagery", IEEE Trans. Geosci. Remote Sens.	HSIs can provide rich band information from different wavelengths and thus get widely used in various research field, such as biological analysis.
6	October, 2011	J. Khodr and R. Younes, "Dimensionality reduction on hyperspectral images: A comparative review based on artificial datas“.	Moreover, due to the high correlation among the neighboring bands, which not only increases the computational complexity of the classifiers but also may have a negative impact on the classification accuracy, dimensionality reduction (DR) should be applied as a preprocessing step to discard the redundant information.
7	December, 2007	A. Martínez-usó, F. Pla, J. M. Sotoca and P. García-sevilla, "Clustering-based hyperspectral band selection using information measures", IEEE Trans. Geosci. Remote Sens.	The importance of a band obtained by unsupervised methods is evaluated by various statistical measures or clustering quality assessment which is unrelated to the labeled sample size.

Dataset

The experiments were conducted over one set of hyperspectral images respectively is Salinas.

Salinas scene was collected by the 204-band AVIRIS sensor over Salinas Valley, California, and is characterized by high spatial resolution (3.7-meter pixels). The area covered comprises 512 lines by 217 samples. This image was available only as at-sensor radiance data. It includes vegetables, bare soils, and vineyard fields. Salinas ground truth contains 16 classes.



Salinas and Ground Truth

Broccoli green weeds 1	Broccoli green weeds 2	Fallow	Fallow rough plow	Fallow smooth
Stubble	Celery	Grapes untrained	Soil vineyard develop	Corn senesced green weeds
Lettuce romaine 4 weeks	Lettuce romaine 5 weeks	Lettuce romaine 6 weeks		
Lettuce romaine 7 weeks	Vineyard untrained	Vineyard vertical trellis	Unlabeled	

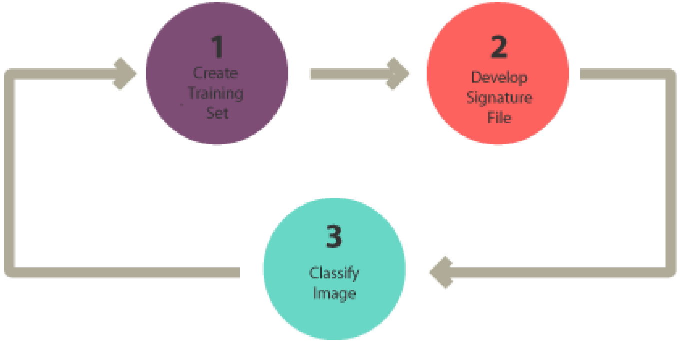
Source: Salinas Dataset, 2021: www.ehu.eus/Hyperspectral_Remote_Sensing_Scenes

Methodology

Image Classification

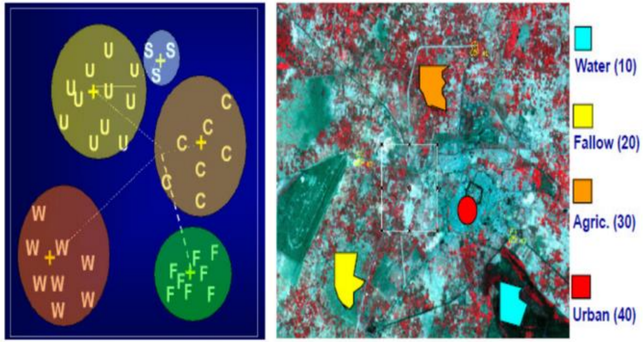
Image classification is the process of categorizing and labeling groups of pixels or vectors within an image based on specific rules. The categorization law can be devised using one or more spectral or textural characteristics.

- Each pixel of the image is assigned to a particular class.
- Classification transforms the image data into an information



1. Supervised Classification

- Identify training set (information class),
- Select sample pixels in an image representing specific class,
- Direct the image processing software to use training sets as references for the classification of all other pixels in the image.



Training Sets

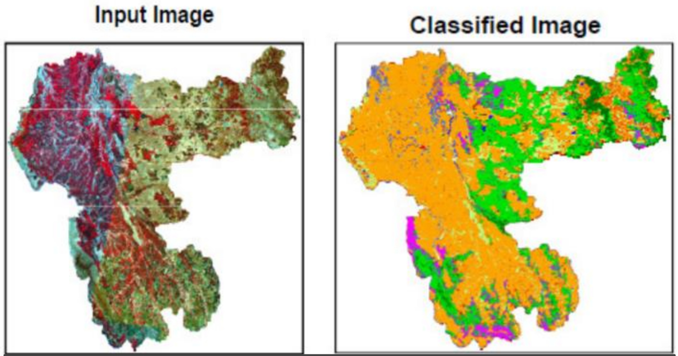


Image Classification

Source: https://gisgeography.com/supervised-unsupervised-classification-arcgis/

2. Unsupervised classification

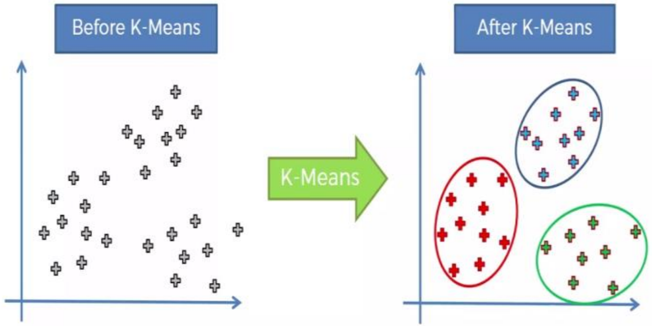
Unsupervised classification requires no advance information about the classes of interest. Rather, it examines the data and breaks it into the most prevalent natural spectral groupings, or clusters, present in the data.

k-means clustering

***k*-means** is a commonly used partitioning based clustering technique that tries to find a user specified number of clusters *(k)*, which are represented by their centroids, by minimizing the square error function. Although *k*-means is simple and can be used for a wide variety of data types.

The steps of the k-means algorithm are written below:

- Initialization: choose randomly *k* pixel vectors (data points) to initialize the clusters.
- Nearest-neighbor search: for each input vector, find the cluster center that is closest, and assign that input vector to the corresponding cluster.
- Mean update: update the cluster centers in each cluster using the mean (centroid) of the input vectors assigned to that cluster.



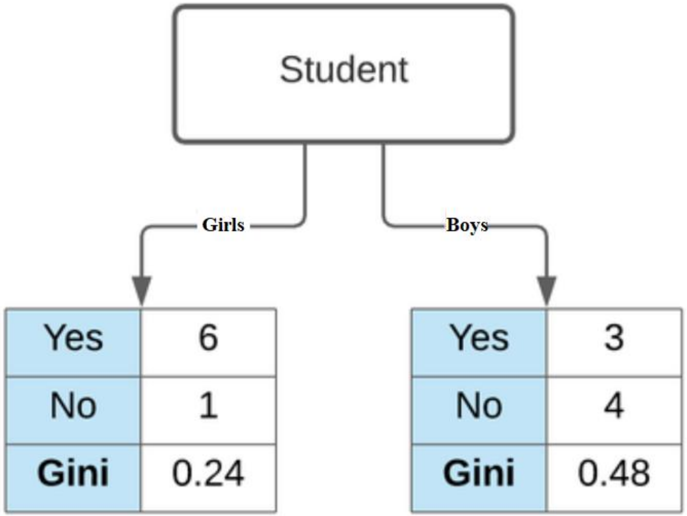
k-means clustering algorithm

Gini Impurity

Gini Impurity measures the probability for a random instance being misclassified when chosen randomly. The **lower** the **Gini Impurity**, the **lower** the **likelihood** of misclassification.

Consider a dataset *D* that contains samples from *k* classes. The probability of samples belonging to class *i* at a given node can be denoted as *pi*. Then the Gini Impurity of is defined as:

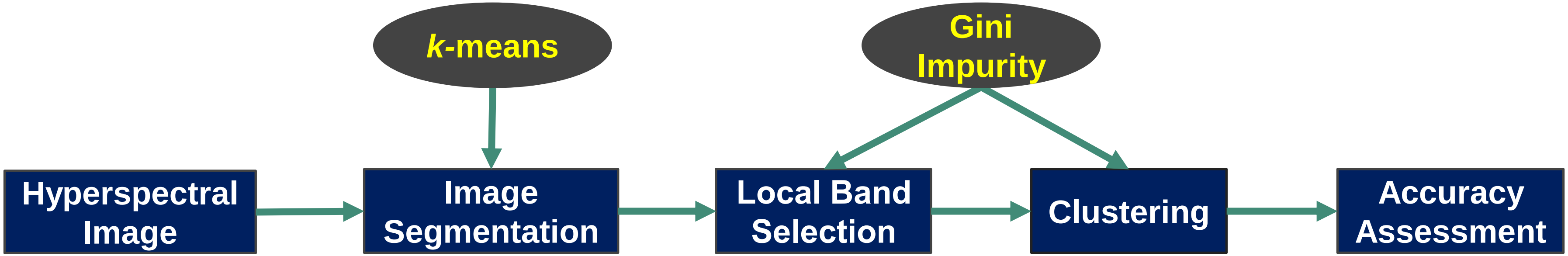
$$Gini\ (D) = 1 - \sum_{i=1}^{k} p_i^2$$



Gini Impurity for Student is 0.367

Source: https://www.learndatasci.com/glossary/gini-impurity/

Proposed Methodology



NMI and Purity

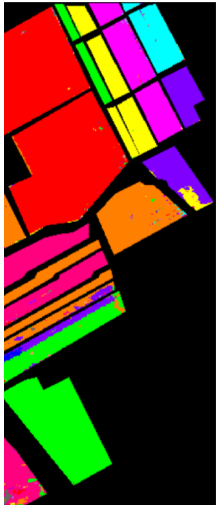
- **Purity** is a measure of the extent to which clusters contain a single class.
- **Mutual Information** is a function that measures the agreement of the two assignments.

$$NMI(\Omega,\mathbb{C}) = \frac{MI(\Omega,\mathbb{C})}{\mathrm{mean}(H(\Omega),H(\mathbb{C}))}$$

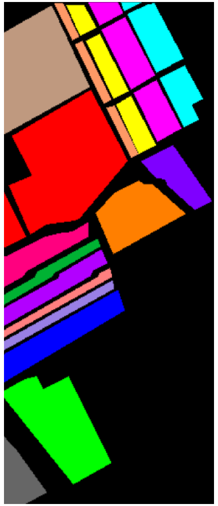
$$MI(\Omega,\mathbb{C}) = \sum_k \sum_j p(\omega_k \cap c_j)\log_2 \frac{p(\omega_k \cap c_j)}{p(\omega_k)\,p(c_j)}$$

$$H(\Omega) = -\sum_k p(\omega_k)\log_2 p(\omega_k)$$

$$Purity(\Omega,\mathbb{C}) = \frac{1}{N}\sum_k \max_j \left|\omega_k \cap c_j\right|$$



Classified



Reference

Broccoli green weeds 1	Broccoli green weeds 2	Fallow	Fallow rough plow	Fallow smooth
Stubble	Celery	Grapes untrained	Soil vineyard develop	Corn senesced green weeds
Lettuce romaine 4 weeks	Lettuce romaine 5 weeks	Lettuce romaine 6 weeks		
Lettuce romaine 7 weeks	Vineyard untrained	Vineyard vertical trellis	Unlabeled	

$\Omega = \{\omega_1,\ \omega_2,\ \omega_3, \ldots\ldots,\ \omega_k\}$ is the set of clusters.

$\mathbb{C} = \{c_1,\ c_2,\ c_3, \ldots\ldots\ldots,\ c_j\}$ is the set of classes obtained from reference image

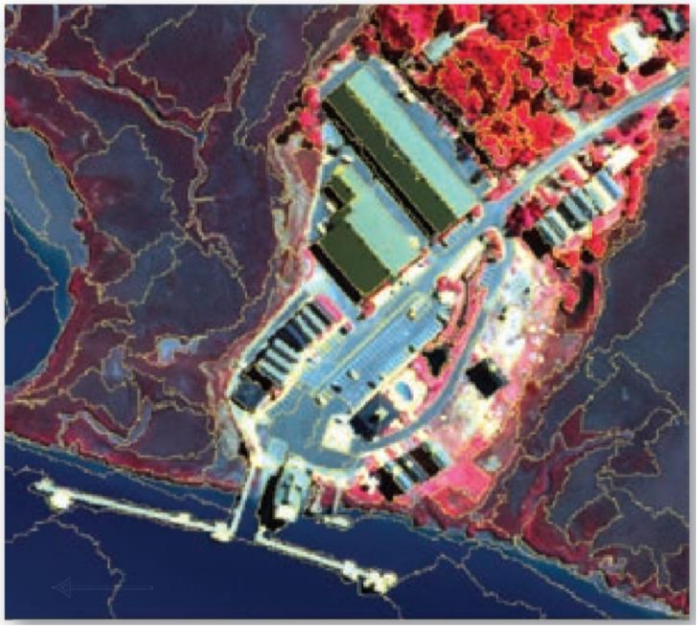
N is total number of pixel sample image

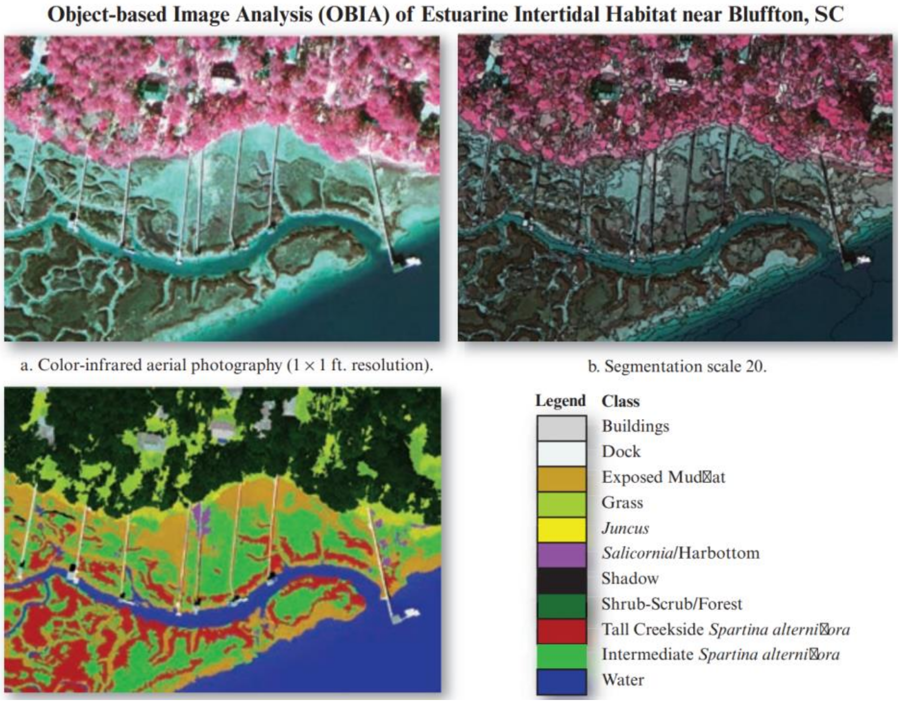
http://nlp.stanford.edu/IR-book/html/htmledition/evaluation-of-clustering-1.html
Cai, D., X. He, and J. Han. 2005. “Document Clustering Using Locality Preserving Indexing.” IEEE Transactions on Knowledge and Data Engineering, 17 (12): 1624-1637.

Image Segmentation

Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image.

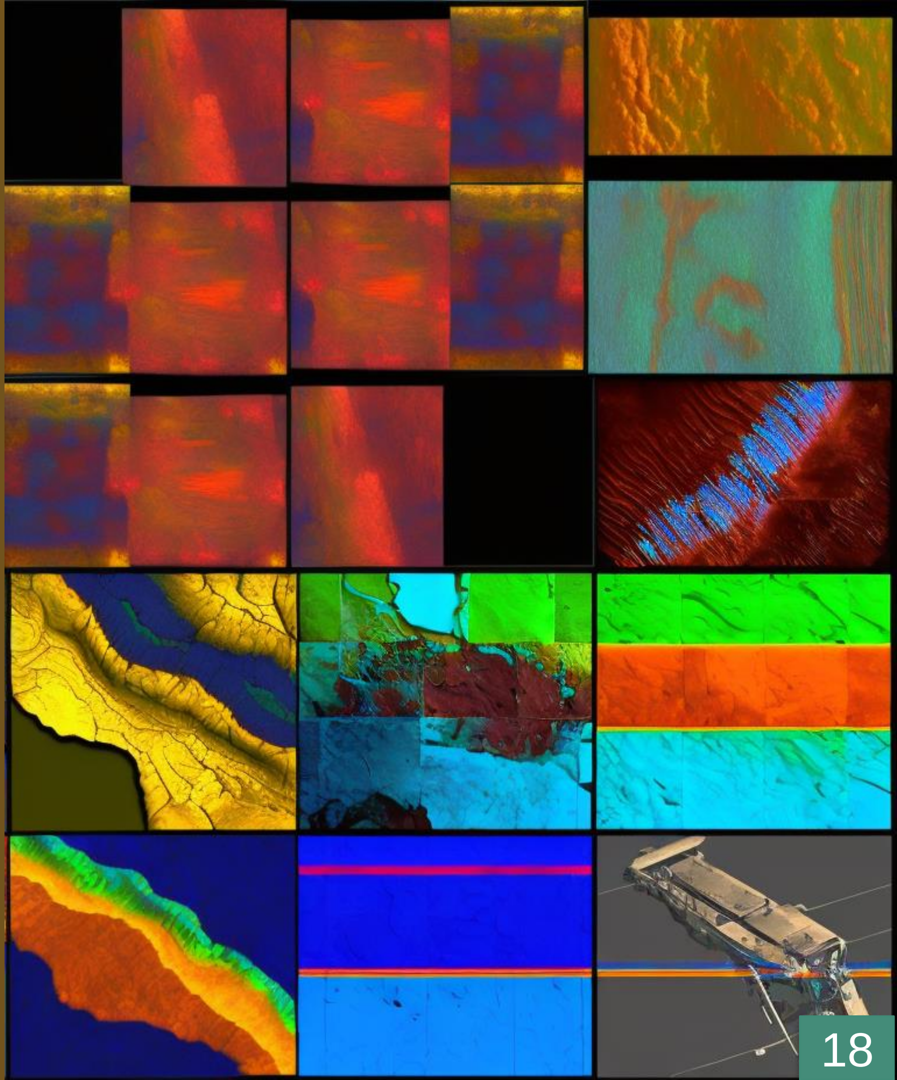
Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture.





John R. Jensen. 2016.Introductory digital image processing: A remote sensing perspective. Pearson, 4th edition.

LOCAL BAND SELECTION



Local Band Selection

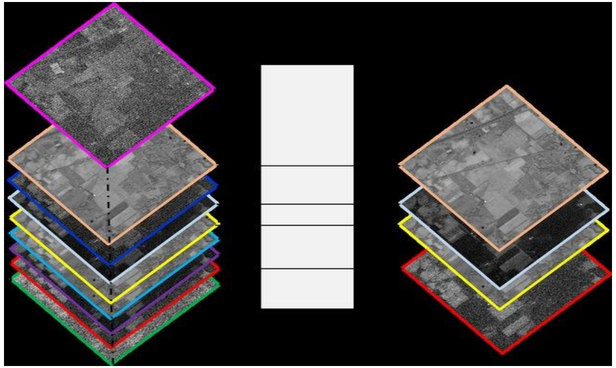
A hyperspectral image has a very high spectral resolution due to the number of pixels and bands it contains. As a result, it's important to arrange number of bands in a dataset without drastically reducing the amount of information maintained.

It is necessary to perform band selection method as:

- These bands make training extremely slow.
- Harder to find a good solution.

Steps for selecting top-ranked bands:

- Gini impurity is used as a ranking criteria to select the top-ranked bands in a sorted sequence containing relevancy and less redundancy.
- A distance-weighted parameter called score is introduced to prevent bands with same gini indices.



Band Selection Technique

Source:
https://www.researchgate.net/profile/PedramGhamisi/publication/322281687/figure/fig1/AS:580431734743040@1515397117915/Hyperspectral-image-dimensionality-reduction_W640.jpg

Local Band Selection

To calculate ***score***, *delta* function is used that stores maximum distance for a test band from all bands whose gini index is higher than that of test band.

Formally, score is formulated in equation as :

$$delta = \max_{GI_j > GI_i} d$$

$$score = (delta) \times (GI_i)$$

where,

d is distance between mean vectors of all pixels in a cluster for particular segment to remaining bands of the segment,

GI is the gini index for corresponding bands,

i and j are band indexes.

```python
gini_band=np.argsort(gini_band)
for i in range(k_cl):
    t = int(sig_gini[i])
    b_dist = np.zeros((d,d))  # to store euclidean distance among all band for a particular segment
    for x in range(d):
        for y in range(d):
            b_dist[x,y] = np.linalg.norm(seg_nxk[t,x] - seg_nxk[t,y])

    for j in range(d):
        max = 0
        for k in range(d):
            #first condition for band whose gini greater than jth band
            if gini_band[t,k] > gini_band[t,j] :
                #finding max distance among band whose gini is greater than jth band
                if b_dist[j,k] > max :
                    max = b_dist[j,k]
        temp_array[i,j] = max

scaler = MinMaxScaler()
m = scaler.fit(temp_array)
delta = m.transform(temp_array)
```

Calculation of delta function, that stores maximum distance for a test band from all bands whose gini index is higher than that of test band.

```python
score = np.zeros((k_cl,d))     #creating a parameter for sorting by multiplying gini and max distance.
for i in range(k_cl):
    t = int(sig_gini[i])
    for j in range(d):
        score[i,j] = gini_band[t,j] * delta[i,j]

score = np.argsort(-score) #sorting in decreasing order
```

Calculation of score, that stores delta × Gini Index for each band.

Bands and their Ginni index →

	195	196	197	198	199	200	201	202	203
1	0.021692	0.0230723	0.0335522	0.0219146	0.0144928	0.020979	0.0384615	0.0880503	0.0229885
2	0.00789323	0.00562622	0.00534442	0.0134615	0.00415007	0.0141213	0.0131356	0.0331633	0.0212264
3	8.20811e-06	8.94757e-06	1.29875e-05	1.45632e-05	1.02886e-05	1.32118e-05	2.68666e-05	5.76632e-05	6.85619e-05
4	0.000737585	0.00070852	0.000668785	0.000666158	0.00067554	0.000713212	0.000872111	0.000294318	0.000585651

Top 12 Significant Bands (L = 12) →

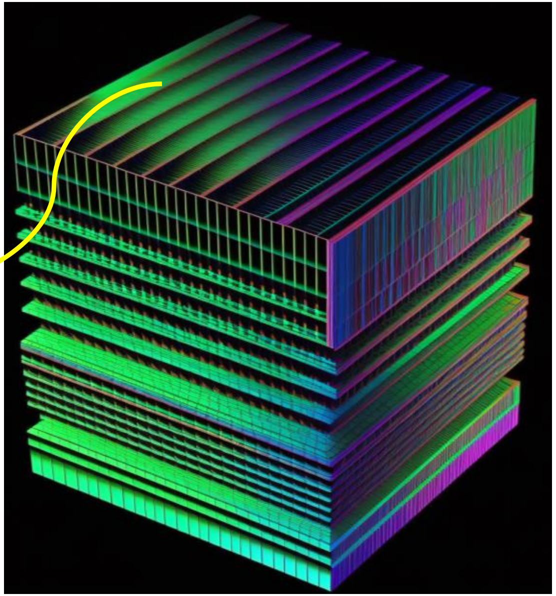
Top 16 Significant Segments (*k*_cl = 16) →

	0	1	2	3	4	5	6	7	8	9	10	11
0	203	31	30	33	29	28	27	32	34	1	26	25
1	0	130	131	132	133	134	135	136	137	138	139	140
2	203	56	59	57	55	54	51	74	58	47	52	50
3	203	31	30	33	29	28	27	32	34	1	26	25
4	203	31	30	33	29	28	27	32	34	1	26	25
5	0	130	131	132	133	134	135	136	137	138	139	140
6	203	31	30	33	29	28	27	32	34	1	26	25
7	203	31	30	33	29	28	27	32	34	1	26	25
8	0	130	131	132	133	134	135	136	137	138	139	140
9	0	130	131	132	133	134	135	136	137	138	139	140
10	203	31	30	33	29	28	27	32	34	1	26	25
11	203	31	30	33	29	28	27	32	34	1	26	25

SEGMENTATION

Input image (in matrix form of size 512 x 217)

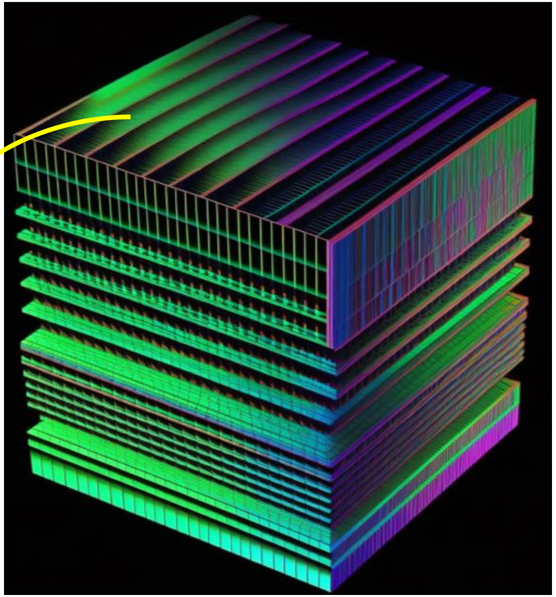
	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100	101	102	103
64	304	304	375	375	375	375	304	446	304	304	375	304	304	375	375	304	304	304	375	375
65	374	231	303	374	303	303	303	231	303	303	231	303	374	303	374	374	303	303	303	303
66	308	308	379	308	308	308	308	308	379	308	308	308	379	308	451	308	308	308	308	379
67	308	308	298	298	298	369	298	298	298	298	298	298	298	298	441	298	298	298	298	369
68	369	298	298	298	298	369	298	298	298	298	298	298	298	298	441	298	298	298	298	369
69	369	227	369	298	298	298	298	441	298	298	369	298	298	227	298	227	298	298	298	298
70	365	365	294	365	294	365	365	365	365	365	294	365	294	365	294	222	365	294	294	436
71	300	300	372	372	372	300	300	300	372	300	300	300	372	300	372	300	372	372	300	372
72	300	300	372	372	372	300	300	300	372	300	300	300	305	305	233	305	305	376	305	447
73	305	305	305	233	305	305	376	376	305	376	376	376	305	305	233	305	305	376	305	447
74	316	245	387	316	387	316	316	316	387	316	387	245	316	316	316	316	316	316	387	387
75	306	306	306	306	235	449	377	377	306	306	306	306	306	306	377	306	306	306	306	306
76	306	306	306	306	305	376	376	305	305	305	305	305	376	305	233	233	376	305	305	305
77	305	233	305	305	305	376	376	305	305	305	305	305	376	305	233	233	308	308	308	308



Segmented image (in matrix form of size 512 x 217)

Total 170 Segments

	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98
64	25	25	23	23	23	23	23	23	16	16	16	21	21	21	21
65	25	25	25	23	23	23	23	23	23	16	16	21	21	21	21
66	25	25	25	25	25	23	23	23	23	16	16	21	21	21	21
67	25	25	25	25	25	25	23	23	23	23	16	16	16	21	21
68	25	25	25	25	25	25	23	23	23	23	16	16	16	21	21
69	25	25	25	25	25	25	23	23	23	23	23	16	16	21	21
70	25	25	25	25	25	25	25	23	23	23	23	16	16	23	21
71	25	25	25	25	25	25	23	23	23	23	23	23	23	23	21
72	25	25	25	25	25	25	23	23	23	23	23	23	23	23	23
73	25	25	25	25	25	25	23	23	23	23	23	23	23	23	23
74	25	25	25	25	25	25	25	23	23	23	23	23	23	23	23
75	25	25	25	25	25	25	25	23	23	23	23	23	23	23	23
76	25	25	25	25	25	25	25	25	23	23	23	23	23	23	23
77	25	25	25	25	25	25	25	25	23	23	23	23	23	23	23



```
gni_mat = np.zeros((numRegns,1))    #gini index for all segment
n_pix = np.zeros((numRegns,1))
k_cl = 16
i = 0
L = 12 # Top bands
```

Calculation of Gini index for each segments.

```
#for significant segments
for prop in regions:
    pxIdLst = prop.coords
    matrix = np.zeros((len(pxIdLst),d))
    for j in range(d):
        band = mat[pxIdLst[:,0],pxIdLst[:,1],j];
        for aa in range(len(band)):
            matrix[aa,j] = band[aa] #matrix for each segment
    gni_mat[i] = gini(matrix)       #gini for each segment
    n_pix[i] = len(pxIdLst)

    i = i + 1
```

```
sig_gini = np.zeros(numRegns)
for i in range(numRegns):
    sig_gini[i] = 50
    if(n_pix[i]> 5):
        sig_gini[i] = gni_mat[i]

sig_gini = np.argsort(sig_gini)
```

Considering only those segments in which no. of pixels is greater than 5 and calculating Significant Segments on the basis of Gini Index and number of pixels.

Segments are arranged (Ascending) based on their Ginni index

	Ginni Index 0	No. of Segments 1
0	0.000524715	0
1	0.000280672	1
2	5.01864e-05	2
3	8.64598e-05	3
4	0.000393657	4
5	0.000217093	5
6	0.000101229	6
7	0.00185795	7
8	0.000696704	8
9	7.55814e-05	9
10	7.44806e-05	10

	Ginni Index 0	No. of Segments 1
0	1.1574e-05	120
1	2.46516e-05	98
2	2.54236e-05	162
3	2.57029e-05	115
4	2.633e-05	135
5	3.01953e-05	21
6	3.22963e-05	130
7	3.43106e-05	12
8	3.48677e-05	108
9	3.75538e-05	125
10	3.77923e-05	136

Best 16 Segments

Pairwise distances of remaining segments from best 16 Segments.

Remaining Segments (16 to 169) →

	164	165	166	167	168	169
4	14766.9	12539.6	15167	16576.8	15707.1	22521.2
5	14938.9	12559.9	15317.2	14621.5	15873.9	23154.6
6	15332	12879.2	15689.3	13183	16255.2	23814.5
7	9925.26	8490.33	10352.3	21179.7	10766.6	16306.1
8	15810.6	13306.8	16150.9	11852.6	16712.8	24468.2
9	9334.36	6868.82	9632.57	14259.5	10174.3	18345.8
10	14626.6	12303.9	15013.8	15421	15567	22685.2
11	14833.3	12702.4	15241.6	17580	15767.7	22305.2
12	9836.59	7815.7	10249.1	18398.5	10781.3	17427.4
13	14978.2	12641.6	15363.9	15235.1	15914.7	23048.5
14	15284.5	12840.3	15647.7	13453.2	16206.1	23705.5
15	14475.1	12440.1	14891.1	18426.5	15404.8	21708.9

Labels are assigned to remaining segments according to minimum distance from best 16.

	0
159	9
160	9
161	7
162	7
163	9
164	9
165	9
166	9
167	8
168	9
169	7

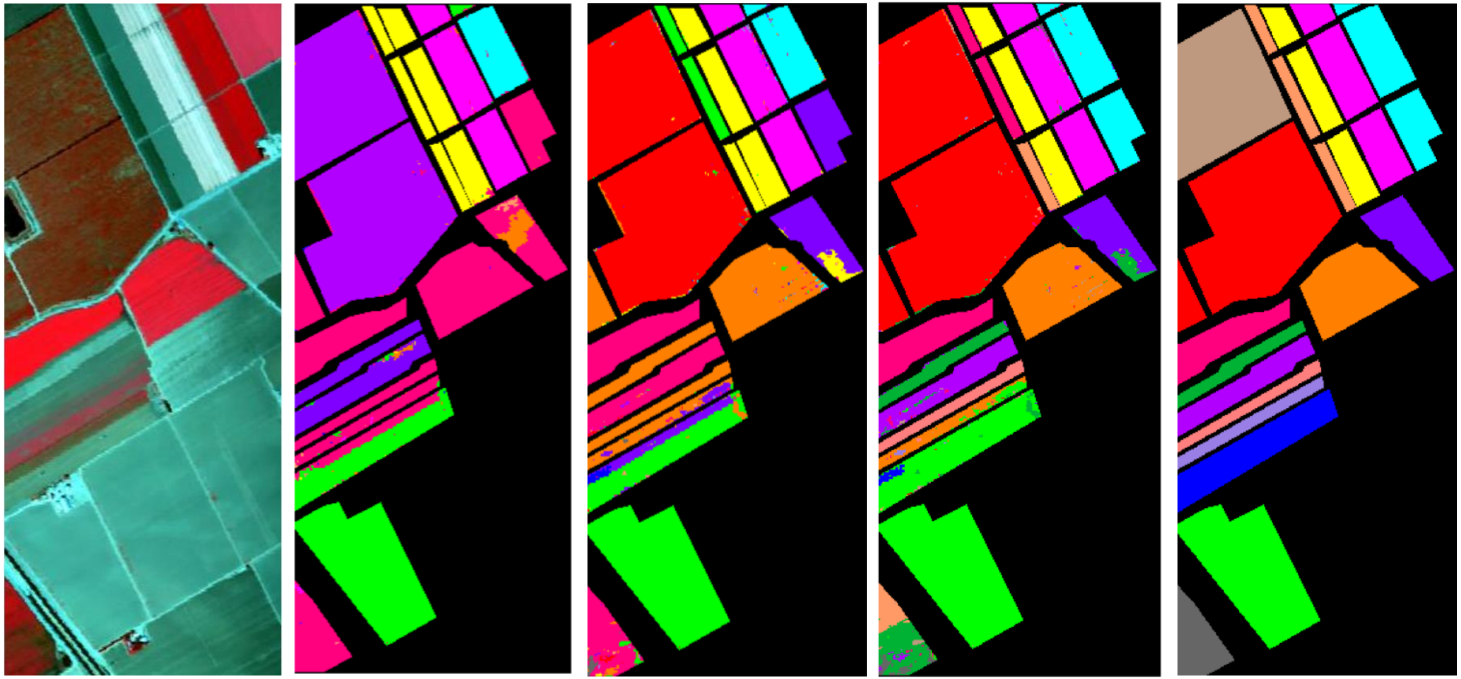
- **Best 16 out 170 segments are identified.**
- **Labels (0 to 15) are given to remaining segments according to minimum distance from best 16.**

Relabelled Segmented image (in matrix form of size 512 x 217)

Total 16 Segments

	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100	101	102	103
64	9	9	14	14	14	14	14	14	15	15	15	4	4	4	4	4	4	4	4	4
65	9	9	9	14	14	14	14	14	14	15	15	4	4	4	4	4	4	4	4	4
66	9	9	9	9	9	14	14	14	14	15	15	4	4	4	4	4	4	4	4	4
67	9	9	9	9	9	9	14	14	14	14	15	15	15	4	4	4	4	4	4	4
68	9	9	9	9	9	9	14	14	14	14	15	15	15	4	4	4	4	4	4	4
69	9	9	9	9	9	9	14	14	14	14	14	15	15	4	4	4	4	4	4	4
70	9	9	9	9	9	9	9	14	14	14	14	15	15	14	4	4	4	4	4	4
71	9	9	9	9	9	9	14	14	14	14	14	14	14	14	4	4	4	4	4	4
72	9	9	9	9	9	9	14	14	14	14	14	14	14	14	14	4	4	4	4	4
73	9	9	9	9	9	9	14	14	14	14	14	14	14	14	14	4	4	4	4	4
74	9	9	9	9	9	9	9	14	14	14	14	14	14	14	14	4	4	4	4	4
75	9	9	9	9	9	9	9	14	14	14	14	14	14	14	14	14	4	4	4	4
76	9	9	9	9	9	9	9	9	14	14	14	14	14	14	14	14	4	4	4	4
77	9	9	9	9	9	9	9	9	14	14	14	14	14	14	14	14	14	14	14	4

Results And Discussion



Salinas | k_seg | k_seg + LBS_R | proposed | Reference

Broccoli green weeds 1 | Broccoli green weeds 2 | Fallow | Fallow rough plow | Fallow smooth
Stubble | Celery | Grapes untrained | Soil vineyard develop | Corn senesced green weeds
Lettuce romaine 4 weeks | Lettuce romaine 5 weeks | Lettuce romaine 6 weeks
Lettuce romaine 7 weeks | Vineyard untrained | Vineyard vertical trellis | Unlabeled

Results And Discussion

Datasets	Salinas	
Methods	**NMI**	**Purity**
k-means	0.7242	0.6734
*k*_seg	0.7921	0.6738
*k*_seg + LBS_R	0.7932	0.6426
proposed (*k*_seg+ LBS)	**0.8130**	**0.7011**

Parameter Settings

← Methods

Variables →	*k_seg*	*k*_cl	L
k-means	-	16	All bands
*k*_seg	5	28	All bands
*k*_seg + LBS_R	7	18	12
proposed (*k*_seg+ LBS)	**6**	**26**	**12**

*k*_seg is number of segments,
*k*_cl is number of significant clusters,
L is number of significant bands taken,
LBS_R is Local Band Selection with Redundant bands,
LBS is Local Band Selection without Redundancy.

Summary

In this study several approaches of image classification based on **segmentation clustering** with **local band selection** techniques through **gini impurity** are preformed in order to enhance relevancy and remove redundancy.

Experiments were performed on Salinas dataset and the results were compared on the basis of accuracy assessment.

- Among the evaluated methods, higher accuracy is achieved by segments consisting less redundant bands.
- The accuracy measurements in terms of NMI for ***k*_seg + *LBS*** for dataset Salinas is **0.8130** respectively.
- While, the other methods have comparatively less accuracy than above mentioned.

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THANK YOU